

CRANFIELD UNIVERSITY

Murad Ellafi

Application of Artificial Neural Networks in the Design of Drainage
Systems in Data-poor Areas

School of Water, Energy and Environment

PhD

Academic Year: 2021 - 2022

Supervisor: Dr Robert Simmons

Associate Supervisor: Dr Lynda Deeks

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This thesis is submitted in partial fulfilment of the requirements for
the degree of PhD

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ABSTRACT

Drainage has been identified as an often-neglected component of irrigated agriculture in arid and semi-arid areas. Even though it is accepted that drainage is often necessary to prevent waterlogging and salinity impacting productivity in irrigated agriculture, it is typically ignored when planning future irrigation schemes. Only 5 – 10% of the total irrigated land in Least Developed Countries (LDCs) that requires drainage is currently drained (compared to 25 – 30% in developed countries). This is partly due to a fundamental lack of spatially and temporally coherent datasets containing key input parameters for drainage models, local expertise and the high cost of drainage installation. Drainage simulation models can provide reliable predictions of multi-component systems to evaluate drainage system design over long periods (1 – 100 years). This study evaluated existing drainage simulation models (i.e. DRAINMOD, SWAP, ADAPT, RZWQM2, EPIC, WaSim and HYDRUS-1D) for their suitability to be applied in data-poor arid and semi-arid regions. Based on a selection criteria, the most applicable model for drainage design in arid and semi-arid areas was DRAINMOD.

DRAINMOD, an agricultural drainage simulation model, is a versatile and readily available model that can be used to evaluate alternative drainage system designs. DRAINMOD requires several key inputs, including saturated hydraulic conductivity (K_{sat}), reference evapotranspiration (ET_0) and the Electrical Conductivity of a saturated soil Extract (EC_e). In LDCs, measuring these parameters is expensive and time-consuming. In addition, existing historic datasets are often spatially and temporally limited. Therefore, indirect approaches are needed to overcome incomplete data records that restrict drainage designs. This thesis evaluates the feasibility of applying indirect methods, with a focus on developing and validating the use of artificial neural networks (ANNs) using available historic measured datasets. The study data draws on the drainage design for Hammam Agricultural Project (HAP) and Eshkeda Agricultural Project (EAP), located in the south of Libya, north of the Sahara Desert.

Soil texture, bulk density, field capacity, and wilting point were used to develop ANNs to predict K_{sat} which were significantly more accurate compared to widely adopted Pedotransfer functions (PTFs) such as Rosetta3. To calculate the daily ET_0 , average monthly maximum and minimum air temperature were used to develop ANNs. Arithmetic Averaging of Neighbouring Stations (AANS), MODAWEC and Era5-Land were among the indirect methods applied to predict ET_0 . Landsat 5 Surface Reflectance bands and the derived salinity indices were applied to develop ANNs to estimate EC_e . The accuracy of the predicted values

of K_{sat} , ET_0 and EC_e were evaluated by using statistical parameters such as coefficient of determination (R^2), mean square error (MSE), and root mean square error (RMSE).

The predicted K_{sat} and ET_0 values were input to DRAINMOD to design drainage systems in EAP and HAP as compared to the optimum design based on measured data. The design focused on how accurately the predicted values were able to estimate drain spacing, relative yield, irrigation depth, and drainage discharge. The key findings showed that the accuracy of predicting K_{sat} greatly impacted predicting the optimum drain spacing and the associated relative yield. Accurate prediction of the optimum spacing between drains will reduce the overall cost by ensuring that the drains are not spaced too closely, but also lowers the risk of raising the water table and negatively impacting the yield by preventing the drains being installed on too wider a spacing. In addition, precisely predicting ET_0 is essential to quantify the irrigation water requirement and drainage discharge. Finally, predicting soil salinity using remote sensing data can be used as an early warning tool to monitor irrigated lands affected by salinity, evaluate the performance of existing drainage systems, and indicate areas that need improvement. Future research recommendations identified by this research include the need for (1) critical evaluation of the accuracy of using ANNs and other machine learning approaches to predict other input parameters required for drainage design such as the water retention curve, depth of impermeable layer, hourly or daily rainfall, and initial water table depth. (2) development and validation of ANNs and other machine learning approaches that can predict K_{sat} , ET_0 , and EC_e on a national level (Libya) and/or regional level (Middle East and North Africa) to overcome the challenge of incomplete data records that restrict drainage designs.

Keywords:

Agricultural drainage design, arid areas, artificial neural networks, saturated hydraulic conductivity, evapotranspiration, soil salinity

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LIST OF ABBREVIATIONS

AANS	Arithmetic Averaging of Neighbouring Stations
ADAPT	Agricultural Drainage and Pesticide Transport
Adl	Above drain level
AET	Actual evapotranspiration
ALMANAC	Agricultural Land Management Alternatives with Numerical Assessment Criteria
ANNs	Artificial neural networks
asl	Above sea level
BD	Bulk density
Bdl	Below drain level
BI	Brightness index
BREC	Blackland Research and Extension Centre
C	Clay
CFMASK	C Version of Function of Mask
CREAMS	Chemicals, Runoff, and Erosion from Agricultural Management Systems
DC	Drainage coefficient
DD	Drainage depth
DEM	Digital elevation model
DOY	Day of the year
DSSAT	Decision Support System for Agrotechnology Transfer
DTC	Drainage Training Center
DTmax	Daily maximum air temperature
DTmin	Daily minimum air temperature
EAP	Eshkeda Agricultural Project
EC	Soil electrical conductivity
ECe	Electrical Conductivity of a saturation extract
ECMWF	European Centre for Medium-Range Weather Forecasts
EPADP	Egyptian Public Authority for Drainage Projects
EPIC	Environmental Policy Integrated Climate
ERA5-Land	5 TH generation ECMWF reanalysis for the global climate
ERATmax	Daily maximum air temperature predicted by ERA5-Land

ERATmin	Daily minimum air temperature predicted by ERA5-Land
ET	Evapotranspiration
ET0	Reference evapotranspiration
FAO	Food and Agriculture Organization
FC	Field capacity
GEE	Google Earth Engine
GIS	Geographical information system
GLEAMS	Groundwater Loading Effects of Agricultural Management Systems
GSI	Grain size index
GTmax	Global daily maximum air temperature simulation data
GTmin	Global daily minimum air temperature simulation data
GWA	General Water Authority in Libya
HAP	Hammam Agricultural Project
HEC-HMS	Hydrologic Engineering Centre-Hydrologic Modelling System
IDWM	Inverse distance weighting method
IPCC	Intergovernmental Panel on Climate Change
IWD	Irrigation water depth
IWR	Irrigation water requirements
Ka	Hydraulic conductivity of the soil above drain level
Kb	Hydraulic conductivity of the soil below drain level
K _g	Geometric mean of saturated hydraulic conductivity
K _{sat}	Saturated hydraulic conductivity
L	Spacing between drains
LDCs	Least Developed Countries
LEDAPS	Landsat Ecosystem Disturbance Adaptive Processing System
LNMC	Libyan National Meteorological Centre
LR	Linear regression
MENA	Middle East and North Africa
MLR	Multiple Linear Regression
MODAWEC	Monthly to Daily Weather Converter
ModTmax	Daily maximum air temperature predicted by MODAWEC
ModTmin	Daily minimum air temperature predicted by MODAWEC

MSE	Mean square error
MTmax	Average monthly maximum air temperature
MTmin	Average monthly minimum air temperature
NDD	Number of dry days
NDSI	Normalized difference salinity index
NDVI	Normalized difference vegetation index
NIR	Near-infrared
NOAA	National Oceanic and Atmospheric Administration
NTmax	Daily maximum air temperature predicted by AANS
NTmin	Daily minimum air temperature predicted by AANS
PEARL	Pesticide Emission Assessment at Regional and Local scales
PEST	Parameter Estimation Software
PET	potential evapotranspiration
PTFs	Pedotransfer functions
r	Radius
R ²	Coefficient of determination
RMSE	Root mean square error
RS	Remote sensing
RZWQM2	Root Zone Water Quality Model 2
S	Sand
SBE	Single best estimator
SD	Sun duration
SHAW	Simultaneous Heat and Water
Si	Silt
SI	Salinity index
SPI	Stream power index
STI	sediment transport index
SWAP	Soil-Water-Atmosphere-Plant
SWAT	Soil and Water Assessment Tool
SWIR	Short-wave infrared
TARWR	Total annual renewable water resources
UKT	UK traditional
UNESCO	United Nations Educational, Scientific and Cultural Organization

VIC	Variable Infiltration Capacity Model
WaSim	Water Simulation model
WI	wetness index
WMO	World Meteorological Organization
WP	Wilting point
WUE	Water use efficiency
XMTmax	Extreme maximum air temperature of the month
XMTmin	Extreme minimum air temperature of the month

1 Introduction

1.1 Introduction

1.1.1 Agricultural drainage in arid and semi-arid in Least Developed Countries (LDCs)

Irrigation has played a critical role in agricultural growth (MacKellar et al., 2021). Irrigation expansion from the mid-1960s to the mid-1980s accounted for more than half of the increase in world food production (Pingali, 2012). Irrigation contributes almost 100% to food production in certain countries, such as India (Ei-Ashry and Duda, 1999). The full benefits of high-yielding crops and fertiliser could not have been realised without this access to water. Synchronically, the average annual growth rates of yields such as maize, wheat, and rice in LDCs are declining, as reported by Ritzema (2009). Ritzema linked that decrease to the declining public spending on agricultural research and development in LDCs (Ritzema, 2009). Currently, around 297.7 million ha (16.4%) of the arable and permanent cropped lands are irrigated (Table 1-1). In LDCs, the percentage of irrigated areas (23.3%) is higher than in developed countries (DCs) (6.8%). However, when it comes to the percentage of sprinkler and micro irrigation applied, DCs are more equipped than LDCs. For example, 37.8% of all irrigated areas in DCs are equipped with sprinkler irrigation compared to 7.5% in LDCs and 9.1% of all irrigated areas in DCs are equipped with micro irrigation compared to 3.9% in LDCs. These irrigation practices (sprinkler and micro irrigation) are known as more efficient technique to provide the crops with their water requirement and reduce the amount of deep percolation compare to surface irrigation.

In addition, in far too many countries, especially LDCs, adequate drainage facilities were not installed or maintained. As a result, the percentage of the drained areas in LDCs (8.6%) is less than in DCs (13.5%) (Table 1-1). Consequently, the advantages of irrigation and related inputs have yet to be realised entirely (Smedema et al., 2000). As of 2008, only 1.2 billion people live in developed countries, whilst 5.4 billion people live LDCs. By 2050, the number of people living in developed countries will not be expected to change, but there will be 8 billion in LDCs (Haub, 2008). The predicted addition of the 2.6 billion people in LDCs will need food production to double by 2050. The capacity to fulfil the demand for food, fodder and fibre does not exist, and

considerable strains will be imposed on LDC's natural resources and developed countries' agricultural exports (Ei-Ashry and Duda, 1999).

Many areas of the world are already experiencing water scarcity, major environmental issues resulting from agricultural practices, and unsustainable agricultural production methods. Libya is no exception (Wheida and Verhoeven, 2007) with many irrigation projects plagued by waterlogging and salinity, diminishing crop yields (Ellafi et al., 2022). According to the Food and Agriculture Organization (FAO), 0.2 million ha of irrigated lands in Libya is experiencing salinity issues and 0.2 million ha has waterlogging problems (Table 1-1). Globally, salinity caused by irrigation affects 38.7 million ha, of which 34.2 million ha are within LDCs and 4.5 million ha are within DCs (Table 1-1). That means more than 88% of the total irrigated areas affected by salinity from irrigation are located in LDCs. Waterlogging problems caused by irrigation is affecting LDCs (19.2 million ha) far more than DCs (0.02 million ha). As of 2019 more than 99% of all areas waterlogged by irrigation are located in LDCs (Table 1-1). Therefore, salinity and waterlogging problems are synonymous with irrigation in arid and semi-arid areas located in LDCs. Globally, salinity and waterlogging issues have led to an annual rate of land loss of ca. 0.5 million ha (Smedema et al., 2000).

Drainage systems have been developed in arid and semi-arid areas to manage and regulate aeration and waterlogging by managing the shallow groundwater table and mitigating salinity issues in irrigated areas. However, about 193.9 million ha of irrigated land are now drained. This represents 10.7% of the total irrigated area that requires drainage (Smedema et al., 2000). Furthermore, according to Smedema et al. (2000), the proportion of agricultural land drained in LDCs is 5-10%, compared to 25-30% in developed countries (DCs) (including humid areas). Drainage development is mainly driven by the level of agricultural development for more profitable land use and further agricultural development (Smedema et al., 2004). More than two-third of the drainage systems have been installed in humid areas and one-third in arid and semi-arid areas. Most of these drainage systems installed in irrigated areas are at least 40 years old (Ritzema, 2009). In the irrigated areas, it is anticipated that existing systems will need to be upgraded or replaced in around 30 million ha. Furthermore, to address irrigation-related waterlogging and salinity issues, new systems will need to be installed in another 30 million ha. About half of these systems are anticipated to be subsurface

drainage systems. This will require an investment of roughly US\$ 19 billion, or US\$ 475 million annually, over the next 40 years (Nijland et al., 2005) at an average cost of US\$ 1,250/ha.

The cost of installing and maintaining a drainage system is one factor contributing to these differences between DCs and LDCs. To overcome the high cost of installing and maintaining drainage systems, farmers in India and Pakistan contribute 15 – 20% of the operation and maintenance costs. In Bangladesh, it is included in the water bill, while to install drainage systems, governments in Egypt, Bangladesh, India and Pakistan offer loans to farmers (Knegt, 2000). Lack of expertise in LDCs is also a factor impacting drainage system design, installation and maintenance. Farmers also tend to use more traditional and less innovative, risk-averse, approaches to irrigation and have less competitive farming attitudes in LDCs than in DCs. In Libya, approximately 9,000 ha of irrigated land (about 2% of total croplands) was reported to be fitted with some sort of drainage system in 2000 (FAO, 2016). This is primarily due to a fundamental lack of expertise. Lack of expertise within LDCs can be overcome. In 1991, the Egyptian Public Authority for Drainage Projects (EPADP) founded the Drainage Training Center (DTC) that annually offers courses and practical training in drainage design, construction, and maintenance. Operators and mechanics are educated on drainage equipment, maintenance, and repair. Modern technology and hands-on training modules are available (Freisem and Scheumann, 2001). In India, the Water Users Associations (WUA) for irrigation offered farmers training programs to adopt the latest irrigation and drainage technology, resulting in improved water and agricultural management (Freisem and Scheumann, 2001).

To further reduce the risk and cost of installing an inadequate drainage system, drainage simulation models can be used as a quick and accurate method to evaluate alternative designs (Skaggs, 1999). However, there is also insufficient spatial soil and contiguous long-term weather data for input into appropriate drainage models (especially within LDCs). This also includes the cost of measuring the input parameters required to design a drainage system, such as the saturated hydraulic conductivity, soil salinity and reference evapotranspiration calculated from contiguous long-term weather data. There is also a lack of validation for the suitability of drainage

models for application in arid and semi-arid areas. The cost of installing drainage is often a limiting factor. Consequently, accurate drainage designs are essential.

Table 1-1: Key indicators of the agricultural water management sector

Indicator	World	DCs	LDCs	Libya	Year	Source of data
Total cultivated area (arable land + permanent crops) (million ha)	1,815.7	759.0	1056.7	2.1	2018	ICID database
Total irrigated area (million ha)	297.7	51.8	245.9	0.4	2018	ICID database
% irrigated area from total cultivated area	16.4	6.8	23.3	19.0	2018	ICID database
of which equipped	12.8	37.8	7.5	-		
% sprinkler irrigation from total irrigated area	4.8	9.1	3.9	-		
% micro irrigation from total irrigated area						
Total drained area (million ha)	193.9	102.7	91.2	0.01	2018	ICID database
% drained area	10.7	13.5	8.6	0.5	2018	ICID database
Total area affected by salinity from irrigation (million ha)	38.7	4.5	34.2	0.2	2019	FAOSTAT
Total area affected by waterlogging from irrigation (million ha)	19.12	0.02	19.1	0.2	2019	FAOSTAT

Where ha is hectare, DCs is developed countries, LDCs is least developed countries, ICID is the international Commission on Irrigation and Drainage, FAOSTAT is The Food and Agriculture Organization Corporate Statistical Database

1.1.2 Drainage models development and applications

Since the development of Darcy's Law of water flow in 1856, researchers and drainage system designers and operators have incorporated it into models used to link the drain depth and spacing to the performance of drainage systems. The water movement in soil formula developed by Colding, (1872) to calculate water table depth in drained lands is also widely adopted (Rosbjerg, 2020). Drainage models span a wide spectrum from complex guidelines that connect soil type to drainage requirements (Skaggs, 1999) to drain spacing equations (Hooghoudt, 1937), and computer models that

simulate the daily performance of multi-component systems based on long-term weather data (Ma et al., 2012; Skaggs, 1977; Van Dam et al., 1997). Therefore, a drainage model can be defined as the compilation of guidelines, equations, or computer programs that are applied objectively to test the performance of a drainage system to be simulated (Skaggs, 1999).

Under the definition mentioned above, analytical and numerical solutions (mathematical models) qualify as drainage models. Mathematical models have been applied to describe drainage events, typically over a limited period (Gurovich and Oyarce, 2015). Mathematical drainage models such as Governing Equations and Boussinesq's Equation often consider a single process, such as drainage under a constant weather condition or water table drawdown for given initial and boundary conditions (Nieber and Feddes, 1999; Youngs, 1999). However, in reality, boundary conditions vary due to temporal and spatial changes in meteorological conditions, land cover, and land-use factors such as soil fertility, soil drainage, and slope. Models that predict the daily impact of the temporal and spatial variability in these key factors on the performance of a drainage system are called simulation models (Skaggs, 1999).

Several simulation models such as DRAINMOD, SWAP and RZWQM2 have been applied to predict drainage systems' daily performance and monitor and control water table levels (Bennett et al., 2013; Ma et al., 2012; Skaggs et al., 2012b). Many simulation models have been developed to describe a specific field condition, such as a shallow water table (Skaggs, 1982), and the relationship between crop yield and drainage water management practices (Skaggs, 1999). In humid areas, simulation models are applied to predict drainage outflow and water table fluctuations (Sanoja et al., 1990), crop production and nitrogen losses (Breve-Reyes et al., 1998), and nitrogen transformation and fate (Ale et al., 2012; Skaggs et al., 2012a). While in arid areas, simulation models such as DRAINMOD have been modified to characterise soil salinity and manage shallow water tables (Wahba and Christen, 2006; Wahba et al., 2002). The downside of these simulation models is the large number of input parameters required to run them.

Around 70% of the global arid and semi-arid areas are located within LDCs (Safriel et al., 2005). Also, in LDCs there is insufficient spatial soil and contiguous long-term

weather data, which has limited the applications of drainage simulation models in arid and semi-arid areas. The drainage simulation models were extensively applied in many humid areas (rainfed agriculture) such as the Midwest of the United States (Gowda et al., 2012; Ma et al., 2012; Skaggs et al., 2012b), Sweden (Salazar et al., 2009), Netherlands (Staarink, 2014), and Canada (Singh et al., 1994). One of the advantages helped to improve the drainage systems in these locations is the availability of the input parameters required to run a drainage simulation model. For example, the California Soil Resource Lab at UC Davis University developed an interactive map that allows user to download soil information at any location in the US within 800m grid cells. The data was obtained from the United States Department of Agriculture and The National Cooperative Soil Survey (USDA-NCSS) soil survey data.

These data include soil physical properties (e.g. soil texture, bulk density, available water holding capacity and saturated hydraulic conductivity), and soil chemical properties (e.g. cation exchange capacity, electrical conductivity, pH number, sodium adsorption ratio and soil organic matter) for depth up to 60 cm from the soil surface (Walkinshaw et al., 2022). Such data are often not available in LDCs, and sometimes available but lack consistency in terms of classification approaches (particularly within countries), and availability of data in undigitized forms. Also, meteorological data in DCs are continually available on daily and sometimes hourly basis. In contrast, missing meteorological data is one of the challenges facing researchers in LDCs.

Data availability limited the applications of drainage simulation models to evaluate the existing drainage systems in arid and semi-arid areas and therefore, it is unclear which drainage simulation model is the most applicable in arid and semi-arid areas. Also, these input parameters are expensive and hard to measure and therefore, there is a need for applying indirect methods to overcome the cost and time required to measure these input parameters and/or to fill in data gaps.

1.1.3 Key processing and parameters influencing the drainage system design in arid and semi-arid areas.

As mentioned earlier, drainage systems are installed in arid and semi-arid areas to control salinity and waterlogging in poorly drained irrigated lands. Figure 1-1 shows the main components influencing the drainage system, and in this section, these

components will be discussed briefly. Evapotranspiration (ET) is the combination of two processes whereby water is lost from the crop via transpiration and from the soil surface by evaporation, respectively. Transpiration and evaporation both take place at the same time, making it difficult to distinguish between the two. The amount of solar radiation that reaches the soil surface, in addition to the topsoil's water content, is the key factor affecting how much moisture evaporates from cropped soil. Over the course of the growing season, this percentage falls as the crop matures and its canopy gradually covers more ground space. When the crop is small, soil evaporation accounts for the majority of water loss, but after the crop is mature and fully covers the soil, transpiration takes over as the primary mechanism (Allen, 1998). The main factors affecting ET are weather parameters, crop factors, and management and environmental conditions. Air temperature is one of the principal climatic factors that determine evapotranspiration. In arid and semi-arid areas, air temperature is normally higher compared to humid regions, hence higher ET values especially in the summer months. Also, the crop type, variety and development stage are important factor when assessing ET from crops grown in large, well-managed fields. Finally, other factors such as soil salinity, low soil fertility, the existence of an impenetrable soil layers, and insufficient soil management may limit the growth of the crop and decrease/increase ET.

According to FAO, the annual rainfall in arid areas ranges from 100 – 400 mm, while in semi-arid areas the annual rainfall ranges from 400 – 600 mm. However, irrigation is absolutely essential for a reliable and good harvest. Some drought resistant crops such as sorghum and millet may give reasonable yields in semi-arid areas, but also there is a risk of unreliable rainfall and subsequent crop failure (Brouwer and Heibloem, 1986). The water on the soil surface received from irrigation and/or rainfall will be moved by three forces. The first is infiltration, and the infiltration rates depends on the head of water, pore size distribution of the soil, and conditions in the underlying layers. The second force is the runoff where the slope in the soil surface will help to move the water to lower soil surface. The third force is ET as discussed earlier. High water table can cause a capillary action of water to the root zone and to the surface without getting the effect by the gravity forces. Capillary rise can also be the source of salinity in the root zone by moving the brackish water to the root zone and the surface,

the water will then be evaporated, and the salt will remain on the surface. Maintaining the water table at manageable levels can help to reduce the impact of capillary rise on crop production (salinity and waterlogging). Sandy soil normally has higher infiltration rates and lower capillary rise and clay soil has lower infiltration rate and higher capillary rise. Drainage system factors (depth and spacing) can play a big role in controlling these components and create a favourable environment for the crops and improve their productivity.

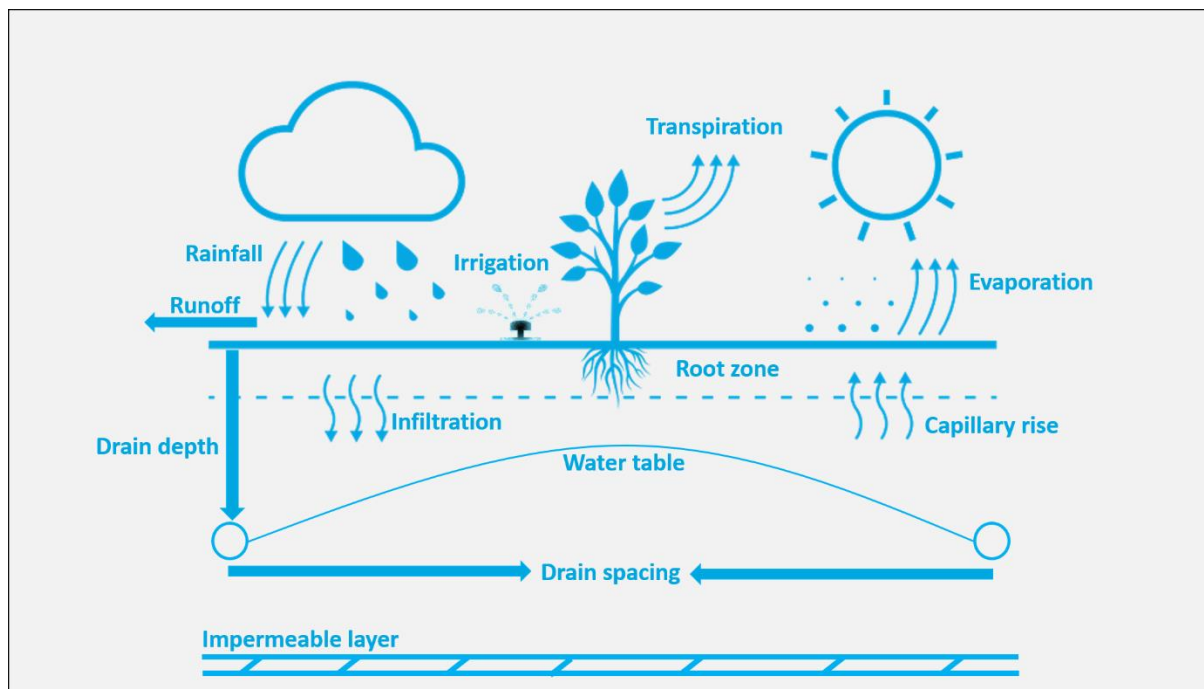


Figure 1-1: A diagram of the key processes influencing agricultural drainage in arid and semi-arid areas.

1.1.4 Artificial neural networks applications

To address both climate change and population growth, agriculture must combine high and sustainable relative yields with water use efficiency. This is true for both irrigated and rainfed agriculture. To achieve these criteria, new data analysis techniques, particularly those developed from artificial intelligence (AI), are increasingly being deployed. Artificial neural networks (ANNs) are a particularly popular AI tool. Artificial neural networks are a mathematical technique for characterising synthetic neurons in order to tackle complicated problems in a way close to the human brain (Agatonovic-Kustrin and Beresford, 2000). There has been an increasing interest in the study of neurological systems and structures since the 1940s. This curiosity has resulted in the

creation of new computational models, known as linking systems or ANNs, based on biological processes and utilised to address complicated issues such as pattern recognition, quick information processing, and adaptability (Huang, 2009). ANNs employ machine learning to recognise complicated non-linear relationships between input and output datasets and are based on the principle of self-adjusting internal control parameters (Ayoubi et al., 2011).

ANNs are commonly utilised in the categorisation and prediction of numerous types of data. They have also been employed in the broader agricultural sector for some time. In predicting soil-water related data, ANNs have been successfully used to predict the depth of the water table and the salinity of groundwater at various drain depths and spacings (Nozari and Azadi, 2017), and to estimate soil salinity (Bouksila et al., 2010). Additionally, ANNs have been successfully used to estimate daily mean, maximum, and minimum temperature (Ustaoglu et al., 2008) which are required as inputs to drainage models. Ustaoglu et al. (2008) successfully used the past seven days' temperatures as inputs to estimate the current day's temperature. In Turkey, Koksali et al. (2017) used ANNs to predict hourly air temperature for ET mapping applications, while Almonacid et al. (2013) developed ANNs to predict hourly air temperature based on daily maximum and minimum air temperature for various geographical regions in Spain. Similarly, Okoh et al. (2015) built ANNs that accurately predicted hourly air temperature in Nigeria based on daily readings, and Zanetti et al. (2007) developed ANN to predict evapotranspiration using limited meteorological data. Recently, ANNs have been used in combination with remote sensing (RS) and geographic information systems (GIS) to produce more accurate soil salinity maps by using the salinity indices and reflectance from satellite images as input parameters for the ANNs (Ellafi et al., 2022; Habibi et al., 2021; Shahabi et al., 2016). Habibi et al. (2021) discovered that when combining salinity indices and reflectance from satellite images, developing ANNs provided more accurate soil salinity maps than Multiple Linear Regression (MLR) based approaches. Mousavi et al. (2017) examined the link between EC_e (Electrical Conductivity of a saturation extract) and vegetation spectral indices using salinity and vegetation spectral indices. They compared ANN salinity prediction models to MLR salinity prediction models and found that ANN was 46% more accurate.

1.2 Gaps in knowledge addressed by this thesis

The key knowledge gaps that this thesis aims to address:

- Assess whether available drainage simulation models can be applied to design drainage systems in arid areas and identify the most appropriate model.
- Are ANNs more accurate at predicting saturated hydraulic conductivity (K_{sat}) than existing and widely adopted Pedotransfer functions (PTFs).
- Critically evaluate the performance and financial implications of using ANN predicted vs measured K_{sat} when designing drainage system.
- Evaluate the suitability of ANNs and existing methods to fill missing daily maximum and minimum air temperature data in long-term metrological datasets in Libya.
- Quantify the potential impacts on the irrigation depth, crop yield, and drainage volume of designing drainage systems using predicted vs measured ET_0 .
- Can reflectance from satellite images be used as input parameters to develop ANNs for accurate soil salinity predictions
- Assess the applicability of running drainage simulation model using predicted vs measured K_{sat} and ET_0 and EC input parameters.
- Can ANNs improve the drainage design in data-poor arid areas located in least developed countries.

1.3 Aim and Objectives

Aim: This research aims to critically evaluate traditional verses alternative methods of acquiring input data for drainage models including the application of ANNs in order to identify appropriate methodologies for 'data-poor' countries. This aim will be met through the following objectives.

Objective 1: Critically evaluate existing drainage design models so as to identify model(s) that are applicable to arid regions.

Objective 2: Assess the potential of alternative methods of data acquisition, specifically ANNs that could be used to fill gaps in missing input data (specifically K_{sat} , ET_0 and EC_e) against physically measured data.

Objective 3: Assess the feasibility of using predicted K_{sat} , ET_0 and E_{Ce} to run the selected drainage model (DRAINMOD) to design drainage systems in arid regions.

1.4 Case study

The study is applied to two agricultural projects located in the south of Libya (Hammam agricultural project (HAP) and Eshkeda agricultural project (EAP)). Both are located in arid areas with annual rainfall rarely exceeding 100mm. The region has no perennial rivers. Only paleo-groundwater from two aquifers is available. Mezda and Murzuq aquifers irrigate HAP and EAP (Tantawi, 2000).

1.4.1 Eshkeda Agricultural Project (EAP)

Eshkeda Agricultural Project (EAP) is located 60 km north of Sabha city. The area has ca. 3000 ha, divided into three sub-areas (Figure 1-2).

- Western Area; 2000 ha
- Central Area; 600 ha
- Eastern Area; 370 ha.

The project implementation started in 1975 and has been under operation since the second half of 1976. In accordance with the installed irrigation wells, the area comprises 25 districts, each with 12 farms (10 ha each). The farms are divided into two plots, each of which is 180 m x 234 m. Windbreaks have been planted between the farm plots and around the farm. Irrigation water is lifted from a deep aquifer (350 – 400 m depth from the surface). The water is pumped into reservoirs from where it is pumped into the irrigation networks to each farm connected with four hydrants. In 1977, the first drainage problems became visible. In 1981, about 35% of the project suffered from shallow water table depth occurring at less than 1 m depth.

In the 1980s, a subsurface drainage system was installed to replace the open ditches dug in the 1970s. the drainage system in EAP has field drains with spacing ranging between 12 – 43m. Field collector drains were installed at the boarder of each plot (the area of the plot is 180 m X 234 m). The field collector drains discharge the water from the field drains to the main drain and finally the main drain discharged the drainage water out of the project to the evaporated pond. The diameter of the drains starts from 50mm for the field drains to 600mm for the main drain.

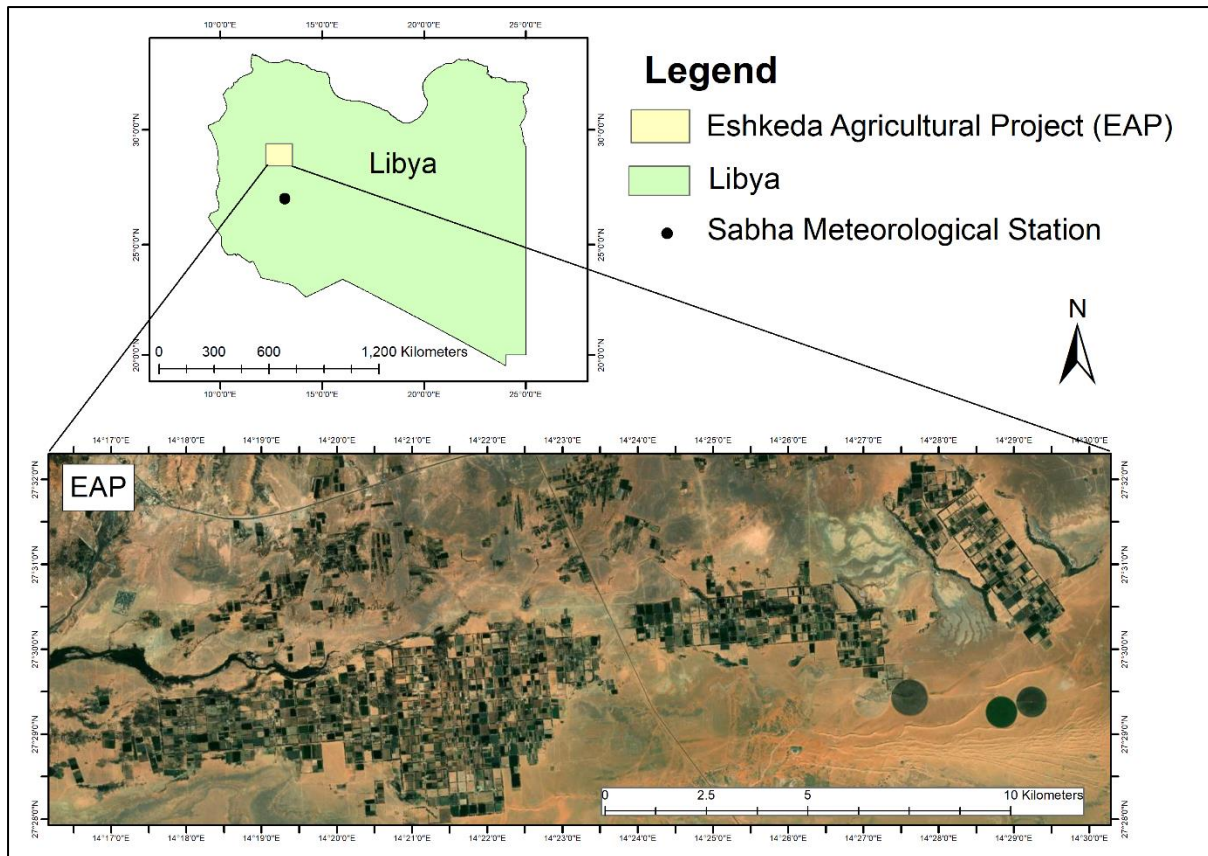


Figure 1-2: The geographical location of EAP on the Libyan map

1.4.2 Hammam Agricultural Project (HAP)

Hammam Agricultural Project (HAP) is located on the north-east side of Sokna Oasis (29°04'01"N 15°47'05"E) at an altitude of 270 meters ASL (Figure 1-3). HAP encompasses 1,200 ha and is split into 182 farms (6 – 8 ha each farm). The work on the project began in 1971, and the reclamation was completed in 1985. Al-Hammam project has a drainage system designed in the 1970s. According to the information from the project-staff the total water discharge from all wells is ca. 2500 m³ hr⁻¹. The water is pumped to a storage tank located at each farm and the capacity of each storage tank is around 115 m³. Surface irrigation through irrigation canals are the main irrigation systems used in HAP. The main crops growing in the project are alfalfa and palm-date trees

The project has a main open drain located on the east side of the project. The main drain discharges the drainage water from the sub-drains to the evaporated pond located north of the project. The area of the evaporated pond is around 33,000 m², and the depth is up to 3 m. the total length of the main ditch is about 7.7 km. The total

length of the sub drains is around 23 km. Six sub-drains are connected to the main drain and these sub-drains collect the drainage water from the field drains (a mix of subsurface drains and open ditches).

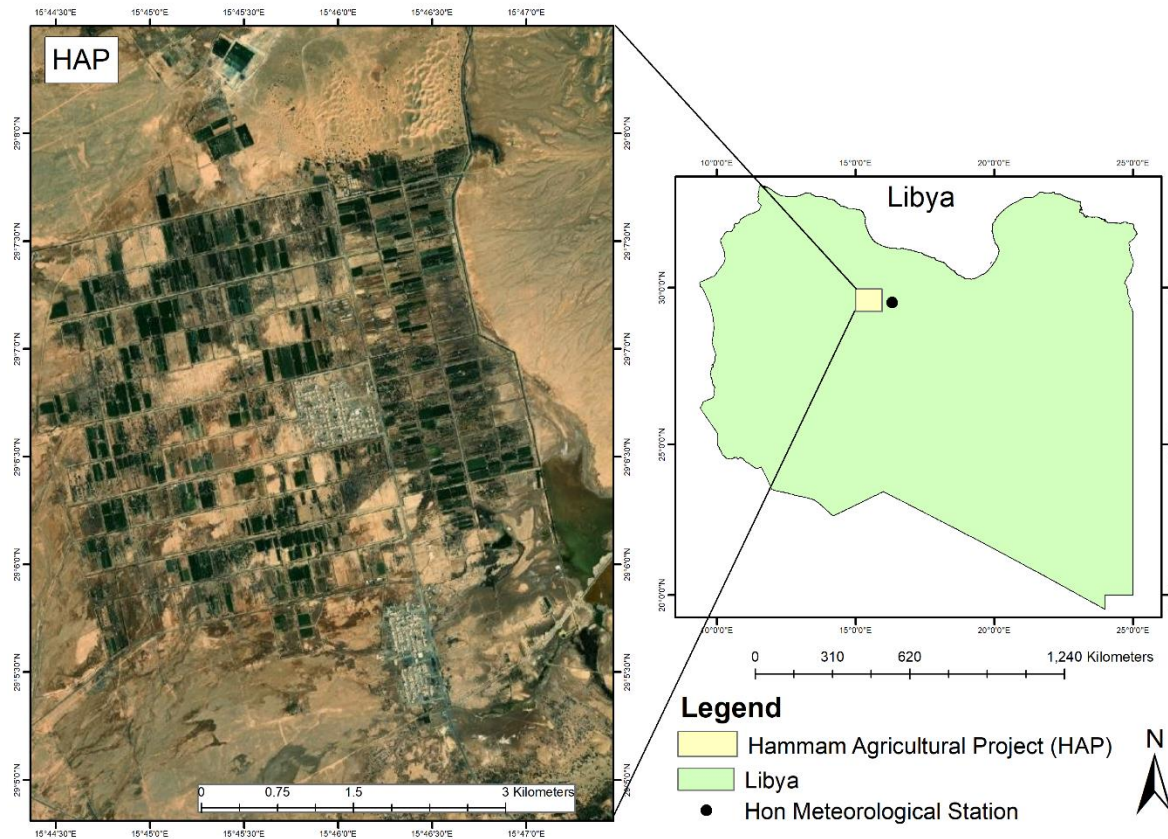


Figure 1-3: Geographical location of HAP on the Libyan map

1.5 Thesis structure

The thesis has been written in a paper format (an approved style by Cranfield University), and therefore the introduction, methods, results and discussion sections are presented for each chapter separately. Each chapter (Chapters 2 – 6) was written either as an academic journal or a book chapter. Because of the similarities in the modelling approach, certain methods are unavoidably repeated throughout chapters (especially Chapters 3 – 6). Chapter 2 is submitted to the Water and Environment Journal as a review paper, and is currently under review. Chapter 3 is already published in the Journal of hydrology: Regional Studies (Ellafi et al., 2021). Chapter 4 will be submitted to Irrigation and Drainage journal. Chapter 5 has already been published as a book chapter (Ellafi et al., 2022). Chapter 6 will be submitted for review to the Agricultural Water Management Journal. Chapter 1 summarises the contextual

background to the research topic and Chapter 7 provides overall research conclusions and sets the research in a wider context. The contributions of authors for each chapter are described in Table 1-2. Also, the thesis structure is represented graphically in Figure 1-4. The chapters structure of this submission is as follows:

- Chapter 2: presents a critical review of the existing drainage simulation models, demonstrates the strengths and weaknesses of each model against selection criteria, and identifies the most applicable model for semi-arid and arid regions.
- Chapter 3: presents a critical evaluation of ANNs derived from data obtained from the two case study agricultural projects in Libya (EAP and HAP) and widely adopted pedotransfer functions to predict the K_{sat} and discusses implications on drain spacing and water table depth.
- Chapter 4: examines the impact of applying predicted vs measured ET_0 (including the development of ANNs) on estimating crop yield, irrigation depth, drainage discharge, actual evapotranspiration, and the number of dry days in both EAP and HAP.
- Chapter 5: investigates the accuracy of developing ANNs to predict soil salinity using selected salinity indices and reflectance from satellite images as input parameters. ANNs to monitor the salinity status in agricultural lands are also developed and evaluated.
- Chapter 6: explores the feasibility of using predicted K_{sat} and reference evapotranspiration (ET_0) to design drainage systems and quantifies and discusses implications on drain spacing and crop yield.
- Chapter 7: highlights contributions to knowledge, summarises key conclusions and puts this research into the wider context of a) hydrological modelling at catchment and regional scales b) availability of soils data in LDCs and c) climate change. Recommendations for future research are also discussed.

Table 1-2: Contributions of authors to each chapter and objectives within the thesis

	Chapter 1	Chapter 2	Chapter 3	Chapter 4	Chapter 5	Chapter 6	Chapter 7
		Objective 1	Objective 2	Objective 2	Objective 2	Objective 3	
		Submitted to the Water and Environment Journal	Published (Ellafi et al., 2021)	Will be submitted to Irrigation & Drainage Journal	Published as a book chapter (Ellafi et al., 2022)	Will be submitted to the Journal of Agricultural Water Management	
M.A. Ellafi	Structure and writing	Literature review, models evaluations, structure, and writing	Writing-original draft, conceptualisation, methodology, validation, formal analysis, investigation	Writing-original draft, conceptualisation, methodology, validation, formal analysis, investigation	Writing-original draft, conceptualisation, methodology, validation, formal analysis, investigation	Writing-original draft, conceptualisation, methodology, validation, formal analysis, investigation	Structure, identification of contributions to knowledge and key conclusions, and writing
R.W Simmons	Guidance on structure, editing	Supervision, writing-review and editing, review of analysis	Supervision, writing-review and editing, review of analysis	Supervision, writing-review and editing, review of analysis	Supervision, writing-review and editing, review of analysis	Supervision, writing-review and editing, review of analysis	Guidance on structure, editing
L.K Deeks	Guidance on structure, editing	Supervision, writing-review and editing, review of analysis	Supervision, writing-review and editing, review of analysis	Supervision, writing-review and editing, review of analysis	Supervision, writing-review and editing, review of analysis	Supervision, writing-review and editing, review of analysis	Guidance on structure, editing
H.A Zurqani					Data collection and analysis, and writing part of the methodology		

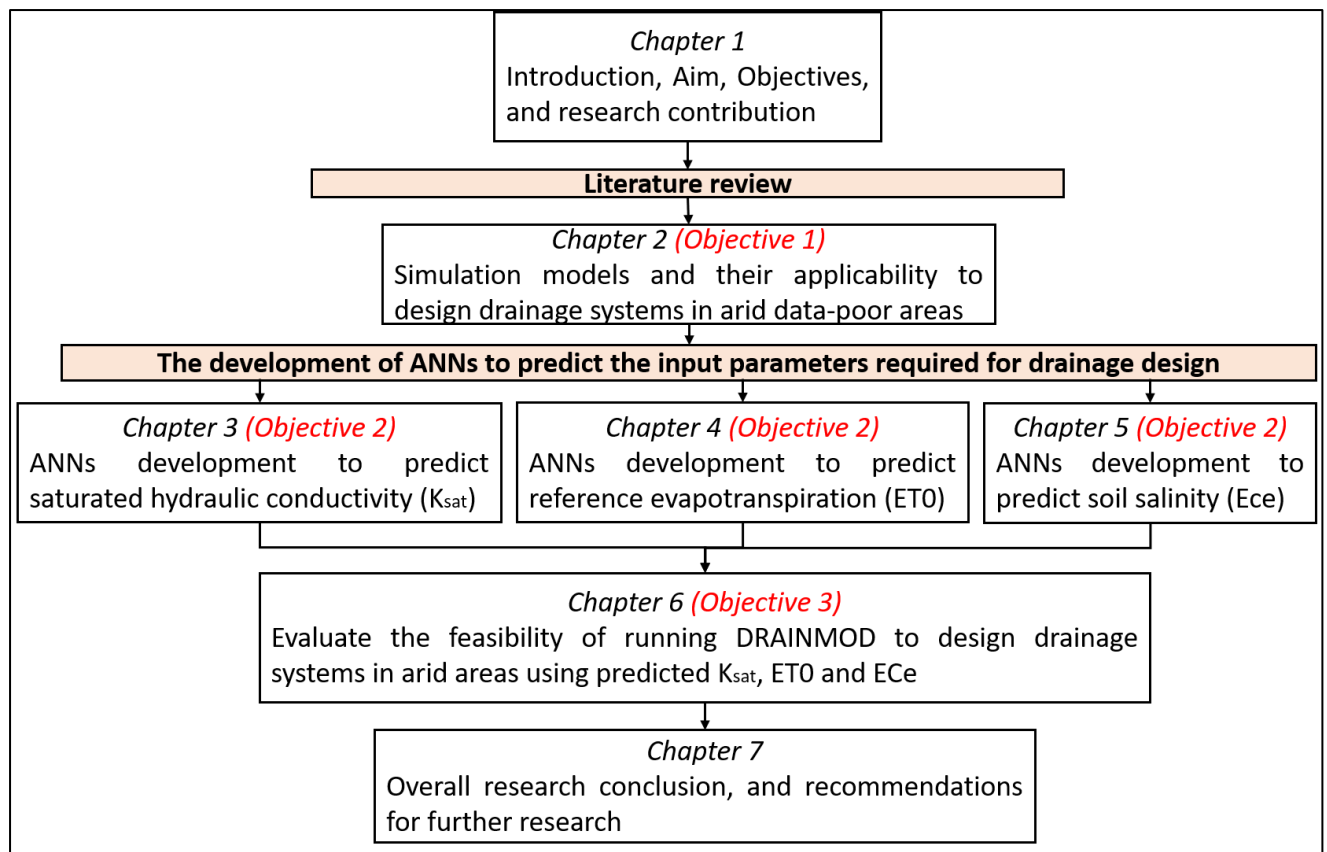


Figure 1-4: Visual representation of the structure of this thesis.

1.6 References

- Agatonovic-Kustrin, S., Beresford, R., 2000. Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research. *J. Pharm. Biomed. Anal.* 22, 717–727. [https://doi.org/10.1016/S0731-7085\(99\)00272-1](https://doi.org/10.1016/S0731-7085(99)00272-1)
- Ale, S., Bowling, L., Youssef, M., Brouder, S., 2012. Evaluation of simulated strategies for reducing nitrate-nitrogen losses through subsurface drainage systems. *J. Environ. Qual.* 41, 217–228.
- Almonacid, F., Pérez-Higueras, P., Rodrigo, P., Hontoria, L., 2013. Generation of ambient temperature hourly time series for some Spanish locations by artificial neural networks. *Renew. Energy* 51, 285–291. <https://doi.org/10.1016/j.renene.2012.09.022>
- Ayoubi, S., Pilehvar, A., Mokhtari, P., L., K., 2011. Application of Artificial Neural Network (ANN) to Predict Soil Organic Matter Using Remote Sensing Data in Two Ecosystems, in: Atazadeh, I. (Ed.), *Biomass and Remote Sensing of Biomass*. InTech Open Access, London, UK, pp. 181–196. <https://doi.org/10.5772/18956>
- Bennett, S.J., Bishop, T.F.A., Vervoort, R.W., 2013. Using SWAP to quantify space and time related uncertainty in deep drainage model estimates : A case study from northern NSW , Australia. *Agric. Water Manag.* 130, 142–153. <https://doi.org/10.1016/j.agwat.2013.08.020>
- Bouksila, F., Persson, M., Berndtsson, R., Bahri, A., 2010. Estimating Soil Salinity Over a Shallow Saline Water Table in Semiarid Tunisia. *Open Hydrol. J.* 4, 91–101.
- Breve-Reyes, M., Skaggs, R.W., Parsons, J., Gillian, J., 1998. Using the DRAINMOD-N model to study the effects of drainage system design and management on crop productivity and NO₃ losses in drainage water. *Agric. Water Manag.* 35, 227–243.
- Brouwer, C., Heibloem, M., 1986. *Irrigation Water Management: Irrigation Water Needs. Training Manual*, Food and Agriculture Organization of the United Nations, Rome, 3.

Colding, A., 1872. Om lovene for Vandets Bevægelse i Jorden (On the laws for movement of water in soil). Vidensk. Selsk. Skr. 5, 563–622.

Ei-Ashry, M.T., Duda, A.M., 1999. Future perspectives on agricultural drainage, in: Agricultural Drainage. pp. 1285–1298. <https://doi.org/10.1002/9780891182306.ch41>

Ellafi, M.A., Deeks, L.K., Simmons, R.W., 2021. Application of artificial neural networks to the design of subsurface drainage systems in Libyan agricultural projects. J. Hydrol. Reg. Stud. 35, 1–17. <https://doi.org/https://doi.org/10.1016/j.ejrh.2021.100832>

Ellafi, M.A., Zurqani, H.A., Deeks, L.K., Simmons, R.W., 2022. DRAINMOD applications to design drainage systems in Libya using soil salinity data predicted by GIS, remote sensing and Artificial Neural Networks, in: Zurqani, H.A. (Ed.), Environmental Applications of Remote Sensing and GIS in Libya. Springer International Publishing AG, Switzerland.

FAO, 2016. Country profile - Libya. Rome, Italy. <https://doi.org/10.1787/9487b828-en>

Freisem, C., Scheumann, W., 2001. Institutional arrangements for land drainage in developing countries. Colombo, Sri Lanka.

Gowda, P., Mulla, D., Desmond, E., Ward, A., Moriasi, D., 2012. ADAPT: Model use, Calibration, and Validation. Trans. ASAE 55, 1345–1352.

Gurovich, L., Oyarce, P., 2015. Modeling Agricultural Drainage Hydraulic Nets. Irrig. Drain. Syst. Eng. 4, 1–9. <https://doi.org/10.4172/2168-9768.1000149>

Habibi, V., Ahmadi, H., Jafari, M., Moeini, A., 2021. Mapping soil salinity using a combined spectral and topographical indices with artificial neural network. PLoS One 16, 1–13. <https://doi.org/10.1371/journal.pone.0228494>

Haub, C., 2008. Global Aging and the Demographic Divide [WWW Document]. Popul. Ref. Bur. URL [https://www.prb.org/resources/global-aging-and-the-demographic-divide/#:~:text=Today%2C there are about 1.2,billion in the developing countries. \(accessed 4.7.22\).](https://www.prb.org/resources/global-aging-and-the-demographic-divide/#:~:text=Today%2C there are about 1.2,billion in the developing countries. (accessed 4.7.22).)

Hooghoudt, S., 1937. Contribution of the knowledge of some physical soil properties. NO 6. Detremination of the conductivity of soils of the second kind (in Dutch). Bijdragen tot de kennis Vaneenige natuurkundige Van den grand,6. Algemeene beschonwing Van het problem Van de d. The Hauge, Netherlands.

Huang, Y., 2009. Advances in artificial neural networks - Methodological development and application. Algorithms 2, 973–1007. <https://doi.org/10.3390/algor2030973>

Knegt, J., 2000. Drainage in Developing Countries: A review of institutional arrangements. Wageningen, The Netherlands.

Koksal, E.S., Cemek, B., Cetin, S., Gowda, P.H., Howell, T.A., 2017. Estimating missing hourly climatic data using artificial neural network for energy balance based ET mapping applications. Meteorol. Appl. 24, 457–465. <https://doi.org/10.1002/met.1644>

Ma, L., Ahuja, L.R., Nolan, B.T., Malone, R.W., Trout, T.J., Qi, Z., 2012. Root Zone Water Quality Model (RZWQM2): Model Use, Calibration, and Validation. Trans. ASAE 55, 1425–1446.

MacKellar, B., Kelley, L., Dong, Y., Miller, S., 2021. Irrigation an important tool for increasing profits, managing risk and utilizing applied nutrients. Michigan State Univ. Ext.

Nieber, J., Feddes, R., 1999. Solutions for Combined Saturated and Unsaturated Flow, in: Skaggs, R., van Schilfgaarde, J. (Eds.), Agricultural Drainage. American Society of Agronomy, Crop Science Society of America, Soil Science Society of America, Madison, Wisconsin, USA, pp. 145–212.

Nijland, H.J., Croon, F.W., Ritzema, H., 2005. Subsurface drainage practices : Guidelines for the implementation, operation and maintenance of subsurface pipe drainage systems. ILRI Publication 60, Alterra, Wageningen University and Research Centre, Wageningen.

Nozari, H., Azadi, S., 2017. Experimental evaluation of artificial neural network for predicting drainage water and groundwater salinity at various drain depths and spacing. Neural Comput. Appl. <https://doi.org/10.1007/s00521-017-3155-9>

- Okoh, D., Yusuf, N., Adedoya, O., Musa, I., Rabiou, B., 2015. Preliminary results of temperature modelling in Nigeria using neural networks. *Weather* 70, 335–336. <https://doi.org/10.1002/wea.2581>
- Pingali, P.L., 2012. Green Revolution: Impacts, limits, and the path ahead. *Proc. Natl. Acad. Sci.* 109, 12302–12308. <https://doi.org/10.1073/pnas.0912953109>
- Plain, G., Mousavi, S.Z., Habibnejad, M., Kavian, A., Solaimani, K., Khormali, F., 2017. Digital Mapping of Topsoil Salinity Using Remote Sensing Indices in Agh-Ghala Plain, Iran. *ECOPERSIA* 5, 1771–1786. <https://doi.org/10.18869/modares.Ecopersia.5.2.1771>
- Ritzema, H.P., 2009. Drain for gain: making water management worth its salt (PhD Thesis). Wageningen University and UNESCO-IHE Delft CRC Press, Balkema.
- Rosbjerg, D., 2020. Hydrology and beyond : The scientific work of August Colding revisited. *Hydrol. Earth Syst. Sci.* 1–15.
- Salazar, O., Wesström, I., Youssef, M.A., Skaggs, R.W., Joel, A., 2009. Evaluation of the DRAINMOD–N II model for predicting nitrogen losses in a loamy sand under cultivation in south-east Sweden. *Agric. Water Manag.* 96, 267–281. <https://doi.org/https://doi.org/10.1016/j.agwat.2008.08.008>
- Sanoja, J., Kanwar, R.S., Melvin, S.W., 1990. Comparison of simulated (DRAINMOD) and measured tile outflow and water table elevations from two field sites in Iowa. *Trans. Am. Soc. Agric. Eng.* 33, 827–833. <https://doi.org/10.13031/2013.31407>
- Shahabi, M., Jafarzadeh, A.A., Neyshabouri, M.R., Ghorbani, M.A., Valizadeh Kamran, K., 2016. Spatial modeling of soil salinity using multiple linear regression, ordinary kriging and artificial neural network methods. *Arch. Agron. Soil Sci.* 63, 151–160. <https://doi.org/10.1080/03650340.2016.1193162>
- Singh, M., Prasher, S.O., Tan, C.S., Tejawat, C.M., 1994. EVALUATION OF DRAINMOD FOR SOUTHERN ONTARIO CONDITIONS. *Can. Water Resour. J. / Rev. Can. des ressources hydriques* 19, 313–326. <https://doi.org/10.4296/cwrj1904313>

Skaggs, R.W., 1999. Drainage Simulation Models, in: Skaggs, R., van Schilfgaarde, J. (Eds.), *Agricultural Drainage*. American Society of Agronomy, Inc., Madison, Wisconsin, USA, pp. 469–500.

Skaggs, R.W., 1982. Field evaluation of a water management simulation model. *Trans. ASAE* 25, 666–674.

Skaggs, R.W., 1977. Evaluation of drainage-water table control systems using a water management model, in: St., A.P. 1-77., Joseph, M.. A. (Eds.), *3rd Natl. Drainage Symposium*. pp. 61–68.

Skaggs, R.W., Youssef, M., Chescheir, G., 2012a. A DRAINMOD-based method to estimate effects of drainage water management on annual nitrogen loss to surface water. *Am. Soc. Agric. Biol. Eng.* 55, 799–808.

Skaggs, R.W., Youssef, M.A., Chescheir, G.M., 2012b. DRAINMOD: model use, calibration, and validation. *Trans. ASABE* 55, 1509–1522. <https://doi.org/10.13031/2013.42259>

Smedema, L.K., Abdel-Dayem, S., Ochs, W.J., 2000. Drainage and agricultural development. *Irrig. Drain. Syst.* 14, 223–235. <https://doi.org/10.1023/A:1026570823692>

Smedema, L.K., Vlotman, W.F., Rycroft, D., 2004. *Modern Land Drainage: Planning, Design and Management of Agricultural Drainage Systems*. Design and Management of, London.

Staarink, H., 2014. Water conservation and controlled drainage. A modelling study for an experimental field in the Netherlands. Wageningen University.

Tantawi, A., 2000. *Water Resources in Libya*. Egyptian Office for the Distribution of Publications, Cairo.

Ustaoglu, B., Cigizoglu, H.K., Karaca, M., 2008. Forecast of daily mean, maximum and minimum temperature time series by three artificial neural network methods. *Meteorol. Appl.* 15, 431–445. <https://doi.org/10.1002/met.83>

Van Dam, J., Huygen, J., Wesseling, J., Feddes, R., Kabat, P., Van Walsum, P.E., Groenendijk, P., van Diepen, C., 1997. Theory of SWAP version 2.0. Simulation of water flow, solute transport and plant growth in the Soil-Water-Atmosphere-Plant environment. Wageningen.

Wahba, M.A., Christen, E., 2006. Modeling subsurface drainage for salt load management in southeastern Australia. *Irrig. Drain. Syst.* 20, 267–282. <https://doi.org/10.1007/s10795-006-9007-x>

Wahba, M.A.S., Kandil, H., Gobran, A., 2002. Evaluation of DRAINMOD-S for Simulating Water Table Management under Semi-Arid Conditions. *Irrig. Drain.* 51, 213–226. <https://doi.org/10.1002/ird.54>

Walkinshaw, M., O'Geen, A., Beaudette, D., 2022. Soil Properties [WWW Document]. Calif. Soil Resour. Lab, 1.

Wheida, E., Verhoeven, R., 2007. An alternative solution of the water shortage problem in Libya. *Water Resour. Manag.* 21, 961–982. <https://doi.org/10.1007/s11269-006-9067-6>

Youngs, E., 1999. Non-Steady Flow to Drains, in: Skaggs, R., van Schilfgaarde, J. (Eds.), *Agricultural Drainage*. American Society of Agronomy, Inc. Crop Science Society of America, Inc. Soil Science Society of America, Inc., Madison, Wisconsin, USA, pp. 265–296.

Zanetti, S.S., Sousa, E.F., Oliveira, V.P.S., Almeida, F.T., Bernardo, S., 2007. Estimating Evapotranspiration Using Artificial Neural Network and Minimum Climatological Data. *J. Irrig. Drain. Eng.* 133, 83–89.

2 Drainage Models: An evaluation of their applicability for the design of Drainage Systems in Arid Regions

Abstract

In least developed countries, only 5 – 10% of the total irrigated area requiring drainage is currently drained. This is due to the lack of knowledge on which drainage models are applicable to arid and semi-arid regions, lack of incomplete data for key input parameters and the high cost of drainage installation. The aims of this review are to (1) evaluate selected drainage simulation models and critically assess their applicability to arid and semi-arid areas, (2) establish and apply selection criteria based on availability of data in least developed countries with Libya as a case study, (3) identify the most suitable model for application in Libya. Seven drainage simulation models (ADAPT, RZWQM2, DRAINMOD, EPIC, HYDRUS-1D, WaSim, and SWAP) were critically evaluated through an assessment of their strengths and weakness against a selection criteria. DRAINMOD received the highest total score of 11 points, while the model with the lowest score was ADAPT with a total score of 4 points. Therefore, based on this selection criteria, the recommendation was to use DRAINMOD to design and evaluate drainage systems in arid regions. The input parameters required by DRAINMOD and their availability in Libya are discussed in detail. Based on the key components of DRAINMOD namely the water balance equation and the mass balance approach, three key input parameters (saturated hydraulic conductivity (K_{sat}), evapotranspiration (ET), and soil electrical conductivity (EC)) were identified as problematic in terms of availability and/or temporal and spatial coherence of data as well as their cost to measure. Alternative approaches to predict missing data points including the application of artificial neural networks are discussed. Evaluating the feasibility of using predicted K_{sat} , ET, and EC as input parameters for simulation models to design drainage systems in data-poor areas, would help the farmers, planners, and decision-makers to reduce the overall cost of drainage system design. Also, it would make DRAINMOD more accessible tool to evaluate different drainage designs.

2.1 Introduction

Food production is expected to rise by up to 100 percent by 2050 to fulfil demand due to an increase in world population (Právělie et al., 2021). However, as a consequence of soil salinisation, desertification, soil erosion, and urbanisation, the world's arable lands are degrading (FAO, 2002). Water use efficiency is a key challenge in arid and semi-arid countries due to increased cross-sector demand for limited water supplies (Elshemy, 2018). It is consequently critical for long-term agricultural development and economic growth in arid and semi-arid regions that drainage system design and management emphasize water use efficiency, particularly in places where the water resource is non-renewable (Qadir et al., 2003; Scheumann and Freisem, 2002). For example, By the 1950s, water needs in arid Libya had exceeded water resources for food self-sufficiency, and similar situations were noted throughout the Middle East and portions of Africa (Qadir et al., 2003).

Only 25 to 50 million ha of irrigated lands (< 30% of the total irrigated area requiring drainage) is currently drained (Smedema et al., 2000), and according to Smedema et al. (2000), the proportion of agricultural land drained in least developed countries is 5-10% compared to 25-30% in developed countries. These differences are due to low levels of agricultural and rural development, adoption of crops and varieties that can tolerate adverse drainage conditions such as salinity and waterlogging. In addition, the cost of installing and maintaining drainage systems, and more traditional (i.e., less innovative, more risk-averse and less competitive) farming attitudes in least developed countries compared to developed countries prohibits drainage system installation. In Libya for example, it was estimated that in 2000, only 9,000 ha (around 2% of all croplands) of irrigated land was equipped with some form of drainage (FAO, 2016). This is due to a fundamental lack of expertise in the country, lack of knowledge on which drainage models are applicable to arid and semi-arid regions, lack of data for key input parameters for drainage models and the high cost of drainage installation.

Drainage simulation models such as DRAINMOD, SWAP, ADAPT, RZWQM2, EPIC, WaSim and HYDRUS-1D can potentially be used to provide reliable predictions of multi-component systems to evaluate drainage system design, over long periods (1 – 100 year). These models have been applied and tested in many areas of the world

such as, the Netherlands (Kroes et al., 2000), Canada (Huang et al., 2011), Egypt (Kandil et al., 1995), USA (Ayars and Evans, 2015), Turkey (Kale, 2011), China (Luo et al., 2009), Brazil (Merigueti et al., 2015) and Australia (Bennett et al., 2013). However, these models require extensive temporal as well as spatial input datasets for soils, hydrology, topography, climate, and crop variables, which is a problem for many least developed countries where availability and temporal and spatial incoherence of data is limited. In addition, operating the models requires trained and experienced users. To meet the dual challenge of sustainable agriculture and water use efficiency in Libya and to optimise yields in irrigated areas, rehabilitation and improvements to existing drainage systems as well as the design of new drainage systems need to be urgently implemented. To enable this, there is a need to determine which drainage simulation models are most appropriate for Libya. This review (1) evaluates selected drainage simulation models and their applicability to arid and semi-arid areas, (2) establishes and applies selection criteria based on availability of data in least developed countries such as Libya and, (3) identifies the most suitable model for application in Libya.

2.2 Drainage Simulation models for arid and semi-arid regions

Drainage simulation models, also known as “Agro-Hydrological Models”, can evaluate and predict the soil-water condition, soil salinity and water table depths under given water management, crop rotation, and climatic conditions (Skaggs, 1999). In addition, drainage simulation models allow multiple scenarios to be applied by considering the effect of capillary rise and deep percolation on the drainage design as well as the effects of drain spacing and depth on crop yield and water table depth. Models such as DRAINMOD and SWAP can be used to evaluate alternative designs such as, the effects of various irrigation strategies and drain spacing and depth on crop yield (Kandil et al., 1995; Merigueti et al., 2015), while ADAPT and HYDRUS can simulate soil moisture status/waterlogging (Gowda et al., 2012; Šimůnek et al., 2012). In the next section, seven simulation models will be reviewed, namely: ADAPT, RZWQM2, DRAINMOD, EPIC, HYDRUS-1D, WaSim, and SWAP. Table 2-1 illustrates the applications of each model in arid and semi-arid areas. The initial selection criteria for the selected seven models in this research are based on: (1) the model must simulate the daily performance of a field which includes a drainage system installed. (2) the

model must be a field scale model, because the field scale is the scale at which farmers make decisions. (3) the model must simulate and predict the potential crop yield based on climatic condition, soil water condition and drainage system. The seven selected models (ADAPT, RZWQM2, DRAINMOD, EPIC, HYDRUS-1D, WaSim, and SWAP) all met the initial selection criteria and therefore are used in this research.

Table 2-1 The drainage simulation models applications in arid and semi-arid countries with the references.

Model name	Applications in arid and semi-arid area
ADAPT	The model has not been applied
RZWQM2	China (Chen et al., 2020; Zenghui et al., 2019), and USA (Kisekka et al., 2017).
DRAINMOD	India (Gupta et al., 1993), and Egypt (Abdel-dayam and Skaggs, 1990; Kandil et al., 1995; Wahba and Christen, 2006; Wahba et al., 2002).
EPIC	Argentina (Bernardos et al., 2001), France (Cabelguenne et al., 1990), Australia (Jones et al., 1989), China (Gao et al., 2017), and USA (Gassman et al., 2005; USDA, 1990).
HYDRUS-1D	Oman (Al-Maktoumi, 2021), China (Chen et al., 2021; Qian et al., 2021), Morocco (Er-Raki et al., 2021), and Tunisia (Kanzari et al., 2021).
WaSim	India (Hirekhan et al., 2007), and Colombia (Depeweg and Fabiola Otero, 2004).
SWAP	Pakistan (Sarwar and Feddes, 2000), India (Bastiaanssen et al., 1996; Verma and Gupta, 2014; Verma and Isaac, 2010), and Argentina (Bastiaanssen et al., 1996).

2.2.1 The Agricultural Drainage and Pesticide Transport (ADAPT) model

The Agricultural Drainage and Pesticide Transport (ADAPT) model is a one-dimensional, daily time step, field-scale simulation model created by the Department of Agricultural Engineering of Ohio State University (Chung et al., 1992). The ADAPT model has three components: hydrology, erosion, and pesticide transport. In the hydrology component the model is capable of simulating the quantity and quality of drainage water linked to water table depth. The ADAPT model integrates two models: the first model is the Groundwater Loading Effects of Agricultural Management Systems (GLEAMS) (Leonard et al., 1987), and the second is DRAINMOD (Skaggs, 1982). ADAPT model can predict hydrology and water quality components such as

subsurface drainage volume, and nitrate losses from subsurface drainage (Gowda et al., 2012). The ADAPT model requires climatic data, drainage design information, soil water content data and crop information (Table 2-2).

Table 2-2 Minimum input parameters required to run the ADAPT model.

Input data requirement	
Climatic data	Daily precipitation, average daily temperature, radiation, relative humidity, wind speed, and potential evapotranspiration
Drainage design	Drain depth and spacing, distance from drain to impermeable layer, initial depth of water table, and maximum surface storage.
Soil water content	Bottom depth of each soil layer and soil layer saturated hydraulic conductivity, water characteristics, water table – volume drained – upward flux, Green–Ampt parameters for different water table depths, percentage of rainfall that penetrates to the water table, and surface cracking parameter.
Crop	Planting and harvesting dates, root depth, tillage, and fertilizer and pesticide applications. In some cases, leaf area index parameter.

One of the strengths of using the ADAPT model is that it has been applied extensively, especially around the Midwest US (humid areas), and is considered to accurately describe hydrological components such as, water table depth, nitrate losses in subsurface drainage and subsurface drainage flow in heavy soil types (heavy soils contain more clay and are sticky and hard to work but tend to be more fertile) (Anand et al., 2007; Gowda et al., 1999a, 2007, 2008; Johansson et al., 2004; Petrolia and Gowda, 2006a, 2006b; Sands et al., 2003; Sogbedji and McIsaac, 2006; Updegraff et al., 2004). Also, the accuracy of ADAPT model has been evaluated to predict the water table depth in comparison to other widely-used models such as DRAINMOD and SWAT (Desmond et al., 1996). The results show that on heavy soil types and humid agroclimatic zones, the performance of ADAPT to predict water table depth is comparable to the results obtained from DRAINMOD and SWAT (Desmond et al., 1996; Gowda et al., 2012). The ADAPT model was accurately applied to evaluate water flow and nutrient discharge at the field scale, and catchment scale in northern Ohio and Minnesota (Dalzell et al., 2004; Davis et al., 2000; Gowda et al., 1999b). In

more recent studies conducted in southern Minnesota, the model was applied to evaluate the impacts of subsurface drain spacing and depth (Nangia et al., 2010b), the rate and timing of N application (Nangia et al., 2010a, 2008), and changes in precipitation (Nangia et al., 2010c) on N losses. However, and critically, the model has not been applied in arid areas to design and/or evaluate drainage systems. Also, ADAPT has not been tested in areas where the soil texture is predominantly sandy, and the rate of saturated hydraulic conductivity (K_{sat}) is high, such as in Libya. For example, the highest value K_{sat} applied in ADAPT model is 2.0 m d^{-1} , while in a study in Libya, the highest values of K_{sat} was 38.0 m d^{-1} (Ellafi et al., 2021). Therefore, the model needs to be tested in more diverse environments, including arid areas, before it can be recommended to design drainage systems in new areas such as in Libya. Limited technical support is available for users and there is no GIS user interface available for ADAPT (the script cannot be directly input into a GIS compatible format). It is a DOS-based model which uses a text editor to create input files (ADAPT was written in FORTRAN with modular programming techniques), which makes it hard to identify errors especially for inexperienced users (Gowda et al., 2012).

2.2.2 RZWQM2 - Root Zone Water Quality Model 2

RZWQM2 is a one-dimensional model that focuses on the effects of water management practices on water quality, water quantity, and crop yields. RZWQM2 model can simulate the soil stratigraphy of up to 30m depth including the root zone for one specific crop at any given time (simulating crop growth and the movement of water, nutrients and pesticides over, within and below the crop root zone of a given unit area). The model includes crop growth parameters for >20 field crops from the Decision Support System for Agrotechnology Transfer (DSSAT) crop modules (Ma et al., 2011). RZWQM2 uses daily steps crop growth, considers the soil water content, pesticide movement, and heat transfer; in addition, it can obtain and utilise up to 10 stratigraphic layer (Ma et al., 2012). To design a drainage system, RZWQM2 requires climatic site description, soil and pesticide property, crop, initial soil condition, and management practice input parameters (Table 2-3).

Table 2-3 Minimum input parameters required for the RZWQM2 model.

Input data requirement	
Climatic data	Daily precipitation (amount and intensity), minimum and maximum daily temperature, solar radiation, relative humidity, and wind speed.
Site description	Latitude, elevation, longitude, and slope
Soil properties	Soil horizon delineation, soil texture, and bulk density. Soil hydraulic properties: soil water content at 33 and 1500 kPa suction, and saturated hydraulic conductivity.
Pesticide properties	General pesticide data such as common name, half-life, adsorption constant, and dissipation pathways.
Management practices	Estimate of dry mass and age of residue on the surface, tillage, irrigation, planting/harvest, fertilization, etc.
Crop	Specifying a crop cultivar from supplied database
Initial soil condition	Initial soil water content/water table; initial soil temperatures; initial soil pH and cation exchange capacity values

RZWQM2 has some strengths that make it unique. First, it can be combined with other models such as the DSSAT crop growth model (Jones et al., 2003), the Simultaneous Heat and Water (SHAW) model (Flerchinger and Saxton, 1989; Flerchinger and Pierson, 1991), and the Parameter Estimation Software (PEST) (Doherty, 2010) this combination helps RZWQM2 to improve the accuracy of simulations in the crop root zone. The RZWQM2 model has been shown to generate accurate predictions across a range of soil types including sandy located in Minnesota (Wu et al., 1999), clay located in Thailand (Shrestha and Manandhar, 2014) silt loam located in Kentucky (Malone et al., 2004), and sandy loam located in New Jersey (Ahmed et al., 2007). It has been applied to humid (Ahmed et al., 2007), tropical (Shrestha and Manandhar, 2014), semi-arid area in the United States (Kisekka et al., 2017) and arid area in China (Chen et al., 2020; Zenghui et al., 2019). The development of a Windows-based user interface has made it more accessible for researchers and drainage managers to use as it does not require expertise in coding (Ma et al., 2000, 2007a). RZWQM2 is one of the few models that simulates pesticide uptake by plants, equilibrium and kinetic adsorption, degradation and irreversible adsorption, volatilization, and macropore transport of pesticides. In addition, RZWQM2 has a unique ability to estimate chemical

losses (e.g., nitrogen) due to runoff. RZWQM2 is also able to simulate subsurface drainage flow, the fluctuation of water table depth, and nutrient losses from agricultural fields through subsurface drains. (Ma et al., 2007d, 2007b, 2007c; Qi et al., 2011). RZWQM2 also has some weaknesses; for example, when the field is heterogeneous, the model should be used either by simulating a sub-field or by using average values for the soil inputs. RZWQM2 is unable to estimate the runoff for each sub-field or able to simulate water retention due to surface roughness. Despite the model including a soil equilibrium chemistry module, the simulation of changes in soil pH and EC is not fully evaluated and the model cannot simulate more than one crop at the same time (Ma et al., 2012).

2.2.3 DRAINMOD

DRAINMOD is a widely adopted simulation model that describes the hydrology of poorly, or artificially drained, shallow water table soils. The first version of DRAINMOD was published in the 1970s (Skaggs, 1980, 1978, 1977). Since then, the model has been modified to include sub-models such as the soil salinity model DRAINMOD-S (Kandil et al., 1995), and field-scale models for predicting nitrogen transformation and fate DRAINMOD-N (Breve-Reyes, 1994) and DRAINMOD-NII (Youssef et al., 2005). DRAINMOD has been used extensively in humid areas (Ale et al., 2012; Breve-Reyes et al., 1998; Sanoja et al., 1990) and by the United States Department of Agriculture - Natural Resource and Conservation Service (USDA-NRCS) to design and evaluate drainage systems in the United States (Ayars and Evans, 2015). DRAINMOD has also been applied successfully in semi-arid areas to predict water table fluctuation in India (Gupta et al., 1993) and salt load, water table depth and drainage discharge in Australia (Wahba and Christen, 2006). DRAINMOD was evaluated in Egypt to simulate the water table depth under two management practices (conventional and controlled drainage) (Wahba et al., 2002). For arid areas, DRAINMOD was first applied to simulate soil salinity changes during irrigation of one crop season, and the results showed that the model could be extended to simulate drainage systems in arid areas (Abdel-dayam and Skaggs, 1990). DRAINMOD has also been successfully applied to predict the effect of soil salinity on crop yield, and to evaluate the impact of different irrigation strategies and drainage designs on crop yields (Kandil et al., 1995).

The input requirements to design a drainage system using DRAINMOD include climatic and soil water content data, drainage design information, and crop information (Table 2-4).

Table 2-4 Minimum input data required to design a drainage system using DRAINMOD.

Input data requirement	
Climatic data	Hourly precipitation, daily maximum and minimum air temperature, and potential evapotranspiration
Drainage design	Drain depth and spacing, distance from drain to impermeable layer, initial depth of water table, and maximum surface storage.
Soil water content	Bottom depth of each soil layer and soil layer saturated hydraulic conductivity; water characteristics; water table – volume drained – upward flux; Green–Ampt parameters for different water table depths.
Crop	Root depth, yield, stress due high-water table, and trafficability parameters.

A key strength of DRAINMOD is its wide adoption in many areas of the world and accurate predictions. In arid and semi-arid areas, DRAINMOD was accurately applied to predict soil salinity, water table depth, and relative crop yield. DRAINMOD is a one-dimensional model, and lateral and downslope seepage can be taken into account (Smedema et al., 2004). Also, DRAINMOD shows potential in predicting hydrologic variables such as infiltration rates, subsurface drainage, surface runoff, evapotranspiration, vertical and lateral seepage, water table depth, and drained or water-free pore space in the soil profile (Skaggs et al., 2012b). DRAINMOD outputs are summarised in a user interface as either daily, monthly, or yearly formats depending on end-user requirements. Additional outputs can be predicted such as crop yields (e.g. rotations of five crops (Kandil et al., 1995)), salinity status, the depth of irrigated water, and variables indicating wetland hydrological status (i.e. the number of continuing days with water table close to the surface). DRAINMOD supports the use of outputs from Pedotransfer functions (PTFs) models (such as Rosetta (Schaap et al., 2001)) as a source of key soil input data including saturated and unsaturated hydraulic conductivity.

2.2.4 The Environmental Policy Integrated Climate model (EPIC)

EPIC (Williams, 1990; Williams et al., 1996, 1984) includes hydrological and environmental models produced by USDA-ARS and Texas AgriLife Blackland Research and Extension Centre (BREC) laboratories in Temple, Texas (Williams et al., 2008). EPIC combines the Groundwater Loading Effects of Agricultural Management Systems (GLEAMS) model (Leonard et al., 1987), the Agricultural Land Management Alternatives with Numerical Assessment Criteria (ALMANAC) model (Kiniry et al., 1992), and Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS) model (Knisel, 1980). EPIC can be applied to simulate drainage areas which are characterised by homogeneous weather, soil, crop rotation, and agricultural management practices for detailed field simulations (Wang et al., 2012). The input requirements to design a drainage system using EPIC include potential evapotranspiration, runoff, crop growing season, soil property, and irrigation parameter variables (Table 2-5).

Table 2-5 Minimum input data required to design a drainage system using EPIC.

Input data requirement	
Potential evapotranspiration	Hargreaves: maximum and minimum temperature, or Penman-Monteith: daily maximum and minimum temperature, relative humidity, wind speed, and solar radiation
Runoff	Curve Number, rainfall amount, potential maximum retention after runoff begins, and initial infiltration rate.
Crop growing season	Fixed dates schedule, planting and harvesting dates, water stress, plant population, winter dormancy, maximum potential leaf area index, harvest index, and biomass-energy ratio.
Soil property	Bulk density, soil field capacity and wilting point, and saturated hydraulic conductivity,
Irrigation	Irrigation ratio, floodplain saturated conductivity, maximum groundwater storage, groundwater residence time, return flow, deep percolation, and groundwater storage threshold

The EPIC model can be subdivided into subarea components including weather, hydrology, erosion-sedimentation, nutrient, pesticide fate, plant growth, soil temperature, tillage economic budgets, and plant environment control (Williams,

1990). Sabbagh et al. (1993) modified, the hydrology component to simulate daily water table fluctuations and the effect of subsurface drainage systems. EPIC is an open-source code written in FORTRAN which has been maintained by the BREC development and user support team. Therefore, EPIC has several Windows and GIS-based versions with detailed user manuals (BREC, 2012). For management practices, EPIC has been calibrated and validated for several studies such as (Gassman et al., 2010) and (Wang et al., 2011). In arid and semi-arid areas, EPIC was accurately applied to predict the crop yield in many areas in the world including, Argentina (Bernardos et al., 2001), south of France (Cabelguenne et al., 1990), Australia (Jones et al., 1989). EPIC was successfully applied in arid China, to predict maize yield and the contribution of shallow groundwater to evapotranspiration (Gao et al., 2017). EPIC has also been applied to predict crop yield in semi-arid areas in Texas and California (Gassman et al., 2005; USDA, 1990). However, and critically, EPIC has limited ability to estimate drainage volume and changes in water table depth due to the volume of water applied (via rainfall and/or irrigation) (Wang et al., 2012). In addition, EPIC needs further development to be able to accurately estimate the volume of water removed from the soil profile through subsurface drainage, which is a key design requirement for drainage systems in arid and semi-arid areas (Gassman et al., 2010).

2.2.5 HYDRUS-1D

The HYDRUS-1D model and its related models such as SWMS-2D, CHAIN_2D, HYDRUS-2D, HYDRUS (2D/3D), UNSATCHEM, HP1, and CW2D have been widely applied to estimate water flow and solute transport in soil profiles and groundwater movement (PC-PROGRESS, 2020a, 2020b; Šimůnek et al., 2011). In 2010, the HYDRUS website (PC-PROGRESS, n.d.) claimed that there were >1000 peer-reviewed journal references in which the HYDRUS programs had been applied (Šimůnek et al., 2012). Critically, HYDRUS has only been applied once for drainage design in an arid area, (Qian et al., 2021). Qian et al. (2021) assessed the influence of subsurface drainage parameters on soil desalination and salt discharge using HYDRUS-1D. However, HYDRUS-1D was successfully applied in arid and semi-arid areas for other proposes such as, monitoring the shallow water table in arid urban zone in Oman (Al-Maktoumi, 2021), estimating groundwater recharge and evapotranspiration in arid inland in China (Chen et al., 2021), predicting soil moisture

at different depth, actual evapotranspiration, and deep percolation of semi-arid area in Morocco (Er-Raki et al., 2021), and evaluating the soil salinisation risks under different climate change scenarios in a semi-arid region of Tunisia (Kanzari et al., 2021). HYDRUS-1D software is free to download either from the HYDRUS or USDA-ARS website. The general approach in HYDRUS-1D model is to choose an objective function to serve as a level of the agreement between measured and predicted data, and which directly or indirectly is related to the adjustable parameters. By minimising this objective function, the best-fit parameters are determined. (Simunek et al., 1998). The HYDRUS-1D models can be used to simulate the movement of water and solute transport (Šimůnek et al., 2012). In addition, HYDRUS-1D can be applied to estimate flow by solving the Richards equation (Richards, 1931). To describe unsaturated or partially saturated soil hydraulic properties, HYDRUS-1D uses PTFs developed by van Genuchten (1980), and Brooks and Corey (1964), as modified by (Durner, 1994; Kosugi, 1996; Vogel and Císlerová, 1988). To predict the saturated hydraulic conductivity the Rosetta PTF model (Schaap et al., 2001) is installed inside HYDRUS-1D. These PTFs were developed mainly on heavier soils unlike the sandy soils existing in Libya (Ellafi et al., 2021). HYDRUS-1D considers both equilibrium and nonequilibrium flow by assuming a fraction of the liquid phase as being mobile and immobile respectively (Šimůnek et al., 2003; Šimůnek and van Genuchten, 2008). HYDRUS-1D has an underlying equation called the Marquardt-Levenberg algorithm (Marquardt, 1963). The Marquardt-Levenberg algorithm is used for inverse estimation of soil hydraulic properties, solute transport, and/or heat transport parameters from the measured transient or steady-state flow and/or transport data (Marquardt, 1963; Šimunek and Hopmans, 2002). A major weakness of the Marquardt-Levenberg algorithm is that the algorithm only searches for a local minimum of the objective function (Šimůnek et al., 2012). This potentially could lead to a problem when running HYDRUS-1D in multiple soil horizons where uncertain initial and boundary conditions are involved (Šimůnek et al., 2012). The input data required to design a drainage system using HYDRUS-1D includes, climatic data, drainage design information, irrigation data, soil water content and crop information (Table 2-6).

Table 2-6 Minimum input data required to design a drainage system using HYDRUS-1D.

Input data requirement	
Climatic data	Daily precipitation, daily air temperature, and potential evapotranspiration
Drainage design	Drain depth and spacing, entrance resistance, saturated hydraulic conductivity above and below drains, depth of impervious layer, and wet perimeter of the drain
Irrigation	Observation node triggering irrigation, pressure head triggering irrigation, irrigation flux, duration of irrigation, and lag time when irrigation triggered after signal is reached
Soil water content	Saturated water content, residual water content, saturated hydraulic conductivity, pore-connectivity parameter, and unsaturated hydraulic conductivity.
Crop	Root depth, initial time of the root growth period, yield reduction due to salinity, pressure head when root can and cannot extract water from soil, and potential transpiration,

2.2.6 Water Simulation model (WaSim)

WaSim model is a one-dimensional daily water balance simulation model developed by Cranfield University and HR Wallingford (Hess and Counsell, 2000). WaSim simulates soil water storage in the root zone and water table depths by predicting the infiltration rates, evapotranspiration and drainage discharge in response to precipitation, irrigation and canal seepage as applicable. WaSim was first developed as a teaching and demonstration tool for irrigation, drainage and salinity management. WaSim can also predict the soil salinity status in response to different management practices such as drainage design and environmental scenarios including soil type and cropping patterns (Counsell and Hess, 2001). WaSim has been successfully applied to simulate water use, runoff and deep percolation under different environmental conditions (Stephens et al., 2001). For semi-arid areas, WaSim was successfully used to predict water table depth, drainage discharge and soil salinity in India (Hirekhan et al., 2007). WaSim was also successfully applied in a semi-arid irrigation district in Colombia to determine irrigation requirement, yield reductions and drain discharge (Depeweg and Fabiola Otero, 2004).

WaSim requires a minimal input dataset as compared with other drainage simulation models (Hess and Counsell, 2000). The input data required to design a drainage system using WaSim includes climate data, crop and soil information, irrigation and salinity data, and drainage information (Table 2-7).

Table 2-7 Minimum input data required to design a drainage system using WaSim.

Input data requirement	
Climatic data	Daily rainfall, and reference evapotranspiration
Drainage design	Drain depth, spacing, diameter, and distance to impermeable layer
Irrigation and salinity	Irrigation time and amount, irrigation water quality, and leaching requirement
Soil water content	Water retention, infiltration rates, and saturated hydraulic conductivity
Crop	Cover development and rooting depths

A strength of WaSim is that it does not required intensive input data and training comparing to other drainage simulation models (Hess and Counsell, 2000). WaSim can be run on a daily time-step, to simulate a drainage scheme for up to 30 years, including up to 3 crops in rotation, and can simulate water table depths under both drained or undrained conditions (Hess and Counsell, 2000; Taguta, 2017). However, WaSim has not been widely applied and validated in drained lands. Also, WaSim does not accept initial soil salinity $> 12 \text{ dS m}^{-1}$ which limits the applicability of WaSim in saline areas (Hirekhan et al., 2007). In addition, when scheduling the irrigation, irrigation dates can only be added as a fixed date and cannot be modified in response to lower or higher evapotranspiration (Hirekhan et al., 2007).

2.2.7 The Soil-Water-Atmosphere-Plant (SWAP)

SWAP is a physically based, detailed, agro-hydrological model that simulates the movement of water, and solutes in the vadose zone in response to plant growth. (Van Dam et al., 1997). SWAP is a widely applied 1-D simulation model which designs and evaluates drainage systems (Samipour et al., 2010). The model uses the Richards equation (Richards, 1931); and includes root water extraction, to compute soil moisture movement in variably saturated soils (Kroes et al., 2008).

SWAP has been used in semi-arid Pakistan, to simulate the impacts of land drainage (12 scenarios of drain depth and spacing) on soil moisture conditions in the root zone and their effect on crop yield and soil salinisation in the Fourth Drainage Project, Punjab, Pakistan (Sarwar and Feddes, 2000). SWAP was also applied to predict the impact of fresh and saline irrigation waters on crop yield in semi-arid region in the state of Uttar, India (Verma and Gupta, 2014) and to predict the relative yield and salinity profile under various management options to manage saline drainage effluents under shallow water table conditions in a semiarid monsoon climate (Verma and Isaac, 2010). SWAP has also been successfully applied to predict crop yield, soil salinity and soil moisture conditions in arid areas of India and Argentina (Bastiaanssen et al., 1996). The input data required to design a drainage system using SWAP include climatic, drainage design, soil water content and crop parameters (Table 2-8).

Table 2-8 Minimum input data required to design a drainage system using SWAP.

Input data requirement	
Climatic data	Radiation, precipitation, temperature, vapour pressure, reference evapotranspiration, and wind speed
Drainage design	Drain depth and spacing, depth of impervious layer, drain entry resistance, level of drain bottom, vertical and horizontal hydraulic conductivity above and below drains, and soil profile depth.
Soil water content	Initial moisture condition, ponding, soil evaporation, and soil hydraulic functions
Crop	Crop height, growing period, irrigation time and depth, yield respond, rooting depth, leaf area index, salt stress, interception, root density, root distribution, root growth, and crop water use

SWAP adheres to the open-source philosophy. This allows other research teams to integrate the model into a variety of Decision Support Systems for example the Pesticide Emission Assessment at Regional and Local scales (PEARL) model for pesticides, and the Agricultural Nutrient Model (ANIMO) for nutrients (Ayars and Evans, 2015; Marinov et al., 2005). However, recent versions of the model are distributed without a Graphical User Interface, which make it hard for new and inexperienced users to use SWAP effectively.

2.3 Model Selection

2.3.1 Simulation models approaches

Simulation models can be categorised based on their spatial (e.g. “Field” or “Catchment”) and temporal scales (Radcliffe et al., 2015). The spatial scale of most drainage simulation models is usually the field scale, but in some catchment-scale models such as SWAT, the drainage system is part of the water routing function (Radcliffe et al., 2015). The field scale is the decision making scale for farmers, whilst the catchment scale is appropriate for managing and planning water resource allocations (Flury, 1996; USEPA, 2014). In this review, the focus will be on field scale models (field scale ranges between 10 square meter to 10 ha) as this is the scale at which farmers make decisions, and the surface and subsurface drainage offer convenient sampling points that integrate small-scale processes (Radcliffe et al., 2015). Simulation models range in temporal scale from minutes to year (Table 2-9), daily values of weather data are recommended, because the records are more available from widely distributed meteorological stations (Skaggs et al., 2012b).

The infiltration equations used in drainage simulation models include the Curve Number method (National Resource Conservation Service (NRCS), 2004), Green-Ampt equation (Green and Ampt, 1911), and Richards equation (Richards, 1931). The Curve Number method is an empirical parameter used to predict runoff and can also be used to predict the infiltration rate from rainfall. The Curve Number was developed by the NRCS in 1985 by knowing the amount of rainfall, runoff and the potential maximum soil moisture retention after runoff begins. This method is widely adopted to predict infiltration rates in drained lands at the catchment scale (King et al., 1999). The Green-Ampt equation depends on the availability of key input variables such as soil suction head, water content and saturated soil hydraulic conductivity. The Green-Ampt equation is widely adopted in many hydrological models such as HEC-HMS (USACE, 2000) and in drainage models such as DRAINMOD, RZWQM2. Other drainage models such as HYDRUS-1D uses the Richards equation which depends on the intensity of rainfall, evaporation, and soil hydraulic properties.

Table 2-9 Summary of model properties related to simulating drainage systems in arid and semi-arid regions.

Model properties	Model						
	ADAPT	RZWQM2	DRAINMOD	EPIC	HYDRUS-1D	WaSim	SWAP
Spatial scale	Field	Field	Field	Field	Field	Field	Field
Temporal Scale	Day	Minute-day	Hour-day	Day-year	Minute-year	Day-year	Hour-day
Infiltration rate	CN	GA	GA	CN or GA	Richards ^[A]	CN	Richards
Management practices	Limited	Extensive	Extensive	Extensive	Limited	Extensive	Extensive
Monitoring water table*	Yes	Yes	Yes	Yes	No	Yes	Yes
Salinity status*	No	Yes ^[B]	Yes	Yes	Yes	Yes	Yes
Ditches/Pipes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Availability	Free	Free	Free	Free	Free	Free	Free
References	(Chung et al., 1992)	(Ma et al., 2009)	(Skaggs, 1977)	(Williams et al., 1984)	(Simunek et al., 1998)	(Hess and Counsell, 2000)	(Kroes et al., 2000)

Where: The Agricultural Drainage and Pesticide Transport (ADAPT), Root Zone Water Quality Model 2 (RZWQM2), The Environmental Policy Integrated Climate (EPIC), Water balance model (WaSim), The Soil-Water-Atmosphere-Plant (SWAP). CN is the Curve Number; GA is the Green-Ampt. *Critical in arid and semi-arid regions. [A] Richards equation, [B] Have not been tested at all.

2.3.2 Model selection criteria

The aim of this review was to identify a suitable drainage model that could be used to design and/or evaluate drainage systems in arid regions, specifically drainage schemes in Libya. A key requirement was that the selected model should meet the minimum criteria established by Skaggs (1999). Firstly, model selection was based on the models capability (the ability to design a successful drainage system in an arid area to prevent salinity and waterlogging problems) and the cost of its application (Skaggs, 1987). The selection of the model depends on the nature of the problem to be solved. In arid areas, the key aspect of drainage system design is defining the optimum water table depth and drain spacing. These are essential to prevent soil salinity and waterlogging affecting crop yield. Therefore, the selected model has to be able to accurately predict the fluctuations of water table depths in response to irrigation amount and the prevailing climatic conditions including rainfall and evapotranspiration on a daily basis.

Moreover, the selected model was required to accurately predict the soil salinity status of the root zone and the amount of irrigation required to maximise crop yield and optimal leaching requirements. In addition, the cost implications of applying the model and the risk of inaccurate predictions must be considered when choosing the model based on applying different alternative designs and choosing the most cost-effective drainage design. The model selection process also considered how frequently each model appeared in the scientific literature as well as whether the application of the model to drainage scheme design was accurate/validated and whether it had been applied to arid regions and soil textural classes typically found in arid regions and Libya, specifically. The availability and cost of generating the input data required by each model and how many input parameters were required to design a drainage system using each model is also an important aspect of the selection criteria.

In addition, the computer requirements and training requirements also need to be considered. In developed countries, usually these requirements are not a major concern and model input data of suitable spatial and temporal frequency and quality are available from multiple sources. However, for least developed countries, the selected model needs to be capable of accommodating data availability limitations that

may be encountered (Table 2-10). If the input data is un- or partially available, of poor quality and/or spatially or temporally dis-contiguous the selected model must support data mining techniques as alternative methods for input data generation. For example, PTFs and Artificial Neural Networks (ANNs) are widely adopted to predict soil water properties such as saturated hydraulic conductivity (K_{sat}). Therefore, the selected model should support the output from or have built-in PTFs and/or ANNs to generate the required input data. In addition, it is preferable that the selected model has the ability to be combined with open source software applications such as QGIS, to pull in remote sensing (RS) data to identify the areas that need to be drained.

Finally, the selected model should consider the effects of other factors on the performance of drainage systems. These factors include drainage water discharge and quality, soil infiltration rates, actual evapotranspiration and relative crop yield. As mentioned previously, the minimum performance requirements for the selected model is that it can address the key irrigation/drainage issues of arid areas namely soil salinity and waterlogging. Therefore, the model needs to be able to accurately predict water table depth, water quality, soil salinity and infiltration rate. Therefore, the more factors that can be described by the model, the lower risk of errors. The key selection criteria used to determine the suitability of the selected models for application in Libya are listed in Table 2-10.

Table 2-10 Suitability criteria for drainage model selection. Justification for criteria are shown in brackets and original objectives shown in italics. (the model score 1 if it can achieve the defined characteristic, and will score 0 if it has not achieved the defined characteristic.

Selection Criteria	Model						
	ADAPT	RZWQM2	DRAINMOD	EPIC	HYDRUS-1D	WaSim	SWAP
Key model characteristics required in order to design drainage systems in Libya							
Has the model been applied and validated to simulate drainage systems in arid regions	0	1	1	1	1	1	1
Has the model been applied to simulate soil salinity status and waterlogging in arid regions	0	0	1	0	1	1	1
Has the model been applied in the least developed countries	0	0	1	1	1	1	1
Does the model have the potential to be applied in arid regions.	1	1	1	1	1	1	1
Is all input data available in Libya	0	0	0	0	0	0	0
Model supports input data derived from data mining techniques (i.e. PTFs, ANNs and/or remote sensing)	1	1	1	1	1	1	1
Does the model consider the effects of other factors (e.g. lateral flow, ET, deep percolation, working days, and crop growth affected by waterlogging and salinity)	1	1	1	1	1	1	0
The model uses widely accepted equations used in the development of drainage simulation models (Richard's equation, water balance approach, Curve Number, and/or Green-Ampt)	1	1	1	1	1	1	1
Has the model been combined with GIS programs.	0	1	1	1	1	0	1
Is the model widely referenced and validated for drainage applications (based on publications >20)	0	0	1	0	0	0	1
Total score of A. Characteristic requirements	4	6	9	7	8	7	8

Table 2-10 continued							
User requirements							
Is the model open source	1	1	1	1	1	1	1
Computer requirements (can run under minimum computer requirements in the least developed countries “£500”)	1	1	1	1	1	1	1
Technical support is available for users	0	1	1	1	1	0	1
Tutorial available to learn how to apply the model	0	1	1	1	1	1	1
The model does not require intensive training is intuitive to use, errors are easy recognise (e.g. windows interface models preferred over Dos-based model)	0	1	1	0	0	1	0
Total score of B. User requirements	2	5	5	4	4	4	4
Total score A+B	6	11	14	11	12	11	12

In Table 2-10, the model selection criteria are divided into key model characteristics required to design drainage systems in Libya and user requirements. The key model characteristics include conditions such as the availability of input data required by each model, and the ability to be applied in arid regions such as Libya. The users' requirements include conditions such as cost of the model, minimum computer requirements and level and availability of the technical training required and user support. Each model was scored against all selection criteria. More positive responses were scored higher than negative ones, for example, if a model has been applied in arid regions, that model was given a score of (1). If the model was not applied in arid areas, it was given a score of (0). The sum of the score of each criterion gave the overall model criteria total score with the selected model having the highest total score.

The selection criteria total scores in Table 2-10 shows that DRAINMOD had the highest total score of 14 points (comprising 9 key model characteristic requirement points and 5 user requirement points). HYDRUS-1D and SWAP had the second highest total scores with 12 points each. This was followed by RZWQM2 and WaSim which had a total score of 11 points each. The model with the lowest total score in Table 2-10 was ADAPT with a total score of 6 points. While RZWQM2 scored well in individual criteria, DRAINMOD had a greater number of publications related to drainage applications, which means greater validation under peer review and was applied more times in arid and semiarid regions. Based on this selection criteria, DRAINMOD was identified as the most suitable model to design and evaluate drainage systems in Libya and other data poor arid regions

2.4 DRAINMOD input data availability and quality of input data in Libya

DRAINMOD considers the effect of salinity, excess water, and drought on crop yield (Wahba et al., 2002). DRAINMOD like other models discussed in this review is dependent on input data, such as daily precipitation and temperature, soil water characteristics (Table 2-4), land use, and topography. Without these data, applying DRAINMOD to design a drainage system in a given target location will not be possible, which is the case in many least developed countries including Libya. Therefore, these data need to be measured or interpolated using PTFs or ANNs to run DRAINMOD. Table 2-11 illustrates the input data required to run DRAINMOD for designing a drainage system in arid areas. Table 2-11 also shows the assessment undertaken by Skaggs et al., (2012b) including the expected range by DRAINMOD for each input parameter. The availability of data input sources for least developed countries and Libya specifically is also included. Table 2-11 also illustrates the ability of DRAINMOD to predict each of the input parameters and other alternative approaches that can be used to predict the required input parameters.

Table 2-11: DRAINMOD inputs data required for drainage system design adopted from (Skaggs et al., 2012b).

Input data	Expected range	Data sources in Libya^A	DRAINMOD prediction^B	Alternative methods of measurements
Drain depth	50 to 300 cm	Drainage maps and reports for HAP and EAP: the source is the archive at the General Water Authority located in Tripoli and the data was produced by (Cornelius-Brochier J.V, 1981; Danenco, 1980; Holzmann-Wakuti, 1974; Italconsult, 1976)	No	Field measurements
Drain spacing	5 to 200 m		No	Field measurements
Depth to restrictive layer	50 to 1000 cm		No	Field measurements
Profile layer depths	5 to 200 cm		No	Field measurements
Drainage coefficient (DC)	0.5 to 10 cm d ⁻¹	Unavailable	No	Field measurements
Surface storage (S1)	0.25 to 10 cm	Unavailable	No	Field measurements
Minor depressional storage (S2)	0.25 to 10 cm	Unavailable	No	Field measurements
Crop or vegetation inputs^C	Evans et al., (1991)	Reports (GWA, 1999) and literature such as (Allen et al., 1998; Evans et al., 1991; Kandil et al., 1995)	No	Experiments
Root depth versus time (cm vs. days)	0 to 100 cm		No	Experiments
Saturated hydraulic conductivity by layer	0.05 to 100 cm h ⁻¹	Field and laboratory measurements for HAP and EAP: available at the General Water Authority (Cornelius-Brochier J.V, 1981; Holzmann-Wakuti, 1974; Italconsult, 1976)	No	These inputs can be predicted by applying widely adopted PTFs such as Rosetta and/or developing ANNs using easily measured data such as soil texture and bulk density
Soil water retention curve by layer h(Θ)	Skaggs, (1980)		Yes	
Soil water content at saturation (Θ_s)	0.3-0.9 cm ³ cm ⁻³		No	
Soil water content at lower limit (Θ_{ll})	($\Theta_s - 0.10$) to ($\Theta_s - 0.26$) cm ³ cm ⁻³		No	

Table 2-11 continued

Drainage volume versus water table depth (Vd)	Skaggs, (1980)	Unavailable	Yes	Laboratory and/or field measurements
Upward flux versus water table depth (Upflux)	Skaggs, (1980)	Unavailable	Yes	Laboratory and/or field measurements
Infiltration parameters versus water table depth	Skaggs, (1980)	Unavailable	Yes	Laboratory and/or field measurements
Initial soil salinity by layer	0 to 18 millimhos cm ⁻¹	Survey and reports for HAP and EAP: the source is the archive at the General Water Authority located in Tripoli and the data was produced by (Cornelius-Brochier J.V, 1981; Danenco, 1980; Holzmann-Wakuti, 1974; Italconsult, 1976).	No	Field measurements or developing ANNs using easily data obtained from remote sensing images from Landsat images.
Groundwater salinity	Measured		No	
Irrigation water salinity	Measured		No	
Irrigation amount	Kandil et al. (1995)		No	Experiments
Daily but preferred hourly precipitation	Observed	Meteorological stations nearby HAP and EAP: the source is the Libyan National Meteorological Centre; however, the daily datasets are partly available with missing values in some days.	No	Meteorological data can be obtained on hourly basis with no missing values from ERA5-Land (Muñoz-Sabater, 2019)
Daily maximum and minimum air temperature	Observed		No	
Daily potential evapotranspiration (PET)	0.0 to 2 cm ⁻¹		No	

[^A] the data sources focused on two agricultural projects located in Libyan arid areas namely: Hammam Agricultural Project (HAP), and Eshkeda Agricultural Project (EAP). [^B] Is DRAINMOD able to predict that input parameters within the model? [^C] The impact of different factors on yield such as excess water stress, deficit water stress, planting delay and salinity stress, PTFs are the pedotransfer functions, ANNs are the Artificial Neural Networks. Methods to obtain input data for DRAINMOD in data-poor arid regions

As discussed in this study, DRAINMOD would be the recommended option for the design and evaluation of drainage systems in arid regions. However, even though DRAINMOD has the ability to predict input data such as the unsaturated hydraulic conductivity, upward flux versus water table depth, and infiltration rates, the model is not suitable to design and evaluate drainage systems in data-poor areas. However, it is crucial to note that DRAINMOD users can maximise the use of DRAINMOD in areas where there are insufficient datasets. DRAINMOD is driven by input data (Table 2-10), this data may be partially or completely unavailable in data-poor low-income countries because of the economic cost and time and expertise required to collect the data. However, utilising alternative ways of generating the required data can make the use of DRAINMOD viable. One such alternative method to accurately generate the missing data is to use artificial neural networks (ANNs).

ANNs have been successfully applied to several agricultural engineering problems, including, yield prediction such as, corn yield (Uhrig et al., 1992; Uno et al., 2005), soybean growth (Zhang et al., 2009), and wheat yield (Ruß et al., 2008). In water management, ANNs have been applied to simulate the groundwater levels in coastal aquifers (Taormina et al., 2012), to predict water table response to change in precipitation (More, 2018), to predict drainage water and groundwater salinity at various drain depths and spacing (Nozari and Azadi, 2017), and to estimate evapotranspiration (Feng et al., 2017). In soil management studies, ANNs has been used to determine soil temperature (Nahvi et al., 2016), to estimate total soil nitrogen, organic carbon and moisture content (Morellos et al., 2016), and to estimate soil hydraulic properties such as soil water content, saturated and unsaturated hydraulic conductivity (Ellafi et al., 2021; Schaap et al., 2001), and reduction in hydraulic conductivity (Ezlit et al., 2014). However, further research is needed to assess how successfully missing input data for DRAINMOD and other models can be derived from ANNs to support drainage system design. In this study, indirect methods to predict three input parameters (i.e. saturated hydraulic conductivity, evapotranspiration, and soil salinity) required by DRAINMOD are discussed as follow:

2.4.1 Saturated hydraulic conductivity (K_{sat})

Saturated hydraulic conductivity is a key input parameter to evaluate drainage system designs. Direct methods of estimating K_{sat} are often difficult, time-consuming and expensive. In DRAINMOD, K_{sat} for each horizon above the restricting layer is an essential parameter because: (1) K_{sat} in DRAINMOD is used to calculate other input parameters such as infiltration rates by applying the Green-Ampt equation, and the capillary rise water table depth relationship. (2) K_{sat} is also integral to the Hooghoudt's steady state equation to calculate drainage flux, water table depth and spacing between drains. In addition, K_{sat} is considered as the most sensitive input parameter in DRAINMOD in terms of predicting the annual subsurface drainage volume, growing season and relative crop yield. Research is needed into the application of indirect methods to estimate K_{sat} such as utilising existing PTFs and/or developing ANNs to estimate K_{sat} from more readily available soil measurements (Cosby et al., 1984; Dane and Puckett, 1994; Julia et al., 2004; Puckett et al., 1985; Saxton et al., 1986; Schaap et al., 2001). Thereafter, validation is required by applying the predicted K_{sat} values in DRAINMOD to design drainage systems as compared to the design based on measured K_{sat} .

2.4.2 Evapotranspiration (ET)

Evapotranspiration is a main component in the water balance equation applied by DRAINMOD. Accurate prediction of ET is also important to justify the crop water requirements and leaching requirements. ET can be directly measured from the soil water balance in lysimeters (Allen et al., 1998). However, such measurements are rarely available in low-income countries, for a given time and location, even within data-rich areas. Alternatively, ET can be calculated from climatological data such as net radiation, temperature, humidity, and wind speed. DRAINMOD can determine ET through inputting the daily maximum and minimum temperature and precipitation. Yet, within data-poor areas, this meteorological data is often absent or discontinuous. Research is needed into alternative methods to estimate these missing values, for example, applying ANNs to predict the missing meteorological data needed for ET calculation, such

as the daily maximum and minimum air temperature (Ustaoglu et al., 2008). Other methods have predicted the missing meteorological data using the Arithmetic Averaging of Neighbouring Stations (AANS) (Xia et al., 1999), predicting daily maximum and minimum air temperature from average monthly data (Liu et al., 2008), or using calculated meteorological data such as ERA5-Land (Muñoz-Sabater, 2019). Also, ANNs can be developed to predict ET from limited climate data (Zanetti et al., 2007). The predicted ET based on each method should be applied in DRAINMOD to evaluate the impact of using each method on crop yield and water table depth in comparison to the ET calculated from observed data.

2.4.3 Soil electrical conductivity (EC)

Soil electrical conductivity is a measure of the amount of salt in a given soil (soil salinity). By knowing the EC with depth, DRAINMOD is able to predict long-term effects of different irrigation and drainage practices on crop yield. Direct measurements of EC are expensive and time consuming. Therefore, research is needed to find an alternative method to predict EC of soil with depth. A potential method may be to develop an ANN model to predict EC from more readily available soil measurements such as groundwater depth and quality, soil texture and irrigation water quality (Bouksila et al., 2010). However, such data may not be available in many areas especially within the least developed countries. Therefore, the potential of using remote sensing images such as Landsat coupled with ANNs to develop a model that can predict soil salinity might be a solution in data-poor areas (e.g. Libya) (Sahbeni, 2021).

2.5 Conclusions

Drainage simulation models such as DRAINMOD, SWAP, ADAPT, RZWQM2, EPIC, WaSim and HYDRUS-1D have been applied to predict the daily performance of drainage systems and to monitor and control water table levels (Malakshahi et al., 2020; Shrestha and Manandhar, 2014; Verma and Gupta, 2014). These models have been developed to describe a specific field condition, such as a shallow water table (Skaggs et al., 2012b), drainage water management practices and their impacts on crop yield (Ma et al., 2012; Verma

and Gupta, 2014), and monitoring soil salinity and irrigation strategies in arid and semi-arid areas (Wahba and Christen, 2006; Wahba et al., 2002). In this study, the applicability of these models to design drainage system in arid and semi-arid areas located in the least developed countries was evaluated and against a selection criterion. The most applicable model was DRAINMOD. Evaluating the feasibility of using predicted K_{sat} , ET, and EC as input parameters for simulation models to design drainage systems in data-poor areas, would help farmers, planners, and decision-makers to reduce the overall cost of drainage system design. Also, it would make these simulation models more accessible tool to evaluate different drainage designs.

2.6 References

Abdel-dayam, S., Skaggs, R.W., 1990. Extension of DRAINMOD for simulating water management in arid regions, in: Vol. II. Proceedings of Symposium on Land Drainage for Salinity Control in Arid and Semi-Arid Regions. Drainage Research Institute, WRC, Cairo, Egypt, pp. 201–212.

Ahmed, I., Rudra, R., Mckague, K., Gharabaghi, B., Ogilvie, J., 2007. Evaluation of the Root Zone Water Quality Model (RZWQM) for Southern Ontario : Part II . Simulating Long-Term Effects of Nitrogen Management Practices on Crop Yield and Subsurface Drainage Water Quality. Water Qual. Res. J. Canada 42, 219–230.

Al-Maktoumi, A., 2021. Shallow Water Table in Arid Urban Zone: Preliminary Study at Sultan Qaboos University Campus, Oman. J. Agric. Mar. Sci. [JAMS] 27, 62–76. <https://doi.org/10.53541/jams.vol27iss1pp62-76>

Ale, S., Bowling, L., Youssef, M., Brouder, S., 2012. Evaluation of simulated strategies for reducing nitrate-nitrogen losses through subsurface drainage systems. J. Environ. Qual. 41, 217–228.

Allen, R.G., Food, of the United Nations, A.O., 1998. Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements, FAO irrigation and drainage paper. FAO.

Anand, S., Mankin, K., McVay, K., Janssen, K., Barnes, P., Pierzynski, G., 2007. Calibration and validation of ADAPT and SWAT for field scale runoff prediction. J. Am. Water Resour. Assoc. 43, 899–910.

Ayars, J.E., Evans, R.G., 2015. Subsurface Drainage - What's Next? Irrig. Drain. 64, 378–392. <https://doi.org/10.1002/ird.1893>

Bastiaanssen, W.G.M., Huygen, J., Schakel, J.K., Broek, B.J. van den, 1996. Modelling the soil-water-crop-atmosphere system to improve agricultural water management in arid zones (SWATRE), in: van den Broek, B.J. (Ed.), Dutch Experience in Irrigation Water Management Modelling. 119, Staring Centrum, , pp. 13–30.

Bennett, S.J., Bishop, T.F.A., Vervoort, R.W., 2013. Using SWAP to quantify space and time related uncertainty in deep drainage model estimates : A case study from northern NSW , Australia. Agric. Water Manag. 130, 142–153. <https://doi.org/10.1016/j.agwat.2013.08.020>

Bernardos, J., Viglizzo, E., Jouvét, V., Lertora, F., Pordomingo, A., Cid, F., 2001. The Use of EPIC Model to Study the Agroecological Change during 93 Years of Farming Transformation in the Argentine Pampas. Agric. Syst. 69, 215–234.

Bouksila, F., Persson, M., Berndtsson, R., Bahri, A., 2010. Estimating Soil Salinity Over a Shallow Saline Water Table in Semiarid Tunisia. Open Hydrol. J. 4, 91–101.

BREC, 2012. APEX Check program [WWW Document]. URL ftp://ftp.brc.tamus.edu/pub/outgoing/jjeong/APEX_Check/ (accessed 5.22.19).

Breve-Reyes, M., 1994. Modeling the movement and fate of nitrogen in artificially drained soils (PhD diss). North Carolina State University, Raleigh, N.C.

Breve-Reyes, M., Skaggs, R.W., Parsons, J., Gillian, J., 1998. Using the DRAINMOD-N model to study the effects of drainage system design and management on crop productivity and NO₃ losses in drainage water. *Agric. Water Manag.* 35, 227–243.

Brooks, R., Corey, A., 1964. Hydraulic properties of porous media. Fort Collins, Colo.

Cabelguenne, M., Jones, C.A., Marty, J., Dyke, P.T., Williams, J., 1990. Calibration and Validation of EPIC for Crop Rotations in Southern France. *Agric. Syst.* 33, 153–171.

Chen, W., Wang, J., Liu, Y., Jin, M., Liang, X., Wang, Z., Ferré, T.P.A., 2021. Using bromide data tracer and HYDRUS-1D to estimate groundwater recharge and evapotranspiration under film-mulched drip irrigation in an arid Inland Basin, Northwest China. *Hydrol. Process.* 35, e14290. <https://doi.org/https://doi.org/10.1002/hyp.14290>

Chen, X., Qi, Z., Gui, D., Sima, M.W., Zeng, F., Li, L., Li, X., Gu, Z., 2020. Evaluation of a new irrigation decision support system in improving cotton yield and water productivity in an arid climate. *Agric. Water Manag.* 234, 1–10. <https://doi.org/https://doi.org/10.1016/j.agwat.2020.106139>

Chung, S., Ward, A., Schalk, C., 1992. Evaluation of the hydrologic component of the ADAPT water table management model. *Trans. ASAE* 35, 571–579.

Cornelius-Brochier J.V, 1981. Wadi Al Shatti: Drainage Design. Tripoli, Libya.

Cosby, B., Hornberger, G., Clapp, R., Ginn, T., 1984. A statistical exploration of soil moisture characteristics to the physical properties of soils. *Water Resour. Res.* 20, 682–690.

Counsell, C., Hess, T., 2001. WaSim User Manual. Bedford, UK.

Dalzell, B., Gowda, P., Mulla, D., 2004. Evaluating feasibility of TMDLs with alternative management practices on an agricultural watershed. *J. Am. Water Resour. Assoc.* 40, 533–543.

Dane, J., Puckett, W., 1994. Field soil hydraulic properties based on physical and mineralogical information, in: *The International Workshop on Indirect Methods for Estimating the Hydraulic Properties of Unsaturated Soils*. Eds MTh van Genuchten et al, University of California: Riverside, CA., pp. 389–403.

Danenco, 1980. Technical Study for Jufra el Hamam Project. Copenhagen, Denmark.

Davis, D., Gowda, P., Mulla, D., Randall, G., 2000. Modeling nitrate nitrogen leaching in response to nitrogen fertilizer rate and tile drain depth or spacing for southern Minnesota, USA. *J. Environ. Qual.* 29, 1568–1581.

Depeweg, H., Fabiola Otero, M., 2004. Optimization of water management in the RUT Irrigation District, Colombia. *Irrig. Drain.* 53, 55–67.
<https://doi.org/doi:10.1002/ird.107>

Desmond, E., Ward, A., Fausey, N., Workman, S., 1996. Comparison of daily water table depth prediction by four simulation models. *Trans. ASAE* 39, 111–118.

Doherty, J., 2010. PEST: Model independent parameter estimation.

Durner, W., 1994. Hydraulic conductivity estimation for soils with heterogeneous pore structure. *Water Resour. Res.* 32, 211–223.

Ellafi, M.A., Deeks, L.K., Simmons, R.W., 2021. Application of artificial neural networks to the design of subsurface drainage systems in Libyan agricultural projects. *J. Hydrol. Reg. Stud.* 35, 1–17.
<https://doi.org/https://doi.org/10.1016/j.ejrh.2021.100832>

Elsahemy, M., 2018. Review of Technologies and Practices for Improving Agricultural Drainage Water Quality in Egypt, in: Unconventional Water Resources and Agriculture in Egypt. Springer Verlag, pp. 163–188. <https://doi.org/10.1007/698>

Er-Raki, S., Ezzahar, J., Merlin, O., Amazirh, A., Hssaine, B.A., Kharrou, M.H., Khabba, S., Chehbouni, A., 2021. Performance of the HYDRUS-1D model for water balance components assessment of irrigated winter wheat under different water managements in semi-arid region of Morocco. *Agric. Water Manag.* 244, 106546. <https://doi.org/https://doi.org/10.1016/j.agwat.2020.106546>

Evans, R.O., Skaggs, R.W., Sneed, R.E., 1991. Stress Day Index Models to Predict Corn and Soybean Relative Yield Under High Water Table Conditions. *J. Am. Soc. Agric. Eng.* 34, 1997–2005.

Ezlit, Y., Ekhmaj, A., Elaalem, M., 2014. Artificial Neural Networks to predict decreasing saturated hydraulic conductivity in soils irrigated. <https://doi.org/10.5027/jnrd.v4i0.05>

FAO, 2016. Country profile - Libya. Rome, Italy. <https://doi.org/10.1787/9487b828-en>

FAO, 2002. Agricultural drainage water management in arid and semi-arid areas, FAO Irrigation and Drainage. <https://doi.org/10.1177/1362361399003003007>

Feng, Y., Peng, Y., Cui, N., Gong, D., Zhang, K., 2017. Modeling reference evapotranspiration using extreme learning machine and generalized regression neural network only with temperature data. *Comput. Electron. Agric.* 136, 71–78. <https://doi.org/10.1016/j.compag.2017.01.027>

Flerchinger, G., Saxton, K., 1989. Simultaneous heat and water model of a freezing snow residue-soil system: I. Theory and development. *Trans. Am. Soc. Agric. Eng.* 32, 565–571.

Flerchinger, G.N., Pierson, F.B., 1991. Modeling plant canopy effects on variability of soil temperature and water. *Agric. For. Meteorol.* 56, 227–246.

Flury, M., 1996. Experimental evidence of transport of pesticides through field soils: A review. *J. Environ. Qual.* 45, 25–45. <https://doi.org/doi:10.2134/jeq1996.00472425002500010005x>

Gao, X., Huo, Z., Qu, Z., Xu, X., Huang, G., Steenhuis, T.S., 2017. Modeling contribution of shallow groundwater to evapotranspiration and yield of maize in an arid area. *Sci. Rep.* 7, 1–13. <https://doi.org/10.1038/srep43122>

Gassman, P., Williams, J., Wang, X., Saleh, A., Osei, E., Hauk, L., Izaurralde, R., Flowers, J., 2010. The Agricultural Policy Environmental Extender (APEX) model: An emerging tool for landscape and watershed environmental analyses. *Trans. ASABE* 53, 711–740.

Gassman, P.W., Williams, J.R., Benson, V.W., Izaurralde, R.C., Hauck, L.M., Jones, C.A., Atwood, J.D., Kiniry, J.R., Flowers, J.D., 2005. Historical Development and Applications of the EPIC and APEX Models. Ames, Iowa. <https://doi.org/10.13031/2013.17074>

Gowda, P., Dalzell, B., Mulla, D., 2007. Model-based nitrate TMDLs for two agricultural watersheds of southeastern Minnesota. *J. Am. Water Resour. Assoc.* 43, 1–10.

Gowda, P., Mulla, D., Desmond, E., Ward, A., Moriasi, D., 2012. ADAPT: Model use, Calibration, and Validation. *Trans. ASAE* 55, 1345–1352.

Gowda, P., Mulla, D., Jaynes, D., 2008. Simulated long-term nitrogen losses for a Midwestern agricultural watershed in the United States. *Agric. Water Manag.* 95, 616–624.

Gowda, P., Ward, A., White, D., Baker, D., Lyon, J., 1999a. An approach for using field-scale models to predict daily peak flows on agricultural watersheds. *J. Am. Water Resour. Assoc.* 35, 1223–1232.

Gowda, P., Ward, A., White, D., Lyon, J., Desmond, E., 1999b. The sensitivity of stream flows to model input parameters used to define hydrologic response units. *Trans. ASAE* 42, 381–389.

Green, W., Ampt, G., 1911. Studies in soil physics: I. The flow of air and water through soils. *J. Agric. Sci.* 4, 1–24. <https://doi.org/doi:10.1017/S0021859600001441>

Gupta, G.P., Prasher, S.O., Chieng, S.T., Mathur, I.N., 1993. Application of DRAINMOD under semi-arid conditions. *Agric. Water Manag.* 24, 63–80.

GWA, 1999. Water and irrigation requirements for the most important crops in Libya [unpublished report]. Tripoli.

Hess, T., Counsell, C., 2000. A water balance simulation model for teaching and learning – WaSim, in: Paper Presented at the ICID British Section Irrigation and Drainage Research Day, 29 March 2000. HR Wallingford. pp. 1–7.

Hirekhan, M., Gupta, S.K., Mishra, K.L., 2007. Application of WaSim to assess performance of a subsurface drainage system under semi-arid monsoon climate. *Agric. Water Manag.* 88, 224–234. <https://doi.org/https://doi.org/10.1016/j.agwat.2006.12.001>

Holzmann-Wakuti, 1974. Hydrogeology of The Joufrah Project Area. Tripoli, Libya.

Huang, M., Barbour, S.L., Elshorbagy, A., Zettl, J.D., Si, B.C., 2011. Infiltration and drainage processes in multi-layered coarse soils. *Can. J. Soil Science* 91, 169–183. <https://doi.org/10.4141/CJSS09118>

Italconsult, 1976. Fezzan Land Reclamation Project: Wadi-Shati Eshkeda Area. Rome, Italy.

Johansson, R., Gowda, P., Mulla, D., Dalzell, B., 2004. Metamodeling phosphorus best management practices for policy use: A frontier approach. *Agric. Econ.* 30, 63–74.

Jones, C.A., Wegner, M., Russell, J., McLeod, I., Williams, J., 1989. AUSCANE—Simulation of Australian Sugarcane with EPIC. Brisbane, Australia.

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T., 2003. The DSSAT cropping system model. *Eur. J. Agron.* 18, 235–265.

Julia, M., Monreal, T., Sanchez del Corral Jimenez, A., Garc Melendez, E., 2004. Constructing a saturated hydraulic conductivity map of Spain using Pedotransfer functions and spatial prediction. *Geoderma* 123, 257–277.

Kale, S., 2011. Field-evaluation of DRAINMOD-S for predicting soil and drainage water salinity under semi-arid conditions in Turkey. *Spanish J. Agric. Res.* 9, 1142–1155.

Kandil, H., Skaggs, R.W., Abdel Dayem, S., Aiad, Y., 1995. DRAINMOD-S : Water management model for irrigated arid lands , crop yield and applications. *Irrig. Drain. Syst.* 9, 239–258.

Kanzari, S., Jaziri, R., Ali, K. Ben, Daghari, I., 2021. Long-term evaluation of soil salinization risks under different climate change scenarios in a semi-arid region of Tunisia. *Water Supply* 21, 2463–2476. <https://doi.org/10.2166/ws.2021.052>

King, K.W., Arnold, J.G., Bingner, R.L., 1999. COMPARISON OF GREEN-AMPT AND CURVE NUMBER METHODS ON GOODWIN CREEK WATERSHED USING SWAT. *Trans. Am. Soc. Agric. Eng.* 42, 919–925.

Kiniry, J., Williams, J., Gassman, P., Debaeke, P., 1992. A general, process-oriented model for two competing plant species. *Trans. ASAE* 35, 801–810.

Kisekka, I., Schlegel, A., Vanderveer, M., Ma, L., 2017. Optimizing preplant irrigation for maize under limited water in the High Plains. *Agric. Water Manag.* 187, 154–163.

Knisel, W., 1980. CREAMS: A field-scale model for chemicals, runoff, and erosion from agricultural management systems. Conservation Research Report No. 26. Washington, D.C.

Kosugi, K., 1996. Lognormal distribution model for unsaturated soil hydraulic properties. *Water Resour. Res* 32, 2697–2703.

Kroes, J., Van Dam, J., Groenendijk, P., Hendriks, R.F., Jacobs, C., 2008. SWAP version 3.2. Theory description and user manual. Wageningen, The Netherlands.

Kroes, J., Wesseling, J.G., Van Dam, J.C., 2000. Integrated modelling of the soil – water – atmosphere – plant system using the model SWAP 2 . 0 an overview of theory and an application. *Hydrol. Process.* 14, 1993–2002.

Leonard, R., Knisel, W., Still, D., 1987. GLEAMS: Groundwater loading effects of agricultural management systems. *Trans. ASAE* 30, 1403–1418.

Liu, J., Williams, J.R., Wang, X., Yang, H., 2008. Using MODAWEC to generate daily weather data for the EPIC model. *Environ. Model. Softw.* 24, 655–664. <https://doi.org/10.1016/j.envsoft.2008.10.008>

Luo, W., Jing, W.H., JIA, Z.H., LI, J., Pan, Y.X., 2009. The effect of PET calculations in DRAINMOD on drain- age and crop yields predictions in a subhumid vertisol soil district. *Sci. China Ser. E Technol. Sci.* 52, 1–5. <https://doi.org/10.1007/s11431-009-0349-0>

Ma, L., Ahuja, L., Ascough II, J., Shaffer, M., Rojas, K., Malone, R., Cameira, M., 2000. Integrating system modeling with field research in agriculture: Applications of Root Zone Water Quality Model (RZWQM). *Adv. Agron* 71, 233–292.

Ma, L., Ahuja, L., Malone, R., 2007a. Systems modeling for soil and water research and management: Current status and further needs in the 21st century. *Trans. ASAE* 50, 1705–1713.

Ma, L., Ahuja, L., Saseendran, S., Malone, R., Green, T., Nolan, B., Bartling, P.N., Flerchinger, G., Boote, K., Hoogenboom, G., 2011. A protocol for parameterization and calibration of RZWQM2 in field research, in: Ahuja, L.R., Ma, L. (Eds.), *Methods of Introducing System Models into Agricultural Research*. Madison, Wisc.: SSSA, pp. 1–64.

Ma, L., Ahuja, L.R., Nolan, B.T., Malone, R.W., Trout, T.J., Qi, Z., 2012. Root Zone Water Quality Model (RZWQM2): Model Use, Calibration, and Validation. *Trans. ASAE* 55, 1425–1446.

Ma, L., Hoogenboom, G., Saseendran, S., Bartling, P.N., Ahuja, L., Green, T., 2009. Estimates of soil hydraulic property and root growth factor on soil water balance and crop production. *Agron. J.* 101, 572–583.

Ma, L., Malone, R., Heilman, P., Ahuja, L., Meade, T., Saseendran, S., Ascough II, J., Kanwar, R., 2007b. Sensitivity of tile drainage flow and crop yield on measured and calibrated soil hydraulic properties. *Geoderma* 140, 284–296.

Ma, L., Malone, R., Heilman, P., Jaynes, D., Ahuja, L., Saseendran, S., Kanwar, R., Ascough II, J., 2007c. RZWQM simulated effects of crop rotation, tillage, and controlled drainage on crop production and nitrate-N loss in drain flow. *Geoderma* 140, 297–309.

Ma, L., Malone, R., Heilman, P., Karlen, D., Kanwar, R., Cambardella, C., Saseendran, S., Ahuja, L., 2007d. RZWQM simulation of long-term crop production, water and nitrogen balances in northeast Iowa. *Geoderma* 140, 247–259.

Malakshahi, A.-A., Naftchali, A.D., Mohseni, B., 2020. Analyzing water table depth fluctuation response to evapotranspiration involving DRAINMOD model. *Agric. Water Manag.* 234, 1–10. <https://doi.org/10.1016/j.agwat.2020.106125>

Malone, R.W., Ma, L., Wauchope, R.D., Ahuja, L.R., Rojas, K.W., Ma, Q., Warner, R., Byers, M., 2004. Modeling hydrology , metribuzin degradation and metribuzin transport in macroporous tilled and no-till silt loam soil using RZWQM. *Pest Manag. Sci.* 60, 253–266. <https://doi.org/10.1002/ps.738>

Marinov, D., Querner, E., Roelsma, J., 2005. Simulation of water flow and nitrogen transport for a Bulgarian experimental plot using SWAP and ANIMO models. *J. Contam. Hydrol.* 77, 145–164.

Marquardt, D.W., 1963. An algorithm for least squares estimation of nonlinear parameters. *SIAM J. Appl. Math.* 11, 431–441.

Meriguetti, V., Reichardt, K., Dam, J. Van, Jong, Q. De, Lier, V., Pereira, I., Durigon, A., Dourado-neto, D., Pivotto, R., 2015. Deep drainage modeling for a fertigated coffee plantation in the Brazilian savanna. *Agric. Water Manag.* 148, 130–140. <https://doi.org/10.1016/j.agwat.2014.09.029>

More, P., 2018. Using Machine Learning to Predict Water Table Levels in a Wet Prarie in Northwest Ohio (MSc Thesis). Bowling Green State University.

Morellos, A., Pantazi, X., Moshou, D., Alexandridis, T., Whetton, R., Tziotzios, G., Wiebensohn, J., Bill, R., Mouazen, A.M., 2016. ScienceDirect Special Issue : Proximal Soil Sensing Machine learning based prediction of soil total nitrogen , organic carbon and moisture content by using VIS-NIR spectroscopy. *Biosyst. Eng.* 1–13. <https://doi.org/10.1016/j.biosystemseng.2016.04.018>

Muñoz-Sabater, J., 2019. ERA5-Land hourly data from 1981 to present [WWW Document]. Copernicus Clim. Chang. Serv. Clim. Data Store.

Nahvi, B., Habibi, J., Mohammadi, K., Shamshirband, S., 2016. Using self-adaptive evolutionary algorithm to improve the performance of an extreme learning machine for estimating soil temperature. *Comput. Electron. Agric.* 124, 150–160. <https://doi.org/10.1016/j.compag.2016.03.025>

Nangia, V., Gowda, P., Mulla, D., 2010a. Evaluation of predicted long-term water quality trends to changes in N fertilizer management practices for a cold climate. *Agric. Water Manag.* 97, 1855–1860.

Nangia, V., Gowda, P., Mulla, D., Sands, G.R., 2010b. Modeling impacts of tile drain spacing and depth on nitrate-nitrogen losses. *Vadose Zo. J.* 9, 61–72.

Nangia, V., Gowda, P., Mulla, D., Sands, G.R., 2008. Water quality modeling of fertilizer management impacts on nitrate losses in tile drains at the field scale. *J. Environ. Qual.* 37, 296–307.

Nangia, V., Mulla, D., Gowda, P., 2010c. Precipitation changes impact stream discharge, nitrate-nitrogen load more than agricultural management changes. *J. Environ. Qual.* 39, 2063–2071.

National Resource Conservation Service (NRCS), 2004. National engineering handbook part 630 [WWW Document]. URL <http://policy.nrcs.usda.gov/viewerFS.%0A.aspx?hid=21422> (accessed 8.27.19).

Nozari, H., Azadi, S., 2017. Experimental evaluation of artificial neural network for predicting drainage water and groundwater salinity at various drain depths and spacing. *Neural Comput. Appl.* <https://doi.org/10.1007/s00521-017-3155-9>

PC-PROGRESS, 2020a. Hydrus-1D References [WWW Document]. URL <https://www.pc-progress.com/en/Default.aspx?h1d-references> (accessed 10.6.20).

PC-PROGRESS, 2020b. HYDRUS 2D/3D for Windows [WWW Document]. URL <https://www.pc-progress.com/en/Default.aspx?hydrus-3d#k3> (accessed 10.6.20).

PC-PROGRESS, n.d. HYDRUS Website [WWW Document]. URL <https://www.pc-progress.com/en/Default.aspx> (accessed 10.6.20).

Petrolia, D., Gowda, P., 2006a. Missing the boat: Midwest farm drainage and Gulf of Mexico hypoxia. *Rev. Agric. Econ.* 28, 240–253.

Petrolia, D., Gowda, P., 2006b. An analysis of the role of tile-drained farmland under alternative nitrogen abatement policies. *Agric. Resour. Econ.* 31, 580–594.

Prăvălie, R., Patriche, C., Borrelli, P., Panagos, P., Roșca, B., Dumitrașcu, M., Nita, I.A., Săvulescu, I., Birsan, M.V., Bandoc, G., 2021. Arable lands under the pressure of multiple land degradation processes. A global perspective. *Environ. Res.* 194. <https://doi.org/10.1016/j.envres.2020.110697>

Puckett, W.E., Dane, J.H., Hajek, B.F., 1985. Physical and Mineralogical Data to Determine Soil Hydraulic Properties 1. *Soil Sci. Soc. Am. J.* 49, 831–836.

Qadir, M., Boers, T.M., Schubert, S., Ghafoor, A., Murtaza, G., 2003. Agricultural water management in water-starved countries: Challenges and opportunities. *Agric. Water Manag.* 62, 165–185. [https://doi.org/10.1016/S0378-3774\(03\)00146-X](https://doi.org/10.1016/S0378-3774(03)00146-X)

Qi, Z., Helmers, M., Malone, R., Thorp, K., 2011. Simulating long-term impacts of winter rye cover crop on hydrological cycling and nitrogen dynamics for a cornsoybean crop system. *Trans. ASAE* 54, 1575–1588.

Qian, Y., Zhu, Y., Ye, M., Huang, J., Wu, J., 2021. Experiment and numerical simulation for designing layout parameters of subsurface drainage pipes in arid agricultural areas. *Agric. Water Manag.* 243, 106455. <https://doi.org/10.1016/j.agwat.2020.106455>

Radcliffe, D.E., Reid, D.K., Blombäck, K., Bolster, C.H., Collick, A.S., Easton, Z.M., Francesconi, W., Fuka, D.R., Johnsson, H., King, K., Larsbo, M., Youssef, M.A., Mulkey, A.S., Nelson, N.O., Persson, K., Ramirez-avila, J.J., Schmieder, F., Smith, D.R., 2015. Applicability of Models to Predict Phosphorus Losses in Drained Fields: A Review. *J. Environ. Qual.* 44, 614–628. <https://doi.org/10.2134/jeq2014.05.0220>

Richards, L., 1931. Capillary conduction of fluid through porous mediums. *Physics (College. Park. Md)*. 1, 318–333. <https://doi.org/doi:10.1063/1.1745010>

Ruß, G., Kruse, R., Schneider, M., Wagner, P., 2008. Data mining with neural networks for wheat yield prediction, in: *Proceeding of Advances in Data Mining—Medical Applications, E-Commerce, Marketing and Theoretical Aspects*, 8th Industrial Conference. Springer-Verlag Berlin Heidelberg, Leipzig, Germany, pp. 47–56.

Sabbagh, G.J., Fouss, J.L., Bengtson, R.L., 1993. COMPARISON OF EPIC-WT AND DRAINMOD SIMULATED PERFORMANCE OF LAND DRAINAGE SYSTEMS. *Am. Soc. Agric. Biol. Eng.* 36, 73–79.

Sahbeni, G., 2021. Soil salinity mapping using Landsat 8 OLI data and regression modeling in the Great Hungarian Plain. *SN Appl. Sci.* 3, 587. <https://doi.org/10.1007/s42452-021-04587-4>

Samipour, F., Rabie, M., Mohammadi, K., Mahdian, M., Naseri, A., 2010. Evaluation of Two Drainage Models in South-West Iran, in: *9th International Drainage Symposium Held Jointly with CIGR and CSBE/SCGAB Proceedings*. CSBE/SCGAB, Québec City, Canada.

Sands, G.R., Jin, C., Mendez, A., Basin, B., Wotzka, P., Gowda, P., 2003. Comparing subsurface drainage flow prediction of the DRAINMOD and ADAPT models for a cold climate. *Trans. ASAE* 46, 645–656.

Sanoja, J., Kanwar, R.S., Melvin, S.W., 1990. Comparison of simulated (DRAINMOD) and measured tile outflow and water table elevations from two field sites in Iowa. *Trans. Am. Soc. Agric. Eng.* 33, 827–833. <https://doi.org/10.13031/2013.31407>

Sarwar, A., Feddes, R., 2000. Evaluating drainage design parameters for the fourth drainage project, Pakistan by using SWAP model: part II- modeling results. *J. Irrig. Drain. Syst.* 14, 281–299.

Saxton, K., Rawls, W., Romberger, J., Papendick, R., 1986. Estimating generalized soil water characteristics from texture. *Soil Sci. Soc. Am. J.* 50, 1031–1036.

Schaap, M.G., Leij, F.J., Genuchten, M.T. Van, 2001. Rosetta : a computer program for estimating soil hydraulic parameters with hierarchical pedotransfer functions. *J. Hydrol.* 251, 163–176.

Scheumann, W., Freisem, C., 2002. The role of drainage for sustainable agriculture. *J. Appl. Irrig. Sci.* 37, 33–61.

Shrestha, S., Manandhar, B., 2014. Evaluation of the Root Zone Water Quality Model (RZWQM) Using Field-Measured Data from the Tropical Zone, Thailand. *Water, Air, Soil Pollut.* 225, 1958. <https://doi.org/10.1007/s11270-014-1958-1>

Šimunek, J., Hopmans, J.W., 2002. Parameter Optimization and Nonlinear Fitting, in: Dane, J.H., Topp, G.C. (Eds.), *Methods of Soil Analysis, Part 1, Physical and Mineralogical Methods*, SSSA, Madison, Wisconsin, USA, pp. 139–157.

Simunek, J., Huang, K., van Genuchten, M.T., 1998. The HYDRUS code for simulating the one-dimensional movement of water, heat, and multiple solutes in variably-saturated media.

Šimůnek, J., Jarvis, N., van Genuchten, M.T., Gärdenäs, A., 2003. Review and comparison of models for describing nonequilibrium and preferential flow and transport in the vadose zone. *J. Hydrol.* 272, 14–35.

Šimůnek, J., van Genuchten, M.T., 2008. Modeling nonequilibrium flow and transport with HYDRUS. *Vadose Zo. J.* 7, 782–797.

Šimůnek, J., van Genuchten, M.T., Šejna, M., 2012. HYDRUS: Model Use, Calibration, and Validation. *Trans. ASABE* 55, 1261–1274.

Šimůnek, J., van Genuchten, M.T., Šejna, M., 2011. The HYDRUS software package for simulating two- and three-dimensional movement of water, heat, and multiple solutes in variably saturated media. *Tech. Manual, Version 2.0.*

Skaggs, R.W., 1999. Drainage Simulation Models, in: Skaggs, R., van Schilfgaarde, J. (Eds.), *Agricultural Drainage*. American Society of Agronomy, Inc., Madison, Wisconsin, USA, pp. 469–500.

Skaggs, R.W., 1987. Model development, selection and use, in: *3rd Int Works Land Drainage*. Ohio State Univ, Columbus, Dec 7–11, pp. 29–3.

Skaggs, R.W., 1982. Field evaluation of a water management simulation model. *Trans. ASAE* 25, 666–674.

Skaggs, R.W., 1980. DRAINMOD Reference Report. Fort Worth, Tex.: USDA-SCS South National Technical Center. Available at: [www.bae.ncsu.edu/soil_water/documents/drainmod/ chapter1.pdf](http://www.bae.ncsu.edu/soil_water/documents/drainmod/chapter1.pdf)., Raleigh.

Skaggs, R.W., 1978. A water management model for shallow water table soils.

Skaggs, R.W., 1977. Evaluation of drainage-water table control systems using a water management model, in: St., A.P. 1-77., Joseph, M. A. (Eds.), *3rd Natl. Drainage Symposium*. pp. 61–68.

Skaggs, R.W., Youssef, M.A., Chescheir, G.M., 2012. DRAINMOD: model use, calibration, and validation. *Trans. ASABE* 55, 1509–1522. <https://doi.org/10.13031/2013.42259>

Smedema, L.K., Abdel-Dayem, S., Ochs, W.J., 2000. Drainage and agricultural development. *Irrig. Drain. Syst.* 14, 223–235. <https://doi.org/10.1023/A:1026570823692>

Smedema, L.K., Vlotman, W.F., Rycroft, D., 2004. *Modern Land Drainage: Planning, Design and Management of Agricultural Drainage Systems*. Design and Management of, London.

Sogbedji, J., McIsaac, G., 2006. Evaluation of the ADAPT model for simulating nitrogen dynamics in a tiledrained agricultural watershed in central Illinois. *J. Environ. Qual.* 35, 1914–1923.

Stephens, W., Hess, T., Knox, J., 2001. The effects of energy crops on hydrology, in: *Aspects of Applied Biology*. pp. 101–108.

Taguta, C., 2017. *Modeling Subsurface Drainage to Control Water-Tables in Selected Agricultural Lands LANDS in South Africa*. Pan African University.

Taormina, R., Chau, K., Sethi, R., 2012. Artificial neural network simulation of hourly groundwater levels in a coastal aquifer system of the Venice lagoon. *Eng. Appl. Artif. Intell.* 25, 1670–1676. <https://doi.org/10.1016/j.engappai.2012.02.009>

Uhrig, J., Engel, B., Baker, W., 1992. An application of neural networks: predicting corn yields, in: *The 4th International Conference on Computers in Agricultural Extension Programs*. Lake Buena Vista, FL, USA, pp. 348–353.

Uno, Y., Prasher, S., Laeroix, R., Goel, P., Karimi, Y., Viau, A., Patel, R., 2005. Artificial neural network to predict corn yield from compact airborne spectrographic imager data. *Comput. Electron. Agric.* 47, 149–161.

Updegraff, K., Gowda, P., Mulla, D., 2004. Watershedscale modeling of the water quality effects of cropland conversion to short-rotation woody crops. *Renew. Agric. Food Syst.* 19, 1–11.

USACE, 2000. Hydrologic Modeling System HEC-HMS User's Manual, Hydrologic Engineering Center. Davis, CA.

USDA, 1990. EPIC — Erosion / Productivity Impact Calculator.

USEPA, 2014. A watershed approach [WWW Document]. URL water.epa.gov/type/watersheds/approach.cfm (accessed 8.27.19).

Ustaoglu, B., Cigizoglu, H.K., Karaca, M., 2008. Forecast of daily mean, maximum and minimum temperature time series by three artificial neural network methods. *Meteorol. Appl.* 15, 431–445. <https://doi.org/10.1002/met.83>

Van Dam, J., Huygen, J., Wesseling, J., Feddes, R., Kabat, P., Van Walsum, P.E., Groenendijk, P., van Diepen, C., 1997. Theory of SWAP version 2.0. Simulation of water flow, solute transport and plant growth in the Soil-Water-Atmosphere-Plant environment. Wageningen.

van Genuchten, M.T., 1980. A closed-form equation for predicting the hydraulic conductivity of unsaturated soils. *SSSA J* 44, 892–898.

Verma, A.K., Gupta, S.K., 2014. Calibration and Validation of SWAP to Simulate Conjunctive Use of Fresh and Saline Irrigation Waters in Semi-Arid Regions 45–55. <https://doi.org/10.1007/s10666-013-9379-x>

Verma, A.K., Isaac, R.K., 2010. Long-term Use of Saline Drainage Waters for Irrigation in Subsurface Drained Lands : Simulation Modelling with SWAP. *J. Agric. Eng.* 47, 15–23.

Vogel, T., Císlerová, M., 1988. On the reliability of unsaturated hydraulic conductivity calculated from the moisture retention curve. *Transp. Porous Media* 3, 1–15.

Wahba, M.A., Christen, E., 2006. Modeling subsurface drainage for salt load management in southeastern Australia. *Irrig. Drain. Syst.* 20, 267–282. <https://doi.org/10.1007/s10795-006-9007-x>

Wahba, M.A.S., Kandil, H., Gobran, A., 2002. Evaluation of DRAINMOD-S for Simulating Water Table Management under Semi-Arid Conditions. *Irrig. Drain.* 51, 213–226. <https://doi.org/10.1002/ird.54>

Wang, X., Kemanain, A., Williams, J., 2011. Special features of the EPIC and APEX modeling package and procedures for parameterization, calibration, validation, and applications, in: Ahuja, L., Ma, L. (Eds.), *Methods of Introducing System Models into Agricultural Research. Advances in Agricultural Systems Modeling 2*. Madison, Wisc.: ASA, CSSA, SSSA., pp. 177–208.

Wang, X., Williams, J., Gassman, P., Baffaut, C., Izaurrealde, R., Jeong, J., Kiniry, J., 2012. EPIC and APEX: Model Use, Calibration, and Validation 55, 1447–1462.

Williams, J., 1990. The erosion productivity impact calculator (EPIC) model: A case history. *Phil. Trans. R. Soc. London B* 329, 421–428.

Williams, J., Arnold, J., Kiniry, J., Gassman, P., Green, C., 2008. History of model development at Temple, Texas. *Hydrol. Sci. J* 53, 948–960.

Williams, J., Nearing, M., Nicks, A., Skidmore, E., Valentin, C., King, K., Savabi, R., 1996. Using soil erosion models for global change studies. *J. Soil Water Conserv.* 51, 381–385.

Williams, J.R., Jones, C.A., Dyke, P.T., 1984. A Modeling Approach to Determining the Relationship Between Erosion and Soil Productivity. *Trans. Am. Soc. Agric. Eng.* 27, 129–144.

Wu, L., Chen, W., Baker, J.M., Lamb, J.A., 1999. Evaluation of RZWQM field measured data from a sandy soil. *Agron. J.* 91, 177–182.

Xia, Y., Fabian, P., Stohl, A., Winterhalter, M., 1999. Forest climatology: estimation of missing values for Bavaria, Germany. *Agric. For. Meteorol.* 96, 131–144.

Youssef, M.A., Skaggs, R.W., Chescheir, G.M., Gilliam, J.W., Plant, N., 2005. The Nitrogen Simulation Model, DRAINMOD–N II 48, 611–626.

Zanetti, S.S., Sousa, E.F., Oliveira, V.P.S., Almeida, F.T., Bernardo, S., 2007. Estimating Evapotranspiration Using Artificial Neural Network and Minimum Climatological Data. *J. Irrig. Drain. Eng.* 133, 83–89.

Zenghui, S., Han, J., Wang, H., 2019. Soft rock for improving crop yield in sandy soil in the Mu Us desert, China. *Arid L. Res. Manag.* 33, 136–154. <https://doi.org/10.1080/15324982.2018.1522385>

Zhang, J., Zhang, L., Zhang, M., Watson, C., 2009. Prediction of soybean growth and development using artificial neural network and statistical models. *Acta Agron. Sin.* 35, 341–347.

3 Application of artificial neural networks to the design of subsurface drainage systems in Libyan agricultural projects

Abstract

Saturated hydraulic conductivity (K_{sat}) is an essential input parameter for drainage system design. Direct measurement of K_{sat} is time-consuming and expensive. Consequently, research has focused on developing indirect methods for estimating K_{sat} such as Pedotransfer Functions (PTFs) and Artificial Neural Networks (ANNs). This study focuses on the drainage design for the Hammam agricultural project (HAP) and Eshkeda agricultural project (EAP), in southern Libya. Six ANNs were developed for both HAP and EAP to estimate K_{sat} and compared with four widely adopted empirical regression-type PTFs equations. ANNs input parameters included %sand, %silt, %clay, bulk density, wilting point and field capacity, or %sand, %silt, %clay and bulk density using data from EAP and HAP. Subsequently, the ANNs and PTFs estimated K_{sat} values were used in EnDrain software to design sub-surface drainage systems as compared with measured K_{sat} values. Results showed that ANNs more accurately predicted K_{sat} than PTFs. Drainage design based on PTFs predictions (1) result in a lower water level and (2) require more drains, increasing costs. Drainage designs based on ANNs predictions gave drain spacing's and water table depth equivalent to those predicted using measured data. The results of this study indicate that ANNs can be developed using existing and under-utilised data sets and applied successfully to data poor areas. This will allow farmers, planners and decision makers, in Libya and other arid and semi-arid countries, to incorporate drainage into their agricultural systems using cost effective drainage design driven by accurate and expeditious ways of estimating K_{sat} .

3.1 Introduction

In the Earth's terrestrial biosphere, soil plays an essential role in managing the mass and energy transferred between the earth and the atmosphere (Amundson et al., 2015; Bittelli et al., 2015). Upper soil horizons have hydraulic properties (governed by pore size distribution, water retention and hydraulic conductivity) that regulate the local water balance through, infiltration, evapotranspiration, surface runoff, and groundwater recharge (Zhang and Schaap, 2019). These soil properties have a fundamental effect on local, regional and global land surface water and energy balances (Montzka et al., 2017; Vereecken et al., 2016; Verhoef and Egea, 2014). For example, approximately 60% of rainfall is returned to the atmosphere through the soil-plant-atmosphere continuum (Katul et al., 2012; Oki and Kanae, 2006), and > 50% of the global biomass production and related carbon cycle depend on soil processes (Cleveland et al., 2013).

Water for agriculture is often unregulated and overexploited. In spite of this, the general belief is that by 2025 irrigated lands have to be extended by 20-30% in order to meet global food demands (FAO, 2002). However, the world's arable lands are degrading due to soil salinization, desertification, erosion, and urbanisation (FAO, 2002). In arid and semiarid areas water use efficiency is a major issue due to increasing cross-sector demand for limited water resources (Elshemy, 2018). Therefore, understanding soil hydrological behaviour is essential in the global drive to expand crop production (Abdelbaki et al., 2009). For example, drainage systems in arid and semiarid areas have been designed and installed to manage and control soil waterlogging and salinity problems in irrigation schemes. However, less than 30% of all irrigated land needing drainage have been effectively drained (Schultz et al., 2007), and the situation is worse in least developed countries (OECD, 2020). According to Smedema et al. (2000), the proportion of agricultural land drained in developing countries is 5-10% as compared to 25-30% in developed countries. This is primarily due to a fundamental lack of data on key soil attributes needed as inputs to design drainage systems (Ayars and Evans, 2015). This paucity of data is often driven by the cost of sample collection and laboratory analysis and/or a lack of adequate laboratory resources. Historically, in many countries, soil data have been routinely gathered

through soil surveys, yet such soil data rarely includes saturated hydraulic conductivity (K_{sat}), an essential parameter in drainage system design (Patil and Singh, 2016).

Accurate quantification of K_{sat} , is essential for multiple aspects of agrohydrology (Zhang and Schaap, 2019). Saturated hydraulic conductivity, is used to quantify water movement through a unit cross-section of soil per unit time (Aimrun et al., 2004) and is used to design subsurface drainage systems, irrigation practices and for modelling agricultural and hydrological processes such as water movement and solute transport in the soil (Abdelbaki et al., 2009). Saturated hydraulic conductivity is also used in subsurface drainage models to determine drain spacing at specific drain depth (Bicknell et al., 2005; Chung et al., 1992; Ma et al., 2012; Skaggs, 1978; Van Dam et al., 1997) . Thus, the accurate determination of K_{sat} is important as it influences the technical and economic feasibility of large-scale agricultural drainage projects.

Saturated hydraulic conductivity can be estimated using either in-situ methods such as the Guelph permeameter (above water-table method) (Reynolds and Elrick, 1985) and the auger hole method (below water-table method) (Beers, 1958), or laboratory-based methods such as the constant head and falling head permeameters (Klute and Dirksen, 1986). However, K_{sat} is highly spatially variable over a range of scales e.g., plot, field and catchment (Hassler et al., 2014). Therefore, a large number of soil samples and measurements are required to accurately describe the hydraulic properties of an area of interest (Sobieraj et al., 2004). These measurements often are difficult, time-consuming and expensive (Fooladmand, 2011; Patil and Singh, 2016). In addition, due to time and financial constraints, researchers, planners and decision-makers in many countries especially in least developed countries are faced with inadequate data to work with (K_{sat} values are simply unavailable) (Patil et al., 2011, 2010). Consequently, multiple researchers have focused on developing indirect methods for estimating K_{sat} such as utilising Pedotransfer functions (PTFs) to estimate K_{sat} from more readily available soil measurement information (e.g., soil texture and bulk density) (Arrington et al., 2013; Dashtaki et al., 2010; Khodaverdiloo et al., 2011).

PTFs were first represented by empirical regression equations relating water and solute transport parameters to the fundamental soil properties that are accessible in soil survey databases (Cosby et al., 1984; Dane and Puckett, 1994; Julia et al., 2004;

Puckett et al., 1985). For example, Ahuja et al. (1986) developed an empirical equation to estimate K_{sat} from the effective porosity only, while Li et al. (2007) developed a PTF to estimate K_{sat} that required percentage (%) sand, silt and clay, bulk density (BD) and soil organic matter. However, Wösten et al. (2001) stated that future developments in PTFs would be derived from more accurate data mining tools such as Artificial Neural Networks (ANNs) and group methods of data mining techniques such as K-Nearest Neighbour, and support vector machine (SVM).

K-Nearest Neighbour have been applied to predict precipitation (Huang et al., 2017), groundwater depth (Kombo et al., 2020) and crop yield (Jothi et al., 2020). Whereas SVM has also been applied to predict groundwater depth (Mallikarjuna et al., 2020) and the discharge coefficient of rectangular side weirs located on trapezoidal channels (Azimi et al., 2019). ANNs have been successfully applied to predict water-table depth and groundwater salinity at different drain depths and spacing (Nozari and Azadi, 2017), estimate soil salinity (Bouksila et al., 2010), and to predict evapotranspiration from limited meteorological data (Zanetti et al., 2007). ANNs have also been applied to predict sediment transport without sedimentation by combining ANNs with the Particle Swarm Optimization (PSO), Imperialist Competitive Algorithm (ICA), Genetic Algorithm (GA) and Decision Tree (DT) methods (Ebtehaj et al., 2020, 2018).

Artificial Neural Networks have been shown to be more flexible and able to deal with multiple sources of input data as compared to PTF-based regression equations (Wösten et al., 2001). In the last two decades, ANNs have been utilised as a special class of PTFs using feed-forward or radial basis functions to approximate any continuous (nonlinear) function (Sobieraj et al., 2004). Detailed statistical and functional reports have been carried out to compare the performance between ANN-based PTFs and regression-type PTFs to predict K_{sat} on different datasets such as soil texture and BD (Agyare et al., 2007; Arshad et al., 2013; Parasuraman et al., 2006). Several authors have demonstrated that ANNs outperform regression techniques, especially when uncertainties in the quality of the data are small (Baker and Ellison, 2008; Merdun et al., 2006; Minasny and Mcbratney, 2002). Therefore, ANNs have the potential to be a more accurate approach to estimating K_{sat} as compared to more conventional PTF regression equations.

This study aims to improve the prediction of saturated hydraulic conductivity (K_{sat}) in order to enhance the efficacy of drainage system design in data-poor areas utilising existing and currently under-utilised datasets. It is envisaged that this will reduce the overall cost of drainage system design making them more accessible to farmers, planners, and decision-makers in least developed countries.

The objectives of this study were to: (1) develop ANNs to estimate K_{sat} , (2) compare the performance of applying ANNs as compared to regression-type PTF equations for the estimation of K_{sat} , and (3) evaluate the performance of drainage systems based on these two contrasting methods of estimating K_{sat} .

3.2 Material and Methods

3.2.1 Case study

Data sets were generated for two established agricultural projects in Libya, Hammam Agricultural Project (HAP) and Eshkeda Agricultural Project (EAP), using seven years (1974-1981) of archived and under-utilised data from the General Authority of Water Resources in Libya. Both study areas are located in the southern part of Libya, north of the Sahara Desert. Both study areas are considered to be in the hyper-arid zone (FAO, 1989) with annual rainfall rarely exceeding 100 mm. There are no perennial rivers in the area of interest. Consequently, the only water source is paleo-groundwater from two aquifers. The Mezda and Murzuq aquifers are the source of irrigation for HAP and EAP respectively (Tantawi, 2000).

The HAP is located in the north-east part of Sokna Oasis (29°04'01"N 15°47'05"E) at an elevation of *circa* 270 m above sea level (asl). The HAP covers 1,200 ha and is divided into 182 farms (6-8ha for each farm). The work on the project began in 1971, and the reclamation was completed in 1985. The HAP project has a drainage system designed in the 1970s. The soil texture in the HAP is highly variable with eight soil texture classes (Table 3-1). According to the USDA textural classification the HAP dataset can be classified as, sand (22.3%), loamy sand (18.3%), sandy loam (31.4%), loam (0.6%), sandy clay loam (21.0%), clay loam (4.2%), sandy clay (1.8%) and clay (0.4%) (Soil Survey Division Staff, 1993) (see Table 3-1 for more details). The other project, EAP, is located north of Sabha city (27°32'45"N 14°16'7"E) at an elevation of

320 m asl. The project was initiated in 1975 and it became operational in the second half of 1976, with a drainage system being designed between 1979-1981. The EAP covers 3000 ha and is divided into three subareas: Western Area (2,000 ha), Central Area (600 ha) and Eastern Area (370 ha). In accordance with the installed irrigation wells, the area comprises 25 districts each with 12 farms of *circa* 10 ha each.

The farms are sub-divided into two farmed plots, each 180 m by 234 m in size. Windbreaks have been planted between the farm plots and around the individual farms. The EAP dataset is associated with four soil texture classes dominated by sand (88.4%) with 8.0%, 3.4% and 0.2% of the set represented by loamy sand, sandy loam and loam, respectively (Table 3-1).

3.2.2 Dataset Description

The data collected from the two project sites included particle size distribution (%sand (S), %silt (Si) and %clay (C)), bulk density (BD) (g cm^{-3}), %wilting point (WP), %field capacity (FC), and K_{sat} (m d^{-1}), summarised in Table 3-1. Soil texture was measured using the hydrometer method following Bouyoucos (1927). The soil BD was measured following the methods described by Buckman and Brady, (1960). Field capacity and wilting point were determined by tensiometers, using the method reviewed by Richards (1949). In the EAP K_{sat} was measured in the field using the average of four replications of the auger-hole method (Beers, 1958). In the HAP K_{sat} was measured in the laboratory using undisturbed samples following the constant head method (Klute and Dirksen, 1986). In total, for the HAP, there were 770 K_{sat} measurements (c. 1 measurement for every 2 ha) while for the EAP there were 442 K_{sat} measurements (c. 1 measurement for every 5 ha). To facilitate ANN development and validation, in both EAP and HAP an area was randomly selected and designated as a 'data-poor' area for which K_{sat} measurements were assumed to be absent. In the EAP a 600 ha area in the central section of the scheme (5.0 km x 1.2 km) was selected as the 'data-poor' area whilst in the HAP a 500 ha area in the western section of the scheme (1.43 km x 3.5 km) was selected. The total number of K_{sat} measurement points in these designated 'data-poor' areas were 82 and 158, in EAP and HAP respectively, which represent 20% of the dataset for each site. The remaining areas of EAP and HAP were assumed to be 'data-rich' areas. The data from 'data-rich' areas was used to develop

the ANNs to predict the K_{sat} in the designated data-poor areas. Data from the data-rich areas of each scheme were assigned into two groups based on the input requirements for the development of ANNs. The first group had limited parameters that included, S, Si, C, and BD as independent variables and K_{sat} as the dependent variable. The second group included the parameters in the first group as well as WP and FC. A statistical summary of the dataset used in this study is given in Table 3-1.

Table 3-1 Statistical summary of the dataset used in this research

	Sand (%)		Silt (%)		Clay (%)		BD (g cm⁻³)		FC (%)		WP (%)		K_{sat} (m d⁻¹)	
Project	EAP	HAP	EAP	HAP	EAP	HAP	EAP	HAP	EAP	HAP	EAP	HAP	EAP	HAP
Min	66.0	25.0	1.0	1.0	1.0	1.0	1.1	1.6	14.0	2.2	15.0	0.7	0.1	0.1
Max	98.0	98.0	36.0	46.0	10.0	41.0	1.9	2.0	23.0	44.0	14.0	14.0	24.0	38.0
Average	92.6	73.0	4.7	13.5	2.8	14.0	1.5	1.9	18.5	18.0	8.3	5.6	5.3	7.2
STDEV	4.0	15.5	3.0	7.8	1.8	10.6	0.2	0.1	1.6	7.0	2.3	2.2	4.5	8.2
Median	94.0	72.0	4.0	14.0	2.0	11.0	1.5	1.9	18.5	17.5	8.5	5.5	3.7	4.2
Percentage of samples associated with textural class														
Project	S	LS	SL	L	SCL		CL		SC		C			
EAP	88.4%	8.0%	3.4%	0.2%	0.0%		0.0%		0.0%		0.0%		0.0%	
HAP	22.3%	18.3%	31.4%	0.6%	21.0%		4.2%		1.8%		0.4%			

Where: S is sand, LS is loamy sand, SL is sandy loam, L is loam, SCL is sandy clay loam, CL is clay loam, SC is sandy clay, and C is clay (Soil Survey Division Staff, 1993).

3.2.3 ANNs model development

Artificial neural networks are a mathematical approach used to characterise synthetic neurons to solve complex problems in a similar way to that of the human brain (Agatonovic-Kustrin and Beresford, 2000). Since the 1940s, there has been growing interest in the study of neurological mechanisms and structures. That interest has led to the development of new computational models, linking systems or ANNs, based on biological processes that have been used to solve complex problems such as pattern recognition and rapid information processing and adaptation (Huang, 2009). ANNs use machine learning based on the principle of self-adjusting internal control parameters and can be used to recognise complex non-linear relationships between input and output datasets (Ayoubi et al., 2011).

ANNs are typically formed of three processing layers, namely an 'input', 'hidden' and 'output' layer (Figure 3-1) (Chollet and Allaire, 2017; Ghatak, 2019; More, 2018). The input layer consists of the selected independent variables. Each variable in the input layer is connected to the 'hidden' layer through a 'weighting' algorithm (Bell, 2015; Chollet and Allaire, 2017; Ghatak, 2019). In some cases, the weights given to each independent variable are generated randomly, in other cases, they are fine-tuned and trained through a process called backpropagation (Bell, 2015; Chollet and Allaire, 2017; Ghatak, 2019). Backpropagation quantifies the error at the output by comparing the currently derived outputs to the expected ones and modify the weights to reduce the error (Bell, 2015; Chollet and Allaire, 2017; Ghatak, 2019). The layer located between the input and the output layers is called the 'hidden' layer. The hidden layer may consist of more than one layer with each layer containing a number of units (a grouping of independent variables). These units, known also as 'neurons', are used to guide the processing of the data contained in the input layer and to generate computational connections between the input and the output layer. There is no specific formula to decide the number of units to be included in the hidden layer. It is generally problem-dependent, with the error tested by varying the number of units and layers in order to determine the appropriate number of units/layers to be used (Bell, 2015). The hidden layer is represented by a group of activation functions including linear functions, logistic functions and hyperbolic functions. Logistic and hyperbolic functions are mainly used in classification problems, because they range between 0 and 1 or

between -1 and 1, while the linear functions (infinity to infinity) are mainly used in regression problems (Ghatak, 2019). The output layer consists of a series of inverse functions, which are used to refine the training and calculate the difference between the output predictions and the measured K_{sat} , and to minimise error. One of the most widely used algorithms for this purpose is the backpropagation algorithm (Bell, 2015). Backpropagation was applied to develop the ANNs in this study. Appendix C (especially Section C.2) covers more information related to the ANNs applied in this Chapter including the pre-processing steps to prepare the data, the functions applied, the codes written, and other outputs.

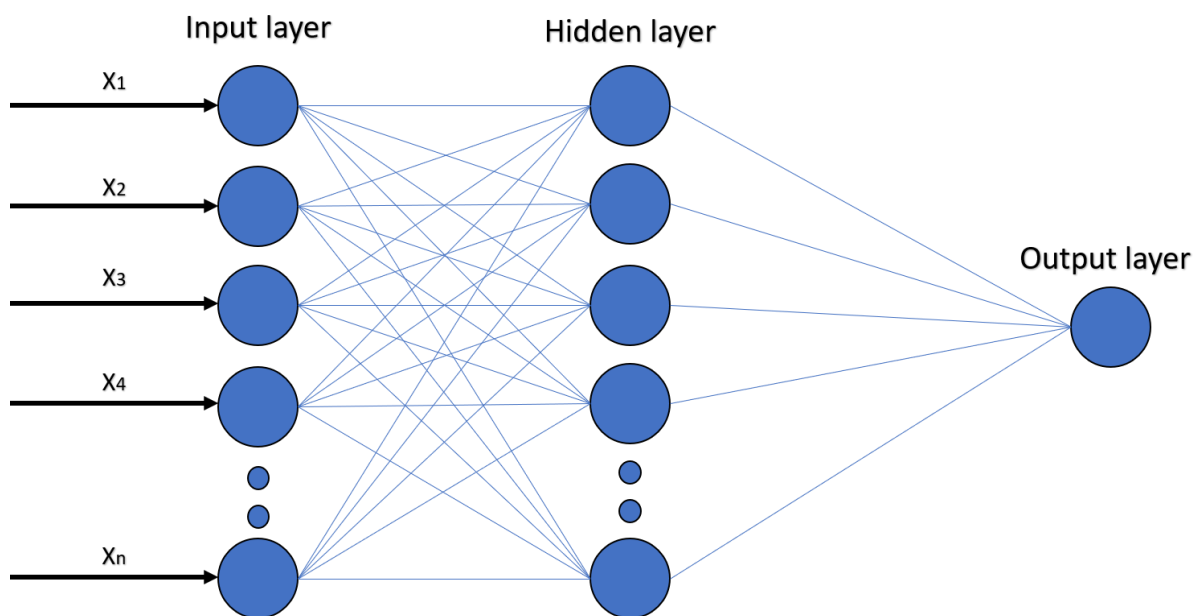


Figure 3-1 Structure of an artificial neural network (based on Khademi and Jamal, 2016).

For the development of ANNs to predict K_{sat} in the designated data-poor areas within EAP and HAP, several processing steps were undertaken. These steps were applied to assure that the developed model is statistically tested and can provide an accurate K_{sat} predictions. The first step was to define a training dataset in order to develop the ANNs. The training dataset was based on 80% of the data from the data-rich areas of the EAP and HAP (leaving 20% of the data as the pseudo 'data-poor area' for testing purposes against the actual measured K_{sat} data from both sites). The second step was to define the appropriate network (number of layers and number of neurons in each

layer). A sequential orthogonal approach (Sun, 2012) was adopted to determine the optimum number of neurons. This approach adds a neuron to the ‘hidden layer’ until the ANN with the smallest error is identified (Sun, 2012). The ANN with the smallest error in predicting K_{sat} within the data-rich area was subsequently applied to the data-poor area (using data from EAP and HAP that had not been used in the development of the model) to validate and test the performance of ANN by comparing the ANN predicted K_{sat} values with measured K_{sat} values. Table 3-2 shows the input parameters used to develop six ANN models to predict K_{sat} . All ANNs were developed for both HAP and EAP using two groups of input parameters. The first group of input parameters included %sand, %silt, %clay, bulk density, wilting point and field capacity were applied in ANN1, ANN3, and ANN5. ANN1 and ANN3 used data only from EAP and HAP respectively, and ANN5 used the combined data set from both EAP and HAP. The second group of input parameters included %sand, %silt, %clay and bulk density were applied in ANN2, ANN4, and ANN6. ANN2 and ANN4 used data only from EAP and HAP respectively, and ANN6 used the combined data set from both EAP and HAP. The reason for having two groups of input parameters is to assess the minimum data set required to predict K_{sat} accurately.

Table 3-2 The ANN models developed for the EAP and HAP study sites.

ANN Model	Inputs required	Project name
ANN1	%Sand, %Silt, %Clay, BD (g cm^{-3}), %FC, %WP, and K_{sat} (m d^{-1})	EAP
ANN2	%Sand, %Silt, %Clay, BD (g cm^{-3}), and K_{sat} (m d^{-1})	EAP
ANN3	%Sand, %Silt, %Clay, BD (g cm^{-3}), %FC, %WP, and K_{sat} (m d^{-1})	HAP
ANN4	%Sand, %Silt, %Clay, BD (g cm^{-3}), and K_{sat} (m d^{-1})	HAP
ANN5	%Sand, %Silt, %Clay, BD (g cm^{-3}), %FC, %WP, and K_{sat} (m d^{-1})	EAP + HAP*
ANN6	%Sand, %Silt, %Clay, BD (g cm^{-3}), and K_{sat} (m d^{-1})	EAP + HAP*

(ANN) Artificial Neural Network, (EAP) Eshkeda Agricultural Project, and (HAP) Hammam Agricultural Project. (WP) wilting point, (FC) field capacity, (BD) bulk density, (K_{sat}) saturated hydraulic conductivity, and *EAP + HAP = combined data set.

The critical evaluation of the ability of the six ANN models developed in this study to accurately predict K_{sat} was undertaken in five steps. Step 1 used the training data (data-rich area) for site-specific ANN model training and the data from the designated data-poor areas as testing datasets. The best performing ANN model in terms of predicting K_{sat} in the designated data-poor areas was selected by applying three statistical parameters.

These were: (1) coefficient of determination (R^2) between the observed and predicted K_{sat} values for the data poor areas (e.g., best performance is equal to 1), (2) mean square error (MSE) and (3) root mean square error (RMSE) (Patil and Singh, 2016; Zhang and Schaap, 2019), which can respectively be defined mathematically as:

$$R^2 = 1 - \frac{\sum_{i=1}^n (P_i - M_i)^2}{\sum_{i=1}^n (M_i - \bar{M}_i)^2} \quad (3-1)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (P_i - M_i)^2 \quad (3-2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (P_i - M_i)^2}{n}} \quad (3-3)$$

Where n represents the number of soil samples, M_i is the measured K_{sat} , P_i is the predicted K_{sat} , and $\bar{M}_i$ is the mean measured K_{sat} .

MSE and RMSE were used to give a quantitative indication of ANN model error in units of K_{sat} (the best performance value is zero). Step 2 tested the four site specific ANN models (Table 3-2) on data-rich areas only using a K-fold cross-validation technique (Bell, 2015; Ghatak, 2019). There are other cross-validation techniques such as, (1) validation set approach (where the data is divided randomly into two sets, one set to train the model and the other set to test the model), (2) Leave one out cross-validation (where one sub-set of the data point is left out, the model is built on the remaining data, and the model is tested using the 'left out' data sub-set) (Bell, 2015; Chollet and Allaire, 2017; Ghatak, 2019). In this study, the K-fold cross-validation

method was applied. In the K-fold cross-validation technique, the training data (data from the pre-defined data-rich areas in both sites) were divided into ten randomly generated sub-sets. For EAP and HAP this resulted in ten randomly generated sub-sets of 36 and 61 data points respectively. During each K-fold cross-validation, nine sub-sets were combined and used as the 'training sub-set' and one part used as the 'testing sub-set'. This process was repeated ten times "rotating out" a testing sub-set each time so that each sub-set used in each ANN was applied in the testing. For both EAP and HAP, this K-fold cross-validation process was also repeated, removing 10 data points from the dataset each time until only 10 data points remained.

This approach was used to quantify the performance (ability to accurately predict K_{sat}) of each of the four site specific ANN models (Table 3-2) against the size of the training set used (Chollet and Allaire, 2017). This technique was used to quantify the ability of the ANNs to predict K_{sat} as the size of training set was reduced randomly and to also determine the 'minimum' training set required to develop the ANN. Step 3 of performance testing compared the outputs of the ANNs against outputs generated from traditional, widely adopted, empirical equations used to predict K_{sat} (Abdelbaki et al., 2009; Minasny and McBratney, 2000a) (Table 3-3). These Pedotransfer functions (PTFs) were selected because of the availability of the input parameters required by these PTFs (i.e. percentage of sand and clay). Also, these PTFs are used by researchers and stakeholders in Libya without evaluating the accuracy of these PTFs. therefore, this research may help to highlight the pros and cons of using PTFS developed from soil data from different regions (e.g. North America, and Europe). Step 4 evaluated the performance of each developed ANNs to predict K_{sat} in the other site (non site-specific). For example, ANN1 and ANN2 were developed and tested in EAP and were applied to predict K_{sat} in HAP and ANN3 and ANN4 were developed and tested in HAP and were applied to predict K_{sat} in EAP. This step was added to evaluate the applicability of applying ANNs, developed in specific locations, to predict K_{sat} in new locations in Libya. In this example, the separation distance between ANN development and application was 225 km (i.e., the separation distance between EAP and HAP). Step 5 developed ANNs by combining the training datasets from the pre-defined data-rich areas of both EAP and HAP to predict K_{sat} in the pre-defined data-poor areas in EAP and HAP. This step was applied to evaluate the accuracy of ANNs

based on larger combined datasets from multiple sites, compared to smaller but site-specific data sets, to predict K_{sat} .

Table 3-3 Pedotransfer functions (PTFs) widely adopted to predict saturated hydraulic conductivity (K_{sat})

Formula (cm hr ⁻¹)	PTF Code	References
$K_{sat} = 15.696 \text{ EXP}[-0.1975C]$	PTF-1	(Puckett et al., 1985)
$K_{sat} = 30.384 \text{ EXP}[-0.144C]$	PTF-2	(Dane and Puckett, 1994)
$K_{sat} = 0.0920e^{0.0491*S}$	PTF-3	(Julia et al., 2004)
$K_{sat} = 2.54 * 10^{(-0.6+0.012*S - 0.0064*C)}$	PTF-4	(Cosby et al., 1984)

Where: C is the % clay, S is the % sand.

3.2.4 Application of ANNs to Drainage Design

Drainage systems can be designed as either surface, subsurface or a combination of both surface and subsurface, depending on the prevailing conditions in the area and crops grown (Luthin, 1978). This study focused on subsurface drainage which is used in both EAP and HAP. The determination of appropriate spacing and depth of drains are the main parameters in the design of subsurface drainage systems that need to be considered (Luthin, 1978). A number of drainage theories and associated equations for designing subsurface drainage systems have been developed (Dagan, 1965; Dumm, 1960, 1954; Hooghoudt, 1940, 1937; Kirkham, 1958; Luthin and Worstell, 1959; van Schilfgaarde, 1963). These equations were developed to relate the spacing and depth of drains to water-table depth and drawdown rates. Methods have been developed to design drainage systems under steady or non-steady state (see reviews by van der Ploeg et al. (1999) and Youngs (1999)). EnDrain (Drainage computer program released by Prof. Oosterbaan in the Netherlands) was applied to design drainage systems in the designated data-poor areas of both EAP and HAP using K_{sat} derived from the ANNs developed in this study (Table 3-2) as compared to widely adopted PTFs (Table 3-3) and the actual measured K_{sat} for these data-poor areas. EnDrain uses Equation (3-4), described by Hooghoudt (1937; cited in Ritzema (1994)), to calculate the distance between drains and the depth of the water-table at the midpoint between two drains (Oosterbaan, 1993):

$$L^2 = \frac{8 \cdot K_b \cdot d \cdot h + 4 \cdot K_a \cdot h^2}{q} \quad (3-4)$$

Where L is drain spacing (m), q is the steady-state drainage discharge rate (m d⁻¹), K_a is the hydraulic conductivity of the soil above drain level (m d⁻¹), K_b is the hydraulic conductivity of the soil below drain level (m d⁻¹), h is the height of water-table above the water level in the drain (m), d is the equivalent depth which is a function of the spacing (L), the depth (in m) of impervious layer below the drain (D_i-D_d in Figure 3-2 2), and the radius (r) of the drain (m). Values for d can be found in tables presented by Hooghoudt, (1940). Van der Molen and Wesseling (1991) developed this further to calculate series solutions for multiple equivalent depths.

EnDrain requires two values of K_{sat} one from above the drain level and one from below the drain level. Therefore, a representative K_{sat} was required as an input to EnDrain. According to Luthin, (1978), the geometric mean (K_g) gives the best representative K_{sat} for a study area. Therefore, representative K_g values for EAP and HAP were generated for input to EnDrain. Equation (3-5) illustrates how the geometric mean was calculated and Table 3-4 shows the different calculations of K_g based on the project area and the source of K_{sat} (e.g., K_{sat} derived from ANNs):

$$K_g = \sqrt[N]{K_{sat1} \cdot K_{sat2} \cdot K_{sat3} \cdot K_{satN}} \quad (3-5)$$

Where the geometric mean (K_g) is found by multiplying the values of K_{sat} (K_{sat1} is the K_{sat} value for sample 1, K_{sat2} is K_{sat} value of sample 2 and so on to N number of values) and then the Nth root of the product of those values is then found (Nth root is equal to the number of values).

Water-table depth based on ANN and PTF generated K_g values (Table 3-4) was compared with water-table depth based on K_g values generated from measured K_{sat} (K_{g1} and K_{g 8} in Table 3-4). The value of R used in EnDrain was the average water requirement for date palm (*Phoenix dactylifer*) and alfalfa (*Medicago sativa*). Date palm was chosen because it is considered to be the most profitable crop for the south of Libya (Elmeer et al., 2016). Alfalfa was adopted as it is grown as a fodder for livestock in both EAP and HAP. The average crop water requirements at this stage of the research is set to be equal to the crop evapotranspiration (ET_c) only and not considering the leaching requirement or the irrigation efficiency (as this will be included

in Chapters 4 – 6 as part of DRAINMOD simulations). Therefore, the crop water requirements (described as the time average recharge (R) in Table 3-5) for date palm is 8.9 mm d^{-1} in EAP and 6.3 mm d^{-1} in HAP, and for alfalfa are 8.3 mm d^{-1} for EAP and 5.9 mm d^{-1} for HAP. These values were taken from an unpublished report based on work undertaken by the Libyan Government in 1999 (GWA, 1999), and the full information on how these values were calculated are available in Appendix B.5. Site investigations of soil properties were undertaken at both sites between 1974-1980 in HAP by Danenco (1980) and Holzmann-Wakuti (1974) and between 1976-1981 in EAP by ITALCONSULT (1976) and Cornelius-Brochier (1981), to design agricultural projects including drainage systems in these areas. The following data were taken from these reports: The average depth of the impermeable layer for both EAP and HAP was assumed to be 3.0 m, two soil layers were assumed with two different K_{sat} values with depth, and the depth of water-table was set at 0.5 m and 1.0 m from the soil surface. The 0.5 m represents the current water table depth at EAP and HAP. This water table is shallow and causing waterlogging problems in EAP and HAP. The drainage design which will help to achieve a 0.5 m water table depth will be compared to a design with water table depth maintained at 1.0 m. The vertical K_{sat} and the horizontal K_{sat} were assumed to be equal (Hess et al., 1992). Table 3-5 shows the input parameters applied in EnDrain.

Figure 3-2 is a schematic representation of a subsurface drainage system and provides an explanation of the input parameters used in Table 3-5 and Equation (3-4).

Finally, an economic analysis was conducted to calculate the initial cost of installing each drainage system in the designated data-poor areas using the measured K_g as well as ANNs and PTFs generated K_g values. The cost of drains installed was assumed to be $\$2.62 \text{ m}^{-1}$ according to Skaggs (2007).

Table 3-4: K_{sat} geometric means (K_g) derived from the ANN and PTF models evaluated in this study and used as input parameters to design a sub-surface drainage system using EnDrain.

Project name	K_g Code	Source of K_{sat} data	K_g Above drain level (A_{dl})	K_g Below drain level (B_{dl})
EAP	K_g1	Measured K_{sat}	$K_g-A_{dl}-1$	$K_g-B_{dl}-1$
	K_g2	K_{sat} from ANN1	$K_g-A_{dl}-2$	$K_g-B_{dl}-2$
	K_g3	K_{sat} from ANN2	$K_g-A_{dl}-3$	$K_g-B_{dl}-3$
	K_g4	K_{sat} from PTF-1	$K_g-A_{dl}-4$	$K_g-B_{dl}-4$
	K_g5	K_{sat} from PTF-2	$K_g-A_{dl}-5$	$K_g-B_{dl}-5$
	K_g6	K_{sat} from PTF-3	$K_g-A_{dl}-6$	$K_g-B_{dl}-6$
	K_g7	K_{sat} from PTF-4	$K_g-A_{dl}-7$	$K_g-B_{dl}-7$
HAP	K_g8	Measured K_{sat}	$K_g-A_{dl}-8$	$K_g-B_{dl}-8$
	K_g9	K_{sat} from ANN3	$K_g-A_{dl}-9$	$K_g-B_{dl}-9$
	K_g10	K_{sat} from ANN4	$K_g-A_{dl}-10$	$K_g-B_{dl}-10$
	K_g11	K_{sat} from PTF-1	$K_g-A_{dl}-11$	$K_g-B_{dl}-11$
	K_g12	K_{sat} from PTF-2	$K_g-A_{dl}-12$	$K_g-B_{dl}-12$
	K_g13	K_{sat} from PTF-3	$K_g-A_{dl}-13$	$K_g-B_{dl}-13$
	K_g14	K_{sat} from PTF-4	$K_g-A_{dl}-14$	$K_g-B_{dl}-14$

(K_{sat}) saturated hydraulic conductivity, (K_g) geometric mean of K_{sat} , (PTF) pedotransfer function, (ANN) Artificial Neural Network, (EAP) Eshkeda Agricultural Project, and (HAP) Hammam Agricultural Project.

Table 3-5: Input parameters for EnDrain required to design a subsurface drainage system for EAP and HAP.

Input parameter	Units	EAP		HAP	
		Date palm	Alfalfa	Date palm	Alfalfa
Time average recharge (R)	mm d ⁻¹	8.9	8.3	6.3	5.9
Depth to the impermeable layer from surface (Di)	m	3.0	3.0	3.0	3.0
Depth water level in drain from surface (Dm+h)	m	1.4	1.4	1.4	1.4
Depth of drain bottom from surface (Dd)	m	1.5	1.5	1.5	1.5
Diameter of Drain (d)	m	0.2	0.2	0.2	0.2
Depth water-table midway between drains (Dm)	m	0.5 and 1.0	0.5 and 1.0	0.5 and 1.0	0.5 and 1.0

Source of data: (Cornelius-Brochier J.V, 1981; Danenco, 1980; GWA, 1999; Holzmann-Wakuti, 1974; Italconsult, 1976). (EAP) Eshkeda Agricultural Project, (HAP) Hammam Agricultural Project

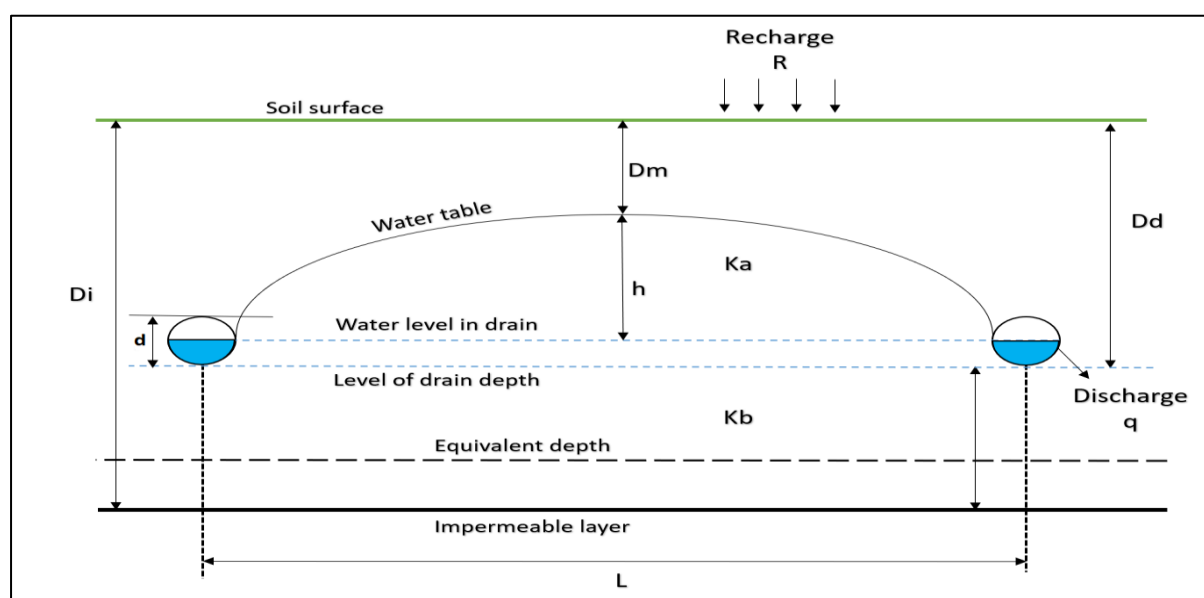


Figure 3-2. Schematic of subsurface drainage system indicating input parameters for EnDrain and Equation (3-4).

3.2.5 Software used

The data was analysed using several software packages. The development of the ANNs utilised a neuralnet package in R (Stefan and Guenther, 2019). Pedotransfer function equations (Table 3-3) used to predict K_{sat} and the representative $K_{sat}(K_g)$ were calculated in Microsoft EXCEL (2016). Finally, subsurface drain spacing, and depth of water-table were calculated using EnDrain (Oosterbaan, 1993).

3.3 Results

3.3.1 Performance of site-specific ANNs and cross-validation

The structure of each of the site-specific ANN models developed in this study, and their Step 1 performance evaluation are presented in Table 3-6. All ANNs were able to predict, based on R^2 , between 0.89-0.96 of the variability in K_{sat} in the designated data-poor areas of EAP and HAP. As expected, the ANN models performed better when using the training data than when the testing data was used. In HAP, the R^2 was slightly better in the testing section ($R^2 = 0.96$ and 0.95) than in the training section ($R^2 = 0.94$ and 0.93 ; Table 3-6).

Table 3-6: Structure performance evaluation of the ANNs to predict K_{sat} implemented in the designated data-poor areas of EAP and HAP.

Model name	Project name	Model Structure*	Number of samples	Training			Number of samples	Testing		
				RMSE m d ⁻¹	MSE m d ⁻¹	R ²		RMSE m d ⁻¹	MSE m d ⁻¹	R ²
ANN1	EAP	6:1:1	360	1.40	1.98	0.95	82	1.92	3.69	0.90
ANN2		4:2:1	360	1.53	2.35	0.94	82	2.00	4.03	0.89
ANN3	HAP	6:4:4:1**	610	2.29	5.26	0.94	158	2.78	7.76	0.96
ANN4		4:5:1	610	2.52	6.36	0.93	158	2.82	7.97	0.95

*Model structure is the structure of the ANNs, for example 6:4:1, 6 is the number neurons representing the input parameters, 4 is the hidden layer neurons, and 1 is the output of the model. **6:4:4:1 means that model has two hidden layers with 4 neurons in each layer. (PTF) Pedotransfer function, (ANN) Artificial Neural Network, (EAP) Eshkeda Agricultural Project, (HAP) Hammam Agricultural Project, (R2) coefficient of determination, (RMSE) Root Mean Square Error, and (MSE) Mean Square Error.

Generally, the ANNs developed in this study showed that there was little difference in performance between the ANNs as R^2 ranged from 0.89-0.90 in EAP and 0.95-96 in HAP. According to the performance results in Table 3-6, models ANN1 and ANN3 performed better than both ANN2 and ANN4. Even though, the number of data points in the ANNs developed for EAP (for training and testing) were almost half the number used in the ANNs developed for HAP (360 in EAP and 610 in HAP), the RMSE and MSE values for the EAP ANNs indicate that they are more accurate.

The results of the Step 2 K-fold cross-validation are shown in Figure 3-3 and Figure 3-4. Figure 3-3 shows the median RMSE across the ten randomly generated sub-sets (dark line inside the boxplot) when the size of training set is fixed to the maximum size (360 in EAP and 610 in HAP). In Figure 3-3 it can be noted that the median RMSE for ANN1, ANN2, ANN3, and ANN4, were 1.65, 0.40, 1.80, and 1.40 m d^{-1} , respectively. Also, the minimum and maximum RMSE ranged between 1.37 – 1.84, 0.10 – 1.40, 1.30 – 8.10 and 0.30 – 2.70 m d^{-1} in ANN1, ANN2 ANN3 and ANN4, respectively. These results showed that the developed ANNs for both EAP and HAP were in the range of the 10-fold cross-validation. Therefore, the training dataset (from the data-rich areas) was effectively used to develop ANNs able to predict K_{sat} . Figure 3-4 indicates how RMSE varies with the size of training dataset. As indicated by the low median RMSE values, the best performing ANNs were developed when the full dataset was used in the training phase (Figure 3-4). However, for both EAP and HAP, even if the training set was reduced to 50, the ANNs were still able to accurately predict K_{sat} (Figure 3-4).

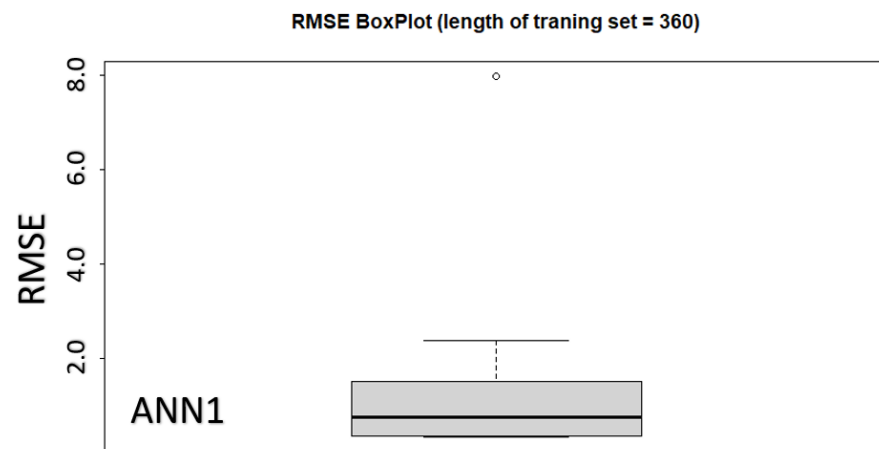
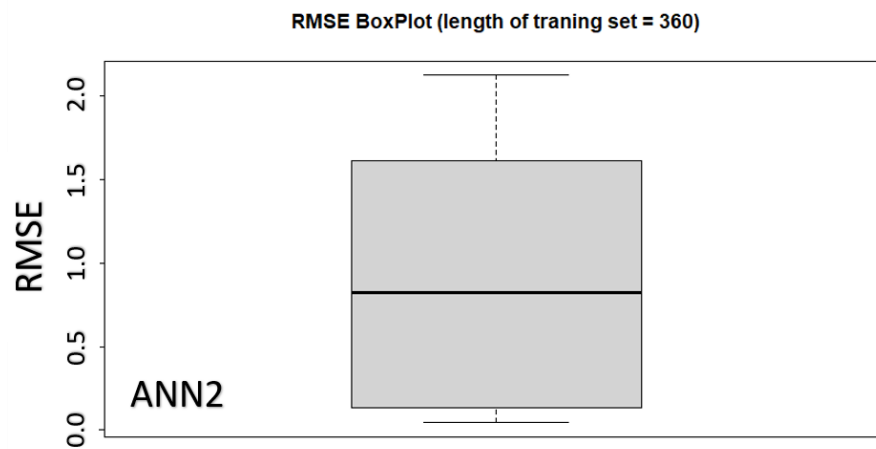
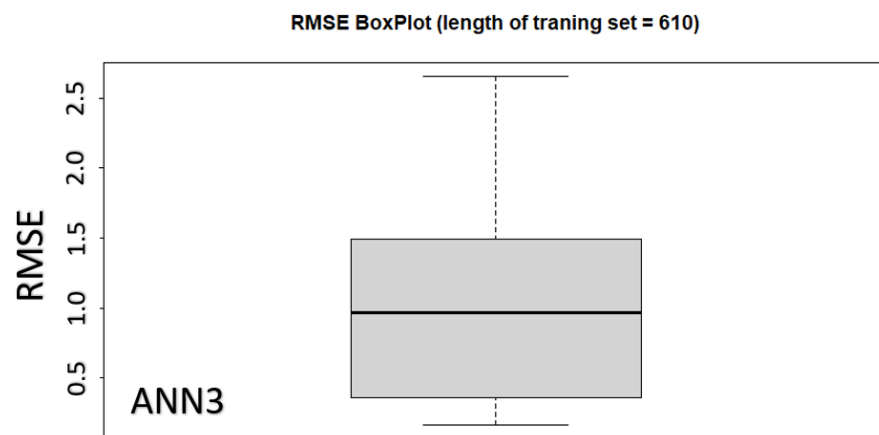
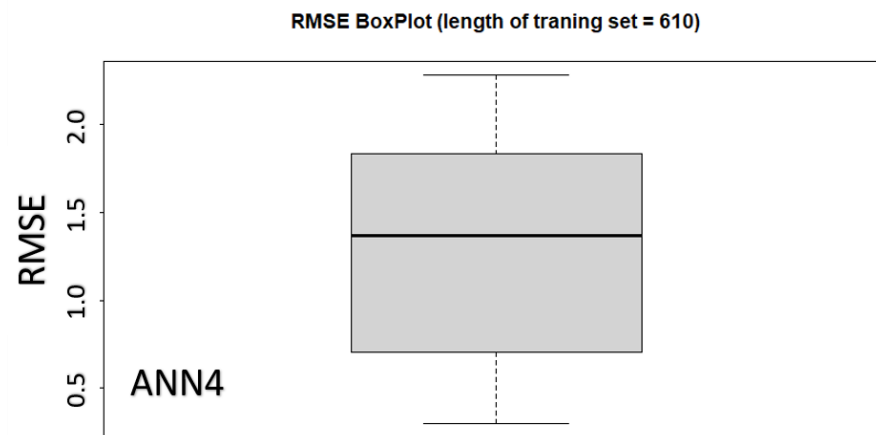


Figure 3-3: Boxplots of the median RMSE for ANN1 – ANN4 in EAP and HAP to predict K_{sat} .

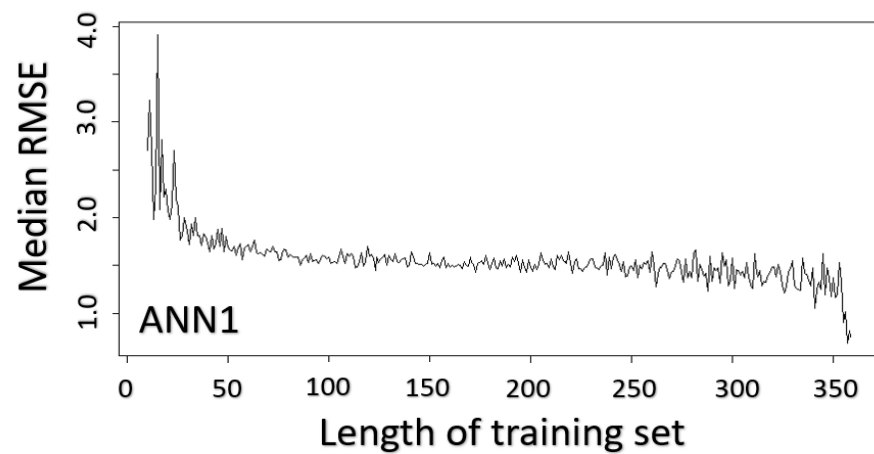
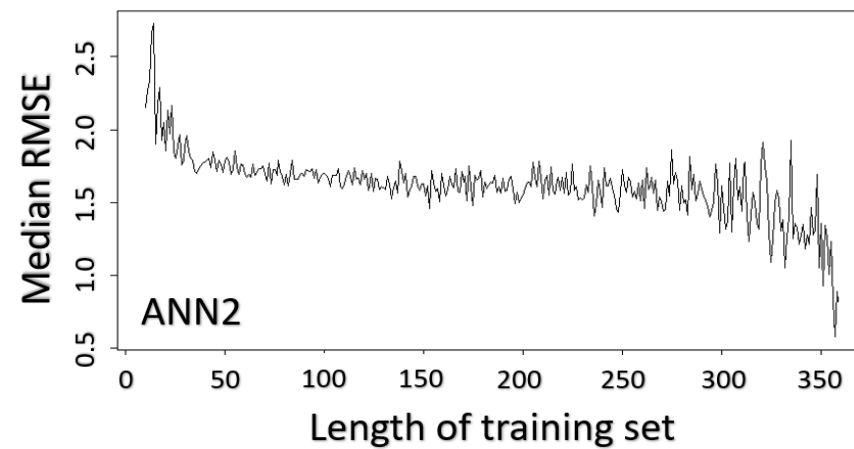
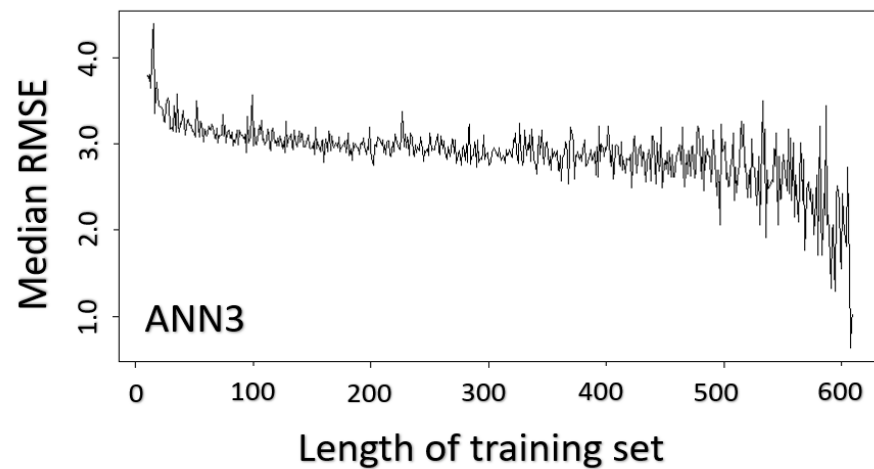
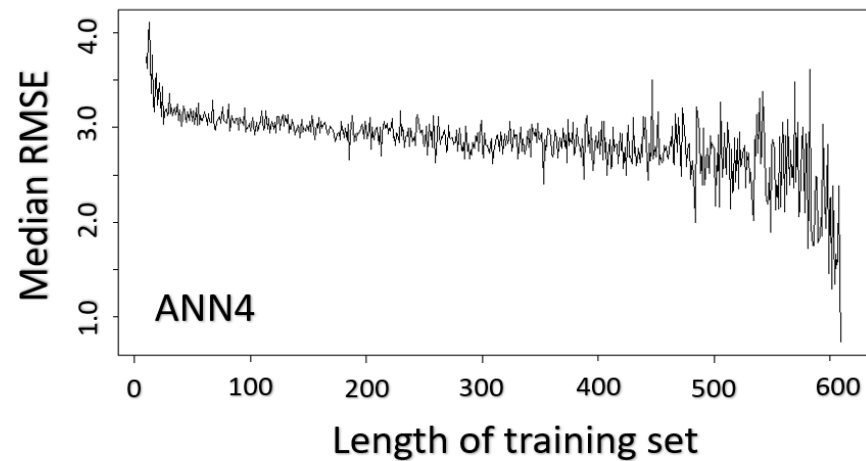


Figure 3-4: Median RMSE for the size of training used in the development of the ANNs for EAP and HAP to predict K_{sat} .

3.3.2 Performance of PTFs and non-site-specific ANNs

Four PTFs that are widely adopted to predict K_{sat} were applied to predict K_{sat} in the designated data-poor areas of EAP and HAP (Table 3-3). In relation to RMSE and MSE, PTF-2 (developed by Dane & Puckett, 1994) performed better than the other PTFs in both EAP and HAP (Table 3-7). However, it is critical to note that all the PTFs were between 2-5 times less accurate at predicting K_{sat} than the site-specific ANNs. For example, the RMSE values of PTF-2 were 4.19 and 12.72 m d⁻¹ for EAP and HAP, respectively. In contrast, the RMSE for all the site-specific ANNs applied to EAP and HAP ranged from 1.92 to 2.82 m d⁻¹. Further, the MSE for the PTFs applied in EAP and HAP ranged from 17.60 to 225.00 m d⁻¹. In contrast, the MSE for the site-specific ANNs applied in EAP and HAP ranged from 3.69 to 7.97 m d⁻¹. For the combined ANNs (ANN5 and ANN6), the accuracy was better than the PTFs but slightly less (3 times less accurate) than the site-specific ANNs. For example, ANN5 in RMSE was 2.11 m d⁻¹ while in ANN1 was 1.92 m d⁻¹, while ANN6 was 6.09 m d⁻¹ in predicting K_{sat} in EAP. Finally, for the non-site-specific ANNs, the accuracy was less than all other ANNs and PTFs with the highest RMSE and MSE values of 15.88 and 252.23 m d⁻¹, respectively, in ANN4 for predicted K_{sat} in EAP.

Table 3-7: The comparative performance of PTFs and ANNs in predicting K_{sat} in the designated data-poor areas of EAP and HAP.

Model name	EAP (82 data points)			HAP (158 data points)		
	RMSE	MSE	R^2	RMSE	MSE	R^2
PTF-1	5.38	29.00	0.00	14.80	218.00	0.73
PTF-2	4.19	17.60	0.00	12.70	162.00	0.74
PTF-3	5.56	31.00	0.01	14.80	220.00	0.90
PTF-4	5.72	32.80	0.00	15.00	225.00	0.88
ANN1	1.92	3.69	0.90	15.14	229.00	-0.26
ANN2	2.00	4.03	0.89	15.47	239.00	0.79
ANN3	7.26	201.87	0.07	2.78	7.76	0.96
ANN4	15.88	252.23	0.01	2.82	7.97	0.95
ANN5	2.11	4.47	0.77	3.39	11.51	0.88
ANN6	6.09	37.11	0.70	4.42	19.61	0.83

(PTF) Pedotransfer function, (ANN) Artificial Neural Network, (EAP) Eshkeda Agricultural Project, (HAP) Hammam Agricultural Project, (R^2) coefficient of determination, (RMSE) Root Mean Square Error, and (MSE) Mean Square Error.

Figure 3-5 and Figure 3-6 show the accuracy of the PTFs specific and non-site-specific ANNs in predicting K_{sat} within the data-poor areas of EAP and HAP. The 1:1 line represents the line of perfect agreement between the predicted and the measured values of K_{sat} . It is of note that the predicted K_{sat} of the site-specific ANNs all closely comply with the 1:1 line. The results indicate that the site-specific ANNs were significantly better at predicting the observed K_{sat} values compared to those predicted by the PTFs and non-site-specific ANNs applied to EAP and HAP. For example, for the highest EAP observed K_{sat} value in EAP of 21.90 m d⁻¹, PTF-1, PTF-2, PTF-3 and PTF-4 predicted K_{sat} values of 2.10, 4.70, 2.20 and 2.00 m d⁻¹, respectively. This is an underprediction of one order of magnitude. In contrast, for the same sample (21.90 m d⁻¹) ANN1 and ANN2 predicted values of 22.40 and 24.50 m d⁻¹ respectively. While ANN3 and ANN4 (developed to predict K_{sat} in HAP) overpredict K_{sat} in EAP with the highest value of prediction 42.20 and 29.80 m d⁻¹ respectively. Furthermore, in EAP the measured K_{sat} ranged between 0.60 to 21.90 m d⁻¹, whereas the prediction values of K_{sat} for all PTFs ranged from 1.20 to 6.30 m d⁻¹.

In contrast, the non-site-specific, K_{sat} ranged between 7.00 to 42.20 m d⁻¹. While, in EAP the predicted K_{sat} values for the site-specific ANNs ranged from 0.60 to 25.30 m d⁻¹. A similar pattern was observed in the HAP (Figure 3-6), where the measured K_{sat} ranged between 0.40 to 38.00 m d⁻¹, whereas the prediction values for all PTFs ranged between 0.03 to 6.30 m d⁻¹, and for non-site-specific ANNs ranged between 0.01 to 3.50 m d⁻¹. In contrast, the site-specific ANNs Predicted K_{sat} in HAP ranged in value between 0.20 to 27.70 m d⁻¹. However, the site-specific ANNs used to predict K_{sat} in HAP were unable to accurately predict K_{sat} when the measured K_{sat} was ≥ 30.00 m d⁻¹. These ANNs underestimate the K_{sat} values ≥ 30.00 m d⁻¹ by 10 - 30%. However, only 6 samples (out of 158) had a K_{sat} value of ≥ 30.00 m d⁻¹. It can be noted that the PTFs tend to under-predict the K_{sat} values when the observed measurements exceed 6.00 m d⁻¹ and 2.00 m d⁻¹, in EAP and HAP respectively. Additionally, it is of note that ANN1 (Figure 3-5) and ANN3 (Figure 3-6) show slightly better compliance with the 1:1 line in comparison to ANN2 (Figure 3-5) and ANN4 (Figure 3-6). Also, ANN5 and ANN6 showed a comparable prediction to the ones obtained by the site-specific ANNs where K_{sat} values ranged between 0.70 to 23.20 m d⁻¹ in EAP and 0.50 to 30.80 m d⁻¹ in HAP. However, ANN6 was slightly less accurate in predicting K_{sat} especially the observed values of >15 m d⁻¹.

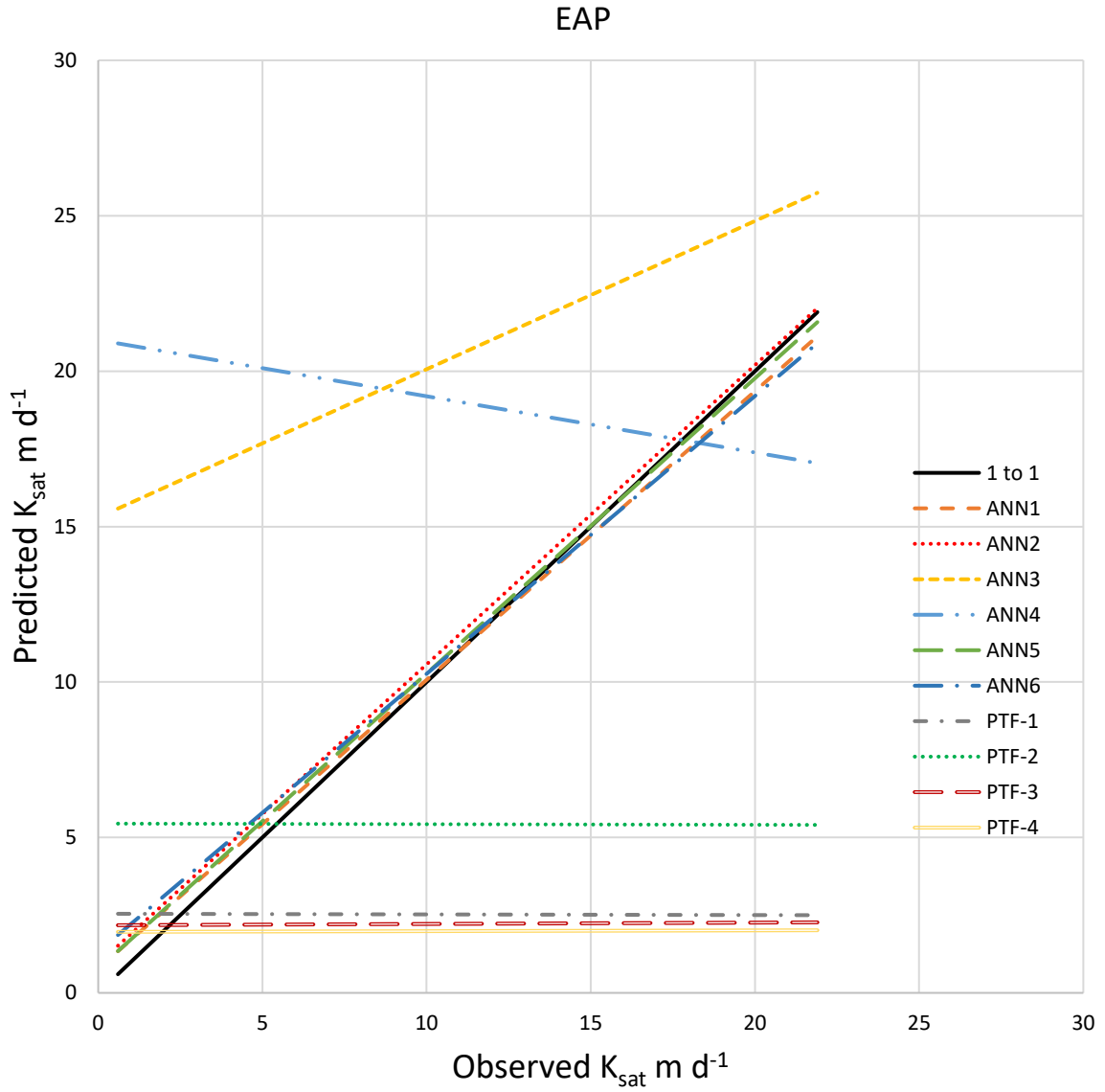


Figure 3-5: Predicted Saturated hydraulic conductivity (K_{sat} in m d^{-1}) versus observed K_{sat} (m d^{-1}) of Pedotransfer Functions (PTF-1 to PTF-4) and Artificial Neural Networks (ANN1 to ANN6) in Eshkeda Agricultural Project (EAP)

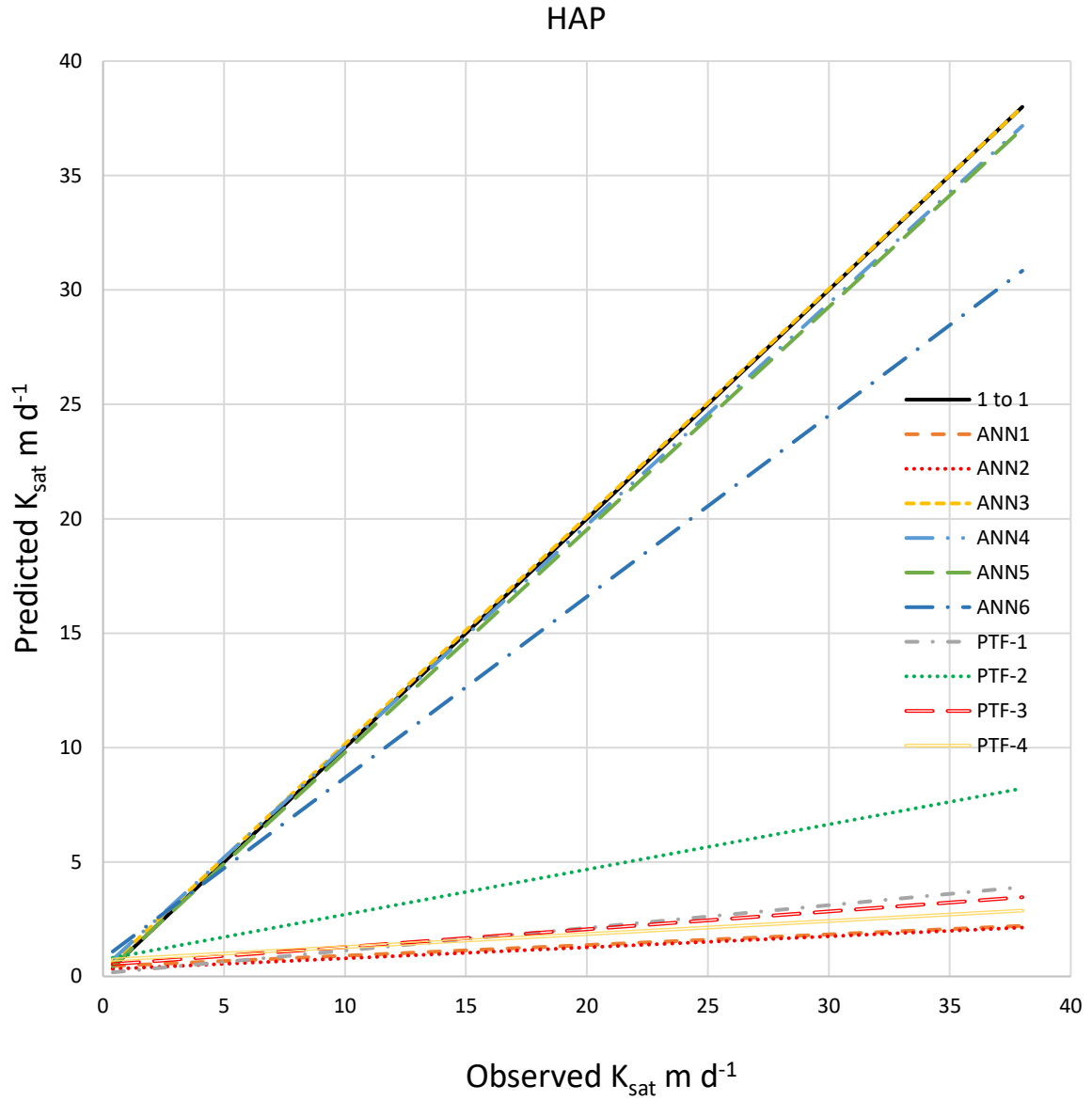


Figure 3-6: Predicted Saturated hydraulic conductivity (K_{sat} in m d⁻¹) versus observed K_{sat} (m d⁻¹) of Pedotransfer Functions (PTF-1 to PTF-4) and Artificial Neural Networks (ANN1 to ANN6) in Hammam Agricultural Project (HAP).

3.3.3 Drain spacing and water-table depths

Equation (3-5) was used to estimate the K_g for the different scenarios presented in Table 3-4, the results of which are given in Table 3-8 and Table 3-8. Estimation of K_g was made above (A_{dl}) and below (B_{dl}) the drain level. These estimated values of K_g were applied in EnDrain to predict the drain spacing and water-table depths for the designated data-poor areas of EAP and HAP. Measured K_{sat} values used to calculate K_g (EAP K_{g1} and HAP K_{g8}), resulted in a drain spacing between two drains of 45 and 76 m (date palm) and 46 and 79 m (alfalfa) for water table depth of 100 cm and 50 cm in EAP. In HAP, the measured drain spacing for 100 cm water table depth is 53 and 54 m for date palm and alfalfa, respectively. In addition, for water table depth of 50 cm the drain spacing is 101 m for palm tree and 105 m for alfalfa.

In general, K_g derived from the four ANNs K_{sat} predictions had the lowest variation in distance between drains compared to the target value based on measured data (K_{g1} and K_{g8}). For EAP, the % variation in drain spacing from the target for ANN1 and ANN2 was for date palm, 1 – 2% and 2 – 4% respectively. In contrast, for the PTFs (K_g 4 – 7) % variation in drain spacing from the measured data ranged from 28 – 37% (Table 3-8 and Table 3-9). For HAP, the highest % variation in drain spacing from the measured data for ANN3 and ANN4 was 2 and 4% respectively. In contrast, for the PTFs (K_g 11 - 14) % variation in drain spacing from the measured data ranged from 50 – 76%. The first target depth of water table for EAP and HAP was 50 cm from the soil surface (as obtained by K_{g1} and K_{g8}) (Figure 3-8). Generally, the variation of water depth based on K_g derived from the four ANNs were closer to the target water table depth with % variation ranging between 4 – 12% and 0 – 4%, in EAP and HAP respectively. In contrast, the % variations in water depth for the PTFs compared to the target design ranged from 74 – 90% in K_g (4 – 7) and 104 – 142% in K_g (11 - 14). The second target depth of water table for EAP and HAP was 100 cm from the soil surface (as obtained by K_{g1} and K_{g8}) (Figure 3-9). Generally, the variation of water depth based on K_g derived from the four ANNs were closer to the target water table depth with % variation ranging between 1 – 2% in EAP and HAP. In contrast, the % variations

in water depth for the PTFs compared to the target design ranged from 15 – 19% in Kg (4 – 7) and 21 – 28% in Kg (11 - 14).

The estimation of the initial cost of installing a drainage system in the designated data-poor areas of EAP (600 ha) and HAP (500 ha) were calculated using measured K_{g1} - K_{g14} for 50 cm water table depth (Table 3-8), and 100 cm water table depth (Table 3-9). The 50 cm water table depth has wider drain spacing compared to the 100 cm, and therefore, the initial cost is less for 50 cm water table depth. Based on measured K_{sat} K_{g1} and K_{g8} , the initial cost for 50 cm water table depth ranges from US\$ 150,000 – 207,000, while for 100 cm water table depth the initial cost ranges from US\$ 291,000 – 349,000. The results show that for both EAP and HAP, installing drainage schemes based on K_{sat} derived from ANNs is more economical than designs using K_{sat} derived from PTFs for both scenarios (50 cm and 100 cm water table depth). In EAP K_{g1} derived from ANN1 resulted in around 2% increase, compared to measured data, in initial installation costs for date palm and alfalfa, respectively (Table 3-8 and Table 3-9). In contrast, K_{g2} derived from ANN2 resulted in around 4% decrease in initial installation costs, compared to measured data, for date palm and alfalfa respectively. In HAP, K_{g9} and K_{g10} derived from ANN3 and ANN4 result in a 0 – 2% and 2 – 4% increase in initial installation costs, compared to measured data, for date palm and alfalfa respectively. In contrast, K_{g11-14} derived from PTFs 1-4 result in substantial 101 – 372% increases in initial installation cost, compared to measured data.

In comparison to the initial drainage costs calculated based on measured data, the extra initial cost of designing drainage systems in EAP and HAP using K_{g2} , K_{g3} , K_{g9} , and K_{g10} ranges between US\$ 0 to US\$ 11,000. In contrast, the extra initial cost of designing drainage systems in EAP and HAP using K_g values derived from PTFs is an order of magnitude higher ranging from US\$ 82,000 to US\$ 918,000.

Table 3-8: Performance of PTF and ANN models in terms of variance (%) from target drain spacing (m) and water-table depth (0.5 m) when applied to the designated data poor areas of EAP and HAP.

Project	Kg Code	K _{sat} source	Spacing (m)		% variation from target design		Initial costs (USD\$ 1000's)		Variation in water-table depth (cm) with respect of spacing and Kg measured	Kg Above drain level (Adl) (m d ⁻¹)	Kg Below drain level (Bdl) (m d ⁻¹)
			Date palm	Alfalfa	Date palm	Alfalfa	Date palm	Alfalfa			
EAP (600ha)	Kg1	Measured	76	79	0	0	207	199	50*	2.6	5.6
	Kg2	ANN1	75	78	1	1	210	202	52	3.0	5.3
	Kg3	ANN2	79	82	4	4	199	192	44	3.1	6.0
	Kg4	PTF-1	50	52	34	34	314	302	93	2.1	2.1
	Kg5	PTF-2	54	56	29	29	291	281	87	2.1	2.6
	Kg6	PTF-3	50	52	34	34	314	302	93	2.0	2.2
	Kg7	PTF-4	48	50	37	37	328	314	95	1.8	2.0
HAP (500ha)	Kg8	Measured	101	105	0	0	156	150	50*	11.2	4.5
	Kg9	ANN3	101	104	0	1	156	151	50	11.5	4.3
	Kg10	ANN4	99	103	2	2	159	153	52	11.2	4.2
	Kg11	PTF-1	27	28	73	73	582	561	121	1.2	0.2
	Kg12	PTF-2	50	52	50	50	314	302	102	3.1	1.0
	Kg13	PTF-3	42	43	58	59	374	366	110	1.5	0.9
	Kg14	PTF-4	43	45	57	57	366	349	109	1.5	1.0

Table 3-9: Performance of PTF and ANN models in terms of variance (%) from target drain spacing (m) and water-table depth (1.0 m) when applied to the designated data poor areas of EAP and HAP.

Project	Kg Code	K _{sat} source	Spacing (m)		% variation from target design		Initial costs (USD\$ 1000's)		Variation in water-table depth (cm) with respect of spacing and Kg measured	Kg Above drain level (Adl) (m d ⁻¹)	Kg Below drain level (Bdl) (m d ⁻¹)
			Date palm	Alfalfa	Date palm	Alfalfa	Date palm	Alfalfa			
EAP (600ha)	Kg1	Measured	45	46	0	0	349	342	100*	2.6	5.6
	Kg2	ANN1	44	45	2	2	357	349	101	3.0	5.3
	Kg3	ANN2	46	48	2	4	342	328	98	3.1	6.0
	Kg4	PTF-1	28	29	38	37	561	542	118	2.1	2.1
	Kg5	PTF-2	31	32	31	30	507	491	115	2.1	2.6
	Kg6	PTF-3	29	30	36	35	542	524	117	2.0	2.2
	Kg7	PTF-4	27	28	40	39	582	561	119	1.8	2.0
HAP (500ha)	Kg8	Measured	53	54	0	0	297	291	100*	11.2	4.5
	Kg9	ANN3	52	54	2	0	302	291	101	11.5	4.3
	Kg10	ANN4	51	53	4	2	308	297	102	11.2	4.2
	Kg11	PTF-1	13	13	75	76	1209	1209	128	1.2	0.2
	Kg12	PTF-2	26	26	51	52	605	605	121	3.1	1.0
	Kg13	PTF-3	23	23	57	57	683	683	123	1.5	0.9
	Kg14	PTF-4	24	24	55	56	655	655	122	1.5	1.0

3.4 Discussion

3.4.1 Development of ANNs

All site-specific ANNs developed in this study were able to accurately predict K_{sat} (see Figure 3-5 and Figure 3-6). In this study, to predict K_{sat} values of soils in designated data-poor areas of EAP and HAP, ANNs were developed using selected key input variables. The input parameters for models ANN2 and ANN4 (% S, Si and C and BD) do not describe the structure or connectivity of void spaces in soil, therefore, they do not explain the connections between soil structures and functions very well (Nemes et al., 2003; Pachepsky et al., 2006). Anderson and Bouma (1973) found that an excellent prediction (as close as possible to the observed values) of K_{sat} can be obtained when pore space is measured directly. Therefore, the ANNs that also include FC and WP (ANN1 and ANN3) increased the accuracy of prediction of K_{sat} in comparison to ANN2 and ANN4 (see Figure 3-5 and Figure 3-6).

The K-fold cross-validation was undertaken to estimate the test error rate within the training dataset in order to confirm the confidence of applying the developed ANN to the designated data-poor areas. The results presented in Figure 3-4 show that for areas with similar soil characteristics to EAP and HAP the number of K_{sat} measurements required to generate an accurate ANN can be reduced to *circa* 50 (taking into account the total area of each scheme ranging between 1000 - 3000 ha). These results support the findings of Yang (1995) where the quality of an ANNs training dataset is more important than the quantity of values used. This can be seen in misprediction of K_{sat} values of 30.0 m d⁻¹ or above in ANN3 and ANN4, when the highest measured K_{sat} value used to develop these ANNs was 28.0 m d⁻¹. In addition, Yang (1995) added that, if the model was trained with a full range of expected situations, then It would require fewer input values to develop the training dataset, which means having all the expected values of the dependent variable within the training dataset.

For example, in this study, K_{sat} was the dependent variable needed to be predicted for a specific location (data-poor area). By having all ranges of K_{sat} within the training dataset, the developed ANN will be more accurate.

Generally, the non-site-specific ANNs failed to accurately predict K_{sat} in EAP and HAP. In EAP, ANN3 and ANN4 over-predict K_{sat} especially the measured values between 0.6 to 10.0 m d⁻¹. Whereas in HAP, ANN1 and ANN2 under-predict K_{sat} . These results show that an ANN developed in a specific location may not be transferrable to another location even within the same pedoclimatic region. However, the combined ANNs (ANN5 and ANN6) illustrate that soil datasets based on more than one location are able to accurately predict K_{sat} .

3.4.2 PTFs performance

The PTFs applied in this study failed to accurately predict K_{sat} values especially for values ≥ 10.0 m d⁻¹, which represent 15.0% and 54.0% of the designated data-poor areas in EAP and HAP respectively. This is due to the PTFs evaluated being developed (trained and tested) for very different soils. For example, the dataset sources used to develop PTF-1, PTF-2 and PTF-4 were US soils, while the dataset source used to develop PTF-3 was from Spain (Cosby et al., 1984; Dane and Puckett, 1994; Julia et al., 2004; Puckett et al., 1985). Critically, the soil texture classes used to develop the PTFs were different to the dominant soil textures in EAP and HAP. For example, the percentage of the dataset associated with sand and loamy sand in EAP was 96.4% (Table 3-1), while the percentage of these soil textures in the dataset used to develop PTF-1, PTF-2, PTF-3 and PTF-4 were 14.0%, 53.0%, 1.1% and 3.0%, respectively. Similarly, the combined percentage of sand, loamy sand and sandy loam soils in HAP was 72.0%. In contrast, the combined percentage of these soil texture classes in the dataset used to develop PTF-1, PTF-2, PTF-3 and PTF-4 were, respectively, 38.0%, 60.0%, 7.0% and 11.6%. Consequently, the K_{sat} values predicted using the PTFs were poorly correlated to the measured values of K_{sat} . In fact, the PTFs predicted K_{sat} with values ranging between 0.002 – 6.3 m d⁻¹ while the measured values ranged between 0.4 – 38.0 m d⁻¹.

The PTFs underestimated K_{sat} by 83.0 – 99.0%. Consequently, at both EAP and HAP, the K_{sat} values predicted by the PTFs was significantly less accurate than those predicted using ANNs. These results support the findings of Pringle et al. (2007), who found that all regression-based PTFs naturally tend to smooth the predicted values. The underestimation of K_{sat} by the selected PTFs is predominantly due to differences in soil texture. The soil texture classes in the dataset used to develop PTF-1, PTF-2, PTF-3 and PTF-4 were dominated by fine textured classes such as loam, sandy clay loam, clay loam, sandy clay and clay (Cosby et al., 1984; Dane and Puckett, 1994; Julia et al., 2004; Puckett et al., 1985).

PTF-2, developed by Dane and Puckett (1994) as compared to the other PTFs had low RMSE (22.0 – 27.0% and 14.0 – 15.0% in EAP and HAP respectively) and low MSE (39.0 – 46.0% and 26.0 – 28.0% in EAP and HAP respectively) in predicted K_{sat} . This observation agrees with the findings of Minasny and McBratney (2000a), where PTF-2 gave better prediction of K_{sat} for sandy soils compared to other PTFs. In addition, this is due to the soil texture classes in the dataset used to develop PTF-2 that comprised 53.0% sandy and loamy sand and 60.0% sandy, loamy sand and sandy loam. However, it is known that PTFs are not as reliable in their predictions when applied to different soils beyond the geomorphological and pedoclimatic region or soil texture from which it was originally derived (Minasny and McBratney, 2000b; Tietje and Hennings, 1996). Therefore, it was advised by Wösten (1997), Nemes (2015) and Van Looy et al. (2017) that PTFs should only be applied to the same pedoclimatic conditions from where they were developed. Nemes et al. (2003) suggested that it is better to use a small set of relevant data to develop PTFs, than to use a large and irrelevant data set for a specific area. Moreover, the application of PTFs in estimating K_{sat} at a specific location that contains different dominant soil textures might yield results with very limited accuracy and relevance if these structural features are disregarded (Lin et al., 1999; Vereecken et al., 2010). These PTFs will therefore be of limited use for estimating water transport in a specific field and/or a specific zone within a field (Parasuraman et al., 2006).

The results of the current study corroborate these findings. Therefore, for field-scale application purposes, developing PTFs from a small set of relevant site-specific data may turn out to be more successful than using PTFs derived from a large but more general dataset where locally specific conditions such as structural features might be missing (Nemes et al., 2003). For the study areas (EAP and HAP) the developed ANNs are a more appropriate and accurate way of estimating K_{sat} than adoption of existing PTFs.

3.4.3 Drainage design implications

In EnDrain, K_{sat} was the only parameter that varied in each design, all other parameters remained constant. An underestimation of K_{sat} by the PTFs resulted in an underestimation of the geometric mean (K_g) by 31.0% to 96.0% from the measured K_{sat} , in EAP and HAP, respectively. The consequence of this was a 31 – 40% and 50 – 76% shorter predicted distance between drains in EAP and HAP, respectively. A drainage design based on these predictions will have: (1) a lower than expected water level, and (2) have a higher drainage density. Such a design will incur significant extra initial cost as well as increased maintenance costs, compared to a design based on measured data. However, the drainage designs based on ANNs predictions gave drain spacing's and water table depth equivalent to the target water table depth, meaning the initial cost and subsequent maintenance costs would be almost equivalent to that based on measured data. This makes the use of ANNs to design drainage systems significantly more economical than the PTFs. Consequently, the ANNs developed in this study have considerable potential to reduce the cost of the design and maintenance of drainage systems as compared to the adoption of PTFs and are a less time-consuming alternative to traditional soil sampling and analyses for a specific area. Therefore, so long as the increase in installation cost in EAP and HAP is less than the saving made in the sampling and analytical programmes, adoption of ANN1-4 is cost-effective. In addition, ANN development indicates that if site-specific ANNs are to be developed, the number of soil samples required to create an accurate ANN can be substantially reduced. Finally, the results in Table 3-8 show that the K_{sat} derived from ANNs can be applied to the design of a drainage

system that would maintain the water table depths at equivalent depths to directly measured data providing those models are developed using datasets that meet at least the minimum quantity and quality requirements. In contrast, designs based on PTFs predictions would result in a water table depth that differed from the target design.

3.5 Conclusions

ANNs as an indirect method of predicting K_{sat} have been applied by several researchers (Agyare et al., 2007; More and Deka, 2018; Schaap et al., 2001; Sedaghat et al., 2016). As a rapid and reliable method, it shows good potential, but its accuracy is dependent on the quality and quantity of the dataset used to develop the ANN. In this research, ANNs were applied to predict K_{sat} in designated data-poor areas of two case study drainage schemes located in the south of Libya. It was possible to demonstrate that ANNs developed using easily measured existing and under-utilised data such as the % of sand, silt and clay, bulk density, field capacity and wilting point, were able to provide highly accurate predictions of K_{sat} . It was also shown that K_{sat} predictions based on ANNs were significantly more comparable to measured K_{sat} results than those predicted using widely adopted PTFs. Only K_{sat} predicted from ANNs could be used to accurately calculate both the target drain spacing as well as water-table depth in a drainage scheme designed using EnDrain. Therefore, assuming sampling cost is not considered, initial drainage design costs (based on length and depth of inserted pipe) would be comparable between designs based on ANN predictions and those based on measured K_{sat} . These results also suggest that ANNs can be successfully developed using existing and under-utilised datasets. As K_{sat} is time-consuming to measure, basing drainage designs on ANN predictions generated from a minimum dataset will be more cost-effective and therefore more accessible to farmers, planners, and decision-makers in least developed countries. However, further research is needed to evaluate the impact of these designs on crop production, salinity control and waterlogging, using a simulation model such as DRAINMOD, as well as, calculating the predicted income based on these designs for different cropping systems.

3.6 References

Abdelbaki, A., Youssef, M.A., Naguib, E.M., Kiwan, M., El-giddawy, E.I., 2009. Evaluation of Pedotransfer Functions for Predicting Saturated Hydraulic, in: ASABE Annual International Meeting. ASABE, Reno, Nevada. <https://doi.org/10.13031/2013.27309>

Agatonovic-Kustrin, S., Beresford, R., 2000. Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research. *J. Pharm. Biomed. Anal.* 22, 717–727. [https://doi.org/10.1016/S0731-7085\(99\)00272-1](https://doi.org/10.1016/S0731-7085(99)00272-1)

Agyare, W.A., Park, S.J., Vlek, P.L.G., 2007. Artificial neural network estimation of saturated hydraulic conductivity. *Vadose Zo. J.* 6, 423–431. <https://doi.org/10.2136/vzj2006.0131>

Ahuja, L., Naney, J., Green, R., Nielsen, D., 1986. Macroporosity to characterize spatial variability of hydraulic conductivity and effects of land management. *Soil Sci. Soc. Am. J.* 48, 699–702.

Aimrun, W., Amin, M.S.M., Eltaib, S.M., 2004. Effective porosity of paddy soils as an estimation of its saturated hydraulic conductivity. *Geoderma* 121, 197–203. <https://doi.org/10.1016/j.geoderma.2003.11.010>

Amundson, R., Berhe, A.A., Hopmans, J.W., Olson, C., Sztein, A.E., Sparks, D.L., 2015. Soil and human security in the 21st century. *Science* (80-.). 348, 1261071(1–6). <https://doi.org/10.1126/science.1261071>

Anderson, J.L., Bouma, J., 1973. Relationships between saturated hydraulic conductivity and morphometric data of an argillic horizon. *Soil Sci. Soc. Am. J.* 37, 408 – 413.

Arrington, K.E., Ventura, S.J., Norman, J.M., 2013. Predicting Saturated Hydraulic Conductivity for Estimating Maximum Soil Infiltration Rates. *Soil Sci. Soc. Am. J.* 77, 748–758. <https://doi.org/10.2136/sssaj2012.0288>

Arshad, R.R., Sayyad, G., Mosaddeghi, M., Gharabaghi, B., 2013. Predicting Saturated Hydraulic Conductivity by Artificial Intelligence and Regression Models. *ISRN Soil Sci.* 2013, Article ID 308159, 8 pages.

Ayars, J.E., Evans, R.G., 2015. Subsurface Drainage - What's Next? *Irrig. Drain.* 64, 378–392. <https://doi.org/10.1002/ird.1893>

Ayoubi, S., Pilehvar, A., Mokhtari, P., L., K., 2011. Application of Artificial Neural Network (ANN) to Predict Soil Organic Matter Using Remote Sensing Data in Two Ecosystems, in: Atazadeh, I. (Ed.), *Biomass and Remote Sensing of Biomass*. InTech Open Access, London, UK, pp. 181–196. <https://doi.org/10.5772/18956>

Azimi, H., Bonakdari, H., Ebtehaj, I., 2019. Design of radial basis function-based support vector regression in predicting the discharge coefficient of a side weir in a trapezoidal channel. *Appl. Water Sci.* 9, 78. <https://doi.org/10.1007/s13201-019-0961-5>

Baker, L., Ellison, D., 2008. Optimisation of pedotransfer functions using an artificial neural network ensemble method. *Geoderma* 144, 212–224. <https://doi.org/10.1016/j.geoderma.2007.11.016>

Beers, W.F.J. Van, 1958. The auger-hole method.

Bell, J., 2015. *Machine Learning with R*, 2nd ed, Machine Learning. PACKT, Birmingham. <https://doi.org/10.1002/9781119642183.ch14>

Bicknell, B., Imhoff, J., Kittle, J., Jobes, T., Donigian, A., 2005. *Hydrological Simulation Program—Fortran (HSPF)*.

Bittelli, M., Campbell, G., Tomei, F., 2015. *Soil Physics with Python: Transport in the Soil-Plant-Atmosphere System*. Oxford University Press, New York, USA.

Bouksila, F., Persson, M., Berndtsson, R., Bahri, A., 2010. Estimating Soil Salinity Over a Shallow Saline Water Table in Semiarid Tunisia. *Open Hydrol. J.* 4, 91–101.

Bouyoucos, G., 1927. The hydrometer as new method for mechanical analysis of soils. *Soil Sci.* 23, 343–353.

Buckman, H., Brady, N., 1960. *The Nature and Properties of Soil*, 6th ed. Macmillan company, New York, USA.

Chollet, F., Allaire, J., 2017. *Deep Learning With R*, MEAP. ed. Manning.

Chung, S., Ward, A., Schalk, C., 1992. Evaluation of the hydrologic component of the ADAPT water table management model. *Trans. ASAE* 35, 571–579.

Cleveland, C.C., Houlton, B.Z., Smith, W.K., Marklein, A.R., Reed, S.C., Parton, W., Del, S.J., Running, S.W., 2013. Patterns of new versus recycled primary production in the terrestrial biosphere. *PNAS* 110, 12733–12737. <https://doi.org/10.1073/pnas.1302768110>

Cornelius-Brochier J.V, 1981. *Wadi Al Shatti: Drainage Design*. Tripoli, Libya.

Cosby, B., Hornberger, G., Clapp, R., Ginn, T., 1984. A statistical exploration of soil moisture characteristics to the physical properties of soils. *Water Resour. Res.* 20, 682–690.

Dagan, G., 1965. Steady drainage of a two-layered soil. *Journal of Irrigation and Drainage Division. Proc. ASCE* 91, 51–64.

Dane, J., Puckett, W., 1994. Field soil hydraulic properties based on physical and mineralogical information, in: *The International Workshop on Indirect Methods for Estimating the Hydraulic Properties of Unsaturated Soils*. Eds MTh van Genuchten et al, University of California: Riverside, CA., pp. 389–403.

Danenco, 1980. *Technical Study for Jufra el Hamam Project*. Copenhagen, Denmark.

Dashtaki, S.G., Homaei, M., Khodaverdiloo, H., 2010. Derivation and validation of pedotransfer functions for estimating soil water retention curve using a variety of soil data. *Soil Use Manag.* 26, 68–74. <https://doi.org/10.1111/j.1475-2743.2009.00254.x>

Dumm, L., 1960. Validity and Use of the Transient-flow Concept in Subsurface Drainage. Am. Soc. Agric. Eng.

Dumm, L., 1954. Drain spacing formula: New formula for determining depth and spacing of subsurface drains in irrigated lands. Am. Soc. Agric. Eng. 10, 726–730.

Ebtehaj, I., Bonakdari, H., Zaji, A.H., 2018. A new hybrid decision tree method based on two artificial neural networks for predicting sediment transport in clean pipes. Alexandria Eng. J. 57, 1783–1795. <https://doi.org/10.1016/j.aej.2017.05.021>

Ebtehaj, I., Bonakdari, H., Zaji, A.H., Gharabaghi, B., Hossein, A., Bahram, Z., 2020. Evolutionary optimization of neural network to predict sediment transport without sedimentation. Complex Intell. Syst. <https://doi.org/10.1007/s40747-020-00213-9>

Elmeer, K., Ahmed, A., Serqiwa, S., 2016. Morphological diversity of three elite date palm (*Phoenix dactylifera* L .) cultivars grown in South of Libya, in: The Fourth Scientific Conference of Environment and Sustainable Development in the Arid and Semi-Arid Regions. University of Ejdabya, Ejdabya, Libya.

Elshemy, M., 2018. Review of Technologies and Practices for Improving Agricultural Drainage Water Quality in Egypt, in: Unconventional Water Resources and Agriculture in Egypt. Springer Verlag, pp. 163–188. <https://doi.org/10.1007/698>

FAO, 2002. Agricultural drainage water management in arid and semi-arid areas, FAO Irrigation and Drainage. <https://doi.org/10.1177/1362361399003003007>

FAO, 1989. Arid zone forestry: A guide for field technicians. Food & Agriculture Org, Rome, Italy.

Fooladmand, H.R., 2011. Pedotransfer functions for point estimation of soil moisture characteristic curve in some Iranian soils. African J. Agric. Res. 6, 1586–1591. <https://doi.org/10.5897/AJAR10.1152>

Ghatak, A., 2019. Deep learning with R. Springer Nature Singapore Pte Ltd, Kolkata, India. <https://doi.org/10.1007/978-981-13-5850-0>

GWA, 1999. Water and irrigation requirements for the most important crops in Libya [unpublished report]. Tripoli.

Hassler, S., Lark, R., Zimmermann, B., Elsenbeer, H., 2014. Which sampling design to monitor saturated hydraulic conductivity ? Eur. J. Soil Sci. 792–802. <https://doi.org/10.1111/ejss.12174>

Hess, K.M., Wolf, S.H., Celia, M.A., 1992. Large-Scale Natural Gradient Tracer Test in Sand and Gravel , Hydraulic Conductivity Variability and Calculated Macrodispersivities. Water Resour. Res. 28, 2011–2027.

Holzmann-Wakuti, 1974. Hydrogeology of The Joufrah Project Area. Tripoli, Libya.

Hooghoudt, S., 1940. Contribution of the knowledge of some physical soil properties. NO 7. Determination of the conductivity of soils of the second kind (in Dutch). Bijdragen tot de kennis Vaneenige natuurkundige Van den grond, 7. Algemeene beschonwing Van het problem Van de . The Hauge, Netherlands.

Hooghoudt, S., 1937. Contribution of the knowledge of some physical soil properties. NO 6. Determination of the conductivity of soils of the second kind (in Dutch). Bijdragen tot de kennis Vaneenige natuurkundige Van den grond, 6. Algemeene beschonwing Van het problem Van de d. The Hauge, Netherlands.

Huang, M., Lin, R., Huang, S., Xing, T., 2017. Advanced Engineering Informatics A novel approach for precipitation forecast via improved K -nearest neighbor algorithm. Adv. Eng. Informatics 33, 89–95. <https://doi.org/10.1016/j.aei.2017.05.003>

Huang, Y., 2009. Advances in artificial neural networks - Methodological development and application. Algorithms 2, 973–1007. <https://doi.org/10.3390/algor2030973>

Italconsult, 1976. Fezzan Land Reclamation Project: Wadi-Shati Eshkeda Area. Rome, Italy.

Jothi, V.L., Neelambigai, A., Nithish, S., Santhosh, K., 2020. Crop Yield Prediction using KNN Model. *Int. J. Eng. Res. Technol.* 8, 4–7.

Julia, M., Monreal, T., Sanchez del Corral Jimenez, A., Garc Melendez, E., 2004. Constructing a saturated hydraulic conductivity map of Spain using Pedotransfer functions and spatial prediction. *Geoderma* 123, 257–277.

Katul, G.G., Oren, R., Manzoni, S., Higgins, C., Parlange, M.B., 2012. Evapotranspiration : A Process Driving Mass Transort and Energy Exchange in The Soil-Plant-Atmosphere-Climte System. *Am. Geophys. Union* 50, 1–25. <https://doi.org/10.1029/2011RG000366>.1.INTRODUCTION

Khademi, F., Jamal, S.M., 2016. Research Papers Predicting the 28 Days Compressive Strength of Concrete Using Artificial Neural Network. *i-manager's J. Civ. Eng.* 6, 1–6. <https://doi.org/10.26634/jce.6.2.5936>

Khodaverdiloo, H., Homaei, M., Th, M., Genuchten, V., Ghorbani, S., 2011. Deriving and validating pedotransfer functions for some calcareous soils. *J. Hydrol.* 399, 93–99. <https://doi.org/10.1016/j.jhydrol.2010.12.040>

Kirkham, D., 1958. Seepage of steady rainfall through soil into drains. *Trans. Am. Geophys. Union* 39, 892–908.

Klute, A., Dirksen, C., 1986. Hydraulic Conductivity and Diffusivity: Laboratory Methods, in: *Methods of Soil Analysis, Part 1, Physical and Mineralogical Methods*,. A. Klute, ed., ASA, Madison, WI, pp. 687–734.

Kombo, O.H., Kumaran, S., Sheikh, Y.H., Bovim, A., Jayavel, K., 2020. Long-Term Groundwater Level Prediction Model Based on Hybrid KNN-RF Technique. *Hydrology* 7, 1–24.

- Li, Y., Chen, D., White, R., Zhu, A., Zhang, J., 2007. Estimating soil hydraulic properties of Fengqiu County soils in the North China Plain using pedo-transfer functions. *Geoderma* 138, 261–271.
- Lin, H., McInnes, K., Wilding, L., Hallmark, C., 1999. Effects of soil morphology on hydraulic properties: II. Hydraulic Pedotransfer Functions. *Soil Sci. Soc. Am. J.* 63, 955–961.
- Luthin, J., 1978. *Drainage Engineering*. Krieger Publishing, Huntington, N.Y.
- Luthin, J., Worstell, R., 1959. The falling water table in tile drainage: III factors affecting the rate of fall. *Trans. ASAE* 2, 45–47, 51.
- Ma, L., Ahuja, L.R., Nolan, B.T., Malone, R.W., Trout, T.J., Qi, Z., 2012. Root Zone Water Quality Model (RZWQM2): Model Use, Calibration, and Validation. *Trans. ASAE* 55, 1425–1446.
- Mallikarjuna, B., Sathish, K., Venkata Krishna, P., Viswanathan, R., 2020. The effective SVM-based binary prediction of ground water table. *Evol. Intell.* <https://doi.org/10.1007/s12065-020-00447-z>
- Merdun, H., Çınar, Ö., Meral, R., Apan, M., 2006. Comparison of artificial neural network and regression pedotransfer functions for prediction of soil water retention and saturated hydraulic conductivity. *Soil Tillage Res* 90, 108–116.
- Minasny, B., Mcbratney, A.B., 2002. The Neuro-m Method for Fitting Neural Network Parametric Pedotransfer Functions. *Soil Sci. Soc. Am. J.* 66, 352–361. <https://doi.org/10.2136/sssaj2002.0352>
- Minasny, B., McBratney, A.B., 2000a. Evaluation and development of hydraulic conductivity pedotransfer functions for Australian soil. *Aust. J. Soil Res.* 38, 905–926. <https://doi.org/10.1071/SR99110>
- Minasny, B., McBratney, A.B., 2000b. Estimation of sorptivity from disc-permeameter measurements. *Geoderma* 95, 305–324. [https://doi.org/10.1016/S0016-7061\(99\)00096-8](https://doi.org/10.1016/S0016-7061(99)00096-8)

Montzka, C., Herbst, M., Weihermüller, L., Verhoef, A., Vereecken, H., 2017. A global data set of soil hydraulic properties and sub-grid variability of soil water retention and hydraulic conductivity curves. *Earth Syst. Sci. Data* 9, 529–543.

More, P., 2018. Using Machine Learning to Predict Water Table Levels in a Wet Prairie in Northwest Ohio (MSc Thesis). Bowling Green State University.

More, S.B., Deka, P.C., 2018. Estimation of saturated hydraulic conductivity using fuzzy neural network in a semi-arid basin scale for murum soils of India. *ISH J. Hydraul. Eng.* 24, 140–146. <https://doi.org/10.1080/09715010.2017.1400408>

Nemes, A., 2015. Why do they keep rejecting my manuscript - Do's and don'ts and new horizons in pedotransfer studies. *Agrokem. es Talajt.* 64, 361–371. <https://doi.org/10.1556/0088.2015.64.2.4>

Nemes, A., Schaap, M.G., Wösten, J.H.M., 2003. Functional Evaluation of Pedotransfer Functions Derived from Different Scales of Data Collection. *Soil Sci. Soc. Am. J.* 67, 1093–1102. <https://doi.org/10.2136/sssaj2003.1093>

Nozari, H., Azadi, S., 2017. Experimental evaluation of artificial neural network for predicting drainage water and groundwater salinity at various drain depths and spacing. *Neural Comput. Appl.* <https://doi.org/10.1007/s00521-017-3155-9>

OECD, 2020. DAC List of ODA Recipients Effective for reporting on 2020 flows [WWW Document]. URL <http://www.oecd.org/dac/financing-sustainable-development/development-finance-standards/DAC-List-of-ODA-Recipients-for-reporting-2020-flows.pdf> (accessed 5.20.20).

Oki, T., Kanae, S., 2006. Global Hydrological Cycles and World Water Resources. *Science* (80-.). 313, 1068–1073.

Oosterbaan, R., 1993. EnDrain: Software program for subsurface drainage equations using the energy balance of groundwater flow, permitting anisotropic and stratified soils, as well as entrance resistance to drains.

Pachepsky, Y.A., Rawls, W.J., Lin, H.S., 2006. Hydropedology and pedotransfer functions. *Geoderma* 131, 308–316. <https://doi.org/10.1016/j.geoderma.2005.03.012>

Parasuraman, K., Elshorbagy, A., Si, B.C., 2006. Estimating Saturated Hydraulic Conductivity In Spatially Variable Fields Using Neural Network Ensembles. *Soil Sci. Soc. Am. J.* 70, 1851–1859. <https://doi.org/10.2136/sssaj2006.0045>

Patil, N.G., Pal, D., Mandal, C., Mandal, D., 2011. Soil water retention characteristics of Vertisols and pedotransfer functions based on nearest neighbor and neural networks approach to estimate AWC. *J. Irrig. Drain. Eng.* 138, 177–184.

Patil, N.G., Rajput, G., Nema, R., Singh, R., 2010. Predicting hydraulic properties of seasonally impounded soils. *J. Agric. Sci. Cambridge* 148, 159–170.

Patil, N.G., Singh, S.K., 2016. Pedotransfer Functions for Estimating Soil Hydraulic Properties: A Review. *Pedosph. An Int. J.* 26, 417–430. [https://doi.org/10.1016/S1002-0160\(15\)60054-6](https://doi.org/10.1016/S1002-0160(15)60054-6)

Pringle, M.J., Romano, N., Minasny, B., Chirico, G.B., Lark, R.M., 2007. Spatial evaluation of pedotransfer functions using wavelet analysis. *J. Hydrol.* 333, 182–198. <https://doi.org/10.1016/j.jhydrol.2006.08.007>

Puckett, W.E., Dane, J.H., Hajek, B.F., 1985. Physical and Mineralogical Data to Determine Soil Hydraulic Properties 1. *Soil Sci. Soc. Am. J.* 49, 831–836.

Reynolds, W., Elrick, D., 1985. In situ measurement of field-saturated hydraulic conductivity, sorptivity, and the α parameter using the Guelph Permeameter. *Soil Sci.* 140, 172–180.

Richards, L., 1949. Methods of measuring soil moisture tension. *Soil Sci.* 68, 95–112.

- Ritzema, H., 1994. Subsurface flow to drains, in: Ritzema, H.. (Ed.), *Drainage Principles and Applications*. International Institute for Land Reclamation and Improvement (ILRI), Wageningen, The Netherlands, pp. 236–304.
- Schaap, M.G., Leij, F.J., Genuchten, M.T. Van, 2001. Rosetta : a computer program for estimating soil hydraulic parameters with hierarchical pedotransfer functions. *J. Hydrol.* 251, 163–176.
- Schultz, B., Zimmer, D., Voltman, W.F., 2007. Drainage under increasing and changing requirements. *Irrig. Drain.* 56, S3–S22. <https://doi.org/10.1002/ird>
- Sedaghat, A., Bayat, H., Sinegani, A.A.S., 2016. Estimation of Soil Saturated Hydraulic Conductivity by Artificial Neural Networks Ensemble in Smectitic Soils 149, 377–387. <https://doi.org/10.1134/S106422931603008X>
- Skaggs, R.W., 2007. Criteria for Calculating Drain spacing and Depth. *Am. Soc. Agric. Biol. Eng.* 50, 1657–1662.
- Skaggs, R.W., 1978. A water management model for shallow water table soils.
- Smedema, L.K., Abdel-Dayem, S., Ochs, W.J., 2000. Drainage and agricultural development. *Irrig. Drain. Syst.* 14, 223–235. <https://doi.org/10.1023/A:1026570823692>
- Sobieraj, J.A., Elsenbeer, H., Cameron, G., 2004. Scale dependency in spatial patterns of saturated hydraulic conductivity. *CATENA* 55, 49–77. [https://doi.org/10.1016/S0341-8162\(03\)00090-0](https://doi.org/10.1016/S0341-8162(03)00090-0)
- Soil Survey Division Staff, 1993. *Soil Survey Manual*. U.S. Department of Agriculture Handbook 18. Natural Resources Conservation Service.
- Stefan, F., Guenther, F., 2019. Package ‘neuralnet’ [WWW Document]. URL <https://cran.r-project.org/web/packages/neuralnet/neuralnet.pdf> (accessed 5.13.20).

Sun, J., 2012. Learning algorithm and hidden node selection scheme for local coupled feedforward neural network classifier. *Neurocomputing* 79, 158–163. <https://doi.org/10.1016/j.neucom.2011.09.019>

Tietje, O., Hennings, V., 1996. Accuracy of the saturated hydraulic conductivity prediction by pedo-transfer functions compared to the variability within FAO textural classes. *Geoderma* 69, 71–84. [https://doi.org/10.1016/0016-7061\(95\)00050-X](https://doi.org/10.1016/0016-7061(95)00050-X)

Van Dam, J., Huygen, J., Wesseling, J., Feddes, R., Kabat, P., Van Walsum, P.E., Groenendijk, P., van Diepen, C., 1997. Theory of SWAP version 2.0. Simulation of water flow, solute transport and plant growth in the Soil-Water-Atmosphere-Plant environment. Wageningen.

van der Molen, W.H., Wesseling, J., 1991. A solution in closed form and a series solution to replace the tables for the thickness of the equivalent layer in Hooghoudt's drain spacing formula. *Agric. Water Manag.* 19, 1–16. [https://doi.org/10.1016/0378-3774\(91\)90058-Q](https://doi.org/10.1016/0378-3774(91)90058-Q)

van der Ploeg, R., Horton, R.M., Kirkham, D., 1999. Steady flow to drains and wells, in: Skaggs, R., van Schilfgaarde, J. (Eds.), *Agricultural Drainage*. Madison, Wisc.: SSSA, pp. 213–264.

Van Looy, K., Bouma, J., Herbst, M., Koestel, J., Minasny, B., Mishra, U., Montzka, C., Nemes, A., Pachepsky, Y.A., Padarian, J., Schaap, M.G., Tóth, B., Verhoef, A., Vanderborght, J., van der Ploeg, M.J., Weihermüller, L., Zacharias, S., Zhang, Y., Vereecken, H., 2017. Pedotransfer Functions in Earth System Science: Challenges and Perspectives. *Rev. Geophys.* 55, 1199–1256. <https://doi.org/10.1002/2017RG000581>

van Schilfgaarde, J., 1963. Design of tile drainage for falling water tables. *J. Irrig. Drain. Div.* 89, 1–12.

Vereecken, A., Schnepf, J., Hopmans, M., Javaux, D., Or, D., Roose, T., Vanderborght, J., Young, M.H., Amelung, W., Aitkenhead, M., Allison, S.D., Assouline, S., Baveye, P., Berli, M., Brüggemann, N., Finke, P., Flury, M., Gaiser, T., Govers, G., Ghezzehei, T., Hallett, P., Franssen, H.J.H., Heppell, J., Horn, R., Huisman, J.A., Jacques, D., Jonard, F., Kollet, S., Lafolie, F., Lamorski, K., Leitner, D., Mcbratney, A., Minasny, B., Montzka, C., Nowak, W., Pachepsky, Y., Padarian, J., Romano, N., Roth, K., Rothfuss, Y., Rowe, E.C., Schwen, A., Šimůnek, J., Tiktak, A., Dam, J. Van, Zee, S.E.A.T.M. Van Der, Vogel, H.J., Vrugt, J.A., 2016. Modeling Soil Processes: Review , Key Challenges , and New Perspectives Brief History of Soil Modeling. *Vadose Zo. J.* 15, 1–57. <https://doi.org/10.2136/vzj2015.09.0131>

Vereecken, H., Weynants, M., Javaux, M., Pachepsky, Y., Schaap, M.G., van Genuchten, M.T., 2010. Using Pedotransfer Functions to Estimate the van Genuchten-Mualem Soil Hydraulic Properties: A Review. *Vadose Zo. J.* 9, 795–820. <https://doi.org/10.2136/vzj2010.0045>

Verhoef, A., Egea, G., 2014. Modeling plant transpiration under limited soil water : Comparison of different plant and soil hydraulic parameterizations and preliminary implications for their use in land surface models. *Agric. For. Meteorol.* 191, 22–32. <https://doi.org/10.1016/j.agrformet.2014.02.009>

Wösten, J.H., Pachepsky, Y., Rawls, W., 2001. Pedotransfer functions: bridging the gap between available basic soil data and missing soil hydraulic characteristics. *J. Hydrol.* 251, 123–150.

Wösten, J.H.M., 1997. Pedotransfer Functions to Evaluate Soil Quality, in: Gregorich, E., Carter, M. (Eds.), *Soil Quality for Crop Production and Ecosystem Health*. ELSEVIER SCIENCE PUBLISHERS B.V., Amsterdam, The Netherlands, pp. 221–245.

Yang, C., 1995. *Applications of Artificial Neural Network Technology in the Design of Water-Table Management Systems*. McGill University, Montreal, Quebec, Canada.

Youngs, E., 1999. Non-steady flow to drains, in: Skaggs, R., van Schilfgaarde, J. (Eds.), *Agricultural Drainage*. Madison, Wisc.: SSSA, pp. 265–296.

Zanetti, S.S., Sousa, E.F., Oliveira, V.P.S., Almeida, F.T., Bernardo, S., 2007. Estimating Evapotranspiration Using Artificial Neural Network and Minimum Climatological Data. *J. Irrig. Drain. Eng.* 133, 83–89.

Zhang, Y., Schaap, M.G., 2019. Estimation of saturated hydraulic conductivity with pedotransfer functions: A review. *J. Hydrol.* 575, 1011–1030. <https://doi.org/10.1016/j.jhydrol.2019.05.058>

4 Critical evaluation of alternative methods to determine evapotranspiration for input to DRAINMOD to design drainage systems in Libyan agricultural projects.

Abstract

Reference evapotranspiration (ET₀) plays an essential role in many hydrological processes including the design of drainage systems. ET₀ has a high impact on the accuracy of using drainage simulation models such as DRAINMOD. Calculated ET₀ from climatic parameters is often recommended as an alternative method to the expensive ET₀ measuring methods. However, in least developed countries most of the climatic data sets required to determine ET₀ are often unavailable at the temporal and spatial scale and have missing data for days or months. This research explores techniques are applied to fill gaps in daily maximum and minimum air temperature records (DT_{max} and DT_{min}) for ET₀ calculations. The study covered two meteorological stations located near two agricultural projects in the south of Libya. MODAWEC, ERA5-Land, Arithmetic averaging of neighbouring stations (AANS) and the development of artificial neural networks (ANNs) are the among the techniques applied to fill gaps in DT_{max} and DT_{min}. Using DRAINMOD, subsequent drainage designs based on these cleaned datasets are critically evaluated against drainage designs predicted using a control dataset consisting of contiguous meteorological data. The results showed that ANNs developed in this study were in general more accurate at predicting DT_{max} and DT_{min} and these ANNs were also more accurate at calculating ET₀ than other indirect methods including AANS, MODAWEC, and ERA5-Land. The output from DRAINMOD simulations showed that the accuracy of the method applied to calculate ET₀ had an impact on the prediction of objective functions such as relative yield, irrigation depth, actual evapotranspiration, drainage depth and the number of dry days. Because measuring ET₀ is expensive and time-consuming, basing drainage designs on ANN predictions generated from alternative datasets would lower the overall cost of drainage designs, making them more accessible to farmers, planners, and decision-makers in least developed countries.

4.1 Introduction

Due to continued global population growth, it is predicted that food production must increase by up to 100% by 2050 in order to meet demand (Právělie et al., 2021). However, the world's arable land area continues to degrade due to soil salinization, desertification, erosion, and urbanisation (Ellafi et al., 2022). Water use efficiency is a significant issue due to increasing cross-sector demand for water resources, especially in water-limited areas of the world (Elshemy, 2018). For example, in arid and semi-arid regions of Libya, the water demands of the population exceeded the capacity of the water resources to support food self-sufficiency back in the 1950s, and similar situations have been observed in the Middle East and parts of Africa (Qadir et al., 2003). For sustainable agricultural development, economic growth and food security, key priorities to improve water use efficacy in arid and semi-arid regions must include drainage system design and management, particularly in areas where the water resource is non-renewable (Qadir et al., 2003).

A key constraint to crop production in arid and semi-arid areas is soil salinity and water table depth (Ayars and Evans, 2015). Soil salinity and waterlogging can be controlled by appropriately designed and effectively managed drainage systems. However, in arid and semi-arid regions <30% of all irrigated land needing drainage (*circa* 125 million ha) has been effectively drained (Schultz et al., 2007), and the situation is worse in least developed countries. According to Smedema et al. (2000), the proportion of agricultural land drained in least developed countries is 5-10% compared to 25-30% in developed countries. In Libya, *circa* 9,000 ha of irrigated land (which represents around 2% of all croplands in Libya) was estimated to be equipped with some form of drainage in 2000 (Ellafi et al., 2021). This is due to a fundamental lack of expertise in-country and the high cost of drainage installation as well as critically, the lack of contiguous input data for their design. To maximise water use efficiency (WUE) and crop production in these areas, there is a need to design drainage systems using easily measured data such as saturated hydraulic conductivity (Ellafi et al., 2021), evapotranspiration, and soil salinity. As a minimum, the design should maintain the water table depth to at least below the crop root zone and ensure low salt concentration in the root zone (Ayars and Evans, 2015).

Successful drainage design in arid and semi-arid areas depends on how the system can maintain the crop water requirement throughout the various crop growth stages to achieve maximum productivity and WUE over 30 years, which is the assumed life of a drainage system (Skaggs, 2007). In addition, the interaction of other factors such as soil characteristics, topography, climate, and trafficability should be considered when a new drainage system is designed. Taking all factors into account typically involves evaluating different scenarios (drain depth and spacing between drains) through in-field scale pilots, which are time-consuming and expensive (Singh et al., 2006). However, computer simulation models can accurately predict the effects of different input variables while minimising costs and shortening the time to drainage system design and installation (Selvaperumal et al., 2020).

DRAINMOD is a widely applied model used to simulate the hydrology of poorly drained and high water table soils (Kandil et al., 1995; Luo et al., 2009; Selvaperumal et al., 2020) including sandy soils located in arid and semi-arid areas (Abdel-dayam and Skaggs, 1990; Kandil et al., 1995; Wahba and Christen, 2006). The water balance in DRAINMOD includes deep percolation, rainfall, surface runoff, and evapotranspiration. Of these variables, evapotranspiration (ET) plays an essential role in many hydrological processes such as water resource management and the design of irrigation and drainage systems. Also, ET has a direct influence on crop yield (Allen et al., 1998). In arid and semi-arid areas, due to high-temperature and aridity, ET is often the crucial parameter for calculating the total amount of water lost by plant transpiration and soil evaporation (Allen et al., 1998). Therefore, average daily ET is a crucial input parameter for DRAINMOD (Skaggs, 1977). In DRAINMOD, ET as presented by Luo et al. (2009) is an input parameter which has an effect on the simulation of drainage discharge. Luo et al. (2009) clearly demonstrated the importance of estimating ET precisely on the accuracy of the DRAINMOD model. Niaghi et al. (2017) also investigated the impact of ET in the accurate simulation of water table depth using DRAINMOD. Niaghi et al. (2017) observed that increasing the accuracy of predicting ET led to a significant improvement (20 – 30%) in the prediction of the water table depth. This indicates that the performance of DRAINMOD is highly dependent on the accurate prediction of ET.

To apply DRAINMOD over a 30-year simulation, the model requires a complete daily ET for the simulated 30-year period as an input. Measured ET data is often unavailable especially in least developed countries because the equipment needed for the measurement is expensive to install and maintain. Calculated ET from climatic parameters is often recommended as an alternative method (Allen et al., 1998). The calculation of daily ET depends on the availability of several climatic parameters (i.e. solar radiation, humidity, wind speed, and temperature on a daily basis), making ET a complex and nonlinear phenomenon. When climatic data are available, Allen et al. (1998) recommend that the Penman-Monteith method is adopted to calculate the reference evapotranspiration (ET₀). However, and crucially, in least developed countries most of the climatic data sets required to determine ET₀ are often unavailable at the temporal and spatial scale required for input to DRAINMOD (hourly or daily) and/or have missing data for days or months. More than 70% of the land area of least developed countries' are considered to have an arid climate (Safriel et al., 2005). Therefore, in these data-poor regions, there is an urgent need to be able to accurately predict missing climatic data in order to accurately calculate ET₀ for input to drainage system design.

Allen et al. (1998) presented procedures to estimate solar radiation data, relative humidity data and/or wind speed data. The Hargreaves ET₀ equation (Hargreaves and Samani, 1982) is also recommended by Allen et al. (1998) as an alternative method to the Penman-Monteith method in order to calculate ET₀ if the available data is limited to daily minimum and maximum temperature, and net radiation. However, in data-poor areas where there may be no daily temperature data available and when temperature data is available only on a monthly basis, and the drainage simulation model (e.g. DRAINMOD) requires data on a daily basis, then methods that can be applied to estimate missing maximum and minimum daily temperature data are essential for accurate drainage system design.

Several traditional methods have been applied to fill gaps in climatic data, including the Arithmetic Averaging of Neighbouring Stations Method (AANS), linear regression (LR), single best estimator (SBE), UK traditional (UKT), and inverse distance weighting method (IDWM) (Kanda et al., 2018). These methods fill the data gaps in the targeted meteorological station (the station which has an incomplete climatic dataset) using

values measured from neighbouring meteorological stations. However, these methods have not been critically evaluated to predict daily maximum and minimum air temperature in data-poor arid and semi-arid areas. Also, a potential limitation is that the missing data associated with the target station may also be missing at the neighbouring stations or the spatial distance between stations prevents accurate prediction (Sattari et al., 2017). One of the methods applied to predict missing temperature data are reanalysed datasets such as ERA5-Land developed by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Muñoz-Sabater, 2019). These datasets were produced by combining earth observation data with data generated from remote sensing across the world. Furthermore, these datasets have been successfully evaluated against observed data from multiple areas of the world including arid and semi-arid areas (Nkiaka et al., 2017; Tarek et al., 2020; Zandler et al., 2020). The advantage of using reanalysis datasets is the temporal contiguity of the required input parameters (Tarek et al., 2020). Artificial Neural Networks (ANNs) have also been adopted to successfully predict daily mean, maximum, and minimum temperature (Ustaoglu et al., 2008). Ustaoglu et al. (2008) applied the temperature of the previous seven days as inputs to predict the current day. Koksall et al. (2017) applied ANNs to predict hourly air temperature for ET mapping applications in Turkey and Almonacid et al. (2013) developed ANNs that predict the hourly air temperature from daily maximum and minimum air temperature for different geographical locations in Spain. Similarly, Okoh et al. (2015), successfully developed ANNs to predict hourly air temperature from daily values in Nigeria.

The aim of this research was to overcome the constraints of poor drainage system designs associated with poor WUE which exacerbate soil salinisation and waterlogging issues in arid and semi-arid countries, such as Libya. At present drainage designs are severely hampered by incomplete data records (e.g. daily maximum and minimum temperature values required for ET calculation). This research paper explores techniques that are available for data-poor areas in least developed countries. These techniques are applied to fill gaps in daily maximum and minimum air temperature records. Using DRAINMOD, subsequent drainage designs based on these cleaned datasets are critically evaluated against drainage designs predicted using a control dataset consisting of contiguous meteorological data.

4.2 Material and methods

4.2.1 Study area and datasets

This study covered two agricultural projects located in the south of Libya, Eshkeda Agricultural Project (EAP) and Hammam Agricultural Project (HAP). EAP is located north of Sabha city ($27^{\circ}32'45''\text{N}$ $14^{\circ}16'7''\text{E}$) at an elevation of 320 m above sea level (asl). The EAP covers *circa* 3000 ha and is divided into three subareas: Western Area (2,000 ha), Central Area (600 ha), and Eastern Area (370 ha). In accordance with the installed irrigation wells, the area comprises 25 districts each with 12 farms of *circa* 10 ha each. The EAP was started in 1975 and was completed in the second half of 1976, with a drainage system constructed between 1979 and 1981. While HAP is located in the north-east part of Sokna Oasis ($29^{\circ}04'01''\text{N}$ $15^{\circ}47'05''\text{E}$) at an elevation of 270 m asl. The HAP covers 1,200 ha and is divided into 182 farms (6 – 8 ha per farm). This HAP agricultural project was started in 1971, and the reclamation was finished in 1985. The drainage system for the HAP project was designed in the 1970s. There are no meteorological stations in either the EAP or HAP, therefore, when the drainage system was designed for each project, the nearest stations to EAP and HAP were used as the source of meteorological input parameters. For this study the same respective stations were selected as the reference stations. The closest station to EAP was Sabha meteorological station (50 km to the south), while the nearest to HAP was Hon meteorological station (15 km to the east). The historical 30-year (1981 – 2010) daily maximum and minimum air temperature (DTmax and DTmin) data for the respective meteorological stations were obtained from the Libyan National Meteorological Centre (LNMC). As in many least developed countries, there are significant data gaps for both stations. Figure 4-1 shows the percentage (%) of DTmax and DTmin values in Sabha and Hon for each year between 1981 – 2010. Missing DTmax and DTmin data was as low as 0% in Sabha between 2009 – 2010, to *circa* 90% for Hon in 1996. In general, the total percentage of missing DTmax and DTmin values between 1981-2010 in Sabha and Hon meteorological stations were 13% and 23% respectively.

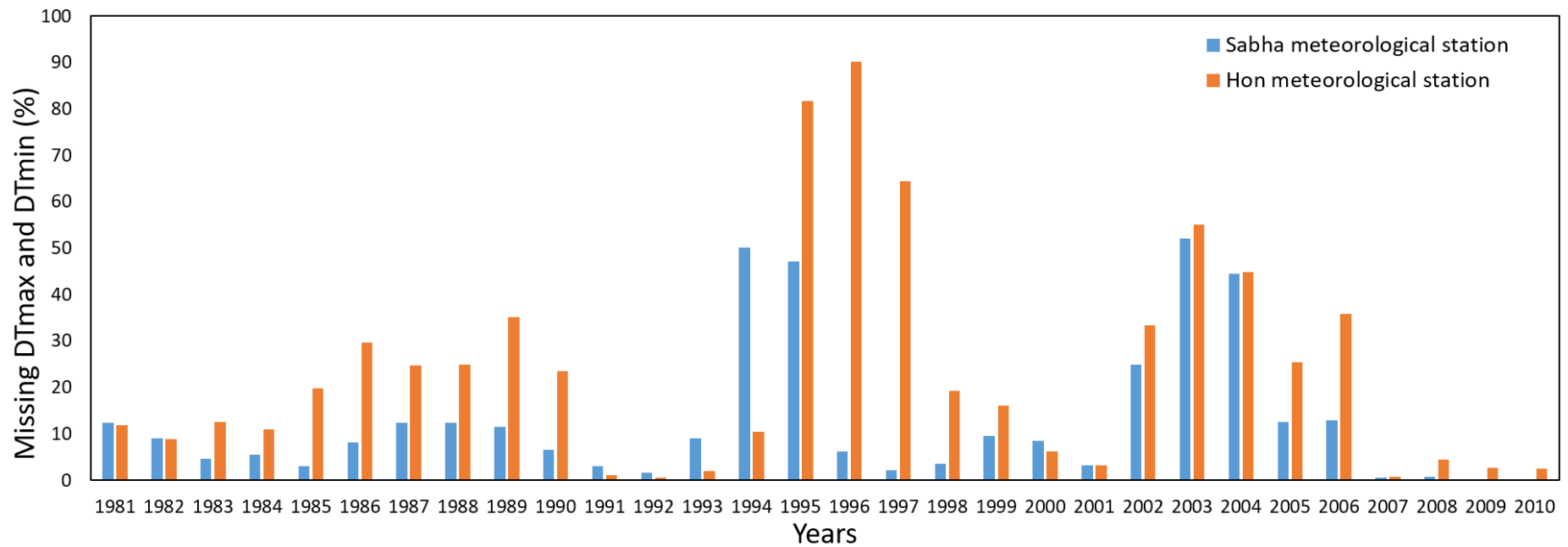


Figure 4-1 Percentage of daily maximum and minimum air temperature (DTmax and DTmin) data missing for the years 1981 – 2010 associated with the Sabha and Hon meteorological stations, Libya.

- In this research, observed climatic data; DTmax and DTmin and average monthly maximum and minimum air temperature (MTmax and MTmin) as well as calculated data such as sunshine duration were collected to predict the missing Sabha and Hon daily DTmax and DTmin. The datasets used in this research as summarised in Table 4-1 and included:
- Complete monthly average MTmax and MTmin, the extreme maximum and minimum air temperature of the month (XMTmax and XMTmin) temperature for each month between 1981-2010 from the Sabha and Hon meteorological stations (LNMC, 2020).
- DTmax and DTmin from Ghadames, Obari, Ghat, Gariat, and Jalu meteorological stations neighbouring Sabha and Hon (LNMC, 2020).
- DTmax and DTmin for In Amenas (Algeria) between 1981 – 2010 were collected from the World Meteorological Organization (WMO) through the National Oceanic and Atmospheric Administration (NOAA). In Amenas was selected because it has a similar climate to that observed in Sabha and Hon.
- Daily sunshine duration for Sabha and Hon was calculated based on geographical location using the solar calculation method proposed by Meeus (1991).
- Using Global TempSIM, the average DTmax and DTmin were calculated for EAP and HAP based on their geographical locations. Global TempSIM predicts the daily average air temperature based upon 30-year (1961-1990) temperature records (including meteorological stations from Libya) that were compiled and interpolated by Legates and Willmott (1990).
- Hourly temperature data were downloaded from The European Centre for Medium-Range Weather Forecasts (ECMWF). ECMWF reanalyses are generated by the Integrated Forecasting System (IFS), a global data assimilation and forecasting system developed by ECMWF for weather forecasts. ERA5-Land and ERA-interim are the most recent data released by ECMWF (Muñoz-Sabater, 2019). Preliminary results conducted by ECMWF showed ERA5-Land's overall improvement compared to ERA-Interim in simulating several different variables including hourly air temperature. The DTmax and DTmin were generated for both Sabha and Hon from the ERA5-Land hourly data. A schematic representation of the methods applied in this study with the source of dataset used for each method evaluated is illustrated in Figure 4-2.

Table 4-1 Description of datasets used in this research to predict the missing values of DTmax and DTmin for the Sabha and Hon meteorological stations.

Data source	Data description	Temporal coverage	Temporal resolution	% of data available	Observed or Calculated
LNMC	DTmax and DTmin	1981 – 2010	Daily	77-87%	Observed
LNMC	MTmax and MTmin	1981 – 2010	Average monthly	100%	Observed
LNMC	XMTmax and XMTmin	1981 – 2010	Monthly	100%	Observed
LNMC and NOAA*	DTmax and DTmin	1981 – 2010	Daily	43-86%	Observed
(Meeus, 1991)	Sunshine duration	1981 – 2010	Daily	100%	Calculated
Global TempSIM	DTmax and DTmin	365 days	Daily for one year	100%	Calculated
ERA5-Land	Air temperature	1981 – 2010	Hourly	100%	Calculated

(LNMC) is the Libyan National Meteorological Centre, (NOAA) is the National Oceanic and Atmospheric Administration, (DTmax) is the daily maximum air temperature, (DTmin) is the daily minimum air temperature, (MTmax) is the average monthly maximum air temperature, (MTmin) is the average monthly minimum air temperature, (XMTmax) extreme maximum air temperature of the month, (XMTmin) extreme minimum air temperature of the month. (*) data source covers 6 neighbouring stations (see Table 4-2).

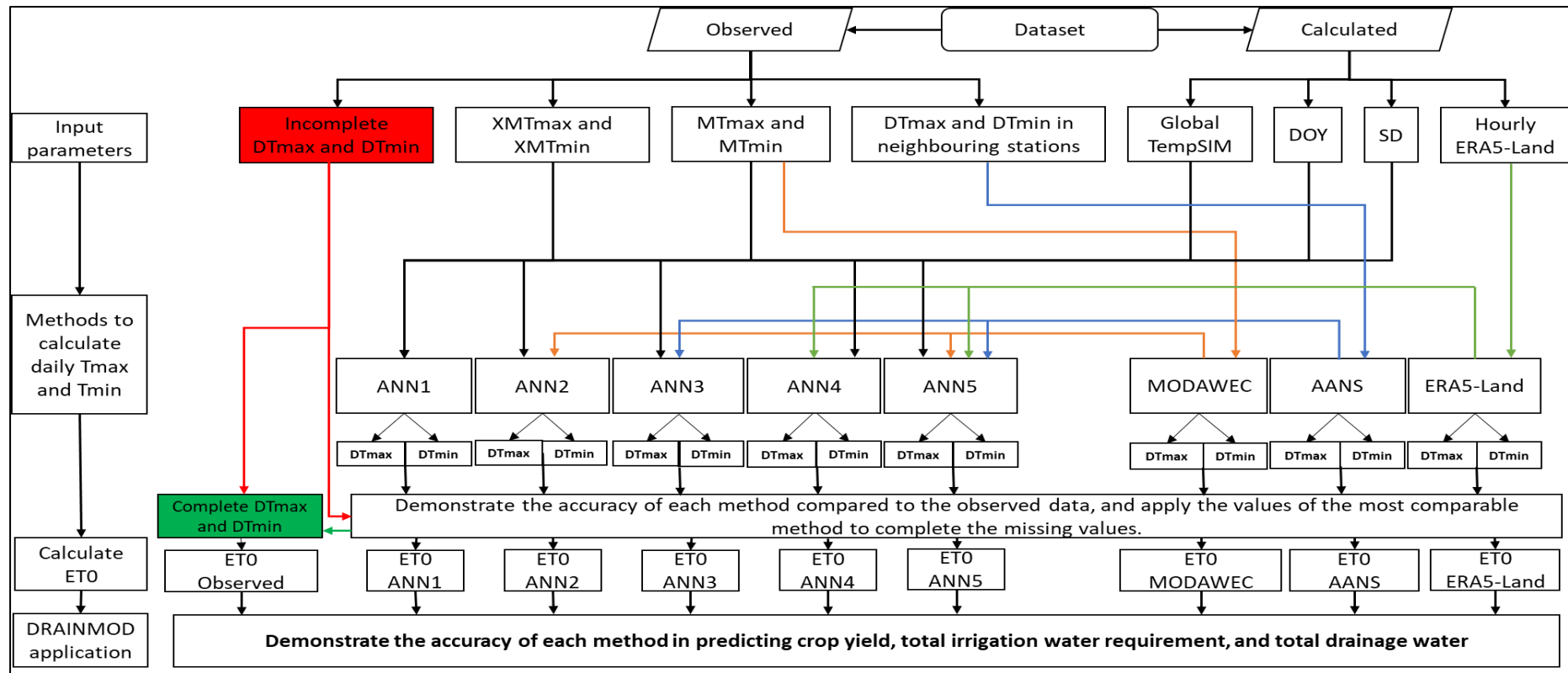


Figure 4-2 Flowchart of the research methodology.

→ Shows which input was used in MODAWEC and in which ANN the outputs of MODAWEC was applied as an input, → shows which input was used in ERA5-Land prediction and where was applied as an input for ANN, → shows which input was used in AANS prediction and where was used as an input for ANN, → shows where the incomplete DTmax and DTmin were used, → shows the step led to complete DTmax and DTmin

4.2.2 Methods to predict missing DTmax and DTmin data

Complete DTmax and DTmin data sets are required to estimate ET₀ used in DRAINMOD. There are several methods that could be adopted to predict the missing DTmax and DTmin, data for Sabha and Hon. This study critically evaluates the Arithmetic Averaging Method (Xia et al., 1999), Monthly to Daily Weather Converter (MODAWEC) (Liu et al., 2008), ERA5-Land reanalysis data (Muñoz-Sabater, 2019) and development several artificial neural networks (ANNs) (Almonacid et al., 2013). These methods were applied to predict the missing DTmax and DTmin values for Sabha and Hon utilising the data sources identified in Table 4-1 as schematically presented in Figure 4-2.

4.2.2.1 Arithmetic Averaging of Neighbouring Stations Method (AANS)

In the AANS method, missing data were obtained by arithmetically averaging data from neighbouring stations (Xia et al., 1999):

$$P_z = \frac{1}{n} \sum_{i=1}^{i=n} P_i = \frac{P_1 + P_2 + P_3 + P_4 + P_5}{n} \quad (4-1)$$

Where: P_z is the estimated value, P_i is the observed DTmax and DTmin of the i^{th} neighbouring station, P_1, P_2, P_3, P_4 and P_5 are the observed DTmax and DTmin for each neighbouring station, and n is the number of neighbouring stations.

This approach has two sub-categories: nearest stations and best-correlated stations methods (Allen et al., 1998). As neighbouring stations may be located far from the target station (>100 km), a correlation coefficient (r) was calculated to indicate the conditions and homogeneity for replacing missing data in the incomplete data set. The correlation coefficient was calculated on the available data from Sabha and Hons meteorological stations and the Ghadames, Obari, Ghat, Gariat, and Jalu neighbouring stations. In all neighbouring stations, the correlation coefficient ranged from 0.89 – 0.98 and 0.84 – 0.91 for DTmax and DTmin respectively (Table 4-2). According to Allen et al. (1998), if the correlation coefficient is ≥ 0.7 , the neighbouring station's values may replace the targeting station's missing values. As shown in Table 4-2, all values meet this critical and therefore the data is considered viable to use.

Table 4-2: The nearest neighbour meteorological stations to Sabha and Hon.

Target station	Neighbour Station	Distance to the target station (km)	Elevation (m)	Percentage of available data	Correlation coefficient	
					DTmax	DTmin
Sabha	In Amenas	490	561	86%	0.95	0.91
	Ghadames	490	357	82%	0.90	0.88
	Hon	260	263	73%	0.96	0.88
	Obari	170	463	43%	0.98	0.91
	Ghat	485	692	37%	0.95	0.85
Hon	In Amenas	620	561	75%	0.93	0.86
	Sabha	260	432	73%	0.96	0.88
	Ghadames	620	357	73%	0.89	0.87
	Jalu	550	60	58%	0.92	0.85
	Gariat	330	497	59%	0.95	0.84

4.2.2.2 MODAWEC model

MODAWEC, initially developed by Liu et al. (2008), converts monthly rainfall, and MTmax and MTmin to daily rainfall and DTmax and DTmin values while maintaining monthly totals and averages. For more information about the MODAWEC model and the equations used in the model, refer to Liu et al. (2008). To predict the DTmax and DTmin, the main inputs of the MODAWEC model included MTmax and MTmin for each year over a given time series e.g. 30 years. When compared to measured daily climatic data in Wisconsin, USA, MODAWEC has been shown to give an accurate prediction of simulated crop yield and ET₀ calculations (Liu et al., 2008). However, the use of MODAWEC has not been evaluated in arid and semi-arid regions. Consequently, MODAWEC was applied to predict the DTmax and DTmin for Sabha and Hon using observed MTmax and MTmin (1981-2010) values. Radchenko et al. (2014) suggested that a combination of MODAWEC with a hydrological model could be a practical tool to simulate water discharge in rivers. Similarly, combining MODAWEC with DRAINMOD might help to improve drainage design. Before making a final judgment on the applicability of MODAWEC to predict missing DTmax and DTmin data and calculate ET₀, it was applied in DRAINMOD to design drainage systems for EAP and HAP.

4.2.2.3 ERA5-Land

ERA5-Land is a reanalysis dataset developed by the European Centre for Medium-Range Weather Forecasts (ECMWF). The ERA5-Land dataset provides consistent temporal and spatial resolution of meteorological data, including the hourly air temperature from 1979 to date, with no missing values (Muñoz-Sabater, 2019). The spatial resolution of ERA5-Land is $0.1^\circ \times 0.1^\circ$ (circa 9 km). This dataset has been successfully evaluated in Russia (Dergunov and Yakubailik, 2020), USA, Canada, and Mexico including arid and semi-arid areas of USA and Mexico (Arsenault et al., 2020), India (Kanda et al., 2018) and Ethiopia (Woldesenbet, 2017). The hourly temperature data at 2.0 m above the land surface was downloaded, and DTmax and DTmin subsequently calculated based on 24 hours. The highest value within 24 hours was taken as DTmax and the lowest value was taken as DTmin.

4.2.2.4 Artificial Neural Networks (ANNs)

Artificial Neural Networks have been successfully applied to predict ET₀ (Zanetti et al., 2007), and DTmax and DTmin (Ustaoglu et al., 2008). ANNs normally have three layers. The first layer is the input layer which contains the independent variable/s and the second layer is the hidden layer which is located between the input layer and the third output (dependent variable) layer. Figure 4-3 illustrates the structure of the ANNs developed in this study. Ellafi et al. (2021) provides detailed information about how ANNs can be used to solve complex problems and their formation.

For this research, three steps were undertaken for the development of ANNs to predict DTmax and DTmin in Sabha and Hon. In step one, 60% of the available DTmax and DTmin data were randomly selected as a training dataset, leaving 40% as a testing dataset. In Hon, the total available DTmax and DTmin values were from 8390 days; 60% of these (5034 days) were randomly selected for the training dataset, and 3356 days' worth of DTmax and DTmin values utilised for testing the model. The second step defined the appropriate network (number of layers and neurons in each layer). The optimum number of layers and neurons was determined by applying the sequential orthogonal approach (Ellafi et al., 2021). This approach adds an additional neuron to the 'hidden layer' until the ANN with the smallest error is identified against the training and testing datasets (Ellafi et al., 2021).

In the third step, the model identified in step two was applied to predict the missing DTmax and DTmin values for the Sabha and Hon meteorological datasets.

Ten ANNs were developed to predict DTmax and DTmin in Sabha and Hon (five ANNs for each station). Table 4-3 illustrates the input parameters of each ANN. Five contrasting groups of input parameters were assigned to each ANN. The first group had eight input parameters including day of the year (DOY), MTmax, MTmin, extreme maximum air temperature of the month (XMTmax), extreme minimum air temperature of the month (XMTmin), sunshine duration (SD), average daily maximum air temperature calculated by the Global TempSIM (GTmax), and average daily minimum air temperature calculated by the Global TempSIM (GTmin). The second, third and fourth groups had ten input parameters which comprise two additional input parameters to the eight input parameters used in the first group (Table 4-3). The two additional input parameters were the daily maximum and minimum air temperature calculated by MODAWEC (ModTmax and ModTmin) for the second group, daily maximum and minimum air temperature of the neighbouring stations (NTmax and NTmin) for the third group, and daily maximum and minimum air temperature calculated by ERA5-Land (ERATmax and ERATmin) for the fourth group. The addition of two different input parameters allowed the identification of which additional input parameters, and hence ANNs, would more accurately predict the missing DTmax and DTmin values for Sabha and Hon. Finally, the fifth group had all fourteen input parameters included in groups 1 – 4. (Table 4-3). Appendix C (especially Section C.3) covers more information related to all ANNs applied in this Chapter including the pre-processing steps to prepare the data, the functions applied, the codes written, and other outputs.

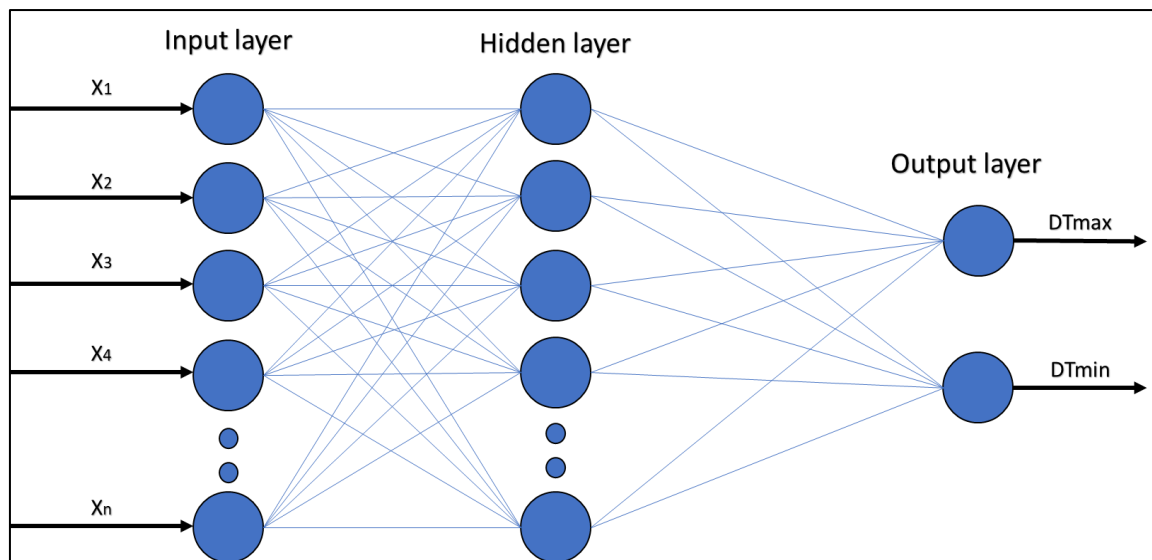


Figure 4-3: Structure of the Artificial Neural Network applied to predict DTmax and DTmin (modified from Ellafi et al., 2021)

Table 4-3: The ANNs developed to predict missing DTmax and DTmin for the Sabha and Hon meteorological stations for the period 1981 – 2010.

Station	Model	Input required	Output
Sabha	ANN1S	DOY, MTmax, MTmin, XMTmax, XMTmin, SD, GTmax and GTmin.	DTmax and DTmin
	ANN2S	DOY, MTmax, MTmin, XMTmax, XMTmin, SD, GTmax, GTmin, ModTmax, and ModTmin.	DTmax and DTmin
	ANN3S	DOY, MTmax, MTmin, XMTmax, XMTmin, SD, GTmax, GTmin, NTmax and NTmin.	DTmax and DTmin
	ANN4S	DOY, MTmax, MTmin, XMTmax, XMTmin, SD, GTmax, GTmin, ERATmax and ERATmin.	DTmax and DTmin
	ANN5S	DOY, MTmax, MTmin, XMTmax, XMTmin, SD, GTmax, GTmin, ModTmax, ModTmin, NTmax, NTmin, ERATmax, and ERATmin	DTmax and DTmin
Hon	ANN1H	DOY, MTmax, MTmin, XMTmax, XMTmin, SD, GTmax and GTmin.	DTmax and DTmin
	ANN2H	DOY, MTmax, MTmin, XMTmax, XMTmin, SD, GTmax, GTmin, ModTmax, and ModTmin.	DTmax and DTmin
	ANN3H	DOY, MTmax, MTmin, XMTmax, XMTmin, SD, GTmax, GTmin, NTmax and NTmin.	DTmax and DTmin
	ANN4H	DOY, MTmax, MTmin, XMTmax, XMTmin, SD, GTmax, GTmin, ERATmax and ERATmin.	DTmax and DTmin
	ANN5H	DOY, MTmax, MTmin, XMTmax, XMTmin, SD, GTmax, GTmin, ModTmax, ModTmin, NTmax, NTmin, ERATmax, and ERATmin	DTmax and DTmin

Where: DTmax is the daily maximum air temperature, DTmin the daily minimum air temperature DOY is DAY of Year, MTmax and MTmin are the average maximum and minimum temperature, XMTmax and XMTmin are the extreme maximum and minimum air temperature for each month, SD is the daily Sun Duration, GTmax and GTmin are the daily maximum and minimum air temperature calculated by Global TempSIM, ModTmax and ModTmin are the daily maximum and minimum air temperature calculated by MODAWEC model (Section 4.2.2.2), NTmax and NTmin are the daily maximum and minimum air temperature calculated by Arithmetic Averaging Method of the neighbouring stations (Section 4.2.2.1), ERATmax and ERATmin are daily maximum and minimum air temperature from ERA5-land dataset (Section 4.2.2.3).

4.2.3 ET0 Calculator

The ET0 Calculator software was developed by FAO's Land and Water Division (FAO, 2009). Its main purpose is to measure reference evapotranspiration (ET0) in accordance with FAO standards. The ET0 Calculator assesses ET0 from climatic data using the FAO Penman-Monteith equation (Allen et al., 1998). This approach was chosen by FAO because it is physically based and explicitly integrates both physiological and aerodynamic parameters (Allen et al., 1998). The ET0 Calculator generates ET0 values on a daily, 10-day or monthly basis from climatic data (i.e., solar radiation, humidity, wind speed, DTmax and DTmin) with the data entered in a wide range of units. If climatic variables are missing (i.e. solar radiation, humidity, and wind speed), these can be predicted by using only measured DTmax and DTmin data, adjusted based on whether it is inland or coastal locations (Ref. Irrigation and Drainage Paper No 56.: "Crop Evapotranspiration") (Allen et al., 1998). Therefore, even if the only available data is DTmax and DTmin, ET0 Calculator is able to predict ET0. For this research the ET0 Calculator was applied to predict ET0 for both Sabha and Hons meteorological stations using the predicted DTmax and DTmin derived from the ANN1S – ANN5S (Table 4-3), AANS (from Section 4.2.2.1), MODAWEC (from Section 4.2.2.2), and ERA5-Land (from Section 4.2.2.3) methods as compared with ET0 derived from observed DTmax and DTmin data (Figure 4-2).

4.2.4 DRAINMOD input data

DRAINMOD is a field scale computer simulation model for shallow water table soils, which was developed for agriculture fields to design and evaluate the long-term (≥ 1 -year) performance of drainage systems (Skaggs, 1977). The input parameters required for DRAINMOD simulations are divided into four categories which are: drainage design, soil properties, climatic data and crop information (Table 4-4). Soil-water data required by the DRAINMOD model include soil water content, initial water table depth, and saturated hydraulic conductivity of each layer. The climatic data required to run DRAINMOD is the calculated ET0 following the methods adopted in Section 4.2.2 and 4.2.3 and the daily rainfall for Sabha and Hon meteorological stations from 1981 – 2010. A 30-year simulation was selected in this study because it is the assumed life of a drainage system (Skaggs, 2007).

The input data for DRAINMOD were obtained from site investigations of soil properties in EAP (Cornelius-Brochier J.V, 1981; Italconsult, 1976) and HAP (Danenco, 1980; Holzmann-Wakuti, 1974). The depth of the impermeable layer in EAP and HAP was obtained from the respective site investigations at 1.5 m as summarised in Table 4-4. Crop information for beans, maize, soybeans, and wheat was obtained as described by Kandil et al. (1995). This crop rotation was chosen because it is a typical rotation of the Nile Delta of Egypt which has similar climatic conditions to EAP and HAP. The General Water Authority in Libya (GWA) also recommended that beans, maize, soybeans, and wheat be grown in EAP and HAP (GWA, 1999).

DRAINMOD was applied eighteen times for the 30-year period 1981-2010 to design drainage systems in EAP and HAP (nine times in each project). DRAINMOD was applied nine times in EAP using ET₀ calculated from DT_{max} and DT_{min} derived from the ANN1S – ANN5S (Table 4-3 and Section 4.2.2.4), AANS (from Section 4.2.2.1), MODAWEK (from Section 4.2.2.2), and ERA5-Land (from Section 4.2.2.3) methods as compared with ET₀ derived from observed DT_{max} and DT_{min} data (Figure 4-2). During each application, input parameters remained the same with the exception of the ET₀ values. Following standard procedures, the DRAINMOD simulation was repeated by adjusting the irrigation volume until the optimum design was identified. The optimum design for each application was defined as when the maximum relative yield was achieved with the minimum irrigation volume (Skaggs, 1977). When the optimum design was achieved for each ET₀ method evaluated, the ET₀ file was replaced with the observed ET₀ values, and DRAINMOD simulation was rerun to evaluate the performance of the design using the observed ET₀. To evaluate the impact of using ET₀ derived from the approaches adopted in this study, several objective functions were calculated in DRAINMOD including: relative yield, irrigation depth, actual ET (actual ET is the quantity of water that is actually removed from a surface due to the processes of evaporation and transpiration), number of dry days, and drainage water depth. These objective functions were then used to compare the drainage system designs based on the evaluated methods for calculating ET₀ against observed ET₀.

Table 4-4: Summary of the input data required to run the DRAINMOD 30-year simulation.

Input parameter	EAP	HAP
Drainage design		
Drain spacing (m)	40	60
Drain depth (cm)	100	100
Depth of restricting layer (cm)	150	150
Effective radius (cm)	1.5	1.5
Drainage coefficient (cm d ⁻¹)	2.5	2.5
Initial water table depth (cm)	50	50
Soil property		
Saturated hydraulic conductivity above drains (m d ⁻¹)	2.6	11.2
Saturated hydraulic conductivity below drains (m d ⁻¹)	5.6	4.5
Saturated water content (cm ³ cm ⁻³)	0.35	0.35
Water content at lower limit (cm ³ cm ⁻³)	0.08	0.04
Required drainage for field work (cm)	3.9	3.9
Climatic data		

Table 4-4 continued								
Daily ET ₀ (mm d ⁻¹)	*Data generated from methods described in Section 4.2.2				*Data generated from methods described in Section 4.2.2			
Daily rainfall (mm d ⁻¹)	Observed precipitation at Sabha station				Observed precipitation at Hon station			
Crop information	Beans	Maize	Soybeans	Wheat	Beans	Maize	Soybeans	Wheat
Number of years for rotations	10	10	10	9	10	10	10	9
Soil salinity threshold (mg l ⁻¹)	640	1088	4000	3800	640	1088	4000	3800
Slope for higher soil salinity values (% per mg l ⁻¹)	2.97×10 ⁻²	1.88×10 ⁻²	2.50×10 ⁻²	7.10×10 ⁻³	2.96×10 ⁻²	1.88×10 ⁻²	2.50×10 ⁻²	7.10×10 ⁻³
Relative yield without deficit stress (%)	100	100	100	100	100	100	100	100
Slope for yield versus deficit stress-day-index	7.20	1.22	7.2	1.22	7.20	1.22	7.20	1.22
Relative yield without wet stress (%)	100	100	100	100	100	100	100	100
Slope for yield versus wet stress-day-index	0.65	0.71	0.65	0.71	0.65	0.71	0.65	0.71
Irrigation water salinity (mg l ⁻¹)	400				400			

*The methods evaluated for EAP were observed ET₀, ANN1S – ANN5S, AANS, MODAWECE, and ERA5-Land, and the methods evaluated for HAP were observed ET₀, ANN1H – ANN5H, AANS, MODAWECE, and ERA5-Land

4.2.5 Evaluation criteria

4.2.5.1 Regression model evaluation metrics

The statistical indices that were used to evaluate the accuracy of predicted DTmax, DTmin, and calculate ET0 compared to observed values were the Root Mean Square Error (RMSE), coefficient of determination (R^2), and Mean Square Error (MSE). The R^2 was used to assess how strong the linear relationship was between observed and predicted values and ranges between 0-1 (where 1 is the best performance). RMSE and MSE were applied to indicate the quantitative error in the predicted values in DTmax, DTmin and ET0 (where the best performance value is zero). These statistical indices were selected because they had been applied successfully to evaluate the performance of developed ANNs predicting DTmax, DTmin, and ET0 in previous studies (Ustaoglu et al., 2008; Zanetti et al., 2007), K_{sat} by Ellafi et al. (2021), and soil salinity by Ellafi et al. (2022). These statistical indices can be defined mathematically as:

$$R^2 = 1 - \frac{\sum_{i=1}^n (P_i - M_i)^2}{\sum_{i=1}^n (M_i - \bar{M}_i)^2} \quad (4-2)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (P_i - M_i)^2 \quad (4-3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (P_i - M_i)^2}{n}} \quad (4-4)$$

Where n represents the number of days, M_i is the observed DTmax, DTmin or calculated ET0, P_i is the predicted DTmax, DTmin or calculated ET0, and $\bar{M}_i$ is the mean observed DTmax, DTmin or calculated ET0.

4.2.5.2 Model efficiency classes for hypothesis testing

In order to define acceptable limitations for model predictions, it is crucial to evaluate model applications (Beven, 2006). Although subjective, this study proposed five ranking performance classes based on the variation from the optimum design (Table 4-5). The optimum design was the output obtained by DRAINMOD based on ET0 values calculated from observed DTmax and DTmin. For example, if the optimum design predicted a relative yield of 100%, and a predicted method of calculating ET0

(e.g. MODAWECC) predicted 90%, the variation from the optimum design was 10%. The five classes ranged between 1 – 5, where 1 is the closest to the optimum design, and 5 the least optimal at predicting the objective function. Class 1 (No risk class) ranged from the optimum design value to 10% from the optimum, class 2 (Low risk class) ranged from 11% – 20%, class 3 (Moderate risk class) from 21% - 40%, class 4 (High risk class) from 41% - 80%, and class 5 (Very high risk class) from 81% to the least optimal value. Five DRAINMOD objective functions were selected to evaluate the performance of each method namely relative yield, irrigation depth, actual ET, number of dry days, and drainage water depth (drainage volume expressed in depth). The average of the four crops classes (beans, maize, soybean, and wheat) were taken as representative of the relative yield. Each objective function had their own weighting based on their relative importance. A weighting of 30%, 30%, 20%, 10% and 10% was applied to relative yield, irrigation depth, drainage depth, actual ET, and the number of dry days, respectively.

Table 4-5: Criteria for selecting the best performance drainage design classes based on the variation from the optimum design.

Performance ranking	Scale		% Variation scale from the optimum design to the lowest performed method
	Lower	Upper	
No risk		1	0 – 10
Low risk	1.1	2	11 – 20
Moderate risk	2.1	3	21 – 40
High risk	3.1	4	41 – 80
Very high risk	4.1	5	>80
% Associated method weight for each objective function			
Relative yield	30		
Irrigation depth	30		
Actual ET	10		
Drainage depth	20		
Number of dry days	10		
Total	100		

4.3 Results

4.3.1 Performance of Artificial Neural Networks to predict DTmax and DTmin

The structure of all ANNs developed in this study and performance evaluation are presented in Table 4-6. In the testing dataset, the five ANNs for both Sabha and Hons were able to predict DTmax and DTmin, with R^2 values, ranging from 0.76-0.96 and 0.69-0.96 for DTmax and 0.72-0.88 and 0.67-0.86 for DTmin, respectively (Table 4-6). The prediction of DTmax were slightly better in Sabha and Hon ($R^2 = 0.69 - 0.96$) than DTmin in Sabha and Hon ($R^2 = 0.67 - 0.88$). The ANNs predicting DTmax and DTmin in Sabha were marginally better than those for Hon (Table 4-6). For Sabha, using the training datasets ANN1S – ANN5S predictions of DTmax and DTmin were associated with RMSE values ranging between 1.53 – 3.89 °C d⁻¹ and 2.34 – 4.26 °C d⁻¹ respectively. Similarly, for Hons using the training dataset ANN1H – ANN5H predictions of DTmax and DTmin were associated with RMSE values ranging between 1.47 – 4.35 °C d⁻¹ and 2.63 – 4.10 °C d⁻¹ respectively (Table 4-6).

In contrast, for Sabha, the RMSE based on the testing dataset for ANN1S – ANN5S ranged between 1.64 – 4.06 °C d⁻¹ and 2.74 – 4.20 °C d⁻¹ for DTmax and DTmin respectively. For Hons, the RMSE based on the testing dataset for ANN1H – ANN5H ranged between 1.48 – 4.50 °C d⁻¹ and 3.43 – 4.47 °C d⁻¹ for DTmax and DTmin respectively. This demonstrates as expected that ANNs will perform better when using a dataset which was used in the development of the ANNs (training dataset) than a new dataset (testing dataset), not used in ANN development.

According to the performance results in Table 4-6, ANN4S, ANN5S, ANN4H, and ANN5H performed better than the other ANNs in predicting data gaps for the Sabha and Hon meteorological stations respectively. Even though, the number of days used to develop ANN4H and ANN5H (5034 days) were 12% less than those used to develop ANN4S and ANN5S (5748 days), the RMSE and MSE values of ANN4H and ANN5H indicate that they are more accurate at predicting the missing DTmax and DTmin values than ANN4S, ANN5S (Table 4-6).

In comparison, ANN2S and ANN2H were less accurate at predicting the missing DTmax and DTmin values than all other ANNs with RMSE values, ranging between 4.06 – 4.20 °C d⁻¹ and 4.47 – 4.50 °C d⁻¹ in Sabha and Hon respectively. Despite the fact that ANN2S and ANN2H used two additional input parameters (ModTmax and ModTmin) compared to ANN1S and ANN1H, the accuracy of the later ANNs at predicting DTmax and DTmin was better with RMSE value ranging from 3.64 – 3.89 and 3.97 – 4.27 °C d⁻¹ in Sabha and Hon respectively (Table 4-6).

Table 4-6: ANNs structure and performance evaluation in predicting missing DTmax and DTmin values in the Sabha and Hon meteorological datasets for the period 1981 – 2010

Station Name	Model Name	*Model Structure	Number of days	RMSE (°C d ⁻¹)		MSE (°C d ⁻¹)		R ²	
				DTmax	DTmin	DTmax	DTmin	DTmax	DTmin
Training ^[1]									
Sabha	ANN1S	8:4:2	5748	3.57	3.53	12.76	12.50	0.81	0.80
	ANN2S	10:5:2	5748	3.89	4.26	15.14	17.44	0.79	0.74
	ANN3S	10:5:2	5748	2.94	2.89	8.67	8.40	0.88	0.88
	ANN4S	10:5:2	5748	1.67	2.85	2.79	8.13	0.96	0.87
	ANN5S	14:6:2	5748	1.53	2.34	2.36	5.51	0.96	0.91
Hon	ANN1H	8:5:2	5034	3.91	3.57	15.30	12.76	0.76	0.76
	ANN2H	10:5:2	5034	4.35	4.10	18.92	16.86	0.72	0.64
	ANN3H	10:6:2	5034	2.06	2.63	4.25	6.94	0.93	0.78
	ANN4H	10:4:2	5034	1.47	2.71	2.18	7.37	0.96	0.79
	ANN5H	14:6:2	5034	1.52	2.87	2.32	8.29	0.96	0.77
Testing ^[1]									
Sabha	ANN1S	8:4:2	3831	3.64	3.89	13.25	14.79	0.81	0.76
	ANN2S	10:5:2	3831	4.06	4.20	16.52	18.15	0.76	0.72
	ANN3S	10:5:2	3831	2.96	3.22	8.80	9.96	0.88	0.83
	ANN4S	10:5:2	3831	1.80	3.03	3.26	8.83	0.95	0.85
	ANN5S	14:6:2	3831	1.64	2.74	2.69	7.10	0.96	0.88

Table 4-6 continued									
Hon	ANN1H	8:5:2	3356	3.97	4.27	15.77	18.28	0.75	0.67
	ANN2H	10:5:2	3356	4.50	4.47	20.32	20.02	0.69	0.67
	ANN3H	10:6:2	3356	2.14	3.51	4.59	12.38	0.91	0.86
	ANN4H	10:4:2	3356	1.48	3.43	2.19	11.80	0.96	0.86
	ANN5H	14:6:2	3356	1.54	3.53	2.36	12.51	0.96	0.86

*Model is the structure of the artificial neural networks (ANNs). For example, 8:4:2, 8 is the number neurons representing the input parameters, 4 is the hidden layer neurons, and 2 is the output of the model. RMSE is the Root Mean Square Error, MSE is the Mean Square Error, R^2 is the coefficient of determination, DTmax, and DTmin are the daily maximum and minimum air temperature. ^[1] The RMSE and MSE in Table 4-6 represents the training and testing dataset separately, while in Table 4-7 the RMSE and MSE values are for the training and testing datasets combined.

4.3.2 Performance of all methods applied to predict DTmax, DTmin, and ET0 calculation

The performance of all methodological approaches adopted in this study to predict missing values of DTmax and DTmin, and subsequent calculation of ET0 for Sabha and Hon meteorological stations are presented in Table 4-6. In Sabha, ANN4S and ANN5S were slightly better at predicting DTmax than all the other methods applied in this study with RMSE 1.72 and 1.60 °C d⁻¹ respectively. ANN4S and ANN5S were also better at predicting DTmin (RMSE = 2.54 – 2.92 °C d⁻¹) and calculating ET0 (RMSE = 0.51 – 0.56 mm d⁻¹). A similar pattern was observed in Hon (Table 4-7), where ANN4H and ANN5H showed more accurate predictions of DTmax than all other methods with RMSE 1.47 – 1.53 °C d⁻¹ respectively. For DTmin predictions at Hon meteorological stations, ERA5-Land showed a more accurate prediction with RMSE 3.12 °C d⁻¹, while the RMSE values in ANN3H, ANN4H and ANN5H ranging between 3.16 – 3.29 °C d⁻¹ (Table 4-7).

The ERA5-Land method showed comparable results to ANN4S, ANN5S, ANN4H, and ANN5H when calculating ET0 with RMSE values between 0.51 – 0.55 mm d⁻¹. Looking at the results for each meteorological station separately, for the Sabha dataset, ANN5S was able to more accurately predict DTmax, DTmin, and ET0 than all other methods with MSE values of 1.60, 2.54 °C d⁻¹, and 0.51 mm d⁻¹, respectively (Table 4-7). For the Hon dataset, ANN4H was able to more accurately predict DTmax, DTmin, and ET0 than all other methods with RMSE values of 1.47, 3.16 °C d⁻¹, and 0.51 mm d⁻¹ respectively (Table 4-7). In contrast, MODAWEC was the least accurate across both stations compared to all other methods with RMSE values ranging from 4.55 – 4.91, 5.16 °C d⁻¹ for DTmax, DTmin and from 0.93 – 0.98 mm d⁻¹ for ET0, respectively.

With the exception of ANN5S and ANN4H, the ERA5-Land method showed the most precise prediction of DTmax, DTmin with MSE values for Sabha and Hon ranging from 5.27 – 10.08 and 4.02 – 9.76 °C d⁻¹, which is more accurate than ANN1S – ANN3S, ANN1H – ANN3H, AANS, and MODAWEC (Table 4-7). The methods that were more accurate in predicting DTmax, and DTmin in Sabha and Hon were also more precise in calculating ET0 (Table 4-7).

For Sabha, ANN5S showed the most accurate ET₀ calculation with an R² of 0.91, MSE value of 0.26 mm d⁻¹, and RMSE value of 0.51 mm d⁻¹. For Hon, ANN4H was associated with the most accurate ET₀ calculation with an R² of 0.92, MSE of 0.27 mm d⁻¹, and RMSE value of 0.51 mm d⁻¹ (Table 4-7). Consequently, ANN5S and ANN4H were used to fill the missing DT_{max} and DT_{min} values and for calculating ET₀ for the Sabha and Hon datasets, respectively.

Table 4-7: Evaluation of the performance of the methods applied to predict missing DTmax and DTmin values for the Sabha and Hon meteorological datasets for the period 1981 – 2010 and for subsequent ET0 calculation.

Station	Method	RMSE			MSE			R2		
		DTmax (°C d ⁻¹)	DTmin (°C d ⁻¹)	ET0 (mm d ⁻¹)	DTmax (°C d ⁻¹)	DTmin (°C d ⁻¹)	ET0 (mm d ⁻¹)	DTmax	DTmin	ET0
Sabha	AANS	2.36	3.01	0.61	5.61	9.10	0.38	0.92	0.86	0.88
	MODAWEC	4.55	5.16	0.93	20.75	26.68	0.87	0.71	0.63	0.74
	ERA5-Land	2.29	3.17	0.51	5.27	10.08	0.27	0.96	0.89	0.92
	ANN1S	3.61	3.72	0.75	13.06	13.87	0.58	0.81	0.78	0.81
	ANN2S	3.96	4.21	0.86	15.70	17.72	0.75	0.77	0.73	0.76
	ANN3S	2.95	3.05	0.74	8.73	9.34	0.55	0.88	0.85	0.83
	ANN4S	1.72	2.92	0.56	2.98	8.55	0.32	0.95	0.86	0.89
	ANN5S	1.60	2.54	0.51	2.56	6.47	0.26	0.96	0.89	0.91
Hon	AANS	2.09	3.33	0.56	4.41	11.13	0.32	0.93	0.81	0.90
	MODAWEC	4.91	5.16	0.98	24.15	26.69	0.97	0.65	0.57	0.73
	ERA5-Land	2.00	3.12	0.55	4.02	9.76	0.30	0.96	0.82	0.92
	ANN1H	3.94	4.00	0.81	15.59	16.07	0.66	0.75	0.70	0.80
	ANN2H	4.41	4.33	0.91	19.49	18.76	0.84	0.70	0.65	0.75
	ANN3H	2.11	3.19	0.57	4.46	10.21	0.34	0.93	0.81	0.90
	ANN4H	1.47	3.16	0.51	2.18	10.04	0.27	0.96	0.81	0.92
	ANN5H	1.53	3.29	0.53	2.34	10.83	0.28	0.96	0.80	0.91

4.3.3 Applications of methods used to predict ET₀ in drainage system design using DRAINMOD

The result of utilising the selected methods, for generating the missing DT_{max} and DT_{min} values and for calculating ET₀ for the Sabha and Hon datasets, in the performance of drainage system design using DRAINMOD, in EAP and HAP, are presented in Table 4-8. Table 4-8 shows the average annual irrigation depth, actual ET, drainage depth and the number of dry days. For EAP, apart from the optimum design (design based on ET₀ calculated from observed DT_{max} and DT_{min}), the highest relative yield for all crops were noted for drainage systems designed using inputs derived from the AANS, MODAWEC, and ANN4S methods with 100% relative yield in all crops (Table 4-8). In contrast, the lowest relative yields were associated with ERA5-Land method with 40%, 30%, 47% and 58% relative yields for beans, maize, soybean, and wheat, respectively (Table 4-8). For EAP, AANS and MODAWEC required the highest irrigation depth of 3160 mm y⁻¹ (15% higher than the optimum design), and 2929 mm y⁻¹ (7% higher than the optimum design), respectively. In contrast, the lowest total irrigation depth was noted for the ERA5-Land with 2480 mm y⁻¹ (10% lower than the optimum design). The irrigation depth closest to the optimum design was predicted in the ANN4S design with 2757 mm y⁻¹. For the actual ET in EAP, MODAWEC predicted the highest value of 2229 mm y⁻¹, with the lowest value for ERA5-Land with 2210 mm y⁻¹ (1% lower than the optimum design based on observed ET₀ measurement).

For EAP, the closest to the optimum design were ANN4S 535 mm y⁻¹ (2% higher than the optimum design) and ANN1S and ANN5S 492 mm y⁻¹ (6% lower than the optimum design). While the furthest from the optimum design was obtained using the AANS method with 937 mm y⁻¹ (79% higher than the optimum design based on observed ET₀), and the lowest value was generated using the ERA5-Land method with 276 mm y⁻¹ (47% lower than the optimum design based on observed ET₀). Finally, the number of dry days for the optimum design was 2 days y⁻¹ days, which was also the same number of dry days obtained from ANN1S, ANN2S, ANN3S, ANN4S, ANN5S MODAWEC and AANS. The highest

number of dry days in EAP was noted in ERA5-Land with a total of 6 days y^{-1} (200% higher than the optimum design based on observed ET0 (see Table 4-8). In HAP, apart from the optimum design, the highest relative yield for all crops was noted for the MODAWEC, ANN4H, and ANN5H methods with 100% relative yield in all crops. In contrast, the lowest relative yield was associated with ANN3H with relative yields ranging from 64 –77% across all crops (Table 4-8). The irrigation depth in HAP ranged between 2494 – 2728 mm y^{-1} , where the lowest was noted in ERA5-Land (7% lower than the optimum design based on observed ET0), and the highest was noted in MODAWEC (2% higher than the optimum design based on observed ET0). The closest methods to the optimum design were ANN4H with 2695 mm y^{-1} (1% higher than the optimum design based on observed ET0) and ANN5H with 2705 mm y^{-1} (1% higher than the optimum design based on observed ET0).

As compared with the optimum design (2191 mm y^{-1}), the actual ET in HAP ranged between 2145 – 2191 mm y^{-1} across all the predicted methods, with the lowest associated with the ERA5-Land method (2% lower than the optimum design based on observed ET0), and the highest with the observed method. The closest match to the optimum design were associated with ANN4H and ANN5H with 2187 mm y^{-1} . The drainage depth in HAP which was associated with the optimum design was 493 mm y^{-1} . The closest drainage depth to the optimum design were obtained for ANN4H with 514 mm y^{-1} (4% higher than the optimum design based on observed ET0), and ANN5H with 523 mm y^{-1} (6% higher than the optimum design based on observed ET0). The drainage depth for all predicted methods ranged between 333 – 549 mm y^{-1} , where the highest value was noted in MODAWEC with 549 mm y^{-1} (12% higher than the optimum design based on observed ET0), and the lowest value was in ANN2H with 333 mm y^{-1} (32% lower than the optimum design based on observed ET0). The number of dry days in HAP observed for the optimum design were 3 days y^{-1} , while for all other methods the number of dry days ranged between 3 – 21 days y^{-1} , where the lowest was noted in MODAWEC, ANN4H and ANN5H with 3 days y^{-1} , and

the highest was noted in ERA5-Land with 21 days y^{-1} (600% higher than the optimum design based on observed ET0).

Table 4-8: DRAINMOD applications in EAP and HAP for the period 1981 – 2010.

name	Method	%Relative yield				*Irrigation depth mm y ⁻¹	% variation from the optimum design	*Actual ET mm y ⁻¹	% variation from the optimum design	*Drainage depth mm y ⁻¹	% variation from the optimum design	*Number Dry days	% variation from the optimum design
		Beans	Maize	Soybean	Wheat								
EAP	Observed	100	100	100	100	2745	0	2226	0	524	0	2	0
	AANS	100	100	100	100	3160	15 ↑	2226	0	937	79 ↑	2	0
	MODAWEC	100	100	100	100	2929	7 ↑	2229	0	701	34 ↑	2	0
	ERA5-Land	40	30	47	58	2480	10 ↓	2210	1 ↓	276	47 ↓	6	200 ↑
	ANN1S	90	90	90	89	2712	1 ↓	2225	0	492	6 ↓	2	0
	ANN2S	70	70	70	76	2618	5 ↓	2225	0	397	24 ↓	2	0
	ANN3S	91	97	97	91	2689	2 ↓	2225	0	468	11 ↓	2	0
	ANN4S	100	100	100	100	2757	0 ↑	2226	0	535	2 ↑	2	0
	ANN5S	97	98	100	93	2712	1 ↓	2225	0	492	6 ↓	2	0
HAP	Observed	100	100	100	100	2680	0	2191	0	493	0	3	0
	AANS	90	79	81	95	2631	2 ↓	2184	0	450	9 ↓	11	260 ↑
	MODAWEC	100	100	100	100	2728	2 ↑	2184	0	549	12 ↑	3	0
	ERA5-Land	79	72	89	89	2494	7 ↓	2145	2 ↓	355	28 ↓	21	600 ↑
	ANN1H	80	80	80	92	2534	5 ↓	2181	0	358	27 ↓	7	145 ↑
	ANN2H	70	70	80	83	2509	6 ↓	2181	0	333	32 ↓	7	145 ↑
	ANN3H	60	60	64	77	2609	3 ↓	2181	0	434	12 ↓	4	33 ↑
	ANN4H	100	100	100	100	2695	1 ↑	2187	0	514	4 ↑	3	0
	ANN5H	100	100	100	100	2705	1 ↑	2187	0	523	6 ↑	3	0

Where * the average annual value for the period 1981 – 2010. EAP is Eshkeda Agricultural Project, HAP is Hammam Agricultural Project, ET0 is reference evapotranspiration, AANS is the Arithmetic Averaging of Neighbouring Stations, MODAWEC is Monthly to Daily Weather Converter, ANN is the Artificial Neural Network, and ET is evapotranspiration.

Table 4-9 shows the results of generating performance ranking of the ET0 methods applied in DRAINMOD for EAP and HAP. Apart from the optimum design based on observed ET0, ANN4S, ANN5S, ANN4H and ANN5H all ranked as 'No risk' class with a total score of 1.0 for EAP and HAP. In EAP, the performance class of 'Low risk' was associated with ANN1S and ANN3S with a total score of 1.3 and 1.7 respectively. The 'Moderate risk' performance class in EAP was associated with AANS, MODAWEC, and ANN2S with a total score of 3.0, 2.5, and 2.8 respectively. Finally, the 'High risk' performance class in EAP was linked with ERA5-Land with a total score of 4.0. In HAP, the 'Low risk' class was associated with MODAWEC with a total score of 1.6. The 'Moderate risk' class in HAP was linked with AANS, ANN1H, and ANN3H with a total score of 2.3, 2.9, and 2.5 respectively. Finally, in HAP, the 'High risk' class was associated with ERA5-Land and ANN2H with a total score of 3.6 and 3.7 respectively (Table 4-9).

Table 4-9: Performance ranking of the ET0 methods applied in DRAINMOD and the scoring for each objective function.

Project name	Method	Individual score ^[1]					Total score	Performance class
		Yield*	IWD	AET	DD	NDD		
EAP	Observed	1	1	1	1	1	1.0	No risk
	AANS	1	5	1	5	1	3.0	Moderate risk
	MODAWEC	1	4	1	4	1	2.5	Moderate risk
	ERA5-Land	4.5	4	3	4	3	4.0	High risk
	ANN1S	2	1	1	1	1	1.3	Low risk
	ANN2S	3.75	3	1	3	1	2.8	Moderate risk
	ANN3S	1.5	2	1	2	1	1.7	Low risk
	ANN4S	1	1	1	1	1	1.0	No risk
	ANN5S	1	1	1	1	1	1.0	No risk
HAP	Observed	1	1	1	1	1	1.0	No risk
	AANS	2.25	2	2	2	4	2.3	Moderate risk
	MODAWEC	1	2	2	2	1	1.6	Low risk
	ERA5-Land	2.5	4	5	3	5	3.6	High risk
	ANN1H	2.75	3	3	3	3	2.9	Moderate risk
	ANN2H	3.5	4	3	4	3	3.7	High risk
	ANN3H	3.75	2	3	2	1	2.5	Moderate risk
	ANN4H	1	1	1	1	1	1.0	No risk
	ANN5H	1	1	1	1	1	1.0	No risk
Weight (%)		30%	30%	10%	20%	10%		

[1] individual score for each objective function, (yield*) is the average yield of the four simulated crops (Beans, Maize, Soybean and Wheat). Irrigation water depth (IWD), actual evapotranspiration (AET), drainage depth (DD), number of dry days (NDD), Eshkeda agricultural project (EAP), and Hammam agricultural project (HAP).

4.4 Discussion

4.4.1 Evaluation of methods applied to predict missing DTmax and DTmin and calculate ET0

The accuracy of the methods applied in this study to predict missing DTmax and DTmin data values in the Sabha and Hon meteorological stations 30yr (1981-2010) datasets, varied. For example, ANN4S and ANN5S, ANN4H, and ANN5H were more accurate in predicting missing DTmax and DTmin, and hence at calculating ET0 than the other methods applied to Sabha and Hon meteorological datasets, respectively. In this study, ANN4S and ANN4H were developed using the same input parameters (DOY, MTmax, MTmin, XMTmax, XMTmin, SD, GTmax, GTmin, ERATmax, and ERATmin). This combination of input parameters generated accurate predictions of DTmax and DTmin. Only the first eight parameters listed above were also included in ANN1S and ANN1H.

Including ERATmax, and ERATmin in the development of ANN4S and ANN4H improved the prediction accuracy by between 24 – 146%. These results support the findings of Fahimi Nezhad et al. (2019), who reported that some input parameters have a stronger influence on the output of the developed ANNs than others. Also, Fahimi Nezhad et al. (2019) found that having more input parameters does not necessarily improve the performance of the ANN, which was noted in this study, where ANN4H (10 input parameters) was more accurate than ANN5H (14 input parameters) by 3 – 4% in RMSE. Also, ANN5S (14 input parameters) was more accurate in predicting DTmax and DTmin than ANN4S by 10 – 11% in RMSE. In addition, for the non-ANNs methods, ERA5-Land gave the most precise prediction. ERA5-Land was up to 5% and 6% more accurate than AANS at predicting missing data values of DTmax and DTmin, respectively. The ERA5-Land dataset had an advantage over all the other methods in that the meteorological parameters were calculated for a specific location on an hourly basis. Therefore, the temporal and spatial resolution of ERA5-Land was much better than the other methods.

ANN1S and ANN1H required the minimum number of input variables (8 input parameters) as compared to all other ANNs developed in this study. The input variables were DOY, MTmax, MTmin, XMTmax, XMTmin, SD, GTmax, and GTmin. This combination is considered the most available in Libya as this dataset is available for 1981-2010 with no missing values. However, the accuracy of ANN1S and ANN1H in the prediction of DTmax and DTmin and subsequent calculation of ET₀ was up to three times less accurate than ANN4S and ANN4H (the most accurate ANNs developed in Sabha and Hon meteorological stations). However, ANN1S and ANN1H were 5-13% more accurate (as indicated by the RMSE values) than ANN2S and ANN2H.

The performance of ANN2S and ANN2H at predicting DTmax and DTmin and calculating ET₀ shows that adding ModTmax, and ModTmin as input parameters did not improve the accuracy of the ANNs. The reason for that might be the way MODAWEC generates DTmax and DTmin. MODAWEC randomly converts MTmax and MTmin to DTmax and DTmin, the conversion ensures that the generated DTmax and DTmin are within the average monthly range. However, the MODAWEC conversion did not result in accurate predictions of DTmax and DTmin, and the ET₀ calculation also did not help ANN2S and ANN2H to assign the right weight for more accurate predictions. Consequently, the least accurate method to predict missing data values of DTmax and DTmin and ET₀ was MODAWEC. MODAWEC was therefore also poor at calculating ET₀. Azmat et al. (2018) applied MODAWEC to examine the potential change in precipitation and temperature under future scenarios. Azmat et al. (2018) suggest that MODAWEC software may be a suitable choice where long-term monthly data are available, but the accuracy of the daily data may not match the observed data.

In comparison ANN3S and ANN3H were more accurate than ANN1S, ANN1H, ANN2S, and ANN2H, and less accurate than ANN4S, ANN4H, ANN5S, and ANN5H. However, in terms of the availability of the datasets to develop the respective ANNs, the disadvantage of applying ANN5S and ANN5H is that they require more input parameters (14) compared to the other ANNs (8 – 10).

For example, to develop ANN3S, ANN3H, ANN5S, and/or ANN5H, the values of NTmax and NTmin from neighbouring stations are required. However, this dataset may not be available, especially in least developed countries where missing climatic data is a common problem, or the nearest neighbour data may be too far away to be considered representative of the study area (Koksall et al., 2017). Therefore, ANNs developed from more readily available datasets are more favourable.

4.4.2 DRAINMOD applications and performance ranking of the ET₀ methods

In EAP, the 30yr DRAINMOD designs based on AANS, MODAWEC, and ANN4S were associated with a relative yield identical to the optimum design (defined as maximum relative yield with the minimum irrigation depth) which was based on observed ET₀ values. However, other key performance indicators differ between these approaches. AANS required an additional 15% irrigation depth and 79% greater drainage depth as compared to the optimum design but had a comparable number of dry days. Based on that, almost all the additional irrigation depth applied will be discharged and lost due to drainage depth. MODAWEC required an additional 7% irrigation (mm y^{-1}), and 34% increase in drainage depth whilst having a comparable ET and dry days, as compared with the optimum design. ANN4S in contrast, accurately predicted the irrigation depth, actual ET, and the number of dry days compared to the optimum design, while associated with 2.2% increases in drainage depths as compared with the optimum design. The advantage of using ANN4S (the same for ANN4H) is that the input parameters used for the development are readily available in Libya.

Based on these results, if the predicted ET₀ method required an irrigation depth equal or greater than the irrigation depth in the optimum design, the predicted relative yield would be identical to the optimum design (which was the case in AANS, MODAWEC, and ANN4S). In contrast, the over-prediction of irrigation depth would cause an increase in water loss due to increased drainage depth.

That loss of water is critical especially in areas already suffering water scarcity such as Libya (Wheida and Verhoeven, 2007). While, predicted irrigation depth less than the optimum design will lead to a reduction in the relative yield. The reduction will depend on percentage difference between the predicted irrigation depth and the optimum irrigation depth.

For HAP, the drainage designs based on DRAINMOD simulations for a 30-yr period (1981 – 2010) showed that MODAWEC, ANN4H and ANN5H had a relative yield similar to the optimum design. However, other critical performance metrics, differed between these methods. To achieve the predicted relative yield, an additional irrigation depth (an average annual of 15 – 48 mm y^{-1}) greater than the optimum design was applied. MODAWEC required an additional 2% irrigation depth, and had an 12% greater drainage depth. In terms of irrigation depth and drainage depth, the findings of MODAWEC in EAP are comparable with this outcome in HAP. MODAWEC required an additional irrigation depth resulting in a loss equivalent to 48 mm y^{-1} depth of irrigation water through drainage compared to the optimum design. Whilst, ANN4H was the most comparable to the optimum design, with only 4% more drainage depth.

Comparing the irrigation water requirements (IWR) predicted by MODAWEC and ANN4H showed that applying the ANN4H method over MODAWEC would save around 33 mm y^{-1} depth of water, which is crucial, especially in a region where the irrigation water comes from a non-rechargeable aquifer and food security is a high priority (Ellafi et al., 2021). Despite ERA5-Land being one of the most accurate methods in predicting DTmax and DTmin and ET0 calculation in Sabha and Hon, when its output was applied in DRAINMOD, the ERA5-Land method led to a reduction in predicted relative yield in both EAP and HAP. The reason for this reduction was that ERA5-Land under-estimate the IWR. Applying ET0 from ERA5-Land as an input for DRAINMOD to design drainage systems in EAP and HAP might help to save irrigation water, however, the relative yield would be affected with an estimated loss of 70% in yield. In contrast, using ERA5-Land as an input to develop ANN4S and ANN4H produced an identical design to the optimum design. The design based on ET0 predicted by ANN4S and ANN4H

secured a relative yield identical to the optimum design based on observed ET₀. Also, that design did not require an extensive amount of irrigation water to achieve that relative yield (only 1% higher than the optimum design). Therefore, less water is lost through the drainage system.

The performance ranking results showed that the drainage design based on ET₀ calculated by ANN4S, ANN5S, ANN4H and ANN5H in EAP and HAP were not dissimilar to the optimum design which was based on observed ET₀. The aforementioned methods have achieved the highest performance class ('No risk'). This result agreed with the other findings in this study, where ANN4S, ANN5S, ANN4H and ANN5H were able to obtain the highest relative yield (similar to the optimum design) with little difference in irrigation water depth. The second highest performance ranking class was the 'Low risk' class. The 'Low risk' class included ANN1S, and ANN3S in EAP and MODAWECEC in HAP. Based on the simulated results of these methods, a reduction of up to 10% in relative yield can be reached. Also, up to 2% additional irrigation depth would be required, and *circa* 12% additional drainage depth would be lost compared to the optimum design.

The next performance class was 'Moderate risk'. This class was associated with six methods, three in EAP (AANS, MODAWECEC and ANN2S), and three in HAP (AANS, ANN1H and ANN3H). Applying one of the methods within the 'Moderate risk' class would cause a reduction in relative yield of up to 40%, require additional irrigation of up 15% depth, and increase drainage depth by nearly 79% compared to the optimum design. Finally, the lowest performance class noted within the applied method was the 'High risk' class. This class was linked with ANN2H in HAP and ERA5-Land in both EAP and HAP.

Adopting a method within this class would cause a reduction in the relative yield of up to 70%, a shortage of up to *circa* 10% in irrigation depth, and a reduction of 47% in drainage depth compared to the optimum design. Therefore, the best option ET₀ methods for drainage design in EAP and HAP were the ones ranked

in the 'No risk' performance class, and of these methods, ANN4S and ANN4H were the most suitable because they required fewer and more readily available input parameters in comparison to ANN5S and ANN5H.

4.5 Conclusions

In many arid and semi-arid areas, soil salinity and waterlogging issues have been heavily linked with inadequate drainage design and poor water use efficiency. To improve drainage systems and therefore water use efficiency, data required in drainage design models, such as DRAINMOD, must be available at appropriate spatial and temporal resolutions. This research has demonstrated that the current limitation of missing and/or incomplete data sets that has historically beset arid and semi-arid areas, can be overcome using ANNs to predict parameters such as DTmax and DTmin. However, choice of input parameters does affect prediction accuracy.

ANNs developed using monthly observed data, the calculated temperature, estimated sunshine duration based on the geographical location, and ERA5-Land were the most accurate at predicting DTmax and DTmin (i.e., ANN4S and ANN4H). These ANNs were also more accurate at calculating ET0 than other indirect methods including Arithmetic Averaging of Neighbouring Stations Method (AANS), Monthly to Daily Weather Converter (MODAWEC), and ERA5-Land reanalysis data.

The output from DRAINMOD simulations showed that the accuracy of the method applied to calculate ET0 had an impact on the prediction of objective functions such as relative yield, irrigation depth, actual evapotranspiration, drainage depth and the number of dry days. This research has also demonstrated through drainage design simulation that the predictive methods worked and those based on measured data for the two agricultural projects in Libya.

Further research is required to determine if the input data combinations and methods used to predict missing DTmax and DTmin values used in this study to develop accurate ANNs are transferrable to in other arid and semi-arid regions.

4.6 References

Abdel-dayam, S., Skaggs, R.W., 1990. Extension of DRAINMOD for simulating water management in arid regions, in: Vol. II. Proceedings of Symposium on Land Drainage for Salinity Control in Arid and Semi-Arid Regions. Drainage Research Institute, WRC, Cairo, Egypt, pp. 201–212.

Allen, R.G., Food, of the United Nations, A.O., 1998. Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements, FAO irrigation and drainage paper. FAO.

Almonacid, F., Pérez-Higueras, P., Rodrigo, P., Hontoria, L., 2013. Generation of ambient temperature hourly time series for some Spanish locations by artificial neural networks. *Renew. Energy* 51, 285–291. <https://doi.org/10.1016/j.renene.2012.09.022>

Arsenault, R., Brissette, F., Martel, J., Troin, M., Lévesque, G., Davidson-chaput, J., Gonzalez, M.C., Ameli, A., Poulin, A., 2020. A comprehensive , multisource database for hydrometeorological modeling of 14,425 North American watersheds. *Sci. Data* 7, 1–12. <https://doi.org/10.1038/s41597-020-00583-2>

Ayars, J.E., Evans, R.G., 2015. Subsurface Drainage - What's Next? *Irrig. Drain.* 64, 378–392. <https://doi.org/10.1002/ird.1893>

Azmat, M., Qamar, M.U., Ahmed, S., Shahid, M.A., Hussain, E., Ahmad, S., Khushnood, R.A., 2018. Ensembling Downscaling Techniques and Multiple GCMs to Improve Climate Change Predictions in Cryosphere Scarcely-Gauged Catchment. *Water Resour. Manag.* 32, 3155–3174. <https://doi.org/10.1007/s11269-018-1982-9>

Beven, K., 2006. A manifesto for the equifinality thesis. *J. Hydrol.* 320, 18–36. <https://doi.org/https://doi.org/10.1016/j.jhydrol.2005.07.007>

Cornelius-Brochier J.V, 1981. Wadi Al Shatti: Drainage Design. Tripoli, Libya.

Danenco, 1980. Technical Study for Jufra el Hamam Project. Copenhagen, Denmark.

Dergunov, A. V, Yakubailik, O.E., 2020. Comparative analysis of data on air temperature based on current weather data sets for 2007-2019 Comparative analysis of data on air temperature based on current weather data sets for 2007-2019, in: IOP Conference Series: Earth and Environmental Science. IOP Publishing Ltd. <https://doi.org/10.1088/1755-1315/548/3/032034>

Ellafi, M.A., Deeks, L.K., Simmons, R.W., 2021. Application of artificial neural networks to the design of subsurface drainage systems in Libyan agricultural projects. J. Hydrol. Reg. Stud. 35, 1–17. <https://doi.org/https://doi.org/10.1016/j.ejrh.2021.100832>

Ellafi, M.A., Zurqani, H.A., Deeks, L.K., Simmons, R.W., 2022. DRAINMOD applications to design drainage systems in Libya using soil salinity data predicted by GIS, remote sensing and Artificial Neural Networks, in: Zurqani, H.A. (Ed.), Environmental Applications of Remote Sensing and GIS in Libya. Springer International Publishing AG, Switzerland.

Elsahemy, M., 2018. Review of Technologies and Practices for Improving Agricultural Drainage Water Quality in Egypt, in: Unconventional Water Resources and Agriculture in Egypt. Springer Verlag, pp. 163–188. <https://doi.org/10.1007/698>

Fahimi Nezhad, E., Fallah Ghalhari, G., Bayatani, F., 2019. Forecasting Maximum Seasonal Temperature Using Artificial Neural Networks “Tehran Case Study.” Asia-Pacific J. Atmos. Sci. 55, 145–153. <https://doi.org/10.1007/s13143-018-0051-x>

FAO, 2009. ETo Calculator.

GWA, 1999. Water and irrigation requirements for the most important crops in Libya [unpublished report]. Tripoli.

Hargreaves, G.H., Samani, Z.A., 1982. Estimating Potential Evapotranspiration. *J. Irrig. Drain. Div.* 108, 225–230. <https://doi.org/10.1061/JRCEA4.0001390>

Holzmann-Wakuti, 1974. Hydrogeology of The Joufrah Project Area. Tripoli, Libya.

Italconsult, 1976. Fezzan Land Reclamation Project: Wadi-Shati Eshkeda Area. Rome, Italy.

Kanda, N., Negi, H.S., Rishi, M.S., Shekhar, M.S., 2018. Performance of various techniques in estimating missing climatological data over snowbound mountainous areas of Karakoram Himalaya. *Meteorol. Appl.* 25, 337–349. <https://doi.org/10.1002/met.1699>

Kandil, H., Skaggs, R.W., Abdel Dayem, S., Aiad, Y., 1995. DRAINMOD-S: Water management model for irrigated arid lands , crop yield and applications. *Irrig. Drain. Syst.* 9, 239–258.

Koksal, E.S., Cemek, B., Cetin, S., Gowda, P.H., Howell, T.A., 2017. Estimating missing hourly climatic data using artificial neural network for energy balance based ET mapping applications. *Meteorol. Appl.* 24, 457–465. <https://doi.org/10.1002/met.1644>

Legates, D.R., Willmott, C.J., 1990. Mean seasonal and spatial variability in global surface air temperature. *Theor. Appl. Climatol.* 41, 11–21. <https://doi.org/10.1007/BF00866198>

Liu, J., Williams, J.R., Wang, X., Yang, H., 2008. Using MODAWEC to generate daily weather data for the EPIC model. *Environ. Model. Softw.* 24, 655–664. <https://doi.org/10.1016/j.envsoft.2008.10.008>

LNMC, 2020. Average Daily and Monthly Meteorological datasets observed in Libyan Meteorological stations [datasets was collected by personal contacts with the Libyan National Meteorological Centre in 2020]. Tripoli, Libya.

Luo, W., Jing, W.H., JIA, Z.H., LI, J., Pan, Y.X., 2009. The effect of PET calculations in DRAINMOD on drain- age and crop yields predictions in a subhumid vertisol soil district. *Sci. China Ser. E Technol. Sci.* 52, 1–5. <https://doi.org/10.1007/s11431-009-0349-0>

Meeus, J., 1991. *Astronomical Algorithms*. Published by Willmann-Bell, Virginia.

Muñoz-Sabater, J., 2019. ERA5-Land hourly data from 1981 to present [WWW Document]. Copernicus Clim. Chang. Serv. Clim. Data Store.

Niaghi, A.R., Jia, X., Scherer, T.F., 2017. Impact of Accurate Evapotranspiration Estimates on DRAINMOD Simulation in North Dakota. 2017 ASABE Annu. Int. Meet., ASABE Paper No. 1701500. <https://doi.org/https://doi.org/10.13031/aim.201701500>

Nkiaka, E., Nawaz, N.R., Lovett, J.C., 2017. Evaluating global reanalysis precipitation datasets with rain gauge measurements in the Sudano-Sahel region: case study of the Logone catchment, Lake Chad Basin. *Meteorol. Appl.* 24, 9–18. <https://doi.org/10.1002/met.1600>

Okoh, D., Yusuf, N., Adedaja, O., Musa, I., Rabi, B., 2015. Preliminary results of temperature modelling in Nigeria using neural networks. *Weather* 70, 335–336. <https://doi.org/10.1002/wea.2581>

Prăvălie, R., Patriche, C., Borrelli, P., Panagos, P., Roșca, B., Dumitrașcu, M., Nita, I.A., Săvulescu, I., Birsan, M.V., Bandoc, G., 2021. Arable lands under the pressure of multiple land degradation processes. A global perspective. *Environ. Res.* 194. <https://doi.org/10.1016/j.envres.2020.110697>

Qadir, M., Boers, T.M., Schubert, S., Ghafoor, A., Murtaza, G., 2003. Agricultural water management in water-starved countries: Challenges and opportunities. *Agric. Water Manag.* 62, 165–185. [https://doi.org/10.1016/S0378-3774\(03\)00146-X](https://doi.org/10.1016/S0378-3774(03)00146-X)

Radchenko, I., Breuer, L., Forkutsa, I., Frede, H.-G., 2014. Simulating Water Resource Availability under Data Scarcity—A Case Study for the Ferghana Valley (Central Asia). *Water* 6, 3270–3299. <https://doi.org/10.3390/w6113270>

Safriel, U., Adeel, Z., Niemeijer, D., Puigdefabregas, J., White, R., Lal, R., Winslow, M., Prince, S., Archer, E., King, C., Shapiro, B., Wessels, K., Nielsen, T., Portnov, B., Reshef, I., Lachman, E., McNab, D., El-kassas, M., Ezcurra, E., 2005. Dryland Systems, in: Hassan, R., Scholes, R., Ash, N. (Eds.), *Ecosystems and Human Well-Being: Current State and Trends: Findings of the Condition and Trends Working Group (Millennium Ecosystem Assessment Series)*. Island Press, Washington, DC, USA, pp. 625–662.

Sattari, M.T., Rezazadeh-Joudi, A., Kusiak, A., 2017. Assessment of different methods for estimation of missing data in precipitation studies. *Hydrol. Res.* 48, 1032–1044. <https://doi.org/10.2166/nh.2016.364>

Schultz, B., Zimmer, D., Voltman, W.F., 2007. Drainage under increasing and changing requirements. *Irrig. Drain.* 56, S3–S22. <https://doi.org/10.1002/ird>

Selvaperumal, A., Thiyagarajan, G., Vallalkannan, S., Muthuchamy, I., 2020. DRAINMOD – Calibration and Validation for Prediction of Drainage Coefficient and Water Table Depth 39, 65–74. <https://doi.org/10.9734/CJAST/2020/v39i930607>

Singh, R., Helmers, M.J., Qi, Z., 2006. Calibration and validation of DRAINMOD to design subsurface drainage systems for Iowa ' s tile landscapes. *Agric. Water Manag.* 85, 221–232. <https://doi.org/10.1016/j.agwat.2006.05.013>

Skaggs, R.W., 2007. Criteria for Calculating Drain spacing and Depth. *Am. Soc. Agric. Biol. Eng.* 50, 1657–1662.

Skaggs, R.W., 1977. Evaluation of drainage-water table control systems using a water management model, in: St., A.P. 1-77., Joseph, M.. A. (Eds.), *3rd Natl. Drainage Symposium*. pp. 61–68.

Smedema, L.K., Abdel-Dayem, S., Ochs, W.J., 2000. Drainage and agricultural development. *Irrig. Drain. Syst.* 14, 223–235. <https://doi.org/10.1023/A:1026570823692>

Tarek, M., Brissette, F.P., Arsenault, R., 2020. Evaluation of the ERA5 reanalysis as a potential reference dataset for hydrological modelling over North America. *Hydrol. Earth Syst. Sci.* 24, 2527–2544. <https://doi.org/10.5194/hess-24-2527-2020>

Ustaoglu, B., Cigizoglu, H.K., Karaca, M., 2008. Forecast of daily mean, maximum and minimum temperature time series by three artificial neural network methods. *Meteorol. Appl.* 15, 431–445. <https://doi.org/10.1002/met.83>

Wahba, M.A., Christen, E., 2006. Modeling subsurface drainage for salt load management in southeastern Australia. *Irrig. Drain. Syst.* 20, 267–282. <https://doi.org/10.1007/s10795-006-9007-x>

Wheida, E., Verhoeven, R., 2007. An alternative solution of the water shortage problem in Libya. *Water Resour. Manag.* 21, 961–982. <https://doi.org/10.1007/s11269-006-9067-6>

Woldesenbet, T.A., 2017. Gap filling and homogenization of climatological datasets in the headwater region of the Upper Blue Nile Basin , Ethiopia. *Int. J. Climatol.* 37, 2122–2140. <https://doi.org/10.1002/joc.4839>

Xia, Y., Fabian, P., Stohl, A., Winterhalter, M., 1999. Forest climatology: estimation of missing values for Bavaria, Germany. *Agric. For. Meteorol.* 96, 131–144.

Zandler, H., Senftl, T., Vanselow, K.A., 2020. Reanalysis datasets outperform other gridded climate products in vegetation change analysis in peripheral conservation areas of Central Asia. *Sci. Rep.* 10, 1–16. <https://doi.org/10.1038/s41598-020-79480-y>

Zanetti, S.S., Sousa, E.F., Oliveira, V.P.S., Almeida, F.T., Bernardo, S., 2007. Estimating Evapotranspiration Using Artificial Neural Network and Minimum Climatological Data. J. Irrig. Drain. Eng. 133, 83–89.

5 DRAINMOD Applications to Design Drainage Systems in Libya Using Soil Salinity Data Predicted by GIS, Remote Sensing and Artificial Neural Networks

Abstract

Soil salinity in irrigated agricultural regions is a growing problem. Saline soil conditions have reduced the value and productivity of considerable areas of land all over the globe. Direct methods of measuring soil salinity are time-consuming and expensive (especially for the least developed countries). Monitoring soil salinity can help to evaluate the effectiveness of having a drainage system installed. Therefore, research effort has been dedicated to developing indirect methods for predicting soil salinity. This study aims to (1) develop Artificial Neural Networks (ANNs) to predict the electrical conductivity of the saturated paste extract (ECe), (2) evaluate the performance of a drainage system based on measured and predicted ECe, and (3) develop soil salinity prediction maps to monitor the initial and simulated salinity under drained and undrained conditions. This research focuses on two agricultural projects in the southern part of Libya, Eshkeda Agricultural Project (EAP) and Hammam Agricultural Project (HAP). Yearly scenes satellite datasets were generated from January to December for 1984, 1990, 2000, and 2010 using the median values of Landsat 5 Surface Reflectance bands for each measurement location in HAP, and EAP. Also, commonly utilised salinity indices were selected and applied as input to ANN in order to predict ECe. A 90% subset of the data was used to train each ANN and the remaining 10% of the salinity values were used in the testing process. K-fold cross validation technique was also applied to ensure the validity of the developed ANN. Two ANNs were developed to predict soil salinity based on input parameters applied. The input parameters for ANN1 were based on the reflections from satellite images, while the input for ANN2 was based on both reflection and the salinity indices. The developed ANNs were then applied to predict soil salinity in 1990, 2000, and 2010. DRAINMOD was also applied to simulate EAP and HAP under drained and undrained conditions.

The results showed that ANN2 was slightly more accurate than ANN1 in predicting soil salinity in EAP and HAP. The results also indicated that by installing a drainage system, soil salinity and salinity stress can be minimised, and production maximised. The results suggest that having an effective drainage system installed and maintained properly will help to significantly improve the potential crop yield and control the salinity stress in agricultural lands effected by saline conditions. Also, the results suggest that ANNs can be used as a tool to evaluate an existing drainage system and specify an area in need of improvement. This supports the frequently stated proposition that drainage, irrigation, and salinity control for arid lands should be considered as components of a water management system and that the design of each component should be dependent on the design of the other components.

5.1 Introduction

Since the 1950s, the water demand in Libya has exceeded the capacity of its water resources to support food production (Qadir et al., 2003). North Africa is considered to be one of the driest regions in the world, with only 5% of the total area of Libya receiving precipitation >100 mm per year (Brika, 2018). Furthermore, the population has increased from 1.1 million in 1950 to 6.7 million in 2019 (United Nations, 2019). This surge in population has put increased pressure on water resources making water scarcity one of the current greatest challenges facing Libya (Brika, 2018). Since the 1970s, water resources have a high consideration of the Libyan governments and their development (Wheida and Verhoeven, 2007).

Between 1961 – 2013, the Libyan government financially supported the agricultural sector in order to meet the increased demand on food and achieve sustainability (FAO, 2016; Wheida and Verhoeven, 2007). Despite 95% of the country being designated as desert, the support from the government helped to increase cultivated area from 1.9 million ha in 1961 to 2.2 million ha in 1996 (FAO, 2018a).

However, this led to an increased use of groundwater (from non-renewable aquifers), exceeding safe groundwater abstraction volume by 1,940 million cubic meter per year (FAO, 2018a). This increased abstraction has led to seawater intrusion advancing by 2 km inland in some coastal areas, and groundwater salinity increasing from 150 mg L⁻¹ in 1950 to 5000 mg L⁻¹ in 1990.

Across many irrigated lands in the world, excessive groundwater abstraction has led to higher soil salinity rates (Elhag, 2016). Soil salinity is the process of enriching soil with soluble salts, which results in salt-affected soil. Saline soil conditions have reduced the value and production of considerable areas of land all over the globe (Elhag, 2016). For example, in Jefara plain (north west Libya), two irrigation schemes built using artesian wells in the 1970s have recently been converted to pumping wells, resulting in some waterlogging, soil salinity and decrease in crop yields (CEDARE, 2014). Soil salinity increases the irrigation water requirement (more water is needed to leach the salt), while decreasing the yields as a result of waterlogging and salinity (FAO, 1994). Same issue (soil salinity, waterlogging and crop yields reduction) was observed in the southern portion of Libya as a result of inadequate drainage (FAO, 2016).

Drainage systems have been installed in arid and semi-arid regions to control the water table levels and to leach the salt below the root zone. However, less than 30% of all irrigated land needing drainage has been effectively drained (Schultz et al., 2007), and the situation is worse in least developed countries. According to Smedema et al. (2000) the proportion of agricultural land drained in the least developed countries is 5-10% compared to 25-30% in developed countries. In Libya, c. 9,000 ha of irrigated land (which represents around 2% of all croplands in Libya) was estimated to be equipped with some form of drainage in 2000 (FAO, 2016). This is due to a fundamental lack of expertise in-country and the high cost of drainage installation as well as the lack of contiguous input data for their design. Computer simulation models can reasonably measure the effects of different input variables while minimising costs and shortening the time to system design (Selvaperumal et al., 2020; Wang et al., 2006).

DRAINMOD is a widely applied model used to simulate the hydrology of poorly drained and high water table soils (Gupta et al., 1993; Kandil et al., 1995; Luo et al., 2009; Selvaperumal et al., 2020; Skaggs et al., 2012b). DRAINMOD can also be used to predict salinity (soil salinity and salinity in drains), it does this by applying a mass balance approach for the total dissolved concentrations of salt in the soil profile at each time step (Kandil et al., 1995). From the prediction of soil salinity, DRAINMOD can be used to estimate the response of crop yield to soil salinity by plotting two linear lines, one a tolerance plateau at 100 percent relative yield up to a salinity threshold, and the other a concentration dependant line, the slope of which reflects the yield loss per unit rise in soil salinity (Maas and Hoffman, 1977). DRAINMOD has been successfully applied to simulate the impact of water management and drainage system design on yield, drainage water quality, and soil salinity in many irrigated areas including Egypt (Kandil et al., 1995; Wahba et al., 2002), Turkey (Kale, 2011), and Iran (Pourgholam-Amiji et al., 2021).

To be able to apply DRAINMOD for salinity control, the initial soil salinity is required as an input parameter (Kandil et al., 1995). A standard method used to determine soil salinity is from the electrical conductivity of the saturated paste extract (ECe) (USDA, 1954). The ECe measure is considered as the most accurate for estimating crop response to salinity. However, this approach is time consuming, tedious, and requires personnel with skills and experience of calculating the saturation percentage (Kargas et al., 2018). In recent decades, satellite imageries have been used as a technique to predict and map soil salinity (Nguyen et al., 2020). Many researchers have developed and evaluated different salinity indices (Asfaw et al., 2018; Elhag, 2016). These indices were then used to develop a prediction map to illustrate the location of the salt affected soils (Asfaw et al., 2018). Recently, artificial neural networks (ANNs) have been combined with Remote Sensing (RS) and Geographical Information System (GIS) to create more accurate soil salinity maps by using salinity indices and reflectance from satellite images as an input for the ANNs (Habibi et al., 2021; Shahabi et al., 2016).

Habibi et al. (2021) found that developing ANNs using salinity indices and reflectance from satellite images produced more accurate soil salinity maps compared to Multiple Linear Regression (MLR). Mousavi et al. (2017) applied salinity and vegetation spectral indices to evaluate the relationship between the ECe parameter and spectral indices. They compared ANN and MLR salinity prediction models and reported that ANN was 46% more accurate. Shahabi et al. (2016) used ANN, Ordinary Kriging, and multiple regression techniques to estimate soil salinity. Environmental factors such as altitude, geographic aspect, slope length, Topographic Wetness Index (TWI), and Normalized Difference Vegetation Index (NDVI) spectral parameters were employed. They found that ANN had a lower Mean Square Error (MSE) and a higher coefficient of determination (R^2) than the other two models.

The purpose of this research is to improve the prediction of ECe in order to increase the efficacy of drainage system design in data-poor areas by utilising salinity indices and reflectance from satellite images. This research builds on the findings of the mentioned above research (Mousavi et al, 2017; Habibi et al, 2021; Shahabi et al, 2016). The research used the salinity indices and reflectance from satellite images as an input to develop ANNs that predict soil salinity. The expectation is that this will provide a low-cost alternative to drainage system design, making it more accessible to farmers, planners, and decision-makers in the least developed countries. The objectives of this study were to: (1) develop an ANN to predict ECe, (2) evaluate the performance of drainage systems based on measured and predicted ECe, and (3) develop soil salinity prediction maps to monitor the initial and simulated salinity under drained and undrained conditions.

5.2 Material and methods

5.2.1 Study area and soil salinity dataset

This research focuses on two agricultural projects in the southern part of Libya, Eshkeda Agricultural Project (EAP) and Hammam Agricultural Project (HAP). EAP is located north of Sabha (27°32'45"N 14°16'7"E) at an altitude of 320 meters above sea level (ASL). The EAP is 3000 hectares in size and is split into

three subareas: The Western Area (2,000 ha), the Central Area (600 ha), and the Eastern Area (370 ha). According to the installed irrigation wells, the land is divided into 25 districts, each with 12 farms of around 10 ha. HAP is located in the north-east side of Sokna Oasis (29°04'01"N 15°47'05"E) at an altitude of 270 meters ASL. The HAP encompasses 1,200 ha and is split into 182 farms (6 – 8ha each farm). The ECe data collected from the two agricultural project areas was measured on water extracted from the saturated soil paste (USDA, 1954). In total, for the HAP, there were 169 ECe measurements (c. 1 measurement for every 7 ha) while for the EAP there were 354 ECe measurements (c. 1 measurement for every 8 ha). Figure 5-1 shows the location of the study area and the ECe measurements points for HAP and EAP.

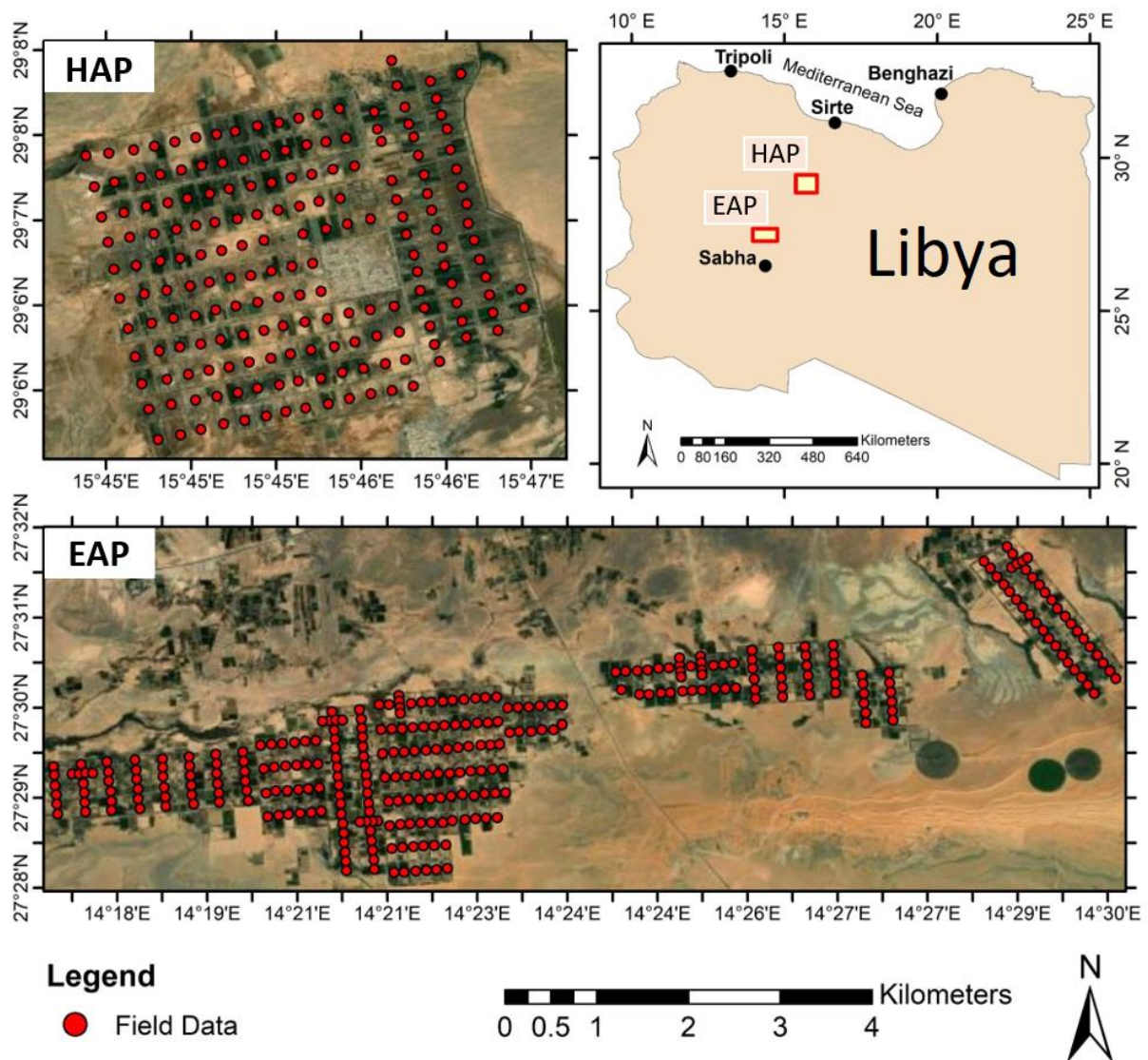


Figure 5-1: The study area and soil salinity measurement locations. HAP is Hammam Agricultural Project, and EAP is Eshkeda Agricultural Project.

5.2.2 Remote Sensing data and salinity indexes

Google Earth Engine (GEE) provides a rapid analysis of Remote sensing using Google's computing infrastructure, which offers online datasets in near-real-time (Zurqani et al., 2018). In this study, all of the satellite data pre-processing was conducted in GEE Code Editor (<https://code.earthengine.google.com>). Yearly scenes were generated from January to December for 1984, 1990, 2000, and 2010 using the median values of Landsat 5 Surface Reflectance bands for each measurement location in HAP, and EAP. These data have been atmospherically corrected using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS), and include a cloud, shadow, water, and snow mask produced using C Version of Function of Mask (CFMASK), as well as a per-pixel saturation mask (Gorelick et al., 2017). Table 5-1 gives detail of the wavelength, and spatial resolution of spectral bands, including the red, green, blue (RGB, 'visible spectrum'), the near-infrared (NIR) bands, and 2 short-wave infrared (SWIR) bands in Landsat 5 TM.

Table 5-1: Band specifications of Landsat 5 TM U.S. Geological Survey (USGS, 2021).

Band	Wavelength (μm)	Resolution (m)
Band 1 Visible (Blue)	(0.45 - 0.52)	30
Band 2 Visible (Green)	(0.52 - 0.60)	30
Band 3 Visible (Red)	(0.63 - 0.69)	30
Band 4 Near-Infrared	(0.76 - 0.90)	30
Band 5 shortwave-infrared	(1.55 - 1.75)	30
Band 7 shortwave infrared	(2.08 - 2.35)	30

In arid and semi-arid regions, several satellite salinity indices have been proposed locally based on environmental conditions (Bannari et al., 2008; Elhag, 2016; Garajeh et al., 2021; Seifi et al., 2020). Based on previous studies, the most commonly utilised satellite salinity indices were selected and applied as input for ANN to predict soil salinity in the present study as detailed in Table 5-2.

Table 5-2: Spectral indices are derived from spectral reflectance at various bands and used for soil salinity prediction.

Indicates	Acronym	Formula	Reference
Normalized difference salinity index	NDSI	$(R - NIR)/(R + NIR)$	(Khan et al., 2005)
Brightness index	BI	$[(R)^2 + (NIR)^2]^{0.5}$	(Khan et al., 2005)
Salinity index 1	SI1	$(G \times R)/B$	(Douaoui et al., 2006)
Salinity index 2	SI2	$(B \times R)/G$	(Khan et al., 2005)
Salinity index 3	SI3	B/R	(Khan et al., 2005)
Salinity index 4	SI4	$(B \times R)^{0.5}$	(Khan et al., 2005)
Salinity index 5	S5	$(G \times R)^{0.5}$	(Khan et al., 2005)
Salinity index 6	SI6	$(R \times NIR)/G$	(Khan et al., 2005)
Salinity index 7	SI7	$[(R)^2 + (G)^2]^{0.5}$	(Douaoui et al., 2006)
Salinity index 8	SI8	$(B - R)/(B + R)$	(Douaoui et al., 2006)
Salinity index 9	SI9	$[(G)^2 + (R)^2 + (NIR)^2]^{0.5}$	(Abbas and Khan, 2007)
Normalized difference vegetation index	NDVI	$(NIR - R)/(NIR + R)$	(Khan et al., 2005)

B, blue band; G, green band; R, red band; NIR, near-infrared band of Landsat 5 images

5.2.3 Artificial Neural Networks (ANNs)

ANNs typically have three layers. The first layer is the input layer, which includes the independent variables (input parameters), and the second layer is a hidden layer, which sits between the input and the output. The hidden layer containing a number of units (a grouping of independent variables). These units, often known as 'neurons,' are used to guide data processing in the input layer and to build computational links between the input and output layers. The output layer, which is the dependent variable, is the third layer. The structure of the ANNs developed in this research is depicted in Figure 5-2.

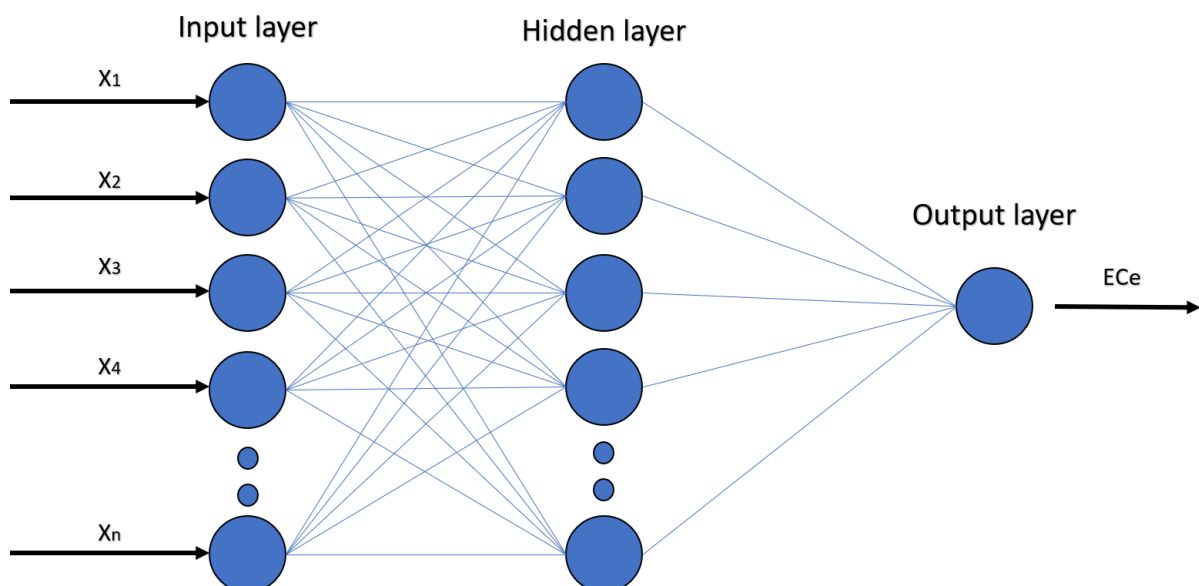


Figure 5-2: the structure of artificial neural network applied in this study, adopted from Ellafi et al., (2021).

For this research, the ANNs were developed following the steps described by Ellafi et al., (2021). In summary, three steps were undertaken in the development of ANNs to predict ECe values. In the first step, the dataset from both study area were combined (the remote sensing data used as an input and the measured data as an output) make a total sample size of 523 samples with 19 input parameters and 1 output (Table 5-3) shows the summary of the dataset). In the second step, the training and testing dataset was defined. Ninety percent of the dataset was defined as a training dataset, leaving 10% as a testing dataset.

In the third step, the appropriate network was defined using the sequential orthogonal approach (Ellafi et al., 2021; Sun, 2012). Table 5-3 shows the two ANNs developed in this study and the input parameters used for each ANN to predict ECe in HAP and EAP. Two groups of input parameters were used, the first group has six input parameters (i.e. Band 1 Visible (Blue), Band 2 Visible (Green), Band 3 Visible (Red), Band 4 Near-Infrared, Band 5 shortwave-infrared, and Band 7 shortwave infrared). The second group has nineteen input parameters included Band 1 Visible (Blue), Band 2 Visible (Green), Band 3 Visible (Red), Band 4 Near-Infrared, Band 5 shortwave-infrared, Band 7 shortwave infrared, Normalized difference salinity index, Brightness index, Salinity index 1, Salinity index 2, Salinity index 3, Salinity index 4, Salinity index 5, Salinity index 6, Salinity index 7, Salinity index 8, Salinity index 9, and Normalized difference vegetation index. The purpose for having two groups of input parameters was to determine the smallest data set necessary to accurately estimate ECe. Appendix C (especially Section C.4) covers more information related to all the ANNs applied in this Chapter including the pre-processing steps to prepare the data, the functions applied, the codes written, and other outputs.

Table 5-3: Statistical summary of the dataset used in this research

Variable	Min	Max	Average	STDEV	Median	SE
BI	3406	6275	4341	433	4309	19
Blue	788	1760	1068	150	1038	6.6
Green	1265	2990	1737	275	1674	12
NDSI	-0.52	-0.03	-0.24	0.09	-0.24	0
NDVI	0.03	0.52	0.24	0.09	0.24	0
NIR	2798	4890	3686	340	3693	15
Red	1363	4125	2265	447	2187	20
SI1	2108	7008	3691	816	3509	36
SI2	849	2428	1392	248	1346	11
SI3	0.39	0.6	0.48	0.04	0.48	0
SI4	1036	2694	1554	260	1500	11
SI5	1313	3512	1983	351	1913	16
SI6	3764	6553	4777	462	4735	20
SI7	1860	5095	2855	520	2752	23
SI8	-0.44	-0.25	-0.35	0.03	-0.35	0
SI9	3651	6951	4679	489	4619	21
SWIR1	2101	20000	3545	1236	3396	54
SWIR2	1145	5048	2443	710	2318	31
ECe	0.35	88	8.5	14.54	2.91	0.64

The ability of the two ANN models developed in this study to accurately predict ECe was critically evaluated in two steps. Step 1 involved developing ANNs using the training dataset and then utilising the testing dataset to select the best performing ANN model in terms of predicting ECe using three statistical parameters. These were: (1) the coefficient of determination (R^2) between the observed and predicted ECe values for the testing dataset (e.g., best performance equals 1), (2) the mean square error (MSE), and (3) the root mean square error (RMSE) (Ellafi et al., 2021) which can be defined mathematically as:

$$R^2 = 1 - \frac{\sum_{i=1}^n (P_i - M_i)^2}{\sum_{i=1}^n (M_i - \bar{M}_i)^2} \quad (5-1)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (P_i - M_i)^2 \quad (5-2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (P_i - M_i)^2}{n}} \quad (5-3)$$

Where n represents the number of soil samples, M_i is the measured ECe, P_i is the predicted ECe, and $\bar{M}_i$ is the mean measured ECe

In Step 2 the developed ANNs were tested by applying the K-fold cross validation technique (Bell, 2015; Ghatak, 2019). In the K-fold cross-validation the dataset was split into ten randomly generated subsets. Nine sub-sets were merged and used as the 'training sub-set' for each K-fold cross-validation, while one part was used as the 'testing sub-set'. This procedure was iterated 10 times, each time “rotating out” a testing sub-set, ensuring that each sub-set used in each ANN was tested. Figure 5-3 illustrates the structure of the cross validation for the dataset divided into 10 subsets. The MSE mean average of the 10 iteration was taking and compared to the MSE gathered from Step 1. This approach was used to quantify the performance of the developed ANNs (ANN1 and ANN2).

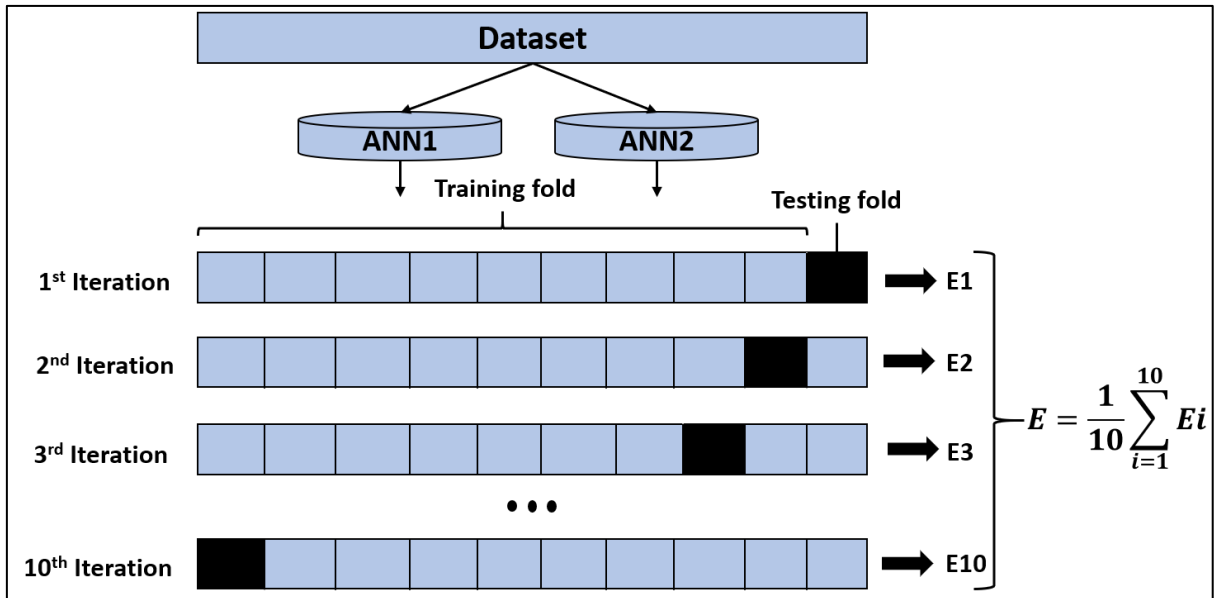


Figure 5-3: A schematic illustration of K-fold cross-validation for K = 10. Where E1 – E10 are the Mean Square Error for each iteration. E is the mean average of E1 – E10.

Finally, the most accurate ANN based on Step1 and Step 2 were then applied to predict soil salinity in years 1990, 2000, and 2010 for EAP and HAP. The predicted values were then used to create soil salinity maps using the classification described by the Food and Agriculture Organization (FAO) (FAO, 1988). The maps were then used to evaluate the salinity status in both EAP and HAP. Table 5-4 shows the soil salinity classes recognised by the FAO (FAO, 1988).

Table 5-4: soil salinity classes and crop growth

Soil salinity class	Soil salinity (ECe in dS m ⁻¹)	Effect on crop plants
Non saline	0 – 2	Salinity effects negligible
Slightly saline	2 – 4	Yields of sensitive crops may be restricted
Moderately saline	4 – 8	Yields of many crops are restricted
Strongly saline	8 – 16	Only tolerant crops yield satisfactorily
Very strongly saline	> 16	Only a few very tolerant crops yield satisfactorily

Where ECe is the electrical conductivity of the saturated paste extract, dS m⁻¹ is a ECe unit are Deci Siemens per meter.

5.2.4 DRAINMOD

DRAINMOD is a field scale computer simulation model for shallow water table soils, which was developed for agriculture fields to design and evaluate drainage systems (Skaggs et al., 2012b). The model needs a range of input parameters (i.e., climatic, soil-water, drainage design, and crop information). The input data for DRAINMOD were gathered during site studies of soil properties in EAP (Cornelius-Brochier J.V, 1981; Italconsult, 1976) and HAP (Danenco, 1980; Holzmann-Wakuti, 1974). The impervious layer depth in EAP and HAP was also determined by site studies. Crop data for beans, maize, soybeans, and wheat were gathered in accordance with the recommendations from the following studies (Evans et al., 1991; Kandil et al., 1995; Maas and Hoffman, 1977). This crop rotation was chosen because it is common in Egypt's Nile Delta (an arid area, with similar climate conditions to EAP and HAP). Additionally, the Libyan General Water Authority (GWA) recommends growing beans, maize, soybeans, and wheat in EAP and HAP (GWA, 1999). The climatic data required to run DRAINMOD was generated from the closest meteorological stations to EAP (Sabha meteorological station located 50 km south of EAP) and HAP (Hon meteorological station located 15 km east of HAP) for the period from 1981 – 2010. Table 5-5 provides a summary of the input data applied in DRAINMOD.

DRAINMOD required the initial soil salinity as an input parameter for the 30-year simulations (1981 – 2010) in HAP and EAP. As there were 523 ECE measurement, representative values were needed to reduce the number of simulations. Therefore, the measured values of ECE were categorised based on FAO soil salinity classes (see Table 5-4). The average value of each category was assumed as a representative value of that class and used as an input for DRAINMOD. Therefore, DRAINMOD was run five times in each project for the period 1981 – 2010. Two scenarios were assumed in DRAINMOD. The first scenario assumed that a drainage system was installed and maintained properly. The second scenario assumed there to be no drainage system installed (Undrained). DRAINMOD does not have an option to simulate without including the drainage design parameters (drain depth and spacing).

Therefore, by having a wider distance between drains (i.e. 500 m) the undrained assumption can be achieved. The median ECe values for the four years, 1981, 1990, 2000, and 2010, were selected to create soil salinity maps for scenarios in EAP and HAP. Finally, the maps were used to evaluate the importance of installing drainage system for salinity control. The relative yield for the 30-year simulations (1981 – 2010) in HAP and EAP were obtained for both scenarios.

Table 5-5: Summary of the input data required to run the DRAINMOD 30-year simulation

Input parameter	EAP	HAP
Drainage design		
Drain spacing (m)	50	50
Drain depth (cm)	100	100
Depth of restricting layer (cm)	150	150
Effective radius (cm)	1.5	1.5
Drainage coefficient (cm d ⁻¹)	2.5	2.5
Initial water table depth (cm)	50	50
Soil property		
Saturated hydraulic conductivity above drains (m d ⁻¹)	2.6	11.2
Saturated hydraulic conductivity below drains (m d ⁻¹)	5.6	4.5
Saturated water content (cm ³ cm ⁻³)	0.35	0.35
Water content at lower limit (cm ³ cm ⁻³)	0.08	0.04
Required drainage for field work (cm)	3.9	3.9
Climatic data		
Daily ET ₀ (mm d ⁻¹)	Generated from Chapter 4	Generated from Chapter 4

Table 5-5 continued								
Daily rainfall (mm d ⁻¹)	Observed precipitation at Sabha station				Observed precipitation at Hon station			
Crop information	Beans	Maize	Soybeans	Wheat	Beans	Maize	Soybeans	Wheat
Number of years for rotations	10	10	10	9	10	10	10	9
Soil salinity threshold (mg l ⁻¹)	640	1088	4000	3800	640	1088	4000	3800
Slope for higher soil salinity values (% per mg l ⁻¹)	2.97×10 ⁻²	1.88×10 ⁻²	2.50×10 ⁻²	7.10×10 ⁻³	2.96×10 ⁻²	1.88×10 ⁻²	2.50×10 ⁻²	7.10×10 ⁻³
Relative yield without deficit stress (%)	100	100	100	100	100	100	100	100
Slope for yield versus deficit stress-day-index	7.20	1.22	7.2	1.22	7.20	1.22	7.20	1.22
Relative yield without wet stress (%)	100	100	100	100	100	100	100	100
Slope for yield versus wet stress-day-index	0.65	0.71	0.65	0.71	0.65	0.71	0.65	0.71
Irrigation water salinity (dS m ⁻¹)	1.25				3.91			
Soil salinity								
Average salinity 0 – 2 in dS m ⁻¹	1.2				1.2			
Average salinity 2 – 4 in dS m ⁻¹	2.9				2.9			
Average salinity 4 – 8 in dS m ⁻¹	5.7				5.7			
Average salinity 8 – 16 in dS m ⁻¹	11.8				11.8			
Average salinity >16 in dS m ⁻¹	40.7				40.7			

5.2.5 Software used

The data was analysed using several software packages. The development of the ANNs utilised a neuralnet package in R (Stefan and Guenther, 2019). The remote sensing data was analysed using ArcGIS 10.7. ArcGIS was also used to create soil salinity maps. DRAINMOD was used to simulate and design drainage systems for salinity control.

5.3 Results

5.3.1 Performance of artificial neural networks to predict soil salinity

Table 5-6 summarizes the structure of the ANN1 and ANN2 developed in this research, as well as their step one performance evaluation. In both (training and testing) ANN1 and ANN2 were able to predict, based on R^2 , between 0.72 – 0.90 of the variability in ECe. As hypothesised, the ANN models performed better when training data was used rather than testing data. According to the performance results in Table 5-6, ANN2 performed better than ANN1 in both phases (training and testing). The R^2 in ANN2 ranged from 0.86 – 0.90, while in ANN1 ranged from 0.72 – 0.78.

Table 5-6: structure performance evaluation of ANN1 and ANN2 implemented in EAP and HAP to predict ECe (dS m⁻¹)

Model name	Training				
	Model structure*	Number of Samples	RMSE (dS m ⁻¹)	MSE (dS m ⁻¹)	R ²
ANN1	6:5:5:1	470	6.74	45.43	0.78
ANN2	18:15:15:1	470	4.60	21.02	0.90
Model name	Testing				
	Model structure*	Number of Samples	RMSE (dS m ⁻¹)	MSE (dS m ⁻¹)	R ²
ANN1	6:5:5:1	53	9.19	84.50	0.72
ANN2	18:15:15:1	53	6.35	40.36	0.86

Where: (*) is the model structure of the ANNs, for example 6:5:5:1, 6 is the number of neurons representing the input parameters, 5:5 two hidden layers with 5 neurons in each layer, and 1 is the output of the model.

The results of Step 2 K-fold cross-validation are shown in Figure 5-4. Figure 5-4 shows the median RMSE across 10 randomly generated subsets (dark line within the boxplot) when the size of the training set is fixed at 470 samples. The RMSE for ANN1 ranged between 6.7 – 11.3 dS m⁻¹, while in ANN2 RMSE ranged between 4.8 – 10.7 dS m⁻¹. Figure 5-5 shows the accuracy of ANN1 and ANN2 in predicting ECe in the training and testing datasets. The 1:1 line indicates the line of complete agreement between predicted and measured ECe values. It is worth noting that the predicted ECe values for ANN1 and ANN2 are close to the 1:1 line. The results indicate that ANN2 was noticeably better at predicting the observed ECe values compared to ANN1 applied to training and testing dataset (see Figure 5-5 and Table 5-6). In general, in both ANN1 and ANN2, there were noticeable outliers in the predicted values of soil sample based on ECe (10 – 40 dS m⁻¹). The outliers occurred on both sides of the 1:1 line and were relatively discrete (Figure 5-5). As expected, the predicted values of ANN1 and ANN2 in the training dataset were closer to the 1:1 line compared to the ANN1 and ANN2 in the testing dataset.

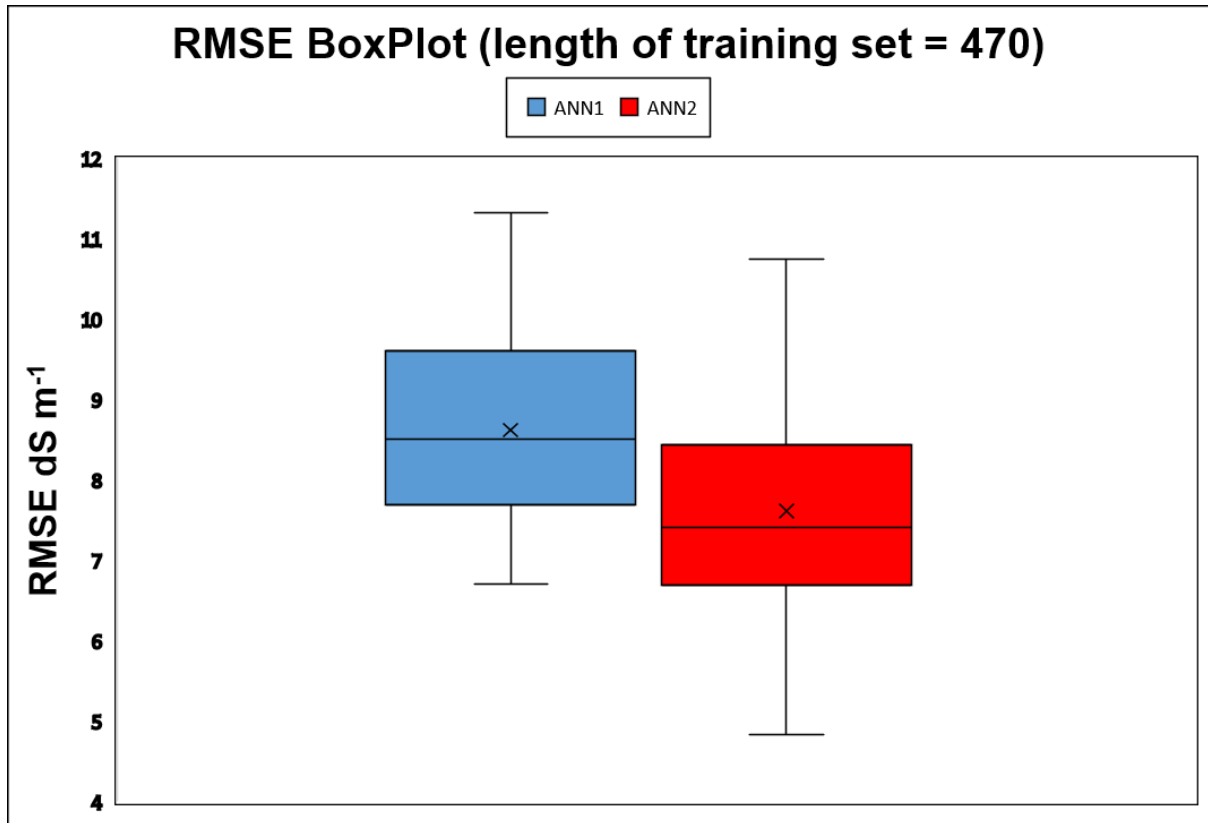


Figure 5-4: Boxplots of the median Root Mean Square Error (RMSE) for the Artificial Neural Networks (ANN1 and ANN2) developed to predict soil salinity.

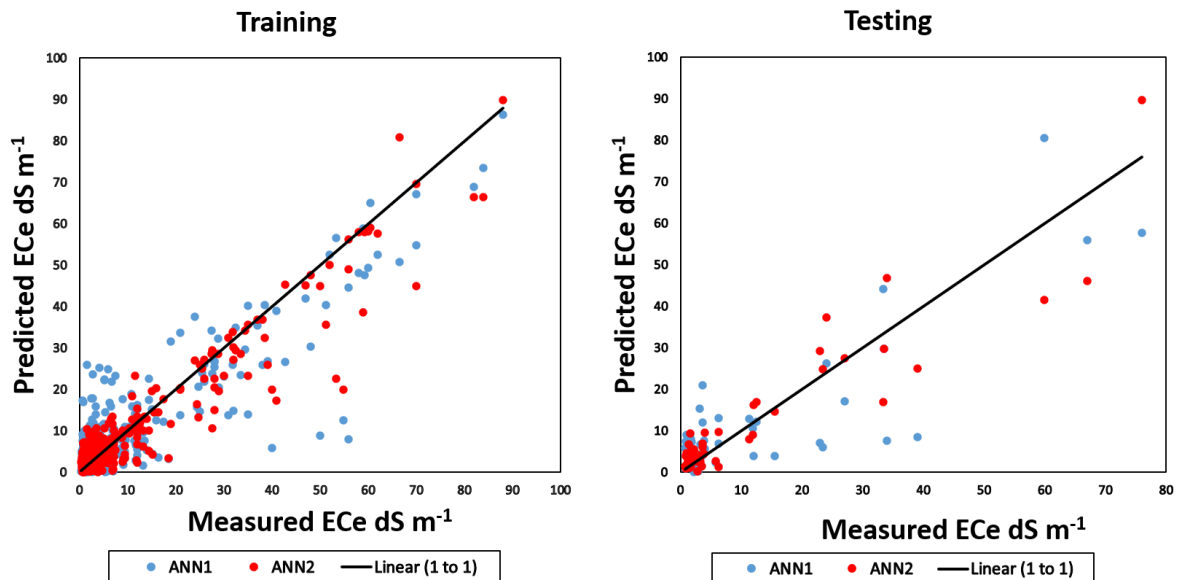


Figure 5-5: Predicted Electrical conductivity of the saturated paste extract (Ece in dS m⁻¹) versus measured Ece in both training and testing dataset.

In this section the performance of the developed ANNs to predict soil salinity is evaluated for salinity levels ranging between 0 – 20 dS m⁻¹. Figure 5-6 shows a

zoomed version of the scatter plot (values from 0 – 20 dS m⁻¹) of the predicted ECe versus the measured ECe for the values. The results indicate that ANN2 was noticeably still better at predicting the observed ECe values compared to ANN1 applied to training and testing dataset. However, there are a lot of noise in the data and the mispredictions are high. These results show that predicting soil salinity is a difficult and complicated task and developed ANNs need more work and maybe considering additional input parameters to improve the prediction.

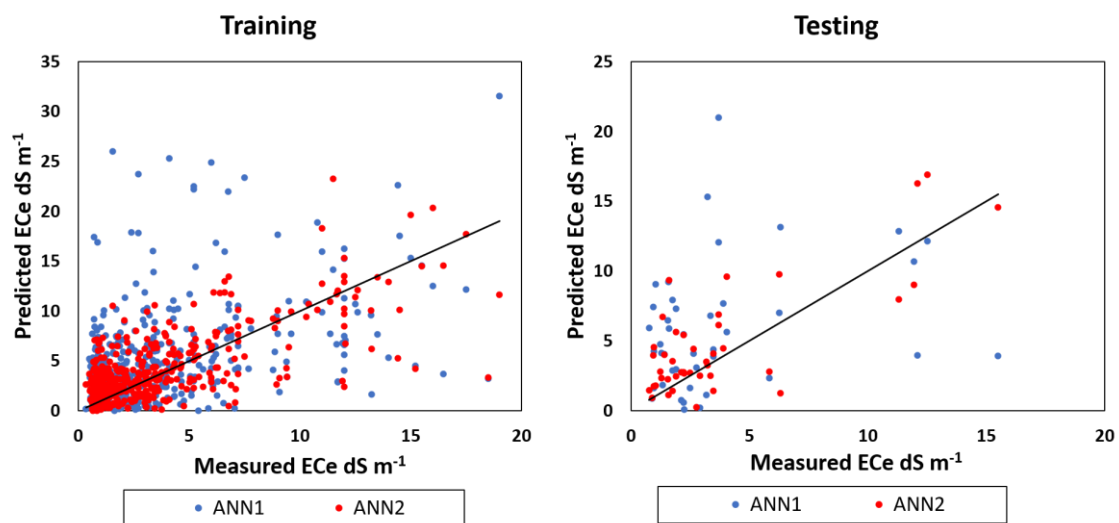


Figure 5-6: predicted ECe by ANN1 and ANN2 for the values ranging from 0 – 20 dS m⁻¹

5.3.2 Potential relative yield simulated by DRAINMOD and soil salinity prediction maps in EAP and HAP

The results of potential relative yields of the four simulated crops results for the 30-year simulation under drained and undrained scenarios are shown in Figure 5-7 for EAP and HAP. In EAP, the simulated relative yield under drained conditions ranged between 70 – 100% (see Figure 5-7d), while in HAP the simulated relative yield ranged between 30 – 100% (Figure 5-7b). In HAP, beans and maize got the relative yield ranging between 30 – 70%, while soybeans and wheat obtained relative yield ranging between 88 – 100%. For the undrained scenarios in EAP and HAP (Figure 5-7a and Figure 5-7c), there was a reduction in relative yield in all crops. The first reduction was noticed on beans, maize, and soybeans with relative yield ranged between 0 – 5% (see Figure 5-7a and Figure

5-7c). According to the simulation results in Figure 5-7a and c, wheat was the only crops to consistently produce a yield under undrained conditions. However, the expected relative yield under undrained conditions ranged between 6 – 38%. Figure 5-7 also shows a rapid decrease in yield for wheat from around 38% in 1981 to under 10% 1997 in both EAP and HAP.

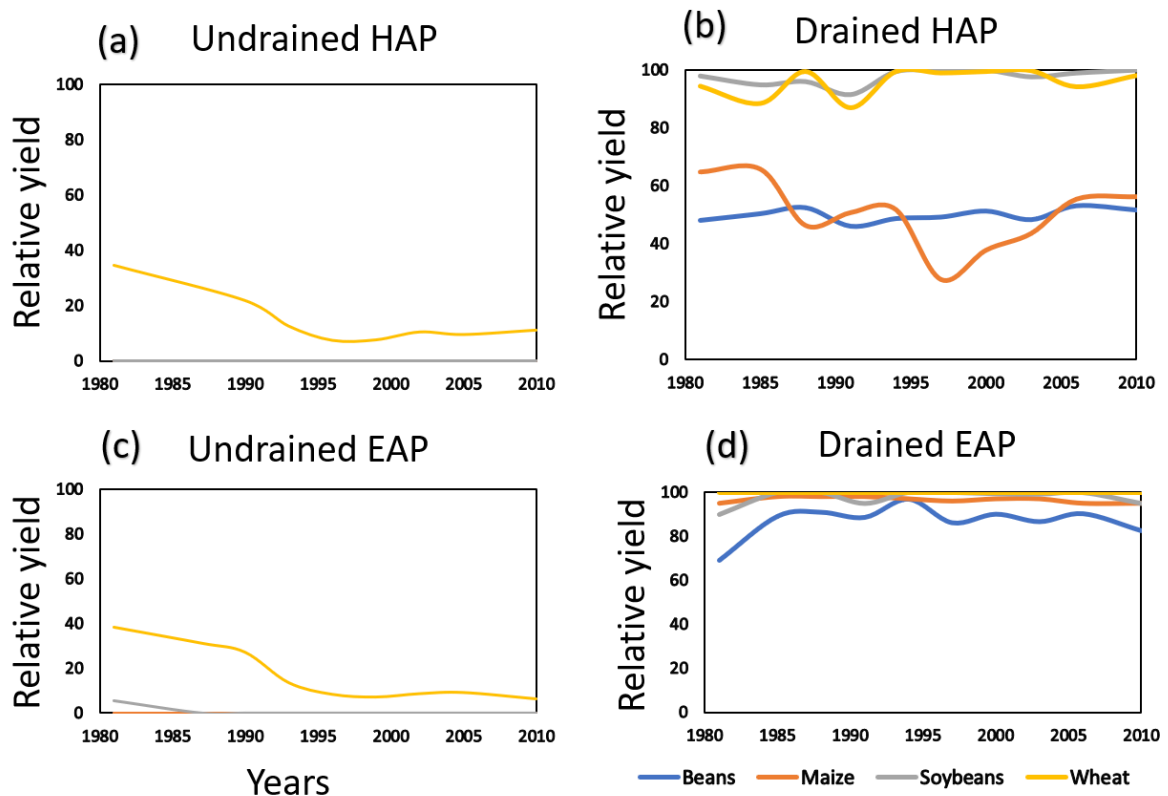


Figure 5-7 a-d: Relative yield results as a percentage for beans, maize, soybeans, and wheat under drained and undrained condition for Eshkeda Agricultural Project (EAP) and Hammam Agricultural Project (HAP) for 30-year simulation.

Figure 5-8 shows the salinity prediction maps of EAP, as predicted with a drainage system installed, without a drainage system installed (DRAINMOD simulation) and based on a prediction using the current salinity condition (ANN2). In Figure 5-8 maps (a), (b), (c), and (d) show the median soil salinity levels in EAP under the current conditions predicted by ANN2 in 1981, 1990, 2000, and 2010 respectively. The current conditions in EAP and HAP which means there are drainage systems installed in EAP and HAP, however, these systems are not

maintained properly (for more information see Appendix A, B and D). From these maps, an increase in soil salinity is noted in 1990 (Figure 5-8b), 2000 (Figure 5-8c), and 2010 (Figure 5-8d) compared to 1981 (Figure 5-8a) (see the red spots in maps Figure 5-8b, c and d). Figure 5-8e, f, g and h show the median salinity conditions simulated by DRAINMOD under drained conditions for years 1981, 1990, 2000, 2010 respectively. From these maps, it is notable that the majority of the area is classified as non-saline, with only a few locations in Figure 5-8e classified as slightly saline.

In comparison, the maps shown in Figure 5-8i, j, k and l, represent the median salinity conditions simulated by DRAINMOD under undrained conditions for years 1981, 1990, 2000, 2010 respectively. From these maps, an increase in soil salinity is evident in maps shown in Figure 5-8k and l compared to Figure 5-8i. For example, maps shown in Figure 5-8k (in 2000) and Figure 5-8l (in 2010) are classified as very strongly saline soils, while the map shown in Figure 5-8i (in 1981) has a higher proportion of the area classified as slightly saline.

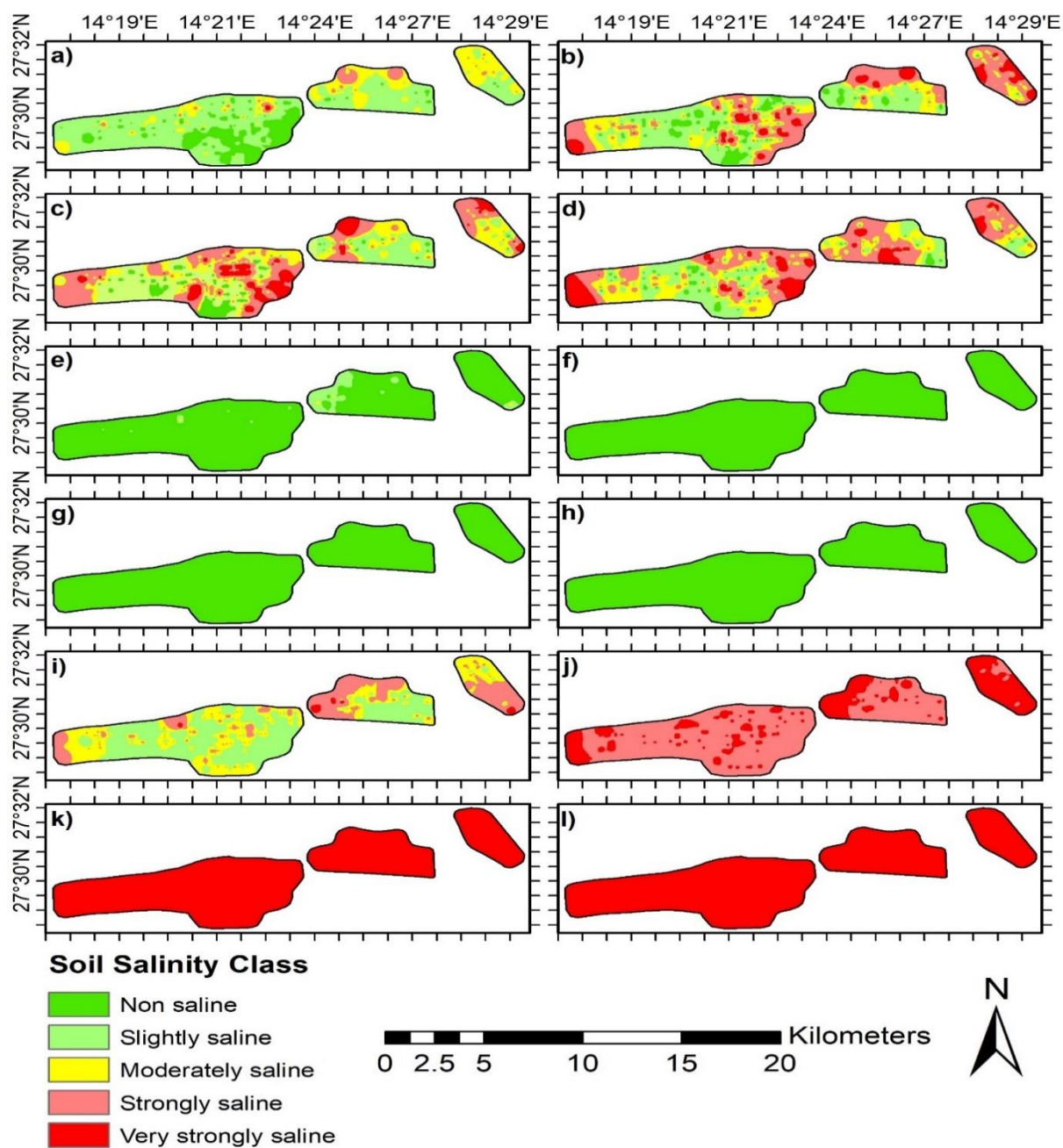


Figure 5-8: the median soil salinity levels in Eshkeda Agricultural Project (EAP).

Figure 5-9 shows the soil salinity prediction maps, with drainage system installed, without drainage system installed (DRAINMOD simulation) and predicting the current salinity condition (ANN2) for HAP. The maps in Figure 5-9 are shown in three groups. The first group includes maps shown in Figure 5-9a, b, c and d, these maps represent the predicted salinity levels based on ANN2 in 1981, 1990, 2000, and 2010 respectively. These maps show, salinity status to be mainly classified as either strongly saline or very strongly saline. Also, there is a slight increase in the proportion of the mapped area that is classified as very strongly saline class in the map in Figure 5-9d (representing 2010) compared to maps in Figure 5-9a, b and c. The second group of maps (Figure 5-9e, f, g and h) show the median salinity conditions simulated by DRAINMOD under drained conditions for years 1981, 1990, 2000, 2010 respectively. From these maps, it is noticeable that the soil salinity in all maps is classified as slightly saline. The third group of maps (Figure 5-9i, j, k and l), show the median salinity conditions simulated by DRAINMOD under undrained conditions for the years 1981, 1990, 2000, 2010 respectively. In these maps, only two classes are represented, strongly saline and very strongly saline. Also, it is notable that maps in Figure 5-9j, k and l are only classified as have very strongly saline class.

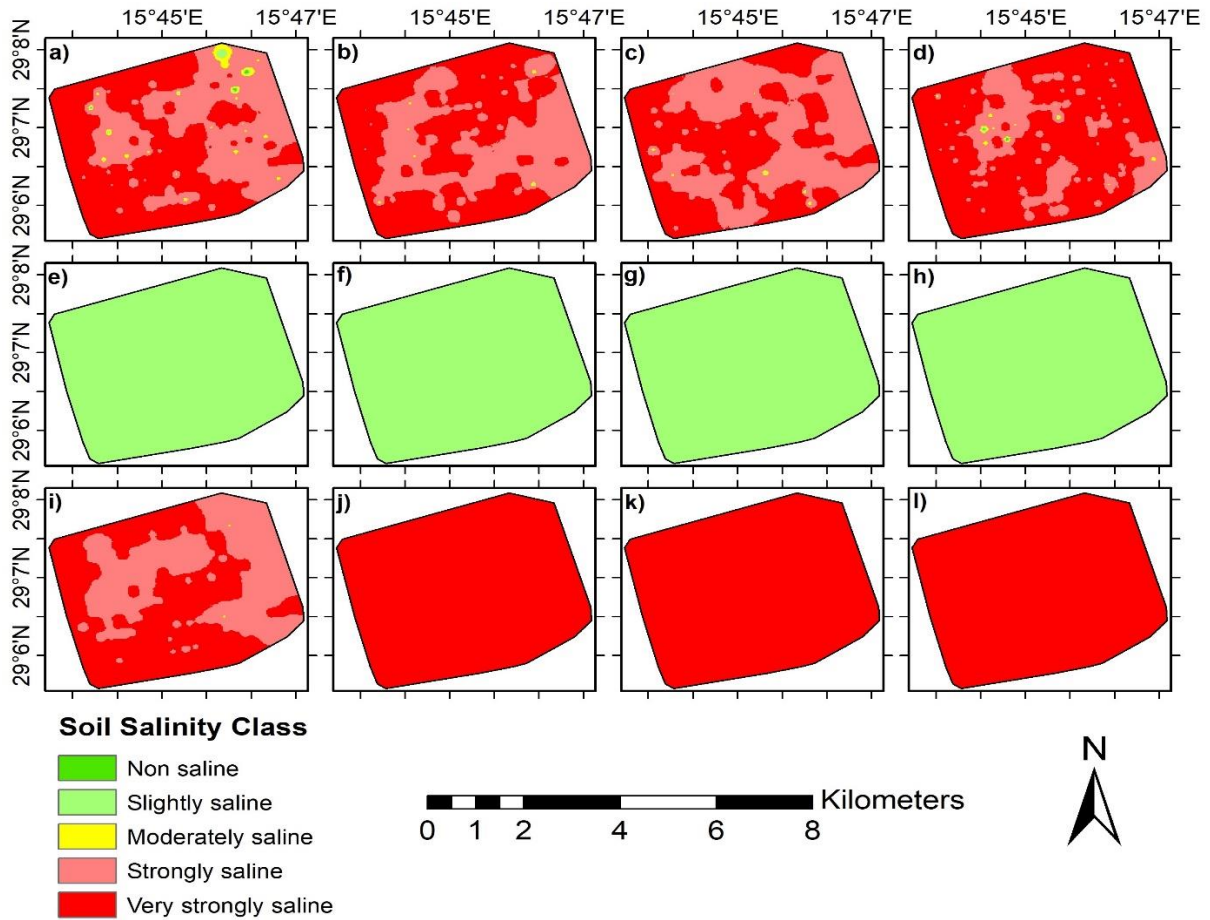


Figure 5-9: the median soil salinity levels in Hammam Agricultural Project (HAP).

5.4 Discussion

5.4.1 Development of ANNs

Using spectral variables to invert soil salt content requires a good mathematical regression model. Artificial neural networks have been widely used in predicting soil properties and modelling (Ellafi et al., 2021; Gholami et al., 2021; Wang et al., 2021; Yang et al., 2020). Wang et al. (2021) developed an ANN that could predict soil salinity with an accuracy of 0.57 in R^2 within the testing dataset. Wang et al. (2021) claim that the low R^2 accuracy is due to the limited number of samples used to develop the ANN (only 160 samples). In contrast, in this study 523 samples were used to develop ANN1 and ANN2 and the accuracy ranged between 0.72 – 0.86 in R^2 (see Table 5-6). Therefore, the results from this research support the findings from Wang et al. (2021), with respect to the performance of the developed ANN being dependent on the number samples in

the training process. Also, the size of the dataset and the range of values within that dataset will also influence the performance of the ANN. If the value range is small, the variance will be small and the offset will be big, making the prediction in the training set much precises than the testing set.

The results of this study showed that ANN2 was 45% more accurate than ANN1 according to the RMSE in the testing set (ANN1 = 9.19 dS m⁻¹, and ANN2 = 6.35 dS m⁻¹). This finding resonates with that of Shahabi et al. (2016). Shahabi et al. (2016) found that the choice of bands and salinity indices as input variables in the ANN model was important and helped to improve the accuracy of the prediction from 0.62 to 0.82 in R². The smallest RMSE obtained by Shahabi et al. (2016) was 11.60 dS m⁻¹ while ANN1 and ANN2 were able to obtain smaller RMSE of 9.19 and 6.35 dS m⁻¹, respectively.

Additionally, Akramkhanov and Vlek. (2012) and Ghorbani et al. (2019) highlighted the advantages of neural networks over other nonlinear techniques for measuring soil surface salinity. Akramkhanov and Vlek. (2012) reported an R² of 0.83 for salinity prediction, whereas Ghorbani et al. (2019) claimed an accuracy of 0.82. Their studies are virtually identical to the current study in terms of the proposed technique and the accuracy of the results. Mohamed et al. (2018) and Morgan et al. (2018) validate the advantages of using bands including visible blue, green, red and Near-Infrared bands in combination with a neural network to map soil salinity, which corroborates our findings. Morgan et al. (2018) used NDVI spectral indices with ANN to produce a salinity map with 0.94 in R² (slightly more accurate than ANN1 and ANN2 with accuracy ranged between 0.72 – 0.86 in R²). Jin et al. (2015) emphasised the importance of using spectral indices from satellite images to create a salinity map as one of the most effective and significant elements in desertification. They agreed that by utilising these indices, soil salinity may be detected, and the kind of salinity determined.

5.4.2 DRAINMOD applications

The results of the simulated drained conditions (see Figure 5-7b and d), even though drainage systems were assumed to be installed in EAP and HAP, resulted

in different relative yields of the crops between the two projects (EAP has much higher yield compared to HAP). For example, the average relative yield in EAP was higher than HAP by 37%, 47%, 0.4% and 4% for beans, maize, soybeans and wheat respectively. The reduction in yield, in HAP, was probably caused by the quality of irrigation water applied (3.91 dS m^{-1}) compared to the irrigation water quality in EAP (1.25 dS m^{-1}). According to the Food and Agriculture Organisation (FAO), if the irrigation water quality (IWQ) applied for wheat exceeds 3.8 dS m^{-1} but less than 5 dS m^{-1} the expected yield will be above 90% but less than 100%, which was true in HAP where IWQ was 3.91 dS m^{-1} and the average yield was 96%. Also, the results of this study showed that an average relative yield of 100% was obtained for wheat in EAP when IWQ was at 1.25 dS m^{-1} (FAO, 1994). The same was true for the other crops (beans, maize and soybeans) simulated in this study, where the obtained yield matched the predicted yield for a specific IWQ. For more information about the influence of IWQ on crop tolerance and crop yield see the Water Quality for Agriculture by FAO (FAO, 1994).

The results of undrained conditions in EAP and HAP show that the predicted yield for beans, maize and soybeans were 0% (except for the years between 1981 – 1985 in EAP where the relative yield ranged between 1 – 7%). Only wheat was considered able to grow and to produce a predicted yield in EAP and HAP. However, a declining trend in the relative yield is showing in Figure 5-7a and c. That decline results in a 30% reduction in predicted yield in both EAP and HAP. According to Kale, (2012) the reason for this is most likely due to the aggravated problems of waterlogging and salinity. Which is true as showing in Figure 5-7 and the predicted soil salinity maps in Figure 5-8 and Figure 5-9 in EAP and HAP (maps j, k and l in Figure 5-8 and Figure 5-9 a noticeable increase of soil salinity for the years 1990, 2000, and 2010 in both EAP and HAP). On drained soils the relative yield of wheat was at least 50% higher compared to the undrained soils. Which is a considerable advantage and shows the importance of installing a drainage system. Based on simulated results and field measurements, Kale (2012) claimed that installing a drainage system in a semi-arid area in Turkey,

increased the overall yield of wheat and beans by 36%. The selection of a crop to grow in a specific area is also an important consideration and should be done by monitoring the soil salinity, IWQ and the condition of drainage system installed.

5.4.3 Soil salinity mapping

Maps shown in Figure 5-8 a – d and Figure 5-9 a – d, show the current soil salinity situation in EAP and HAP for the years 1981, 1990, 2000, and 2010 respectively. From these maps, it can be noticed that the current drainage systems in both projects did not help to reduce the salinity stress. According to the World Bank Organisation (WBO), it is a common problem in least developed countries, because of the lack of financial resources for drainage system design, operation, and management, as well as a lack of stakeholder participation (rather than drainage users) (Knecht, 2000), (which is true for EAP and HAP). Ahmed and Ramadan. (2007) studied the irrigation water quality in EAP and suggested that installing and maintaining an adequate drainage system would help to reduce the salinity problem in the project. Ramadan and Elssaidi. (2017) have also done research on the soil salinity issues in the region including EAP and their recommendation was to improve the drainage system to lower the shallow water table and grow more tolerant crops. In addition, Ramadan and Elssaidi. (2017), suggested that a model needed to be developed to predict soil salinity in the region including EAP.

The situation is similar in HAP, where the drainage is not maintained properly resulting in high soil salinity status. In 2003, the General Water Authority in Libya (GWA) found that open ditches at HAP were blocked and causing waterlogging and salinity problems (GWA, 2003). Later on GWA contracted a local company to help with cleaning and unblock those ditches (GWA, 2003). The National Committee to Combat Desertification in Libya (NCCD) evaluated the situation at HAP and they found the main problems facing the farmers at HAP are similar to the ones in EAP. The first problem is the soil salinity as the salt spot can be easily seen on the soil surface. The second problem is the shallow water table caused by over irrigation by the farmers (trying to flush the salt). The over irrigating

caused another problem which is water scarcity (pumping from non-rechargeable aquifer). Finally, the current drainage system is ineffective (NCCD, 2005). Experts from the GWA in Libya visited the HAP in 2007, and their recommendations were to design and install a new drainage system as the current one was ineffective (GWA, 2007).

Maps in Figure 5-8 and Figure 5-9 (e, f, g and h) show how the salinity situation would be if a drainage system were installed and maintained properly in EAP and HAP for the simulated years 1981, 1990, 2000, 2010 respectively. From these maps the importance of having a proper drainage system is noticeable. In EAP and HAP, the soil salinity decreased and the salinity classes in all the project converted to non-saline soils (in EAP, see Figure 5-8) and slightly saline soils (in HAP, see Figure 5-9). Also, it helped to improve the potential crop yield. The maps in Figure 5-8 and Figure 5-9 (i, j, k, and l) show the simulation results of how the salinity situation will be in EAP and HAP if no drainage system were installed for the years 1981, 1990, 2000, and 2010 respectively. For both projects, it is notable that the salinity levels increased, and the soil salinity class became very strongly saline at the end of the simulations (see Figure 5-8 and Figure 5-9). Also, as a result of the that, a massive reduction of crop yields was noted (Figure 5-7). These findings highlight the importance of installing a drainage system to reduce salinity issues and increase production. In addition, the findings of this study clearly illustrate the relationship between drainage design and soil salinity. This supports the frequently stated proposition that drainage, irrigation, and salinity control for arid lands should be considered as components of a water management system and that the design of each component should be dependent on the design of the other components.

5.4.4 Uncertainty in generating ECe values using ANNs

The evaluation of the developed ANNs to predict soil salinity indicates a significant amount of uncertainty in the results. The scatter plot of the predicted ECe versus the measured ECe values reveals a considerable amount of noise in the data, which could be due to a variety of factors. For instance, the data used

to train and test the ANNs may not be representative of the broader population or the quantity of the dataset is not enough to develop more accurate ANNs. Furthermore, there may be errors in the data collection process or measurement errors that contribute to the uncertainty in the results. This assumption is unlikely to happen because the dataset was collected from different soil survey (see Appendix A, B and D).

Another factor may contribute to the uncertainty of the results is the complexity of the prediction task. Predicting soil salinity is a complicated task, and there are many variables that can influence the results. For example, soil type, irrigation practices, irrigation water quality, and climate conditions can all affect soil salinity. The ANNs may not have been able to capture all of the relevant variables (as it was developed using satellite images only), resulting in additional uncertainty in the results.

Despite these uncertainties, the ANNs still showed promise in predicting soil salinity, particularly when compared to conventional statistical models. However, to reduce the level of uncertainty and improve the accuracy of the predictions, additional research is needed. This could include refining the ANNs with additional input parameters, improving the data collection process, and conducting more rigorous testing to ensure that the results are representative of the broader population. Ultimately, by reducing the level of uncertainty in the results, the ANNs can be used to inform decisions related to soil management, helping to improve soil health and productivity.

Using satellite images as input for ANNs to predict soil salinity can also contribute to uncertainty in the results. Satellite images can provide valuable information about land use, vegetation cover, and soil moisture, which can all affect soil salinity. However, there are several factors that can affect the accuracy of the satellite images, and thus the accuracy of the ANNs predictions. One of the key factors affecting the accuracy of satellite images is atmospheric interference. Atmospheric conditions such as clouds, haze, and aerosols can all affect the quality of the satellite images, making it difficult to extract accurate information

from them. This can lead to uncertainty in the input data used to train the ANNs. However, in this study, the dataset were corrected using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS), and include a cloud, shadow, water, and snow mask produced using C Version of Function of Mask (CFMASK), as well as a per-pixel saturation mask (Gorelick et al., 2017).

Another factor is the spatial resolution of the satellite images. The spatial resolution determines the level of detail captured in the images. Higher resolution images can capture more detailed information, but they may not cover a large enough area to be representative of the broader population. Lower resolution images, on the other hand, may cover a larger area, but they may not provide enough detail to accurately capture the variables affecting soil salinity. In this study, Landsat 5 was used as the measured ECe data were from the 1980s. Landsat 5 has a spatial resolution of 60 meters compared to only 15 meters spatial resolution in Landsat 8. Therefore, if this work will be replicated using more recent measured ECe and Landsat 8, the accuracy of the developed ANNs may improve.

To reduce the uncertainty in the results when using satellite images as input for ANNs to predict soil salinity, it is important to address these factors. This can include using high-quality satellite images with a suitable spatial and temporal resolution, calibrating and validating the algorithms used to process the satellite images, and combining the satellite images with other sources of data to improve the accuracy of the predictions. Additionally, it is important to acknowledge the uncertainty in the results and communicate this uncertainty to users to ensure that decisions are not based solely on the ANNs predictions.

5.5 Conclusions

Artificial neural networks (ANNs) as an indirect method of predicting soil salinity from the reflections of the satellite images have been successfully applied by researchers (Ghorbani et al., 2019; Habibi et al., 2021; Mohamed et al., 2018; Morgan et al., 2018; Shahabi et al., 2016). ANNs were applied to predict soil salinity in two case study drainage schemes in the south of Libya.

It was shown that artificial neural networks developed from the reflection bands of satellite images and the derived salinity indices were capable of making highly accurate predictions of soil salinity. Additionally, predictions of soil salinity based on ANN generated using both reflection bands and salinity indices were slightly more comparable to observed soil salinity than predictions based only on reflection bands. The more accurate ANN were then successfully applied to predict the soil salinity status in different years to evaluate the effectiveness of the current drainage systems in two case study. In addition, DRAINMOD was applied to simulate the crop yield and salinity levels under drained and undrained conditions. The results suggest that having an effective drainage system installed and maintained properly can help to improve the potential crop yield and control the salinity stress in agricultural lands. Also, the results suggest that ANNs can be used as a tool to evaluate an existing drainage system and specify an area in need of improvement. However, further research is needed to evaluate the productivity of existing agricultural projects under salinity stress using ANNs combined with the applications of DRAINMOD in other least developed countries. These tools are of value to farmers and decision-makers, helping them to evaluate the most appropriate drainage design to maximise crop production.

5.6 References

Abbas, A., Khan, S., 2007. Using Remote Sensing Techniques for Appraisal of Irrigated Soil Salinity, in: MODSIM 2007 International Congress on Modelling and Simulation. Modelling and Simulation Society of Australia and New Zealand, Bright, Australia.

Ahmed, O., Ramadan, A., 2007. The effect of irrigation water on soil deterioration in the region of Wadi Ashati, in: Desert and Desertification Conference. Sabha University, Sabha, Libya, pp. 1–10.

Akramkhanov, A., Vlek, P.L.G., 2012. The assessment of spatial distribution of soil salinity risk using neural network. *Environ. Monit. Assess.* 184, 2475–2485. <https://doi.org/10.1007/s10661-011-2132-5>

Asfaw, E., Suryabhagavan, K. V., Argaw, M., 2018. Soil salinity modeling and mapping using remote sensing and GIS: The case of Wonji sugar cane irrigation farm, Ethiopia. *J. Saudi Soc. Agric. Sci.* 17, 250–258. <https://doi.org/10.1016/j.jssas.2016.05.003>

Bannari, A., Guedon, A.M., El-Harti, A., Cherkaoui, F.Z., El-Ghmari, A., 2008. Characterization of Slightly and Moderately Saline and Sodic Soils in Irrigated Agricultural Land using Simulated Data of Advanced Land Imaging (EO-1) Sensor. *Commun. Soil Sci. Plant Anal.* 39, 2795–2811. <https://doi.org/10.1080/00103620802432717>

Bell, J., 2015. Machine Learning with R, 2nd ed, Machine Learning. PACKT, Birmingham. <https://doi.org/10.1002/9781119642183.ch14>

Brika, B., 2018. Water Resources and Desalination in Libya: A Review. *Proceedings* 2, 586. <https://doi.org/10.3390/proceedings2110586>

CEDARE, 2014. Libya Water Sector M&E Rapid Assessment Report. Monitoring & evaluation for water in North Africa (MEWINA) Project.

Cornelius-Brochier J.V, 1981. Wadi Al Shatti: Drainage Design. Tripoli, Libya.

Danenco, 1980. Technical Study for Jufra el Hamam Project. Copenhagen, Denmark.

Douaoui, A.E.K., Nicolas, H., Walter, C., 2006. Detecting salinity hazards within a semiarid context by means of combining soil and remote-sensing data. *Geoderma* 134, 217–230.
<https://doi.org/https://doi.org/10.1016/j.geoderma.2005.10.009>

Elhag, M., 2016. Evaluation of Different Soil Salinity Mapping Using Remote Sensing Techniques in Arid Ecosystems , Saudi Arabia. *J. Sensors* 2016, 1–8.

Ellafi, M.A., Deeks, L.K., Simmons, R.W., 2021. Application of artificial neural networks to the design of subsurface drainage systems in Libyan agricultural projects. *J. Hydrol. Reg. Stud.* 35, 1–17.
<https://doi.org/https://doi.org/10.1016/j.ejrh.2021.100832>

Evans, R.O., Skaggs, R.W., Sneed, R.E., 1991. Stress Day Index Models to Predict Corn and Soybean Relative Yield Under High Water Table Conditions. *J. Am. Soc. Agric. Eng.* 34, 1997–2005.

FAO, 2018. FAOSTAT statistical database.

FAO, 2016. Country profile - Libya. Rome, Italy.
<https://doi.org/10.1787/9487b828-en>

FAO, 1994. Water quality for agriculture, Rev. 1. ed. FAO Irrigation and Drainage Paper 29, Rome, Italy.

FAO, 1988. Salt-Affected Soils and their Management [WWW Document]. Food Agric. Organ. URL <http://www.fao.org/docrep/x5871e/x5871e00.htm#Contents> (accessed 2.5.18).

- Garajeh, M.K., Malakyar, F., Weng, Q., Feizizadeh, B., Blaschke, T., Lakes, T., 2021. An automated deep learning convolutional neural network algorithm applied for soil salinity distribution mapping in Lake Urmia, Iran. *Sci. Total Environ.* 778, 1–16.
<https://doi.org/https://doi.org/10.1016/j.scitotenv.2021.146253>
- Ghatak, A., 2019. *Deep learning with R*. Springer Nature Singapore Pte Ltd, Kolkata, India. <https://doi.org/10.1007/978-981-13-5850-0>
- Gholami, V., Sahour, H., Hadian Amri, M.A., 2021. Soil erosion modeling using erosion pins and artificial neural networks. *CATENA* 196, 1–11.
<https://doi.org/https://doi.org/10.1016/j.catena.2020.104902>
- Ghorbani, M.A., Deo, R.C., Kashani, M.H., Shahabi, M., Ghorbani, S., 2019. Artificial intelligence-based fast and efficient hybrid approach for spatial modelling of soil electrical conductivity. *Soil Tillage Res.* 186, 152–164.
<https://doi.org/https://doi.org/10.1016/j.still.2018.09.012>
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sens. Environ.* 202, 18–27.
<https://doi.org/https://doi.org/10.1016/j.rse.2017.06.031>
- Gupta, G.P., Prasher, S.O., Chieng, S.T., Mathur, I.N., 1993. Application of DRAINMOD under semi-arid conditions. *Agric. Water Manag.* 24, 63–80.
- GWA, 2007. A field visit to Hammam Agricultural project to investigate the Sokna flood. Tripoli, Libya.
- GWA, 2003. Report on the Hammam Agricultural Project and the current drainage system in Jufra district. Tripoli, Libya.
- GWA, 1999. Water and irrigation requirements for the most important crops in Libya [unpublished report]. Tripoli.

Habibi, V., Ahmadi, H., Jafari, M., Moeini, A., 2021. Mapping soil salinity using a combined spectral and topographical indices with artificial neural network. PLoS One 16, 1–13. <https://doi.org/10.1371/journal.pone.0228494>

Holzmann-Wakuti, 1974. Hydrogeology of The Joufrah Project Area. Tripoli, Libya.

Italconsult, 1976. Fezzan Land Reclamation Project: Wadi-Shati Eshkeda Area. Rome, Italy.

Jin, P., Li, P., Wang, Q., Pu, Z., 2015. Developing and applying novel spectral feature parameters for classifying soil salt types in arid land. Ecol. Indic. 54, 116–123. <https://doi.org/https://doi.org/10.1016/j.ecolind.2015.02.028>

Kale, S., 2012. Impact of drained and un-drained soil conditions on water table depths , soil salinity and crop yields. African J. Agric. Res. 7, 2935–2945. <https://doi.org/10.5897/AJAR12.101>

Kale, S., 2011. Field-evaluation of DRAINMOD-S for predicting soil and drainage water salinity under semi-arid conditions in Turkey. Spanish J. Agric. Res. 9, 1142–1155.

Kandil, H., Skaggs, R.W., Abdel Dayem, S., Aiad, Y., 1995. DRAINMOD-S : Water management model for irrigated arid lands , crop yield and applications. Irrig. Drain. Syst. 9, 239–258.

Kargas, G., Chatzigiakoumis, I., Kollias, A., Spiliotis, D., Kerkides, P., 2018. An Investigation of the Relationship between the Electrical Conductivity of the Soil Saturated Paste Extract E_{Ce} with the Respective Values of the Mass Soil/Water Ratios 1:1 and 1:5 (EC_{1:1} and EC_{1:5}). Proceedings 2, 661. <https://doi.org/10.3390/proceedings2110661>

Khan, N.M., Rastoskuev, V. V, Sato, Y., Shiozawa, S., 2005. Assessment of hydrosaline land degradation by using a simple approach of remote sensing indicators. *Agric. Water Manag.* 77, 96–109. <https://doi.org/https://doi.org/10.1016/j.agwat.2004.09.038>

Knegt, J., 2000. *Drainage in Developing Countries: A review of institutional arrangements*. Wageningen, The Netherlands.

Luo, W., Jing, W.H., JIA, Z.H., LI, J., Pan, Y.X., 2009. The effect of PET calculations in DRAINMOD on drain- age and crop yields predictions in a subhumid vertisol soil district. *Sci. China Ser. E Technol. Sci.* 52, 1–5. <https://doi.org/10.1007/s11431-009-0349-0>

Maas, E. V., Hoffman, G.J., 1977. Crop Salt Tolerance - Current Assessment. *ASCE J Irrig Drain Div.* 103, 115–134. <https://doi.org/10.1061/jrcea4.0001137>

Mohamed, E.S., Saleh, A.M., Belal, A.B., Gad, A.A., 2018. Application of near-infrared reflectance for quantitative assessment of soil properties. *Egypt. J. Remote Sens. Sp. Sci.* 21, 1–14. <https://doi.org/https://doi.org/10.1016/j.ejrs.2017.02.001>

Morgan, R.S., El-hady, M.A., Rahim, I.S., 2018. Soil salinity mapping utilizing sentinel-2 and neural networks. *Indian J. Agric. Res.* 52, 524–529. <https://doi.org/10.18805/IJARE.A-316>

Mousavi, S.Z., Habibnejad, M., Kavian, A., Solaimani, K., Khormali, F., 2017. Digital Mapping of Topsoil Salinity Using Remote Sensing Indices in Agh-Ghala Plain, Iran. *ECOPERSIA* 5, 1771–1786.

NCCD, 2005. *The national plan to combat desertification*. Tripoli, Libya.

Nguyen, K., Liou, Y., Tran, H., Hoang, P., Nguyen, T., 2020. Soil salinity assessment by using near- infrared channel and Vegetation Soil Salinity Index derived from Landsat 8 OLI data : a case study in the Tra Vinh Province , Mekong Delta , Vietnam. *Prog. Earth Planet. Sci.* 7, 1–16.

Pourgholam-Amiji, M., Liaghat, A., Ghameshlou, A.N., Khoshravesh, M., 2021. The evaluation of DRAINMOD-S and AquaCrop models for simulating the salt concentration in soil profiles in areas with a saline and shallow water table. *J. Hydrol.* 598, 126259. <https://doi.org/10.1016/j.jhydrol.2021.126259>

Qadir, M., Boers, T.M., Schubert, S., Ghafoor, A., Murtaza, G., 2003. Agricultural water management in water-starved countries: Challenges and opportunities. *Agric. Water Manag.* 62, 165–185. [https://doi.org/10.1016/S0378-3774\(03\)00146-X](https://doi.org/10.1016/S0378-3774(03)00146-X)

Ramadan, A., Elssaidi, M.A., 2017. Salinization of Agricultural Soils as Development Issues in Wadi Al-Shatti Region. *J. Mar. Sci. Environ. Technol.* 3, 29–45.

Schultz, B., Zimmer, D., Voltman, W.F., 2007. Drainage under increasing and changing requirements. *Irrig. Drain.* 56, S3–S22. <https://doi.org/10.1002/ird>

Seifi, M., Ahmadi, A., Neyshabouri, M.-R., Taghizadeh-Mehrjardi, R., Bahrami, H.-A., 2020. Remote and Vis-NIR spectra sensing potential for soil salinization estimation in the eastern coast of Urmia hyper saline lake, Iran. *Remote Sens. Appl.* 20, 1–9. <https://doi.org/10.1016/j.rsase.2020.100398>

Selvaperumal, A., Thiyagarajan, G., Vallalkannan, S., Muthuchamy, I., 2020. DRAINMOD – Calibration and Validation for Prediction of Drainage Coefficient and Water Table Depth 39, 65–74. <https://doi.org/10.9734/CJAST/2020/V39i930607>

Shahabi, M., Jafarzadeh, A.A., Neyshabouri, M.R., Ghorbani, M.A., Valizadeh Kamran, K., 2016. Spatial modeling of soil salinity using multiple linear regression, ordinary kriging and artificial neural network methods. *Arch. Agron. Soil Sci.* 63, 151–160. <https://doi.org/10.1080/03650340.2016.1193162>

Skaggs, R.W., Youssef, M.A., Chescheir, G.M., 2012. DRAINMOD: model use, calibration, and validation. *Trans. ASABE* 55, 1509–1522. <https://doi.org/10.13031/2013.42259>

Smedema, L.K., Abdel-Dayem, S., Ochs, W.J., 2000. Drainage and agricultural development. *Irrig. Drain. Syst.* 14, 223–235. <https://doi.org/10.1023/A:1026570823692>

Stefan, F., Guenther, F., 2019. Package ‘neuralnet’ [WWW Document]. URL <https://cran.r-project.org/web/packages/neuralnet/neuralnet.pdf> (accessed 5.13.20).

Sun, J., 2012. Learning algorithm and hidden node selection scheme for local coupled feedforward neural network classifier. *Neurocomputing* 79, 158–163. <https://doi.org/10.1016/j.neucom.2011.09.019>

United Nations, 2019. World Population Prospects: The 2019 Revision, Online Edition [WWW Document]. United Nations Popul. Div. URL <http://data.un.org/Data.aspx?q=LIBYA&d=PopDiv&f=variableID%3A12%3BcrID%3A434> (accessed 9.7.21).

USDA, 1954. Diagnosis and Improvement of Saline and Alkaline Soils. *Agric. Handb.* No 60 18, 348. <https://doi.org/10.2136/sssaj1954.03615995001800030032x>

USGS, 2021. U.S. Geological Survey [WWW Document]. Landsat Mission. URL https://www.usgs.gov/core-science-systems/nli/landsat/landsat-5?qt-science_support_page_related_con=0#qt-science_support_page_related_con. (accessed 4.14.21).

Wahba, M.A.S., Kandil, H., Gobran, A., 2002. Evaluation of DRAINMOD-S for Simulating Water Table Management under Semi-Arid Conditions. *Irrig. Drain.* 51, 213–226. <https://doi.org/10.1002/ird.54>

Wang, J., Peng, J., Li, H., Yin, C., Liu, W., Wang, T., Zhang, H., 2021. Soil Salinity Mapping Using Machine Learning Algorithms with the Sentinel-2 MSI in Arid Areas, China. *Remote Sens.* 13. <https://doi.org/10.3390/rs13020305>

Wang, X., Mosley, C.T., Frankenberger, J.R., Kladvko, E.J., 2006. Subsurface drain flow and crop yield predictions for different drain spacings using DRAINMOD. *Agric. Water Manag.* 79, 113–136. <https://doi.org/10.1016/j.agwat.2005.02.002>

Wheida, E., Verhoeven, R., 2007. An alternative solution of the water shortage problem in Libya. *Water Resour. Manag.* 21, 961–982. <https://doi.org/10.1007/s11269-006-9067-6>

Yang, J., Wang, X., Wang, R., Wang, H., 2020. Combination of Convolutional Neural Networks and Recurrent Neural Networks for predicting soil properties using Vis–NIR spectroscopy. *Geoderma* 380, 1–16. <https://doi.org/https://doi.org/10.1016/j.geoderma.2020.114616>

Zurqani, H.A., Post, C.J., Mikhailova, E.A., Schlautman, M.A., Sharp, J.L., 2018. Geospatial analysis of land use change in the Savannah River Basin using Google Earth Engine. *Int. J. Appl. Earth Obs. Geoinf.* 69, 175–185. <https://doi.org/https://doi.org/10.1016/j.jag.2017.12.006>

6 Integrating ANNs Predicted Saturated Hydraulic Conductivity and Evapotranspiration to Optimise Drainage System Design

Abstract

Agricultural drainage in irrigated lands reduces soil salinity and waterlogging. However, less than 10% of irrigated lands in least developed countries (LDCs) requiring drainage are currently drained. DRAINMOD is a versatile and readily available model that can be used to evaluate alternative drainage designs. DRAINMOD requires several inputs, including saturated hydraulic conductivity (K_{sat}) and reference evapotranspiration (ET_0). In LDCs, measuring these data is expensive and time-consuming. This research aims to (1) evaluate alternative methods of predicting K_{sat} and ET_0 to overcome incomplete data records that restrict drainage designs and (2) justify through economic analysis which drainage spacing would produce the most profit for two Libyan irrigation schemes and the economic implications if drain spacing was inaccurately predicted. K_{sat} predictions used Artificial Neural Networks (ANNs), Rosetta3, and ET_0 predictions used ANNs, MODAWEC, and Era5-Land. Four combinations of data inputs were used to predicted K_{sat} and ET_0 values (G2, G3, G4, and G5) in order to run DRAINMOD for the Eshkeda Agricultural Project (EAP) and the Hammam Agricultural Project (HAP) in Libya. G1 used measured K_{sat} and ET_0 from EAP and HAP and represented the optimum design. G2 used ANN2 and ANN4 (Chapter 3) and ANN1S and ANN1H for predicting ET_0 (Chapter 4). G3 uses ANN1 and ANN3 (Chapter 3) and ET_0 from ANN4S and ANN4H. G4 and G5 used Rosetta3 to predict K_{sat} and ET_0 from MODAWEC and ERA5-Land, respectively. The results showed that G2 and G3 predicted drain spacing more accurately than G4 and G5. G2 and G3 drainage systems are similar to the optimal design. However, using G4 and G5 would result in wheat and beans losses over a similar 30-year period of \$180,000 and \$285,000, respectively. As K_{sat} and ET_0 are time-consuming and expensive to measure, constructing drainage systems based on ANNs projections would be more cost-effective and accessible in Libya and other LDCs. However, further research is needed to evaluate the impacts of reusing drainage water to irrigate more salt-tolerant crops and further improve water use efficiency.

6.1 Introduction

Food security, a global problem, is challenging to achieve without concomitantly improving water use efficiency (WUE) and increasing agricultural productivity (Fadul et al., 2020; Yin et al., 2021). Due to continuous population growth, it is anticipated that food production will need to increase by *circa* 100% by 2050 to fulfil potential demand (Právělie et al., 2021). Achieving better agricultural WUE is crucial if this demand is to be met, especially in arid and semi-arid areas, where there are increasing cross-sectoral conflicts for limited water resources (Elshemy, 2018). Soil salinity and a shortage of fresh irrigation water are significant issues in arid and semi-arid regions, particularly in areas where the water table is shallow and waterlogging occurs in the root zone (Nozari et al., 2021). Poorly designed drainage systems can cause salt accumulation in the root zone, reducing soil fertility and crop yield over time. Conversely, correctly designed subsurface drainage systems offer an effective option to make inadequately drained land more productive (Nozari et al., 2021).

Agricultural drainage has been successfully installed and maintained in many arid and semi-arid areas, including the USA (Grismer and Bali, 2015; Grismer, 2015; USBR, 1993), Egypt (Elshemy, 2018; Kandil et al., 1995), China (Chen et al., 2020), Australia (Jones et al., 1989), India (Bastiaanssen et al., 1996; Verma and Gupta, 2014), Morocco (Er-Raki et al., 2021) and Tunisia (Kanzari et al., 2021). However, in arid and semi-arid areas, only around 30% of all irrigated land that requires drainage (*circa* 125 million ha) has been adequately drained (Schultz et al., 2007). In least developed countries (LDCs), the situation is far worse. It has been estimated that only 5 – 10% of all agricultural land in LDCs is drained compared to 25 – 30% in developed countries (Smedema et al., 2000). As of 2000, around 9,000 ha of irrigated land (approximately 2% of all croplands in Libya) was projected to be equipped with some sort of drainage system (FAO, 2016). This is due to a lack of local expertise and capacity, the high cost of installing and maintaining drainage systems, and the absence of contiguous input data for drainage system design.

Lack of expertise within LDCs can be overcome. In 1991, the Egyptian Public Authority for Drainage Projects (EPADP) founded the Drainage Training Center (DTC) that annually offers courses and practical training in drainage design, construction, and

maintenance. Operators and mechanics are educated on drainage equipment, maintenance, and repair. Modern technology and hands-on training modules are available (Freisem and Scheumann, 2001). In India, the Water Users Associations (WUA) for irrigation offered farmers training programs to adopt the latest irrigation and drainage technology, resulting in improved water and agricultural management (Freisem and Scheumann, 2001). To overcome the high cost of installing and maintaining drainage systems, farmers in India and Pakistan contribute 15 – 20% of the operation and maintenance costs. In Bangladesh, it is included in the water bill, while to install drainage systems, governments in Egypt, Bangladesh, India and Pakistan offer loans to farmers (Knecht, 2000).

To further reduce the risk and cost of installing an inadequate drainage system, drainage simulation models can be used as a quick and accurate method to evaluate alternative designs (Skaggs, 1999). DRAINMOD is a popular and readily accessible model for simulating the hydrology of poorly drained and high-water table soils (Skaggs et al., 2012b). DRAINMOD has also been successfully applied to evaluate the performance of alternative drainage designs and irrigation practices in arid and semi-arid areas, including Egypt (Kandil et al., 1995), Turkey (Kale, 2011), India (Gupta et al., 1993), and the USA (Ayars and Evans, 2015). DRAINMOD requires input parameters, including drainage design parameters (drain depth, spacing, and radius, depth to restricting layer, and drainage coefficient), soil properties (saturated hydraulic conductivity (K_{sat}), soil water content at field capacity, and wilting point), climatic data (daily reference evapotranspiration (ET_0), daily minimum and maximum temperature and daily rainfall), and crop information (crop soil salinity threshold, irrigation water salinity, drought stress, and wet stress). However, and crucially these input parameters are often unavailable in many areas, especially in LDCs. Therefore, in order to be able to apply DRAINMOD to design drainage systems that maximise WUE and agricultural productivity in arid areas, alternative cost effective methods that can predict key input parameters such as K_{sat} (Ellafi et al., 2021) and reference evapotranspiration (ET_0) (Malakshahi et al., 2020; Niaghi et al., 2017) need to be developed. These input parameters were selected because they are among the most sensitive parameters in DRAINMOD, and the accuracy of predicting K_{sat} and ET_0 will greatly impact the accuracy of model outputs (Niaghi et al., 2017; Skaggs et al.,

2012b). Applying indirect methods to predict these input parameters may help reduce the overall cost of installing a drainage system in a specific area (Ellafi et al., 2021).

Saturated hydraulic conductivity (K_{sat}) can be measured in-situ using methods such as the Guelph permeameter for soils above water-table level (Reynolds and Elrick, 1985) and the auger hole method for soil horizons below the water table (Beers, 1958) or in the laboratory using a constant head or falling head permeameter (Klute and Dirksen, 1986). However, K_{sat} varies between scales (plot, field, and catchment) (Hassler et al., 2014). Multiple soil samples and measurements are needed to accurately define an area's representative K_{sat} value (Sobieraj et al., 2004). These measurements are difficult, time-consuming, and often expensive (Fooladmand, 2011; Patil and Singh, 2016). In addition, in many countries, specifically LDCs, K_{sat} values are unavailable due to a lack of expertise, capacity and financial restrictions (Patil et al., 2011, 2010).

Pedotransfer functions (PTFs) can be used to estimate K_{sat} from more readily available soil measurement information (e.g., soil texture and bulk density) (Arrington et al., 2013; Dashtaki et al., 2010; Khodaverdiloo et al., 2011). One commonly applied PTF is the Rosetta model (Zhang and Schaap, 2019). Schaap et al. (2001) first developed the Rosetta model to predict soil hydraulic parameters, including K_{sat} . The newest version, Rosetta3, can provide more accurate predictions. However, Rosetta3 has not been tested in sandy soils located in arid and semi-arid areas. (Ellafi et al., 2021) developed a site-specific artificial neural network (ANN) that accurately predicted K_{sat} from easily measured soil data such as soil texture and bulk density. Ellafi et al. (2021) found that the accuracy of K_{sat} strongly influences estimated drain depth and spacing. However, their design based on predicted K_{sat} was not applied to evaluate long term impacts on crop yield and irrigation water requirement.

Measured ET data is typically unavailable, especially in LDCs, due to the high installation and maintenance costs. Calculating ET from climate parameters is recommended as an alternative method (Allen et al., 1998).

Daily ET calculations depend on the availability of several climatic parameters (i.e., solar radiation, humidity, wind speed, and temperature on a daily basis), making ET a complicated and nonlinear phenomenon (Kumar et al., 2002). Allen et al. (1998)

recommended using the Penman-Monteith method to calculate reference evapotranspiration (ET₀). However, in LDCs, most climatic datasets necessary to calculate ET₀ are either unavailable at the temporal resolution required (hourly or daily basis) or have days or months of missing values. Around 70% of the global arid and semi-arid areas are located within LDCs (Safriel et al., 2005). Therefore, a reliable way of estimating missing meteorological data to accurately calculate ET₀ for input into drainage system design in these data-poor areas is crucial and would have a considerable impact. Allen et al. (1998) suggested that ET₀ can be reasonably obtained from daily maximum air temperature (DT_{max}) and daily minimum air temperature (DT_{min}).

One of the current methods applied to generate DT_{max} and DT_{min} is the MODAWEC model (Liu et al., 2008). MODAWEC converts monthly average maximum and minimum air temperature to a daily basis. However, the model is limited to the availability of the monthly data in the first place (MODAWEC development and applications are discussed in detail in Chapter 4). Another widely adopted approach uses the traditional Arithmetic Averaging of Neighboring Stations Method (AANS) (Kanda et al., 2018). However, the limitation of this approach is the availability of DT_{max} and DT_{min} in neighbouring stations. An alternative is to use reanalysis datasets such as ERA5-Land (Muñoz-Sabater, 2019) and MERRA-2 (Gelaro et al., 2017), which provide a spatially contiguous DT_{max} and DT_{min} in any geographical area location on the globe (0.1° x 0.1°; Native resolution is 9 km). These datasets have been produced by combining earth observations and remote sensing data (Gelaro et al., 2017; Muñoz-Sabater, 2019) and have been successfully applied in arid and semi-arid areas (Nkiaka et al., 2017; Tarek et al., 2020; Zandler et al., 2020).

This research aims to overcome the constraints of inadequate drainage designs that contribute to soil salinisation and waterlogging and are linked with poor WUE and sub-optimal yield in arid and semi-arid areas such as Libya. This research considers alternative approaches that can help overcome the constraints of incomplete data records that severely restrict drainage designs (e.g. K_{sat} and ET₀) in LDCs.

The objective of this research is to investigate strategies accessible to data-poor areas in LDCs. These approaches were used to predict K_{sat} and ET₀ and applied to drainage

design in Libya's agricultural projects. Drainage systems designs based on these datasets are critically compared to drainage designs based on measured K_{sat} and ET_0 . An economic analysis justifies which drainage spacing would produce the maximum profit to farmers for selected crops grown in EAP and HAP agricultural projects. The economic implications of inaccurately predicted drain spacing are also quantified.

6.2 Materials and methods

6.2.1 Case study

The current study covers two agricultural projects south of Libya, the Eshkeda Agricultural Project (EAP) and the Hammam Agricultural Project (HAP). EAP is located north of Sabha city ($27^{\circ}32'45''N$ $14^{\circ}16'7''E$) at an elevation of 320 m above sea level (asl). EAP covers 3000 hectares and is divided into three subareas: The Western Area (2,000 ha), the Central Area (600 ha), and the Eastern Area (370 ha). As per the installed irrigation wells, the project is divided into 25 districts with 12 farms (approximately 10 ha each). The agricultural project began in 1975 and was completed in 1976. The drainage system was constructed between 1979 and 1981. HAP is located on the north-east part of Sokna Oasis ($29^{\circ}04'01''N$ $15^{\circ}47'05''E$) at an elevation of 270 m asl. HAP covers 1,200 ha and is divided into 182 farms (6 – 8 ha for each farm). The project started in 1971, and the reclamation was finished in 1985. The drainage system for the HAP project was designed in the 1970s.

6.2.2 Saturated hydraulic conductivity

Available datasets from EAP and HAP include particle size distribution (percentage of sand (S), silt (Si), and clay (C)), bulk density (BD) ($g\ cm^{-3}$), %wilting point (WP), %field capacity (FC), and K_{sat} ($m\ d^{-1}$). They are the same datasets used by Ellafi et al. (2021). The hydrometer technique was used to measure soil texture (Bouyoucos, 1927). The Buckman and Brady method was used to measure soil BD (Buckman and Brady, 1960). Tensiometers were used to determine % FC and %WP, using methods reviewed by Richards (1949). In the EAP, K_{sat} was measured in the field using the auger-hole approach (Beers, 1958). While undisturbed soil samples were collected in HAP and K_{sat} were measured in the laboratory using the constant head method (Klute and Dirksen, 1986). A total of 770 K_{sat} measurements were taken in HAP and 442 K_{sat} measurements in the EAP. Ellafi et al. (2021) used these datasets to develop site-

specific ANNs for K_{sat} prediction. Table 6-1 illustrates the input parameters used by Ellafi et al. (2021) to develop the ANNs in EAP (ANN1 and ANN2) and HAP (ANN3 and ANN4). More information about the development of the ANNs and data structure can be found in Ellafi et al. (2021). Also, Appendix C covers more information related to the ANNs applied in this Chapter including the pre-processing steps to prepare the data, the functions applied, the codes written, and other outputs. These same datasets were applied in Rosetta3 to predict K_{sat} . Rosetta3 was developed by Zhang and Schaap (2017) and used the same input parameters applied to develop the site-specific ANNs (Table 6-1).

Table 6-1: The ANNs models developed for EAP and HAP and Rosetta3

Model name	Inputs required	Agricultural Project	Reference
ANN1	%Sand, %Silt, %Clay, BD (g cm^{-3}), %FC and %WP	EAP	(Ellafi et al., 2021)
ANN2	%Sand, %Silt, %Clay, and BD (g cm^{-3})	EAP	(Ellafi et al., 2021)
ANN3	%Sand, %Silt, %Clay, BD (g cm^{-3}), %FC, and %WP	HAP	(Ellafi et al., 2021)
ANN4	%Sand, %Silt, %Clay, and BD (g cm^{-3})	HAP	(Ellafi et al., 2021)
Rosetta3	%Sand, %Silt, %Clay, BD (g cm^{-3}), %FC and %WP	EAP+HAP	(Zhang & Schaap, 2017)

Where EAP is Eshkeda agricultural project, HAP is Hammam agricultural project, ANN is the artificial neural network, BD is the bulk density, %FC is the field capacity, and %WP is the wilting point.

6.2.3 Evapotranspiration

There are no meteorological stations in either EAP or HAP; therefore, the nearest stations to EAP and HAP were utilised for meteorological input parameters when each project's drainage system was constructed. The same stations were used as the reference stations for this study. Sabha meteorological station was the closest to EAP (50 km to the south), whereas Hon meteorological station was the closest to HAP (15 km to the east). The Libyan National Meteorological Centre provided historical 30-year (1981–2010) DTmax and DTmin data for each meteorological station (LNMC, 2020). There were major data gaps for both stations. Missing DTmax and DTmin data ranged

from 0% in Sabha during 2009 and 2010 to almost 90% in Hon in 1996. Between 1981 and 2010, the cumulative proportion of missing DTmax and DTmin readings in Sabha and Hon meteorological stations was 13% and 23%, respectively. This current study also uses methods applied in Chapter 4 (i.e. ANNs, MODAWEC, and ERA5-Land) to predict DTmax and DTmin and calculate ET₀ (Table 6-2).

Table 6-2: Methods evaluated to predict DTmax and DTmin in EAP and HAP agricultural projects.

Station	Agricultural project	Model	Input required	Reference
Sabha	EAP	ANN1S	DOY, MTmax, MTmin, XMTmax, XMTmin, SD, GTmax and GTmin.	Chapter 4
		ANN4S	DOY, MTmax, MTmin, XMTmax, XMTmin, SD, GTmax, GTmin, ERATmax and ERATmin.	Chapter 4
		MODAWEC	MTmax and MTmin	(Liu et al., 2008)
		ERA5-Land	Latitude and Longitude	(Muñoz-Sabater, 2019)
Hon	HAP	ANN1H	DOY, MTmax, MTmin, XMTmax, XMTmin, SD, GTmax and GTmin.	Chapter 4
		ANN4H	DOY, MTmax, MTmin, XMTmax, XMTmin, SD, GTmax, GTmin, ERATmax and ERATmin.	Chapter 4
		MODAWEC	MTmax and MTmin	(Liu et al., 2008)
		ERA5-Land	Latitude and Longitude	(Muñoz-Sabater, 2019)

Where DTmax and DTmin are the daily maximum and minimum air temperature, respectively, MTmax and MTmin are the average monthly maximum and minimum air temperature, respectively, XMTmax and XMTmin are the extreme maximum and minimum air temperature of the month, respectively, and DOY is the day of the year, SD is the sunshine duration, MODAWEC is Monthly to Daily Weather Converter, ANN is the artificial neural network, ET₀ is the reference evapotranspiration, ERATmax and ERATmin are generated from ERA5-Land, which is a reanalysis data, Global TempSIM is GTmax, and GTmin calculated for one year based on geographical location (Legates and Willmott, 1990), and Eshkeda agricultural project (EAP), and Hammam agricultural project (HAP).

6.2.4 DRAINMOD

6.2.4.1 DRAINMOD input data

DRAINMOD is a field-scale computer simulation model for shallow water table soils, developed for agriculture fields to design and evaluate the long-term (30-year) performance of drainage systems (Skaggs et al., 2012b). The input parameters required for DRAINMOD simulations and the source of these parameters are described in detail in Chapters 5. For this study, the focus was on K_{sat} and ET_0 . The predicted values of K_{sat} and ET_0 were divided into five groups (G1, G2, G3, G4, and G5). All groups contain measured data required for DRAINMOD simulation (the same values). The difference between groups G1, G2, G3, G4 and G5 were the input values of K_{sat} and ET_0 , which were dependent on the method used in their prediction. In G1, measured K_{sat} and ET_0 values were used in EAP and HAP (which represents the optimum design). In G2, the ANNs developed by Ellafi et al. (2021) with fewer input parameters ANN2 for K_{sat} and ANN1S for ET_0 were used in EAP and ANN4 for K_{sat} and ANN1H for ET_0 in HAP (Table 6-2 and Table 6-3). In G3, the more accurate ANNs developed by Ellafi et al. (2021) for predicting K_{sat} and ET_0 were used. These were ANN1 for K_{sat} and ANN4S for ET_0 in EAP and ANN3 for K_{sat} , and ANN4H for ET_0 in HAP (Table 6-2 and Table 6-3). In G4, K_{sat} predicted by Rosetta3, and ET_0 predicted by MODAWEC were used. Finally, in G5, K_{sat} predicted by Rosetta3, and ET_0 predicted by ERA5-Land were used.

Table 6-3: Five groups (G1 – G5) categorised by the source of the predicted or measured K_{sat} and ET0

Group	Agricultural Project	K_{sat} Method	K_{sat} reference	ET0 Method	ET0 reference
G1	EAP	Measured	(Cornelius-Brochier J.V, 1981; Italconsult, 1976)	Measured	(LNMC, 2020)
	HAP	Measured	(Danenco, 1980; Holzmann-Wakuti, 1974)	Measured	(LNMC, 2020)
G2	EAP	ANN2	(Ellafi et al., 2021)	ANN1S	Chapter 4
	HAP	ANN4	(Ellafi et al., 2021)	ANN1H	Chapter 4
G3	EAP	ANN1	(Ellafi et al., 2021)	ANN4S	Chapter 4
	HAP	ANN3	(Ellafi et al., 2021)	ANN4H	Chapter 4
G4	EAP	Rosetta3	(Zhang & Schaap, 2017)	MODAWEC	(Liu et al., 2008)
	HAP	Rosetta3	(Zhang & Schaap, 2017)	MODAWEC	(Liu et al., 2008)
G5	EAP	Rosetta3	(Zhang & Schaap, 2017)	ERA5-Land	(Muñoz-Sabater, 2019)
	HAP	Rosetta3	(Zhang & Schaap, 2017)	ERA5-Land	(Muñoz-Sabater, 2019)

Where G1 – G5 are Group 1 – Group 5. K_{sat} is the saturated hydraulic conductivity, ET0 is the reference evapotranspiration, ANN is an artificial neural network, MODAWEC is a Monthly to Daily Weather Converter, ERA5-Land is a reanalysis data method, and EAP is the Eshkeda agricultural project, and HAP is the Hammam agricultural project.

6.2.4.2 Objective functions

A 30-year simulation was run based on a rotation of four crops wheat, beans, maize and soybeans. This crop rotation was chosen as it is a typical rotation in Egypt's Nile Delta (which has similar climatic conditions to EAP and HAP). In addition, The General Water Authority in Libya (GWA) recommended growing these crops in EAP and HAP (GWA, 1999).

These crops have different tolerance to salt concentration in the root zone and the irrigation water quality (beans are among the most sensitive crops, wheat is the least sensitive, while maize and soybeans are moderately sensitive) (FAO, 1988). The simulations were conducted on a drain spacing of 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, and 200 m. The irrigation water requirements (IWR) in EAP and HAP for these crops were recommended by GWA (GWA, 1999). Drain spacing and the associated relative yield were then used to compare the drainage system designs generated by DRAINMOD based on the predicted methods of K_{sat} and ET_0 (G2 – G5) against the optimum design (G1) based on measured K_{sat} and ET_0 . Also, the impact of salinity and waterlogging related to each drain spacing based on the optimum design (G1) will be presented.

6.2.5 Economic analysis

As mentioned in Section 6.2.4.2, DRAINMOD simulations were applied for a 30-year period for each drain spacing, and the average annual relative yield was obtained for wheat and beans. Because of their salt tolerance, these crops were chosen for economic analysis (wheat is the most tolerant, and beans are the least tolerant to salt concentration in soil and irrigation water). Annual income for a specific drainage spacing design was computed by multiplying the relative yield for wheat and beans (simulated by DRAINMOD) by the base or prospective yield by the assumed unit crop value. Base or prospective yield is the average yield that would be obtained if soil water stress, due to both excessive and deficit soil water conditions, and planting data delays are eliminated. For example, where the relative yield for wheat is 90%, and the average expected yield is 2740 kg ha^{-1} , the average predicted yield is $0.9 \times 2740 = 2466 \text{ kg ha}^{-1}$. If the average unit price of wheat in Libya were assumed to be US\$ 0.24 kg^{-1} (H. Elmahmody, personal communication, 15/03/2022), the annual income would be $2466 \times 0.24 = \text{US\$ } 591.8 \text{ ha}^{-1}$.

The economic analysis considered two categories of expenditures: (a) yearly drainage system costs, which comprised the initial cost amortized over its expected useful life (30 years) plus a maintenance allowance as described by Fernandez et al. (2006); and Skaggs. (2007), and (b) typical wheat and beans production costs. Farmers in Libya estimated production costs for wheat and beans, which comprised total fixed

and variable expenses (excluding the land costs), to be US\$ 250 ha⁻¹ and US\$ 500 ha⁻¹, respectively (H. Elmahmody, personal communication, 15/03/2022). The initial cost of subsurface drains installation was assumed to be US\$ 2.62 m⁻¹ (Ghane and Askar, 2021; Skaggs, 2007). The calculated initial cost was then amortized over the 30-year period, the assumed life expectancy of the drainage system (Skaggs, 2007). Total annual costs, including drainage system and wheat and beans production costs, are given in Table 6-4.

The annual return or profit was calculated by subtracting the estimated annual costs from the estimated annual income. For example, assuming a 90% relative yield for wheat again was obtained using a 30 m drain spacing. The total annual cost, including the production cost, would be US\$ 279 ha⁻¹ (Table 6-4), and the average annual return would be US\$ 591.8 - US\$ 279 = US\$ 312.2.

Table 6-4: Predicted total annual cost for wheat and beans productions as affected by drain spacing

Drain spacing (m)	Drain length (m ha ⁻¹)	Initial cost (US\$ ha ⁻¹)	Annual drainage system cost (US\$ ha ⁻¹)	Annual production cost (US\$ ha ⁻¹)		Total annual cost (US\$ ha ⁻¹)	
				Wheat	Beans	Wheat	Beans
10	1000	2620	87	250	500	337	587
20	500	1310	44	250	500	294	544
30	333	873	29	250	500	279	529
40	250	655	22	250	500	272	522
50	200	524	17	250	500	267	517
60	167	438	15	250	500	265	515
70	143	375	12	250	500	262	512
80	125	328	11	250	500	261	511
90	111	291	10	250	500	260	510
100	100	262	9	250	500	259	509
200	50	131	4	250	500	254	504

6.2.6 Drainage water reuse

In this section, the irrigation water quality applied in DRAINMOD will be degraded to 2X, 3X and 4X the original irrigation quality. For example, the irrigation water quality in EAP is 1.25 dS m^{-1} , DRAINMOD will be run on irrigation water quality of 2.5 dS m^{-1} , 3.75 dS m^{-1} , and 5.0 dS m^{-1} . In HAP, the irrigation water quality is 3.91 dS m^{-1} and DRAINMOD simulation will be run on irrigation water quality of 7.81 dS m^{-1} , 11.73 dS m^{-1} and 15.64 dS m^{-1} . DRAINMOD will be run on the optimum drainage design based on the results from Section 6.2.4 and 6.2.5. all other inputs will be the same as described in Section 6.2.4.1.

6.3 Results

6.3.1 DRAINMOD applications for predicted Vs. measured K_{sat} and ET_0 in EAP and HAP

Figure 6-1 a – d: shows the influence of drain spacing on relative yield for wheat (Figure 6-1a), beans (Figure 6-1b), maize (Figure 6-1c), and soybeans (Figure 6-1d) in EAP. For wheat, beans, and soybeans, the maximum relative yield (100%) may be reached on a drain spacing between 10m and 70m, according to the G1 (DRAINMOD simulation results based on observed K_{sat} and ET_0). In contrast, the maximum relative yield for maize can be achieved for drain spacing ranging between 10 – 100m. Therefore, the widest drain spacing that may help achieve the maximum relative yield, is 70m for wheat, beans, and soybeans and 100m for maize. G2 – G5 were all able to predict the 100m drain spacing associated with the highest yield for maize, but the accuracy for the other crops was different. For example, G2 predicted that the widest spacing with the highest yield is 80m for wheat, beans, and soybeans, whereas G3 was the most accurate simulation and predicted 70m drain spacing (similar to the optimum design in G1). G4 and G5 were the least accurate predictions for the wider drain spacing related to the highest relative yield for wheat, beans, and soybeans with 100m and 90m, respectively (Figure 6-1).

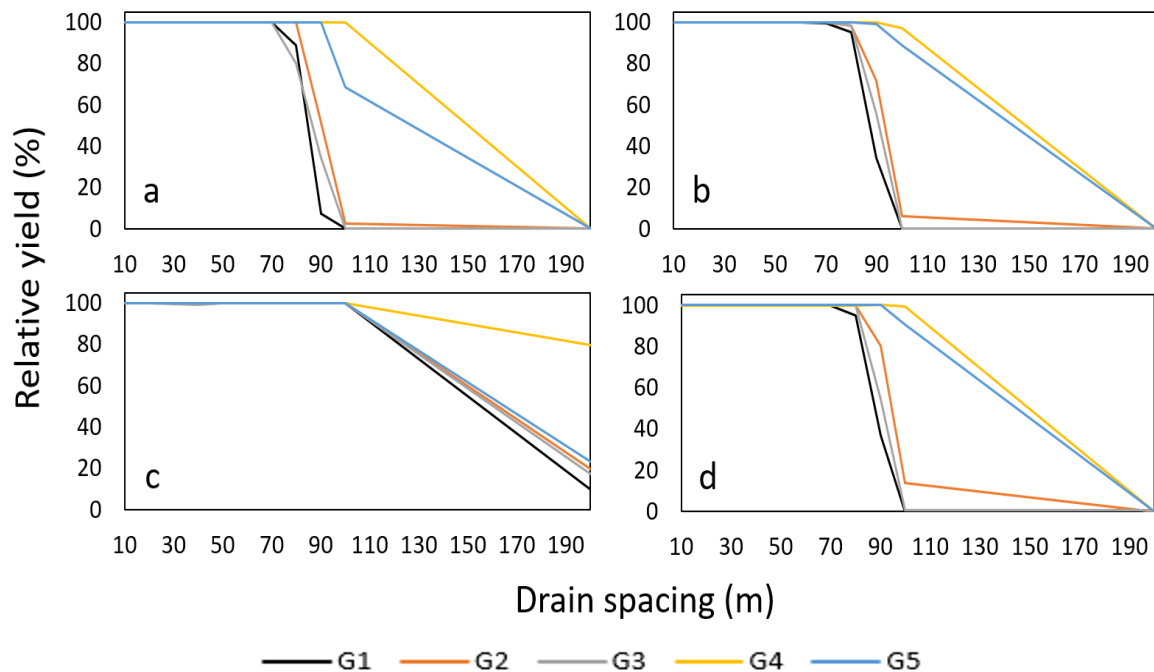


Figure 6-1 a – d: Impact of drain spacing on relative yield for wheat (a), beans (b), maize (c) and soybeans (d) in the Eshkeda Agricultural project (EAP). The average yield for each approach (G1 – G5) based on the source of K_{sat} and ET_0 was obtained for a 30-year simulation using DRAINMOD

Figure 6-2 illustrates the drain spacing and its impact on the average combined relative yield of the four crops (wheat, beans, maize, and soybeans) in EAP. Based on the G1 (DRAINMOD simulation results based on measured K_{sat} and ET_0), the highest relative yield (100%) can be obtained on a drain spacing of 10 – 70m. The spacing from 80 – 100m will cause a loss in yield ranging for the crops evaluated from 10 – 75% based on G1. In addition, the drainage design with spacing ranging between 100 – 200m will result in a total yield loss of up to 95% based on G1. Therefore, the widest drainage spacing that would ensure the highest relative yield across all crops simulated in this study was predicted to be 70m (based on G1, which is the optimum design). G1 simulations would help to guarantee 100% average relative yield of the four simulated crops. The results showed that G2 and G3 were significantly better at predicting the spacing between drains than G4 and G5. G3 and G2 predicted maximum drain spacing to achieve 100% relative yield for all crops (wheat, beans, maize and soybeans) was 70m and 80m, respectively.

In comparison, G4 and G5 predicted a spacing of 100m and 90m, respectively. In all simulations (G1 – G5), spacing between drains ranging from 10m to 70m had few negative impacts on the relative yield, and no yield losses were identified. However, if a drainage system was designed and installed in EAP, with 80m spacing between drains based on the K_{sat} and ET_0 values generated from G2, an annual yield loss (as an average across all crops) of 10% may occur. A design based on the G3 dataset would be comparable to the optimum design obtained from G1 based on measured K_{sat} and ET_0 . Whereas G4 and G5 were the least accurate methods at predicting the wider spacing that can provide the highest annual relative yield, and a design based on G4 and G5 would potentially result in loss in yields of 75% and 60%, respectively, in EAP as an average of the four crops (Figure 6-2).

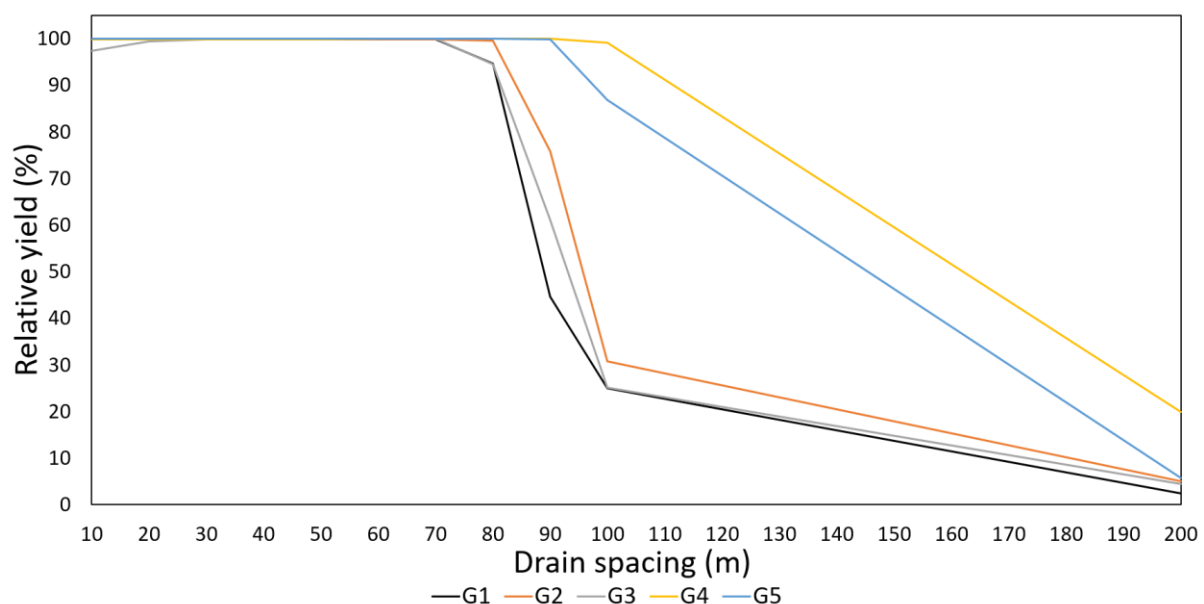


Figure 6-2: Effect of drain spacing on average combined relative yield of wheat, beans, maize and soybeans in Eshkeda agricultural project (EAP). Average yields for each of the approaches (G1 – G5) as based on the source of K_{sat} and ET_0 were obtained for a 30-year simulation using DRAINMOD.

Figure 6-3 a – d illustrates the effect of drain spacing on the yield for wheat, beans, maize and soybeans in HAP. According to the optimum design based on measured K_{sat} and ET_0 (G1), the relative yield starts at the highest values and decreases incremental increases in drain spacing. For example, for wheat, the relative yield decreased from 98% for drain spacing up to 30m, and 97% yield for drain spacing up to 50m; after that, the yield decreasing dramatically to 0% yield at 200m drain spacing.

For other crops, the relative yield begins 73% for beans, 90% for maize, and 99% for soybeans (Figure 6-3a – d). In the other groups (G2 – G5), G3 was the most accurate in predicting yield for all crops as impacted by drain spacing compared to the optimum design (G1). The second most accurate was G2 with comparable predicted yields for each drain spacing for three (i.e. beans, maize and soybeans) out of the four crops. G4 and G5 obtained the least accurate prediction. Up to 30m drain spacing G4 and G5's predictions were comparable with to the optimum design, but for wider spacing, G4 and G5 tend to inaccurately predict the impact of drain spacing on yield (Figure 6-3).

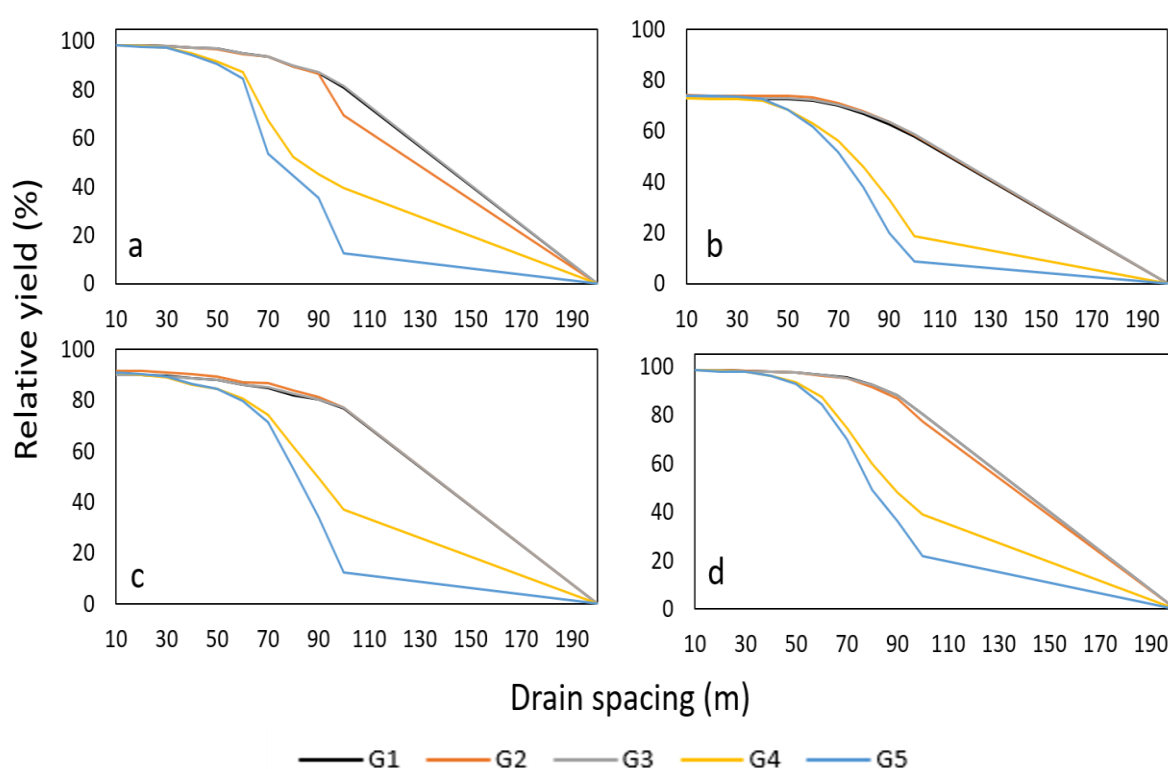


Figure 6-3 a – d: Impact of drain spacing on relative yield for wheat (a), beans (b), maize (c) and soybeans (d) in Hammam Agricultural project (HAP). The average yield for each approach (G1 – G5) based on the source of K_{sat} and ET_0 was obtained for a 30-year simulation using DRAINMOD.

Figure 6-4 shows the average combined annual predicted yield for wheat, beans, maize and soybeans, plotted as a function of drain spacing for HAP. Based on the results shown in Figure 6-4, the highest relative yield (90%) was associated with drain spacing from 10 – 50m. The relative yield rapidly decreased with increased spacing

until it reached the lowest yield (0%) at 200m spacing. G2 and G3 predict a comparable relative yield and drain spacing to the one obtained by G1. G4 and G5 indicated that the highest relative yield could only be obtained with drain spacing ranging from 10 – 30m. Therefore, a design based on G4 and G5 datasets would not impact the yield but would require a higher total drainage length and hence higher installation costs because of the closer spacing than the design based on the measured dataset (i.e. G1).

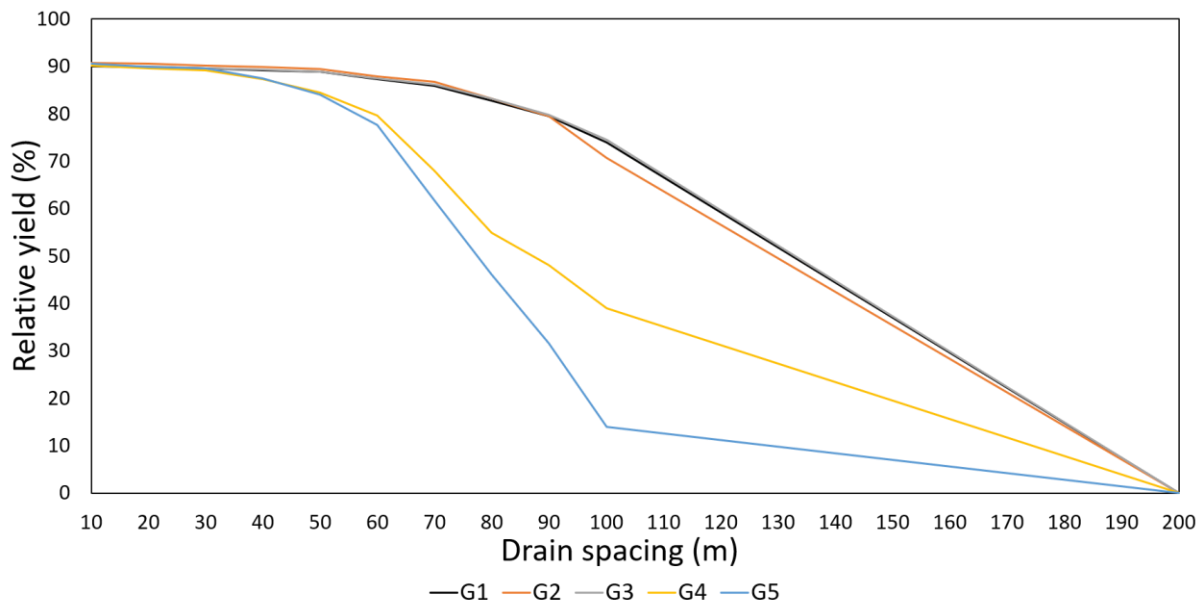


Figure 6-4: Effect of drain spacing on average combined relative yield of wheat, beans, maize and soybeans in Hammam agricultural project (HAP). Average yields for each of the approaches (G1 – G5) based on the source of K_{sat} and ET_0 were obtained for a 30-year simulation using DRAINMOD.

Figure 6-5 a – h shows the effect of salinity and waterlogging on crop yield (wheat, beans, maize, and soybeans) at different drain spacing in EAP and HAP. Figure 6-5a – d represents wheat, beans, maize and soybeans in EAP, respectively. Figure 6-5e – h represent wheat, beans, maize and soybeans in HAP, respectively. In EAP, the salinity impact is only observed at a drain spacing ranging from 90 – 200m, with the highest impact of less than 20% reduction in yield (Figure 6-5 a – d). Also, the reduction in yield caused by waterlogging was only observed with a drain spacing between 80 – 200m. However, the impact is much higher than salinity and would achieve 100% yield reduction, especially for wheat, beans and soybeans (Figure 6-5a – d).

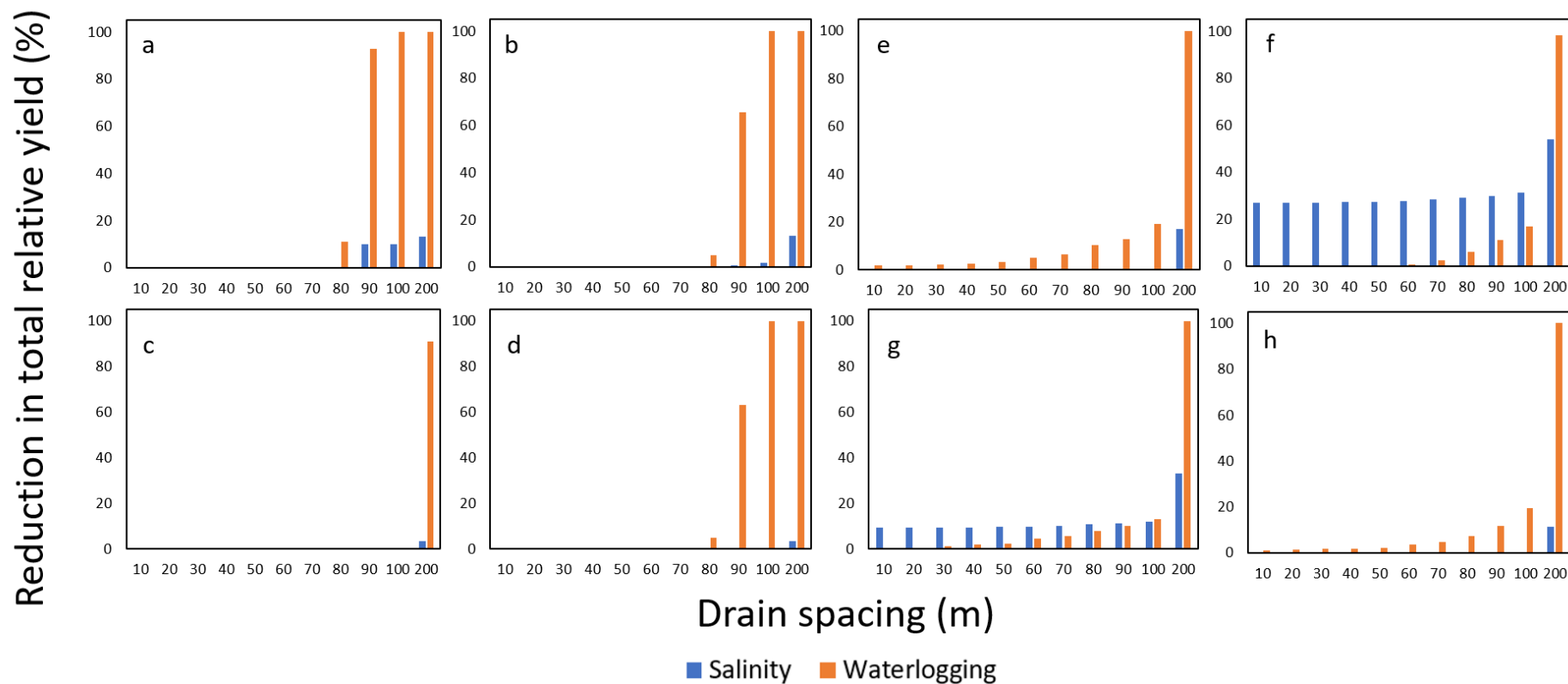


Figure 6-5 a – h: The impact of salinity and waterlogging on relative yield (%) as a function of drain spacing (m) in the Eshkeda Agricultural Project (EAP) and Hammam Agricultural Project (HAP). Where a is wheat, b beans, c is maize and d is soybeans in EAP and e, f, g and h are wheat, beans, maize and soybeans in HAP, respectively.

6.3.2 Economic analyses for using predicted Vs. measured K_{sat} and ET_0 in designing drainage systems in EAP and HAP

The annual and overall return over 30 years for wheat and beans in EAP, for a given drain spacing, are summarised in Table 6-5. After subtracting the total annual cost (Table 6-4) for wheat, the average annual return ranged from -259 to 395 US\$ ha⁻¹. The highest annual return as an average for both wheat and beans was associated with 70m drain spacing, and the lowest annual return was associated with 100m spacing between drains (Table 6-5). Across the EAP (3000 ha), 70m spacing would help secure an annual return on wheat of US\$ 1,185,000 and US\$ 35,560,000 over the assumed 30-year life-span of the drainage system. This is US\$ 189,000 more than the 60m spacing and US\$ 6,428,000 more than 80m spacing between drains over the drainage system lifetime. For beans, the highest annual return of 3,178 US\$ ha⁻¹ was associated with 60m spacing between drains. Multiplying this by the total EAP area (3000 ha) will increase the annual return to US\$ 9,534,000 which equates to US\$ 286,021,000 over the 30-year assumed life expectancy of the drainage system (Table 6-5). However, the total return for both crops can be achieved by either 60m or 70m drain spacing, and therefore 70m would be more favourable by reducing the cost of installing the drainage system in EAP.

The 'Groups' column in Table 6-5 shows which approach (G2 – G5) was able to predict the optimum design (G1) based on measured K_{sat} and ET_0 . G3 was the only approach that predicted the optimum spacing, which would help to achieve the highest annual return (US\$ 395 ha⁻¹ for wheat and US\$ 3,176 ha⁻¹ for beans), based on 70m spacing between drains. G2 predicted an 80m drain spacing which would help to achieve an annual return of about US\$ 324 ha⁻¹ and US\$ 3,004 ha⁻¹ for wheat and beans, respectively. G5 predicted a spacing of 90m between drains in EAP. Even though 90m spacing between drains may help to reach an annual return of US\$ 763 ha⁻¹ from beans, the 90m spacing would may cause a loss from growing wheat up to US\$ -213 ha⁻¹. G4 suggested that 100m spacing between drains would be ideal in EAP. However, that design would cause a loss in return for both wheat and beans with annual returns of US\$ -259 and US\$ -509 ha⁻¹, respectively.

Table 6-6 summarised the estimated return for wheat and beans in HAP associated with different drain spacing. The results show that the annual return for wheat and beans (based on G1 simulations) increased from US\$ 309 ha⁻¹ and US\$ 2,106 ha⁻¹ at 10m spacing to US\$ 370 ha⁻¹ and US\$ 2,165 ha⁻¹ (the highest return) at 50m spacing in HAP, respectively. After that, the annual return with drop dramatically with the increase in drain spacing until it reaches the lowest annual return for wheat (US\$ -254 ha⁻¹) and beans (US\$ 504 h⁻¹) at 200m. G2 and G3 were the only groups that predicted the same highest annual return at 50m spacing between drains (Table 6-6). G4 and G5 predicted a drain spacing of 30m, and that design can help to achieve an annual return of US\$ 365 ha⁻¹ and US\$ 2,157 ha⁻¹ for wheat and beans, respectively.

6.3.3 Drainage water reuse

Figure 6-6 shows the impacts of using drainage water on yield in EAP and HAP. The results show that degrading the irrigation water quality can cause a significant reduction in crop yield, especially in HAP. Increasing the irrigation water salinity in HAP causes a yield reduction for beans ranges from 73% using irrigation water quality of 3.91 dS m⁻¹ to 0% using 15.64 dS m⁻¹. A significant reduction in yield was also simulated for maize ranging from 88% to 2%. Soybeans was the third impacted crop by the degradation of irrigation water quality with a reduction in yield from 98% to 40%. Finally, in HAP the least impacted crop was wheat and the lowest yield (79%) was simulated using irrigation water quality of 15.64 dS m⁻¹. In EAP, the simulated reduction was noted only for beans and maize with relative yield ranging from 100 – 60% and 100 – 78%, respectively.

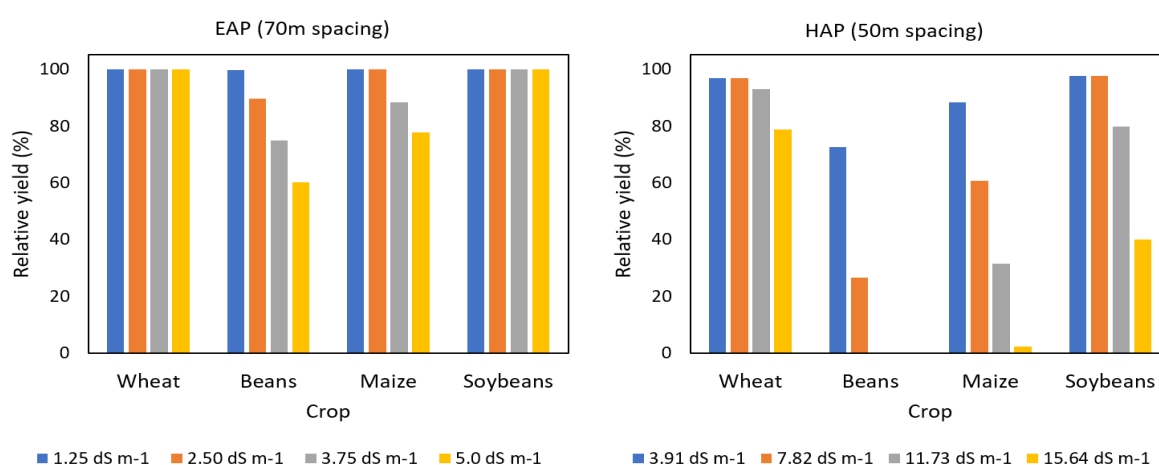


Figure 6-6: Drainage water reuse impacts on yield in EAP and HAP

Table 6-5: Estimated average annual return* based on G1 (measured K_{sat} and ET_0) and return over the 30-year simulation for each drain spacing in EAP as compared with Groups G2 – G5

Drain spacing	EAP							
	Wheat				Beans			
	Annual return (US\$ ha ⁻¹)	Annual for EAP ¹ (US\$1000's)	² Return over 30 yrs. (US\$1000's)	Groups	Annual return (US\$ ha ⁻¹)	Annual for EAP ¹ (US\$1000's)	² Return over 30 yrs. (US\$1000's)	Groups
10	320	961	28824	/	3105	9316	279474	/
20	364	1092	32754	/	3149	9447	283404	/
30	379	1136	34067	/	3164	9491	284717	/
40	386	1157	34719	/	3171	9512	285369	/
50	390	1170	35112	/	3175	9525	285762	/
60	393	1179	35371	/	3178	9534	286021	/
70 ⁱ	395	1185	35560	G1 & G3	3176	9529	285877	G1 & G3
80	324	971	29132	G2	3004	9012	270368	G2
90	-213	-639	-19170	G5	763	2289	68680	G5
100	-259	-776	-23286	G4	-509	-1526	-45786	G4
200	-254	-763	-22893	/	-504	-1513	-45393	/

*All the returns are rounded to the nearest US\$. ¹Assuming a total area of 3000ha. ²Assuming a total area of 3000ha and life expectancy of drainage system of 30yrs (Skaggs, 2007).

ⁱ 70m was highlighted because it is the optimum design based on measured K_{sat} and ET_0 .

Table 6-6: Estimated average annual return* based on G1 (measured K_{sat} and ET0) and return over the 30-year simulation for each drain spacing in HAP as compared with Groups G2 – G5.

Drain spacing	HAP							
	Wheat				Beans			
	Annual return (US\$ ha ⁻¹)	Annual for EAP ¹ (US\$1000's)	² Return over 30 yrs. (US\$1000's)	Groups	Annual return (US\$ ha ⁻¹)	Annual for EAP ¹ (US\$1000's)	² Return over 30 yrs. (US\$1000's)	Groups
10	309	371	11127	/	2106	2528	75826	/
20	352	423	12675	/	2146	2575	77264	/
30	365	438	13130	G4 & G5	2157	2589	77656	G4 & G5
40	369	442	13272	/	2164	2597	77917	/
50 ⁱⁱ	370	444	13311	G1, G2 & G3	2165	2598	77941	G1, G2 & G3
60	359	431	12941	/	2146	2575	77246	/
70	354	424	12733	/	2074	2489	74657	/
80	329	395	11842	/	1957	2348	70451	/
90	312	374	11223	/	1803	2163	64901	/
100	272	326	9790	/	1626	1951	58542	/
200	-254	-305	-9157	/	-504	-605	-18157	/

*All the returns are rounded to the nearest US\$. ¹Assuming a total area of 1200ha. ²Assuming a total area of 1200 ha and life expectancy of drainage system (Skaggs, 2007).

ⁱⁱ 50m was highlighted because optimum design based on measured K_{sat} and ET0.

6.4 Discussion

6.4.1 Assessing DRAINMOD applications with predicted Vs. measured K_{sat} and ET_0

Multiple DRAINMOD simulations were conducted in order to evaluate the combined effect of using K_{sat} and ET_0 data derived from directly measured and indirect prediction methods on the accuracy of DRAINMOD outputs, especially the annual yield predictions and corresponding drain spacing. This process reflects the most likely situation when DRAINMOD is used to design large scale drainage schemes in LDCs. The results showed that the accuracy of the methods applied to predict K_{sat} and ET_0 has a major impact on DRAINMOD outputs, estimated yields, annual and long-term farm incomes. The two most effective methods for predicting drain spacing comparable to the optimum design (obtained using measured K_{sat} and ET_0 values) were achieved using the ANNs applied in G2 and G3 for EAP and HAP. Even within these ANNs, G3 was slightly more accurate than G2, resulting in a more precise prediction compared to the optimum spacing of 70m in EAP, with G2 predicting 80m and G3 predicting 70m. These results confirm the findings of Abdelbaki (2011), who observed that the accuracy of the applied predicted K_{sat} influenced DRAINMOD predictions at four locations in the Midwest, USA.

Methodological approaches G4 and G5 were the least accurate at predicting drain spacing and relative yield in EAP and HAP. Even though Rosetta3 is much more accurate in estimating K_{sat} than many pedotransfer functions, Rosetta3 was developed and tested on soil types in different geographical locations (soils mainly from North America and Europe) than those found at either EAP or HAP (Nemes et al., 2003; Van Looy et al., 2017; Zhang and Schaap, 2017). Also, the accuracy of the methods applied to predict ET_0 using G4 (MODAWEC) and G5 (ERA5-Land) impacted negatively on the DRAINMOD predictions (Chapter 4). MODAWEC converts the MT_{max} and MT_{min} to DT_{max} and DT_{min} , the conversion ensures that the generated DT_{max} and DT_{min} are within the range of temperatures observed for MT_{max} and MT_{min} . However, the MODAWEC conversion did not result in an accurate calculation of ET_0 .

Even though ERA5-Land was more accurate than MODAWEC in estimating DTmax and DTmin, as well as ET0 calculation for missing data from Sabha and Hon meteorological stations, the ERA5-Land technique coupled with Rosetta3 K_{sat} prediction (G5) resulted in inaccurate drain spacing and relative yield prediction in EAP and HAP when used in DRAINMOD and were comparable to G4 predictions. Therefore, ET0 from ERA5-Land would not improve DRAINMOD predictions of drain spacing and the associated relative yield in EAP or HAP.

6.4.2 Drain spacing and relative yield relationship

Narrow drain spacings reduce and, in many cases, eliminated yield losses caused by planting date delay, drought, salinity and excessive soil water conditions (waterlogging). For EAP and HAP, the relationship between relative yield and drain spacing were similar. For example, in EAP, the relationship between relative yield and drain spacing was comparatively consistent for all simulations (G1 – G5) up to 70m. After that, each group (G1 – G5) has its own maximum relative yield associated with the wider drain spacing for each group. The highest relative yield is associated with the wider drain spacing known as the threshold (Skaggs et al., 2006). G1 and G3 have a threshold at 70m, G2 at 80m, G5 at 90m and G4 at 100m. In HAP, the relationship between relative yield and drain spacing was consistent up to 30m spacing; after that, the groups divided into two thresholds. Groups G1, G2 and G3 had a threshold at 50m spacing, while for G4 and G5 the threshold was at 30m. This can largely be explained by the comparative accuracy of the methods applied to predict K_{sat} and ET0 (i.e. Rosetta3, MODAWEC and ERA5-Land). This study showed that salinity and waterlogging problems can be managed when a proper drainage system is installed, especially with narrow drain spacings (up to 70m in EAP and up to 50m in HAP). For example, in EAP, the impact of salinity and waterlogging was not observed for drain spacing ranging from 10 – 70m. After that, the wider the distance between drains, the greater the impact of salinity and waterlogging on crop yield. From a waterlogging perspective, the wider spacing between drains will cause a higher water table. The higher water table will negatively affect the crop yield (up to 100% reduction in yield in EAP and HAP at high drain spacings).

In EAP, the salinity levels in irrigation water were within the tolerance of the four crops hence it did not cause a reduction in yield. In contrast, the quality of the water applied in HAP caused a reduction of almost 30% for beans and around 10% for maize. Salinity impact increases with wider drain spacing installed for beans and maize in HAP.

6.4.3 Cost implications of applying predicted Vs. measured K_{sat} and ET_0

Drainage system design should consider the system's installation and maintenance costs, water savings and impact on yields. The purpose is often to maximise the farmer's profit or net return. Land costs, or rental, and management time are not factored into the calculations for this study, nor is the cost of installing and maintaining drainage outlets. Therefore, the net annual average return is not the net profit but the return on land, crops and water management. In EAP, the drainage design based on measured data, including K_{sat} and ET_0 (G1), suggested that a spacing of 70m and 60m would be the optimum for wheat and beans, respectively. However, as an average for the four crops in rotation, 70m spacing between drains would be economically cheaper (i.e. the cost of installing drainage systems) than 60m. A design based on G2 predictions would assume that 80m spacing between drains was predicted to be optimal in EAP. However, if the drainage system was installed based on the G2 simulation, a loss of 18% on return for wheat and 5.5% for beans might occur. This would for the 3,000 ha of EAP equate to a total return loss of US\$ 6,428,000 for wheat or US\$ 15,653,000 for beans over 30 yrs compared to the simulation for G1. The input parameters used in G3 resulted in a drain spacing of 70m (as an average for the four crops), which was a comparable simulation to G1. Using G3 predictions to design a drainage system should therefore have no financial implications in EAP. Predictions based on parameters used in G4 and G5 were the least accurate compared to G1 and consequently posed the highest financial risk. For example, G4 and G5 suggested 100m and 90m spacing between drains. These designs will not provide any economic return, and the money invested in installing the drainage system will be lost.

These results show how important the accuracy of predicting K_{sat} and ET_0 is for drainage system design and associated yield potential. In HAP, the optimum design obtained from G1 suggested an average drain spacing for the four crops evaluated of 50m. Using G2 and G3 input parameters, it was possible to predict the same spacing as G1. Installing a drainage system based on G2 or G3 would be similar to that of the optimum design and hence would provide the maximum return over the entire HAP area over 30 yrs of US\$ 13,311,000 and US\$ 77,941,000 for wheat and beans, respectively. Using G4 and G5 parameters gave a 30m spacing as optimal. However, a design based on these suggestions would over 30 yrs due to higher installation costs, result in a loss of US\$ 180,000 and US\$ 285,000 for wheat and beans, respectively.

6.5 Conclusions

The objective of this study was to critically evaluate the implications of designing a drainage system using the drainage simulation model (DRAINMOD) using indirect measurements of K_{sat} and ET_0 as compared to measured data. The results of the resultant simulations demonstrate that G2 and G3 were more accurate (closest to the optimum design) in predicting the potential yield and the associated drain spacing than G4 K_{sat} predicted by Rosetta3, and ET_0 predicted by MODAWEC) and G5 K_{sat} predicted by Rosetta3, and ET_0 predicted by ERA5-Land) for EAP and HAP. However, G3 was slightly more accurate than G2 in EAP. Therefore, assuming that the cost of the land, or rental, and management time are not factored into the calculations, the annual and total return estimated by the ANNs methods (G2 and G3) are comparable to the optimum design based on the measured dataset. As K_{sat} and ET_0 are time-consuming and expensive to measure, designing drainage systems based on ANNs predictions would not only lower the risks of drains being inappropriately spaced (either too wide or too close), but it would also be more cost-effective and accessible to farmers, planners and decision-makers in Libya and other LDCs. Further research is needed to further enhance water use efficiency by reusing drainage water generated from EAP and HAP to irrigate more salt-tolerant crops.

6.6 References

- Abdelbaki, A., 2011. Assessing the feasibility of using Pedotransfer functions and automatic calibration methods for estimating DRAINMOD inputs. Cairo University.
- Allen, R.G., Food, of the United Nations, A.O., 1998. Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements, FAO irrigation and drainage paper. FAO.
- Arrington, K.E., Ventura, S.J., Norman, J.M., 2013. Predicting Saturated Hydraulic Conductivity for Estimating Maximum Soil Infiltration Rates. *Soil Sci. Soc. Am. J.* 77, 748–758. <https://doi.org/10.2136/sssaj2012.0288>
- Ayars, J.E., Evans, R.G., 2015. Subsurface Drainage - What's Next? *Irrig. Drain.* 64, 378–392. <https://doi.org/10.1002/ird.1893>
- Bastiaanssen, W.G.M., Huygen, J., Schakel, J.K., Broek, B.J. van den, 1996. Modelling the soil-water-crop-atmosphere system to improve agricultural water management in arid zones (SWATRE), in: van den Broek, B.J. (Ed.), *Dutch Experience in Irrigation Water Management Modelling*. 119, Staring Centrum, , pp. 13–30.
- Beers, W.F.J. Van, 1958. The auger-hole method.
- Bouyoucos, G., 1927. The hydrometer as new method for mechanical analysis of soils. *Soil Sci.* 23, 343–353.
- Buckman, H., Brady, N., 1960. *The Nature and Properties of Soil*, 6th ed. Macmillan company, New York, USA.
- Chen, X., Qi, Z., Gui, D., Sima, M.W., Zeng, F., Li, L., Li, X., Gu, Z., 2020. Evaluation of a new irrigation decision support system in improving cotton yield and water productivity in an arid climate. *Agric. Water Manag.* 234, 1–10. <https://doi.org/https://doi.org/10.1016/j.agwat.2020.106139>
- Cornelius-Brochier J.V, 1981. *Wadi Al Shatti: Drainage Design*. Tripoli, Libya.

Danenco, 1980. Technical Study for Jufra el Hamam Project. Copenhagen, Denmark.

Dashtaki, S.G., Homaei, M., Khodaverdiloo, H., 2010. Derivation and validation of pedotransfer functions for estimating soil water retention curve using a variety of soil data. *Soil Use Manag.* 26, 68–74. <https://doi.org/10.1111/j.1475-2743.2009.00254.x>

Ellafi, M.A., Deeks, L.K., Simmons, R.W., 2021. Application of artificial neural networks to the design of subsurface drainage systems in Libyan agricultural projects. *J. Hydrol. Reg. Stud.* 35, 1–17. <https://doi.org/https://doi.org/10.1016/j.ejrh.2021.100832>

Elshehry, M., 2018. Review of Technologies and Practices for Improving Agricultural Drainage Water Quality in Egypt, in: *Unconventional Water Resources and Agriculture in Egypt*. Springer Verlag, pp. 163–188. <https://doi.org/10.1007/698>

Er-Raki, S., Ezzahar, J., Merlin, O., Amazirh, A., Hssaine, B.A., Kharrou, M.H., Khabba, S., Chehbouni, A., 2021. Performance of the HYDRUS-1D model for water balance components assessment of irrigated winter wheat under different water managements in semi-arid region of Morocco. *Agric. Water Manag.* 244, 106546. <https://doi.org/https://doi.org/10.1016/j.agwat.2020.106546>

Fadul, E., Masih, I., De Fraiture, C., Suryadi, F.X., 2020. Irrigation performance under alternative field designs in a spate irrigation system with large field dimensions. *Agric. Water Manag.* 231, 1–12. <https://doi.org/https://doi.org/10.1016/j.agwat.2019.105989>

FAO, 2016. Country profile - Libya. Rome, Italy. <https://doi.org/10.1787/9487b828-en>

FAO, 1988. Salt-Affected Soils and their Management [WWW Document]. Food Agric. Organ. URL <http://www.fao.org/docrep/x5871e/x5871e00.htm#Contents> (accessed 2.5.18).

Fernandez, G., Chescheir, G., Skaggs, R.W., Amatya, D., 2006. DRAINMOD-GIS: A lumped-parameter, watershed-scale drainage and water quality model. *Agric. Water Manag.* 81, 77–97.

Fooladmand, H.R., 2011. Pedotransfer functions for point estimation of soil moisture characteristic curve in some Iranian soils. *African J. Agric. Res.* 6, 1586–1591. <https://doi.org/10.5897/AJAR10.1152>

Freisem, C., Scheumann, W., 2001. Institutional arrangements for land drainage in developing countries. Colombo, Sri Lanka.

Gelaro, R., McCarty, W., Suárez, M.J., Todling, R., Molod, A., Takacs, L., Randles, C.A., Darmenov, A., Bosilovich, M.G., Reichle, R., Wargan, K., Coy, L., Cullather, R., Draper, C., Akella, S., Buchard, V., Conaty, A., da Silva, A.M., Gu, W., Kim, G., Koster, R., Lucchesi, R., Merkova, D., Nielsen, J.E., Partyka, G., Pawson, S., Putman, W., Rienecker, M., Schubert, S.D., Sienkiewicz, M., Zhao, B., 2017. The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2). *J. Clim.* 30, 5419–5454. <https://doi.org/10.1175/JCLI-D-16-0758.1>

Ghane, E., Askar, M.H., 2021. Predicting the effect of drain depth on profitability and hydrology of subsurface drainage systems across the eastern USA. *Agric. Water Manag.* 258, 107072. <https://doi.org/10.1016/j.agwat.2021.107072>

Grismer, M., Bali, K., 2015. Use of Saline Drain Water for Crop Production. ANR Publ. p.8554.

Grismer, M.E., 2015. Use of Shallow Groundwater for Crop Production. ANR Publ. p.8521.

Gupta, G.P., Prasher, S.O., Chieng, S.T., Mathur, I.N., 1993. Application of DRAINMOD under semi-arid conditions. *Agric. Water Manag.* 24, 63–80.

GWA, 1999. Water and irrigation requirements for the most important crops in Libya [unpublished report]. Tripoli.

Hassler, S., Lark, R., Zimmermann, B., Elsenbeer, H., 2014. Which sampling design to monitor saturated hydraulic conductivity ? *Eur. J. Soil Sci.* 792–802. <https://doi.org/10.1111/ejss.12174>

Holzmann-Wakuti, 1974. Hydrogeology of The Joufrah Project Area. Tripoli, Libya.

Italconsult, 1976. Fezzan Land Reclamation Project: Wadi-Shati Eshkeda Area. Rome, Italy.

Jones, C.A., Wegner, M., Russell, J., McLeod, I., Williams, J., 1989. AUSCANE—Simulation of Australian Sugarcane with EPIC. Brisbane, Australia.

Kale, S., 2011. Field-evaluation of DRAINMOD-S for predicting soil and drainage water salinity under semi-arid conditions in Turkey. *Spanish J. Agric. Res.* 9, 1142–1155.

Kanda, N., Negi, H.S., Rishi, M.S., Shekhar, M.S., 2018. Performance of various techniques in estimating missing climatological data over snowbound mountainous areas of Karakoram Himalaya. *Meteorol. Appl.* 25, 337–349. <https://doi.org/10.1002/met.1699>

Kandil, H., Skaggs, R.W., Abdel Dayem, S., Aiad, Y., 1995. DRAINMOD-S : Water management model for irrigated arid lands , crop yield and applications. *Irrig. Drain. Syst.* 9, 239–258.

Kanzari, S., Jaziri, R., Ali, K. Ben, Daghari, I., 2021. Long-term evaluation of soil salinization risks under different climate change scenarios in a semi-arid region of Tunisia. *Water Supply* 21, 2463–2476. <https://doi.org/10.2166/ws.2021.052>

Khodaverdiloo, H., Homaei, M., Th, M., Genuchten, V., Ghorbani, S., 2011. Deriving and validating pedotransfer functions for some calcareous soils. *J. Hydrol.* 399, 93–99. <https://doi.org/10.1016/j.jhydrol.2010.12.040>

Klute, A., Dirksen, C., 1986. Hydraulic Conductivity and Diffusivity: Laboratory Methods, in: *Methods of Soil Analysis, Part 1, Physical and Mineralogical Methods*, A. Klute, ed., ASA, Madison, WI, pp. 687–734.

Knegt, J., 2000. *Drainage in Developing Countries: A review of institutional arrangements*. Wageningen, The Netherlands.

Kumar, M., Raghuwanshi N, S., Singh, R., Wallender W, W., Pruitt W, O., 2002. Estimating Evapotranspiration using Artificial Neural Network. *J. Irrig. Drain. Eng.* 128, 224–233. [https://doi.org/10.1061/\(ASCE\)0733-9437\(2002\)128:4\(224\)](https://doi.org/10.1061/(ASCE)0733-9437(2002)128:4(224))

Legates, D.R., Willmott, C.J., 1990. Mean seasonal and spatial variability in global surface air temperature. *Theor. Appl. Climatol.* 41, 11–21. <https://doi.org/10.1007/BF00866198>

Liu, J., Williams, J.R., Wang, X., Yang, H., 2008. Using MODAWEC to generate daily weather data for the EPIC model. *Environ. Model. Softw.* 24, 655–664. <https://doi.org/10.1016/j.envsoft.2008.10.008>

LNMC, 2020. Average Daily and Monthly Meteorological datasets observed in Libyan Meteorological stations [datasets was collected by personal contacts with the Libyan National Meteorological Centre in 2020]. Tripoli, Libya.

Malakshahi, A.-A., Naftchali, A.D.-, Mohseni, B., 2020. Analyzing water table depth fluctuation response to evapotranspiration involving DRAINMOD model. *Agric. Water Manag.* 234, 1–10. <https://doi.org/10.1016/j.agwat.2020.106125>

Muñoz-Sabater, J., 2019. ERA5-Land hourly data from 1981 to present [WWW Document]. Copernicus Clim. Chang. Serv. Clim. Data Store.

Nemes, A., Schaap, M.G., Wösten, J.H.M., 2003. Functional Evaluation of Pedotransfer Functions Derived from Different Scales of Data Collection. *Soil Sci. Soc. Am. J.* 67, 1093–1102. <https://doi.org/10.2136/sssaj2003.1093>

Niaghi, A.R., Jia, X., Scherer, T.F., 2017. Impact of Accurate Evapotranspiration Estimates on DRAINMOD Simulation in North Dakota. 2017 ASABE Annu. Int.

Meet., ASABE Paper No. 1701500.
<https://doi.org/https://doi.org/10.13031/aim.201701500>

Nkiaka, E., Nawaz, N.R., Lovett, J.C., 2017. Evaluating global reanalysis precipitation datasets with rain gauge measurements in the Sudano-Sahel region: case study of the Logone catchment, Lake Chad Basin. *Meteorol. Appl.* 24, 9–18. <https://doi.org/10.1002/met.1600>

Nozari, H., Liaghat, A., Azadi, S., Poursadri, A., Ghanbarian, B., 2021. Simulation of real-time variations of saline drainage water: comparing system dynamics with DRAINMOD-S. *Water Pract. Technol.* 16, 1277–1289. <https://doi.org/10.2166/wpt.2021.060>

Patil, N.G., Pal, D., Mandal, C., Mandal, D., 2011. Soil water retention characteristics of Vertisols and pedotransfer functions based on nearest neighbor and neural networks approach to estimate AWC. *J. Irrig. Drain. Eng.* 138, 177–184.

Patil, N.G., Rajput, G., Nema, R., Singh, R., 2010. Predicting hydraulic properties of seasonally impounded soils. *J. Agric. Sci. Cambridge* 148, 159–170.

Patil, N.G., Singh, S.K., 2016. Pedotransfer Functions for Estimating Soil Hydraulic Properties: A Review. *Pedosph. An Int. J.* 26, 417–430. [https://doi.org/10.1016/S1002-0160\(15\)60054-6](https://doi.org/10.1016/S1002-0160(15)60054-6)

Prăvălie, R., Patriche, C., Borrelli, P., Panagos, P., Roșca, B., Dumitrașcu, M., Nita, I.A., Săvulescu, I., Birsan, M.V., Bandoc, G., 2021. Arable lands under the pressure of multiple land degradation processes. A global perspective. *Environ. Res.* 194. <https://doi.org/10.1016/j.envres.2020.110697>

Reynolds, W., Elrick, D., 1985. In situ measurement of field-saturated hydraulic conductivity, sorptivity, and the α parameter using the Guelph Permeameter. *Soil Sci.* 140, 172–180.

Richards, L., 1949. Methods of measuring soil moisture tension. *Soil Sci.* 68, 95–112.

Safriel, U., Adeel, Z., Niemeijer, D., Puigdefabregas, J., White, R., Lal, R., Winslow, M., Prince, S., Archer, E., King, C., Shapiro, B., Wessels, K., Nielsen, T., Portnov, B., Reshef, I., Lachman, E., McNab, D., El-kassas, M., Ezcurra, E., 2005. Dryland Systems, in: Hassan, R., Scholes, R., Ash, N. (Eds.), *Ecosystems and Human Well-Being: Current State and Trends: Findings of the Condition and Trends Working Group (Millennium Ecosystem Assessment Series)*. Island Press, Washington, DC, USA, pp. 625–662.

Schaap, M.G., Leij, F.J., Genuchten, M.T. Van, 2001. Rosetta : a computer program for estimating soil hydraulic parameters with hierarchical pedotransfer functions. *J. Hydrol.* 251, 163–176.

Schultz, B., Zimmer, D., Voltman, W.F., 2007. Drainage under increasing and changing requirements. *Irrig. Drain.* 56, S3–S22. <https://doi.org/10.1002/ird>

Skaggs, R.W., 2007. Criteria for Calculating Drain spacing and Depth. *Am. Soc. Agric. Biol. Eng.* 50, 1657–1662.

Skaggs, R.W., 1999. Drainage Simulation Models, in: Skaggs, R., van Schilfgaarde, J. (Eds.), *Agricultural Drainage*. American Society of Agronomy, Inc., Madison, Wisconsin, USA, pp. 469–500.

Skaggs, R.W., Youssef, M.A., Chescheir, G.M., 2012. DRAINMOD: model use, calibration, and validation. *Trans. ASABE* 55, 1509–1522. <https://doi.org/10.13031/2013.42259>

Skaggs, R.W., Youssef, M.A., Chescheir, G.M., 2006. Drainage design coefficients for eastern United States. *Agric. Water Manag.* 86, 40–49. <https://doi.org/10.1016/j.agwat.2006.06.007>

Smedema, L.K., Abdel-Dayem, S., Ochs, W.J., 2000. Drainage and agricultural development. *Irrig. Drain. Syst.* 14, 223–235. <https://doi.org/10.1023/A:1026570823692>

Sobieraj, J.A., Elsenbeer, H., Cameron, G., 2004. Scale dependency in spatial patterns of saturated hydraulic conductivity. *CATENA* 55, 49–77. [https://doi.org/10.1016/S0341-8162\(03\)00090-0](https://doi.org/10.1016/S0341-8162(03)00090-0)

Tarek, M., Brissette, F.P., Arsenault, R., 2020. Evaluation of the ERA5 reanalysis as a potential reference dataset for hydrological modelling over North America. *Hydrol. Earth Syst. Sci.* 24, 2527–2544. <https://doi.org/10.5194/hess-24-2527-2020>

USBR, 1993. *Drainage Manual*. Washington, DC, USA.

Van Looy, K., Bouma, J., Herbst, M., Koestel, J., Minasny, B., Mishra, U., Montzka, C., Nemes, A., Pachepsky, Y.A., Padarian, J., Schaap, M.G., Tóth, B., Verhoef, A., Vanderborght, J., van der Ploeg, M.J., Weihermüller, L., Zacharias, S., Zhang, Y., Vereecken, H., 2017. Pedotransfer Functions in Earth System Science: Challenges and Perspectives. *Rev. Geophys.* 55, 1199–1256. <https://doi.org/10.1002/2017RG000581>

Verma, A.K., Gupta, S.K., 2014. Calibration and Validation of SWAP to Simulate Conjunctive Use of Fresh and Saline Irrigation Waters in Semi-Arid Regions 45–55. <https://doi.org/10.1007/s10666-013-9379-x>

Yin, Z., Luo, Q., Wu, Jianfeng, Xu, S., Wu, Jichun, 2021. Identification of the long-term variations of groundwater and their governing factors based on hydrochemical and isotopic data in a river basin. *J. Hydrol.* 592, 1–13. <https://doi.org/https://doi.org/10.1016/j.jhydrol.2020.125604>

Zandler, H., Senftl, T., Vanselow, K.A., 2020. Reanalysis datasets outperform other gridded climate products in vegetation change analysis in peripheral conservation areas of Central Asia. *Sci. Rep.* 10, 1–16. <https://doi.org/10.1038/s41598-020-79480-y>

Zhang, Y., Schaap, M.G., 2019. Estimation of saturated hydraulic conductivity with pedotransfer functions: A review. *J. Hydrol.* 575, 1011–1030. <https://doi.org/10.1016/j.jhydrol.2019.05.058>

Zhang, Y., Schaap, M.G., 2017. Weighted recalibration of the Rosetta pedotransfer model with improved estimates of hydraulic parameter distributions and summary statistics (Rosetta3). *J. Hydrol.* 547, 39–53. <https://doi.org/https://doi.org/10.1016/j.jhydrol.2017.01.004>

7 Conclusions and Recommendations

7.1 Introduction

This research assessed the feasibility of designing drainage systems using a drainage simulation model in arid and semi-arid data-poor areas, especially in least developed countries (LDCs). The literature review (Chapter 2) identified that DRAINMOD is the most applicable model to design drainage systems in those areas. However, the input parameters required to run DRAINMOD are the most significant obstacle limiting the applications in LDCs. The ability to use indirect methods to predict the required input parameters (including the development of artificial neural networks) would, in theory, reduce the overall cost of designing and installing drainage systems and help improve the drainage design in arid and semi-arid areas in LDCs.

This research aimed to:

critically evaluate traditional verses alternative methods of acquiring input data for drainage models including the application of artificial neural networks in order to identify appropriate methodologies for ‘data poor’ countries.

To meet this aim, three objectives were set:

Objective 1: Critically evaluate existing drainage design models so as to identify model(s) that are applicable to arid regions.

Objective 2: Assess the potential of alternative methods of data acquisition, specifically artificial neural networks that could be used to fill gaps in missing field data (specifically K_{sat} , ET_0 and EC) against physically measured data.

Objective 3: Assess the feasibility of using predicted K_{sat} , ET_0 and EC to run the selected model to design drainage systems in arid regions.

7.2 Research achievements in relation to research objectives

7.2.1 Objective 1

‘Critically evaluate existing drainage design models so as to identify model(s) that are applicable to arid regions’

To achieve Objective 1, the literature on drainage simulation models for drainage design was critically reviewed (Chapter 2). The key outcomes of this review were as follows:

- Each drainage simulation model was evaluated based on input parameters needed to run the model, demonstrating the strengths (e.g. applications in arid and semi-arid regions) and weaknesses (e.g. difficulty of using the model and the absence of technical support) of each model (focusing on the design of drainage systems in arid and semi-arid areas). This provided a useful comparison tool for currently existing drainage simulation models.
- A selection criterion was created to help identify the most applicable model for drainage design by taking into consideration: (1) the capability requirements in arid and semi-arid areas (the ability to design a successful drainage system to prevent salinity waterlogging problems). (2) the ability to define the optimum drain spacing, water table depth, salinity status in the root zone, and the potential crop yield. (3) the availability and cost of generating the input data required by each model. (4) how many input parameters each model required to design a drainage system. (5) applicability in LDCs, for example, is the selected model capable of accommodating the unique requirements such as availability and capability of the computer required to run the model, availability of training material (including written manual and step-by-step videos tutorial), and most importantly, (6) the feasibility of using indirect methods to predict some of the missing input parameters.
- DRAINMOD was identified as the most suitable model for drainage system design in arid and semi-arid LDCs. DRAINMOD is widely applied in agricultural water management and especially in agricultural drainage in many areas, including the arid and semi-arid regions.

The model has successfully predicted the salinity impacts on crop yield, the water table depth fluctuations, and drainage discharge volume. Extensive printed instruction manual and more than 30 video lessons are available (open access) through the DRAINMOD website. Furthermore, the number of publications makes DRAINMOD the most commonly used drainage simulation model. Therefore, farmers, researchers, and decision-makers in LDCs can adopt DRAINMOD as a useful tool to evaluate alternative designs in arid and semi-arid areas if the input parameters are available.

7.2.2 Objective 2

‘Assess the potential of alternative methods of data acquisition, specifically artificial neural networks that could be used to fill gaps in missing field data (specifically K_{sat} , ET_0 and EC) against physically measured data.’

This objective was achieved by developing and validating artificial neural networks (ANNs) to predict the saturated hydraulic conductivity (K_{sat}) (Chapter 3), reference evapotranspiration (ET_0) (Chapter 4), and the Electrical Conductivity of a saturated soil Extract (EC_e) (Chapter 5). Easily measured and available input datasets were used to develop the ANNs for K_{sat} , ET_0 and EC_e predictions. The developed ANNs were trained and tested against the measured values and compared to other indirect methods. The following conclusions were drawn in meeting this objective:

- In Chapter 3, K_{sat} predictions based on EAP and HAP specific ANNs were shown to be more accurate than predictions based on widely adopted PTFs. To develop a precise ANN for K_{sat} predictions, the number of soil samples can be as low as 50 for up to 3000 ha, as long as it represents the field variability. Designing a drainage system in both EAP and HAP using K_{sat} predicted by site-specific ANNs would be similar (in terms of drain spacing and water table depth) to a design based on measured K_{sat} and, therefore, would save the time and cost of measuring K_{sat} .
- In Chapter 4, indirect methods were successfully used to fill gaps in missing long-term (30 yrs.) daily maximum and minimum air temperature (DT_{max} and DT_{min}) for meteorological stations relevant to EAP and HAP.

This is required in order to accurately determine ET₀ a key input parameter for DRAINMOD. The ANNs developed using monthly observed data, Global TempSIM predicts the daily average air temperature, estimated sunshine duration based on the geographical location, and ERA5-Land were the most accurate at predicting DT_{max} and DT_{min}. The output from DRAINMOD simulations using these ANNs showed that the accuracy of the method applied to calculate ET₀ had a major impact on the prediction of objective functions including relative yield and irrigation depth for both EAP and HAP. This research has also demonstrated through drainage design simulation that ANN4S and ANN4H worked as well as those based on measured data, for the two-case study agricultural projects in Libya.

- In Chapter 5, ANNs were successfully developed to accurately predict EC_e in EAP, and HAP. ANNs developed using reflection bands of satellite images and the derived salinity indices were slightly more accurate than ANNs developed from only the reflection bands of satellite images. ANNs can be used as a tool to evaluate and monitor an existing drainage system and specify an area in need of improvement.

7.2.3 Objective 3

‘Assess the feasibility of using predicted K_{sat}, ET₀ and EC to run the selected model to design drainage systems in arid regions.’

Objective 3 was addressed by critically evaluating the viability of applying predicted K_{sat}, and ET₀ to design a drainage system on both EAP and HAP. Five scenarios (Groups: G1 – G5) for each project were assigned to design drainage systems in both EAP and HAP (Chapter 6). G1 represented the measured values of K_{sat} and ET₀ (the optimum design), G2 used ANNs that require fewer input parameters for predicting K_{sat} and ET₀, G3 included the most accurate ANNs, G4 uses K_{sat} predicted by Rosetta3 and ET₀ predicted by MODAWEC, and finally, G5 has Rosetta3 predictions for K_{sat} and ERA5-Land predictions for ET₀. The following conclusions were drawn in meeting this objective:

- In comparison to the measured data (G1), for both EAP and HAP, G2 and G3 were more accurate at predicting the optimum spacing between drains compared to G4 and G5. It was clear that, the accuracy of the methods used for predicting K_{sat} and ET_0 had a major impact on DRAINMOD predictions. The results showed that the accuracy of the DRAINMOD simulations was mainly influenced by the performance of the applied methods in estimating K_{sat} and ET_0 . The best two approaches to predicting drain spacing comparable to the optimum design (obtained using measured K_{sat} and ET_0 values) were estimated by the ANNs applied in G2 and G3 for both EAP and HAP.
- Installing a drainage system based on G2 or G3 would be similar to the optimum design in G1 and hence would over the 30-year lifespan of the drainage design, provide the maximum return of US\$ 13,311,000 and US\$ 77,941,000 for wheat and beans, respectively. In contrast, G4 and G5 predicted a 30m spacing, and a design based on these suggestions may of 30 years, cause a loss of US\$ 180,000 and US\$ 285,000 for wheat and beans, respectively.

7.3 Strengths and weaknesses of the research

7.3.1 Chapter 2

In this chapter, an evaluation of the existing drainage simulation models was made, and a novel selection criterion was developed based on the recommendations from Skaggs (1999). Skaggs discussed from his point of view, the main factors that need to be taken into consideration when a model is chosen for a specific application. Chapter 2 incorporated these factors and applied it to select the most applicable model for drainage design in arid and semi-arid areas (Libya as a case study). However, this was the only research article, in which drainage model selection was discussed in detail, and it was not possible to find a discussion related to drainage model selections in the literature. Also, it was not possible to find or undertake a survey of farmers, decision-makers and

stakeholders' point of view on model selection criteria (especially from those live in the least developed countries).

7.3.2 Chapter 3

In this chapter, ANNs were developed to predict K_{sat} in EAP and HAP. ANNs were developed using the soil texture data (percentage of sand, silt and clay), bulk density, wilting point, and field capacity as input parameters. Even though the developed ANNs were reasonably accurate in predicting K_{sat} (RMSE ranging between 1.92 – 2.82 m d⁻¹), K_{sat} does not depend only on these specific input parameters. Soil chemical parameters such as organic matter content, pH, gypsum and phosphorous contents have an impact on estimating K_{sat} . However, these soil chemical characteristics data were not available and therefore, these ANNs were only developed based on the four input parameters mentioned above. The developed ANNs, were then evaluated against the widely adopted Pedotransfer functions (PTFs). There are tens of Pedotransfer functions developed to predict K_{sat} . However, again, the availability of the required inputs were the main factors for selecting the PTFs used in Chapter 3. Arguably, predictions based on these PTFs were lower than expected, this may be a limitation of using these PTFs outside their region of development. However, farmers and decision-makers in least developed countries (especially in Libya) are still applying these PTFs and make field management decisions based on the outputs of these PTFs. Therefore, this research highlights the risks of applying the tested PTFs for drainage design in arid and semi-arid areas (Libya as a case study). The input parameters for ANN2 and ANN4 (% S, Si and C and BD) do not describe the structure or connectivity of void spaces in soil, therefore, they do not explain the connections between soil structure and soil functions very well (Nemes et al., 2003; Pachepsky et al., 2006). Anderson and Bouma (1973) found that an excellent prediction (as close as possible to the observed values) of K_{sat} can be obtained when pore space is measured directly. Therefore, the ANNs that also include FC and WP (ANN1 and ANN3) increased the accuracy of prediction of K_{sat} in comparison to ANN2 and ANN4.

7.3.3 Chapter 4

In this chapter, ANNs proved to be an accurate approach to fill the gap in daily maximum and minimum air temperature and therefore calculating ET₀. However, and critically, other climatic factors are important in calculating ET₀, such as the wind speed, humidity, and radiation. Including these climatic parameters may improve the ET₀ predictions. This research focused on a specific time period (1981 – 2010), with the potential to be applied on a larger time period (e.g. 50 years), also it can be applied to predict the future daily maximum and minimum air temperature (which can help researchers who are interested in climate change and meteorological data).

7.3.4 Chapter 5

In this chapter, two ANNs were developed to predict EC_e in EAP and HAP using remote sensing data. This chapter was the most difficult one throughout this research. First, the number of samples were not enough to develop a more accurate ANN. Second, before choosing remote sensing data as an input parameter to predict EC_e, other input parameters were tested including the irrigation water quality of the nearest well, the depth to the impervious layer, soil texture, and water table depth. However, the development of ANNs were not possible. Therefore, remote sensing data was introduced based on its successful use by other researchers (Akramkhanov and Vlek, 2012; Ghorbani et al. 2019). Akramkhanov and Vlek (2012) and Ghorbani et al. (2019) highlighted the advantages of neural networks over other nonlinear techniques for measuring soil surface salinity. Akramkhanov and Vlek (2012) reported an R² of 0.83 for salinity prediction, whereas Ghorbani et al. (2019) claimed an accuracy of 0.82. Their studies are virtually identical to the current study in terms of the proposed technique and the accuracy of the results. The coefficient of determination (R²) of 0.83 does not indicate if an ANN model provides an adequate fit to data (A good model can have a low R² value. On the other hand, a biased model can have a high R² value). That was noted when the ANNs in this study were developed. ANNs can be a useful approach to predict soil salinity by testing other related variable and gathering large datasets.

7.3.5 Chapter 6

In this chapter, predicted values of K_{sat} (Chapter 3), and predicted ET0 (Chapter 4) were applied in scenarios to evaluate the feasibility of applying predicted input parameters (i.e. K_{sat} and ET0) for drainage design in arid and semi-arid areas. After checking the literature, no research was found which evaluated the feasibility of using predicted K_{sat} and ET0 for drainage design in arid and semi-arid areas. Economic analysis was conducted to compare the scenarios of the designs based on predicted values to the optimum design (see Appendix A, B and D) based on measured data. However, it was not possible to find data from different places in Libya on the price of the four simulated crops, and therefore the research was conducted based on personal communications with an experienced farmer who farms in Libya. This research also helped to evaluate the newly released Rosetta3 to predict K_{sat} .

7.4 Wider impact of the research across the Middle East and North Africa (MENA)

7.4.1 Hydrological modelling at catchment and regional levels

Water scarcity is a major global problem that is aggravated by the imbalance in distribution of rainfall from north to south, as well as an increasing population and misuse of water resources for agricultural purposes. Water scarcity has become a global issue due to socio-economic development and population growth, as well as climate change effects (DeNicola et al., 2015; Frederick and Major, 1997; Vörösmarty et al., 2000). Water scarcity is a problem in the Middle East and North Africa (MENA). In fact, water stress has been exacerbated by water extractions that exceed annual renewable resources, due to population growth and irrigation water demand (Milewski et al., 2020). Out of 23 countries located in the MENA, 17 and 13 countries have a total annual renewable water resources (TARWR) per capita of $<1000 \text{ m}^3$ and $<500 \text{ m}^3$ respectively (FAO, 2018b).

According to the United Nations Educational, Scientific and Cultural Organization (UNESCO), when TARWR falls below 1000 m^3 , the population faces water

scarcity, and below 500 m³ means that the population is in absolute scarcity (UNESCO, 2012).

In order to contribute to the future management of water resources in the MENA, multidisciplinary studies and research are required. Knowledge of catchment runoff provides a perspective of available water to restore the water balance in the catchment and is thus critical in the management of both drinking and agricultural water. To assess the effect of changes in land, water, and wildlife uses and to plan integrated water resource management, catchment-scale hydrological models are required (Paul, 2016; Paul et al., 2017; Shao et al., 2017; Wang et al., 2016). This study covered the use of ANNs at field scale using drainage simulation models, however, more catchment-scale hydrological models could be used/applied supported by the use of ANNs to predict missing input parameters. Catchment-scale models such as the Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998), the Hydrologic Engineering Centre-Hydrologic Modelling System (HEC-HMS) (Feldman, 2000), and the Variable Infiltration Capacity Model (VIC) (Liang et al., 1994), are frequently used at regional levels for planning and decision-making in relation to many activities related to water resources including droughts, flooding and water scarcity. For example, SWAT has been successfully applied to predict the effects of land management practices on water, sediments, and agricultural chemical inputs in large, complex catchments with a variety of soils, land use, and management conditions (Arnold et al., 2012). However, hydrological models at catchment-scale, have a number of limitations to their application in LDCs, including a lack of data at an appropriate temporal and spatial scale. Measuring spatial processes at an inappropriate scale can result, inefficiencies, and in inaccurate predictions (Avelino et al., 2016).

7.4.2 Soil information

Water erosion, dust storms, salinity and alkalinity, decline of soil fertility, desertification, urbanisation, improper soil management practices, waterlogging, and soil contamination (poor management of chemicals and pesticides) are

among the challenges and problems that soils face in different countries across the MENA region. These difficulties need a variety of conservation/management interventions, which will vary by country. The necessity for a robust soil information system that guides the decision-making process is, nevertheless, a common denominator throughout the various countries. Soil data are often old and/or lack consistency in terms of classification approaches (particularly within countries), mapping scale and/or resolution, and availability of data in non-electronic forms. At the same time, governments urgently want information on the distribution and types of soils in order to manage land use to improve productivity in response to rising food demands, as well as to maintain land productivity by decreasing land degradation. More precisely, decision makers at all levels (from farmers to policymakers) need knowledge of soil classification and distribution, soil fertility, degree of land degradation, and suitability.

To provide soil data, a novel cost-effective and time-effective soil mapping technique is required. This data would support the management of both soil and water resources, the preparation of agricultural development plans and activities including drainage, and the improvement of production while maintaining natural resources. However, there is a scarcity of data on the suitability of soils and land for various land uses. These are critical as the data would assist decision-makers in selecting and implementing the best land use and management practices based on biophysical potential. Furthermore, integrating this data with socio-economic factors when making land-use choices is critical. Nonetheless, since a large portion of the region is of limited agricultural relevance, expenditures on soil data collection and detailed soil data coverage should be emphasized. The first step would be to establish criteria for identifying places with high potential, which would be determined by local and regional specialists.

Climate (rainfall and temperature), topography (especially slope steepness), water resources availability, and accessibility, among other factors, might be utilised to identify locations for extensive soil data collection. To create up-to-date soil databases, new soil mapping tools/approaches including GIS and remote sensing as well as optimizing the use of existing historical soils datasets are

required. To guarantee the investment's long-term viability, national employees must also be properly trained in the creation, maintenance, and use of these databases.

This study demonstrated that ANNs can be successfully developed and applied to predicted K_{sat} in two case study locations in Libya (Ellafi et al., 2021) using historical soil datasets. This has the potential to be applied to the wider MENA region to predict K_{sat} as well as other soil hydraulic properties such as unsaturated hydraulic conductivity, available water capacity, and water retention curves. By looking at the publications and research undertaken in the MENA, it is clear that there is currently a lack of soil hydraulic properties in existing datasets in most of the region unless it has been intentionally redacted by researchers and decision-makers. It is likely that relevant data is in non-electronic forms or is retained within relevant government departments. In addition, such datasets may also be archived by international consultancy companies previously commissioned to undertake detailed soil sampling and analytical programs for drainage system design. Furthermore, in many places around the world, soil data is not available on a regional scale. In these areas, researchers, planners, and decision-makers are often challenged with insufficient data (Patil et al., 2011, 2010). During the development of ANNs to predict K_{sat} in EAP and HAP (Chapter 3), it was noted that the quality of the dataset (soil measurements) was more important than the quantity (Ellafi et al., 2021). Therefore, soil surveys and samples can be reduced by designing soil sampling programs that facilitate cost effective sampling for a specific location. In addition, Agronomists need soil temperature and moisture readings in addition to typical climatic data. Although these measurements (namely soil moisture) are becoming recognized for their importance in seasonal forecasting, they are less frequently recorded.

More of these observations are required, especially in LDCs where the use of technology-based solutions to reduce climate risk is severely limited. However, the need for soil data is growing, yet physical surveying is becoming less popular, and new indirect methods are being used to acquire information. Subsequently,

easy to measure soil datasets at regional level are needed as input parameters (predictor) for predicting parameters such as K_{sat} .

One promising source of information that is widely available are satellite images (e.g. Landsat 8). Indices derived from satellite images with a resolution of 30 m such as the Brightness index (BI) (Khan et al., 2001), Grain size index (GSI) (Xiao et al., 2006) and Normalized difference vegetation index (NDVI) (Rouse et al., 1974) can be used as input parameters to estimate soil hydraulic properties such as the infiltration rate, unsaturated hydraulic conductivity, available water capacity, and the water retention curve. In addition, a global digital elevation model (DEM) mapped at 30 m resolution can also be used to generate other indices such as stream power index (SPI), wetness index (WI) and sediment transport index (STI) (Wilson and Gallant, 2000), which can be applied as an input parameters in developing ANNs. The methods applied to develop ANNs for predicting the surface soil salinity in EAP and HAP (Chapter 5), have the potential to be applied across the MENA region. Soil salinisation is a negative consequence of the ecological environment's reverse succession, and continued succession will result in a natural disaster. The lack of appropriate drainage systems installed causes an increase in soil salinity, which leads to a decrease in soil fertility, reduction in cropping choices and/or no crop yield. Salinity also leads to soil degradation, and surface crusting, all of which result in irreversible losses to agriculture and the economy. Artificial neural networks coupled with satellite images (e.g. Landsat 8) can be used to develop an early warning system to predict the degree of future soil salinization. Such an early warning system would be invaluable to decision-makers, farmers and stakeholders. Reporting the situation according to the salinity monitoring and predictions in a specific location would help to control the salinity levels by changing the land management (Ainwal, 2013).

7.4.3 Climate change

Middle East and North Africa's population is expected to double by 2050, which, along with climatic impacts, would place immense demand on water and other

resources. Regional food imports are already high, 50% of regional wheat and barley, 40% of rice, and 70% of maize are imported. The area has dealt with its water shortage by utilizing both renewable and no-renewable groundwater extraction, desalinization, and wastewater treatment. Gulf countries (such as Bahrain, Kuwait, Oman, Saudi Arabia, Qatar, and United Arab Emirates) consume more water per capita than the global average, and Arab household water and energy markets are strongly subsidised. Extreme temperatures and low precipitation are common in MENA. In future decades, it is expected that these extremes will only become worse. Changed precipitation patterns, water scarcity, and expected sea level rise are all posing substantial difficulties to the region's development, especially in the areas of agriculture, livelihoods, and food security.

According to the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) by 2100 the average global temperature is estimated to rise between 2°C to 4°C and there is a 10% chance that it will exceed the 4°C (IPCC, 2014). It is expected that an increase in global temperature by 2°C, will be actually mean warming by 3°C in inland Algeria, Libya and large parts of Egypt by the end of the century. An increase of 4°C average global temperature would mean that the summer temperatures would be expected to increase by 8°C in parts of Algeria, Saudi Arabia and Iraq. Also, it is predicted that 30% of the summer months in almost all of MENA would face heat extremes. A population of 60 million are at risk in coastal cities in MENA from a predicted 0.5 m rise in sea level and annual losses would increase to US\$ 58 billion. Agriculture would also be impacted by climate change in MENA. Without considering adaptation, a reduction in agricultural output of between 30 – 60% is expected. The low rainfall and high temperature would shorten the growing season for wheat in MENA. Also, the increase in temperature would increase evapotranspiration and therefore more irrigation would be needed for agriculture (IPCC, 2014). Developing ANNs that predict the agro-climatic data (agricultural climatology) over a number of years (e.g. 10 – 20 years) based on the current climate change

trend, would help to inform farmers and decision-makers ahead of time, allowing them to adapt and mitigate the impact of climate change.

Agro-climatic data is based on long-term observations of climatological data gathered across large areas and over extended periods of time. These data are used to study climatic variability and change, as well as to find statistically significant links between climatological variables and soil and plant processes, animal, and pest development. However, in many areas in the world (especially in LDCs) climatological data is not available on a daily basis or has missing values. This demonstrated that ANNs can be used to accurately predict the missing daily maximum and minimum air temperature (DTmax and DTmin) and to calculate the reference evapotranspiration (ET0) for the design of drainage systems (Chapter 4). Agricultural climatology is based on fundamental physical laws which are applied to plant, animal, soil, and environments (Takle, 2003). The methods used in this research to develop the ANNs for predicting DTmax and DTmin can also be used to predict other important climatological parameters in the agricultural sector in arid and semi-arid areas such as radiation (White, 2017), wind speed (Takle, 2003), precipitation (Nangia et al., 2010c) and humidity (Dutta and Mitra, 2011). These climatic parameters can then be used to understand climate change impacts on MENA region including floods, heatwaves and droughts.

7.5 Recommendations for future work

In this study, DRAINMOD was selected as the most applicable model for designing drainage systems in arid and semi-arid regions such as Libya because it had the highest score against the selection criteria. However, other models had similar total score compared to DRAINMOD. Therefore, further research is needed to evaluate the applicability of running other simulation models such as SWAP, HYDRUS-1D, RZWQM2, and EPIC (including the catchment-scale simulation models e.g. SWAT and HEC-HMC), by using predicted values of E_{Ce}, K_{sat} and ET0. This would help to understand the importance of accurately predict those input parameters. This study focused on three input parameters required

by DRAINMOD which were K_{sat} , ET_0 and E_{ce} . DRAINMOD requires other input parameters, such as water retention curve, depth of impermeable layer, hourly or daily rainfall, and initial water table depth. Research needs to be undertaken to develop ANNs that predict these input parameters using easily measured data such as data derived from satellite images.

Soil moisture determines water availability that subsequently signifies the crop growth. Dropping below the management allowable depletion leads to a decrease in crop growth rate and evapotranspiration. Soil water content is the actual amount of water present in the soil measured as a percentage of water by volume (%). Accurate quantification of the soil moisture variation during the growing season enables irrigation scheduling that can subsequently be helpful in modeling crop stress and yield reduction. As mentioned earlier, climate change has affected the climatological patterns. For example, in humid areas, more intense rainfall events are recorded for a shorter period of time and longer dry period between rainfall events is noticed. In arid and semi-arid areas, the temperature is getting higher and lower rainfall amounts received, and that is affecting the soil moisture content. In addition, none of the available drainage simulation models have the ability to predict the soil moisture in soil layers. The key to accurate simulation is specification of field capacity and permanent wilting point, and the specification of root activity in each soil layer as a function of time. An additional benefit of this approach is that adjusting root activity algorithms to match simulated and observed water contents can indicate root growth patterns during the growing season. There is a need to extend or develop a new drainage simulation model that can accurately predict the soil moisture content in soil layer.

This study focused on designing conventional subsurface drainage systems in EAP and HAP. Other types of subsurface drainage designs have been successfully designed and installed (especially within developed countries) and need to be evaluated under Libyan condition (arid and semi-arid areas). The first type is conventional drainage with drainage water reuse, this research evaluated the impacts of drainage water reuse as irrigation water in EAP and HAP. The results show that, using a high salinity water can cause a tremendous reduction

in crop yield. However, more in-depth research is needed to evaluate the impact of reusing drainage water for irrigation on crop yield and salinity levels in agricultural projects such as EAP and HAP. This will significantly improve overall WUE. The second type is controlled drainage, controlled drainage systems have been shown to have an impact on reducing drainage discharge and nutrient loads in humid areas, but further research is needed to evaluate the benefits of installing controlled drainage systems in arid areas with and without subirrigation. These evaluations can help to improve the understanding of applying different agricultural water management practices and help to achieve the Best Management Practices (BMPs) in arid and semi-arid areas.

Five widely adopted Pedotransfer functions (PTFs) were evaluated in this study to predict K_{sat} . This number does not represent all the available PTFs, but it represents the PTFs which require input parameters available in EAP and HAP (i.e. percentage of sand, silt and clay, bulk density, field capacity and wilting point). Other PTFs, which require different input parameters which were not available in EAP and HAP, for example organic matter content, pH number, gypsum and phosphorous contents were not tested in EAP and HAP. Therefore, if these input parameters were found or measured, there is a need for a research that evaluates the accuracy of these additional PTFs. Also, if additional input parameters become available it is recommended that ANNs are developed and compared to the accuracy of the ANNs developed in this study.

This research mainly focused on the development of ANNs, and ANNs are a type of machine learning algorithm. Other machine learning algorithms exist, such as Decision Support Trees, Random Forest Models, Naive or Informed Bayesian Belief Networks and K-nearest Neighbour approaches are available. Research needs to be undertaken to predict K_{sat} , ET_0 and E_{ce} using these machine learning algorithms. Those ANNs developed using a combination of datasets from EAP and HAP have shown that accurate prediction of K_{sat} can be made using machine learning algorithms. Research is needed to develop more comprehensive ANNs and/or other machine learning algorithms approaches that predict K_{sat} at a national level (e.g. Libya) and/or regional level (MENA).

The ANNs developed to predict DTmax and DTmin to calculate ET₀ showed that more accurate predictions helped to accurately predict irrigation requirement, and drainage discharge in EAP and HAP. Research is needed to evaluate the importance of predicting other climatic data influencing ET₀ such as wind speed, sunshine duration, and humidity. In this study, ANNs developed using reflectance from satellite images were also able to accurately monitor surface soil salinity in EAP and HAP. Further research is needed to monitor the salinity status of other existing agricultural projects in the MENA region.

The results from this research, generated using a the drainage simulation model (DRAINMOD), need to be tested in pilot fields in EAP and HAP in order to demonstrate to decision-makers in Libya that this method offers an true economic alternative to the current practice.

7.6 References

Ainwal, S., 2013. Establishment of an early warning model for soil salinization in the Oasis-Kujiahe Delta oasis [D].

Arnold, J., Moriasi, D., Gassman, P., Abbaspour, K., White, M., Srinivasan, R., Santhi, C., Harmel, R., van Griensven, A., Van Liew, M., Kannan, N., Jha, M., 2012. SWAT: Model Use, Calibration, and Validation. *Trans. ASABE* 55, 1491–1508.

Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large Area Hydrologic Modeling And Assessment Part I: Model Development. *J. Am. Water Resour. Assoc.* 34, 73–89. <https://doi.org/https://doi.org/10.1111/j.1752-1688.1998.tb05961.x>

Avelino, A.F.T., Baylis, K., Honey-Rosés, J., 2016. Goldilocks and the Raster Grid: Selecting Scale when Evaluating Conservation Programs. *PLoS One* 11, e0167945.

DeNicola, E., Aburizaiza, O.S., Siddique, A., Siddique, A., Khwaja, H., Carpenter, D.O., 2015. Climate Change and Water Scarcity: The Case of Saudi Arabia. *Ann. Glob. Heal.* 81, 342–353.

Dutta, B., Mitra, S., 2011. Better prediction of humidity using Artificial Neural Network, in: *Fourth International Conference on the Applications of Digital Information and Web Technologies (ICADIWT 2011)*. IEEE, pp. 59–64. <https://doi.org/10.1109/ICADIWT.2011.6041395>.

Ellafi, M.A., Deeks, L.K., Simmons, R.W., 2021. Application of artificial neural networks to the design of subsurface drainage systems in Libyan agricultural projects. *J. Hydrol. Reg. Stud.* 35, 1–17. <https://doi.org/https://doi.org/10.1016/j.ejrh.2021.100832>

FAO, 2018. AQUASTAT Database [WWW Document]. Food Agric. Organ.

Feldman, A., 2000. Hydrologic Modeling System HEC-HMS: Technical Reference Manual.

Frederick, K.D., Major, D.C., 1997. Climate Change and Water Resources. *Clim. Change* 37, 7–23. <https://doi.org/10.1023/A:1005336924908>

IPCC, 2014. Climate Change 2014: Synthesis Report. Geneva, Switzerland.

Khan, N.M., Rastoskuev, V. V, Shalina, E. V, Sato, Y., 2001. Mapping Salt-affected Soils Using Remote Sensing Indicators-A Simple Approach With the Use of GIS IDRISI -.

Liang, X., Lettenmaier, D., Wood, E., Burges, S., 1994. A simple hydrologically based model of land surface water and energy fluxes for general circulation models. *J. Geophys. Res.* 99, 14415–14428.

Milewski, A., Seyoum, W.M., Elkadiri, R., Durham, M., 2020. Multi-Scale Hydrologic Sensitivity to Climatic and Anthropogenic Changes in Northern Morocco. *Geosciences* 10. <https://doi.org/10.3390/geosciences10010013>

Nangia, V., Mulla, D., Gowda, P., 2010. Precipitation changes impact stream discharge, nitrate-nitrogen load more than agricultural management changes. *J. Environ. Qual.* 39, 2063–2071.

Patil, N.G., Pal, D., Mandal, C., Mandal, D., 2011. Soil water retention characteristics of Vertisols and pedotransfer functions based on nearest neighbor and neural networks approach to estimate AWC. *J. Irrig. Drain. Eng.* 138, 177–184.

Patil, N.G., Rajput, G., Nema, R., Singh, R., 2010. Predicting hydraulic properties of seasonally impounded soils. *J. Agric. Sci. Cambridge* 148, 159–170.

Paul, M., 2016. Impacts of land use and climate changes on hydrological processes in South Dakota Watersheds. South Dakota State University.

Paul, M., Rajib, M.A., Ahiablame, L., 2017. Spatial and Temporal Evaluation of Hydrological Response to Climate and Land Use Change in Three South Dakota Watersheds. *JAWRA J. Am. Water Resour. Assoc.* 53, 69–88. <https://doi.org/https://doi.org/10.1111/1752-1688.12483>

Rouse, J., Haas, R., Deering, W., Schell, J., Harlan, J., 1974. Monitoring the Vernal Advancement and Retrogradation (Green Wave Effect) of Natural Vegetation. Greenbelt, MD.

Shao, W., Cai, J., Liu, J., Luan, Q., Mao, X., Yang, G., Wang, J., Zhang, H., Zhang, J., 2017. Impact of Water Scarcity on the Fenhe River Basin and Mitigation Strategies. *Water* 9. <https://doi.org/10.3390/w9010030>

Takle, E.S., 2003. Agricultural Meteorology And Climatology, in: Holton, J.R.B.T.-E. of A.S. (Ed.), *Encyclopedia of Atmospheric Sciences*. Academic Press, Oxford, pp. 54–60. <https://doi.org/https://doi.org/10.1016/B0-12-227090-8/00009-9>

UNESCO, 2012. *Managing Water under Uncertainty and Risk*. Paris, France.

Vörösmarty, C.J., Green, P., Salisbury, J., Lammers, R.B., 2000. Global Water Resources: Vulnerability from Climate Change and Population Growth. *Science* (80-.). 289, 284–288. <https://doi.org/10.1126/science.289.5477.284>

Wang, R., Bowling, L.C., Cherkauer, K.A., 2016. Estimation of the effects of climate variability on crop yield in the Midwest USA. *Agric. For. Meteorol.* 216, 141–156. <https://doi.org/https://doi.org/10.1016/j.agrformet.2015.10.001>

White, M., 2017. *Radiation in Agriculture*.

Wilson, J., Gallant, J., 2000. *Terrain Analysis: Principles and Applications*. John Wiley & Sons, Ltd, New York, USA.

Xiao, J., Shen, Y., Tateishi, R., Bayaer, W., 2006. Development of topsoil grain size index for monitoring desertification in arid land using remote sensing. *Int. J. Remote Sens.* 27, 2411–2422. <https://doi.org/10.1080/01431160600554363>

8 APPENDICES

Appendix A Detailed Information on The Study Sites

This appendix provides detailed information on the study sites, including region background, current drainage and irrigation systems, and the location of the nearest meteorological stations.

A.1 Eshkeda Agricultural Project (EAP)

The project area of Eshkeda is located 60 km north of Sabha city in Fezzan region. The area covers ca. 3000 ha, divided into three sub-areas:

- Western Area; 2000 ha
- Central Area; 600 ha
- Eastern Area; 370 ha.

The project implementation started in 1975 and has been under operation since the second half of 1976. In accordance with the installed irrigation wells, the area comprises 25 districts, each with 12 farms (10 ha each). The farms are divided into two plots, each of which is 180 m x 234 m. Windbreaks have been planted between the farm plots and around the farm. Irrigation water is lifted from a deep aquifer (350 – 400 m depth from the surface). The water is pumped into reservoirs from where it is pumped into the irrigation networks to each farm connected with four hydrants. In 1977, the first drainage problems became visible. In 1981, about 35% of the project suffered from shallow water table depth occurring at less than 1 m depth (GWA, 2018, 2005, 2001).

Due to the raised water table, a drainage system was designed and executed in conformity with the farm size. The general map (not included in the thesis) of the drainage system (prepared by Italiana Lavori in June 1979) shows the layout of the drainage system. The conductor drains (main drains) are open ditches that convey the surplus water to natural depressions (sabkhas) and the valley, where it percolates and evaporates without practical use. The previous drainage design (up to 1983) did not function properly due to the following:

- Maintenance of ditches is problematic; because of the unstable sandy soils and proliferation of reeds, the open ditches gradually became wider and shallower, resulting in insufficient outlets.
- Field and collector drains had not been installed, which caused salinity and waterlogging problems and resulted in a low project yield.

To prevent loss of yields or even crop failure, the groundwater table has to be drawn down by an efficient drainage system. Drainage aims to remove a surplus of water so that soil structure and aeration are maintained or recovered and to control water tables that would otherwise rise to the near soil surface. Therefore, the government started thinking about finding a solution, including designing and installing subsurface drainage in the project. Cornelius-Brochier was hired in 1981 to design and install subsurface drainage in Brak Eshkeda, which was completed in 1983 (Cornelius-Brochier, 1981).

A.1.1 Background of Regional Development

The development of the Fezzan region is based on availability and access to groundwater resources. All inhabited land corresponds to zones of shallow water and the string of oases following the low-lying terrain is the traditional settlement feature. Until the 1970s only a few farm areas relied on deep groundwater exploitation, but such exploitation was strongly promoted in the 1980s (Al-Barouni, 2013). Migration effects have influenced the region's population growth significantly. There is a considerable in-migration from Libya's southern neighbours, revealed by the fact, that more than 50 % of the population had their place of birth outside their present place of residence. But the population inflow is more accentuated at the main settlements, especially the population drain from the rural surroundings towards the Fezzan capital Sabha. Not only the governmental facilities and services but also the private sector offers wage-earning job opportunities particularly to the population age group 15 to 25 years' (Hamilla, 2018).

The rapid growth of service employment and its favourable wage level has discouraged the incentive, people may have had to engage in agriculture. The

present decline in agriculture throughout the Fezzan is more a result of the attractiveness of non-agricultural jobs than of the lack of agricultural potential. The social status of agriculture, tending to become a part-time activity providing additional money to the family incomes, contrasts sharply with the fact that agriculture is still the economic basis of the region. The high fragmentation of land, being reflected in the average holding size of half a hectare, prohibits investments in cultivation machinery and irrigation technology by the individual farmers. Furthermore, the farmers lack capital and are not in the position to invest and change from the present subsistence to market orientated production. Efforts to raise the productivity by improving farming practices and water management also face the constraints of lowering and exhausting the groundwater bearing strata as well as of salinization of soil surface. A second constraint is the rising groundwater table in range of rooting depth so that affects a large proportion of irrigated areas, which suffer from poor land drainage.

A.1.2 Current Drainage System

In a subsurface drainage system, one can distinguish three categories of drains (field drains, collector drains and main drains). Field drains serve primarily to control the fluctuation of the groundwater table but may also collect surface runoff. The water in the field drains flows into collector drains which convey the water to the main drainage system, which is carried to the outlet of the area. The main drainage system must provide a free and reliable outlet for the field drains. This is why the previous drainage system did not function properly, and therefore a subsurface drainage system has been proposed and installed (GWA, 2005, 2001; Hamilla, 2018).

The final design for the main drain and field drainage system was carried out in four phases. The area requiring drainage was less than the total area because about one-third is higher levelling land (the impervious layer is located greater than 4 meters from the soil surface) or land where the soil has a high hydraulic conductivity and a deep groundwater level or not to be drained due to a shallow impervious layer (van Alphen and Kor, 1984). Table A-1 illustrates the four

phases taken to design the drainage system in Brak Eshkeda and the drainable area for each phase.

Table A-1: the phases for installing a drainage system in Brak Eshkeda

Phase	Total area (ha)	Drainable area (ha)
A	1080	900
B	940	480
C	580	520
D	370	240
A – D	2970	2140

The design parameter and design criteria were:

- The main drains were dimensioned independently according to the gross irrigation area if the field drainage system was executed at a rate of 2.5 mm d⁻¹ (This value covers the summer peak drainage rate at a 20% safety margin).
- The hydraulic calculation of the main drainpipes was based on a discharge of 75% of the total flow capacity.
- The minimum gradient applied in the design was 0.5%.
- The minimum pipe diameter was (diameter nominal (DN)) 160 mm, and the maximum diameter was DN 600 mm, fixed in the contract for execution.
- Usually, smooth pipes with a minimum diameter of DN 200, respectively DN 250 mm, were laid in open trenches. Where the drain depth was less than 2.0 m, corrugated PVC pipes with a diameter of DN 160 mm up to 200 mm can be installed by a trenchless drainage machine.
- Control shafts were provided with a spacing of about 250 m on each collector drain outfall and at locations of changing alignments.
- The depth of the main drain depended on the diameter, gradient and depth of the feeder/collector pipe system, particularly at the upstream end of the mains.
- Some drain outlets were installed to serve maintenance and control drain discharge.

Finally, as a summary of the layout of the field drainage system installed in Brak Eshkeda:

- The spacing between field drains was adapted to the crops' planting system, primarily orchards planted in a grid system of about 6 m. Therefore, the drain spacing was a multiple of 6 m, and the plot size of 234 x 180 m is a reasonable distance too.
- Field drains were installed lengthwise. Then field collectors were installed broad wise and lengthwise, respectively. According to DIN 1185, the maximum slope was given to the collector drain.
- To connect the field drains to the field collectors, 45° junctions were executed.
- The inspection shafts were constructed at the drain outlet of each farm plot and each angle in the field collector.
- The inspection shafts were designed with a sand trap and had to be buried at a depth of about 0.5 m below the ground surface.
- The normal discharge of field drainage was set up at 3.0 mm d⁻¹. Only some farm plots surrounded by elevated irrigated land were calculated with an increased discharge of 4.5 mm d⁻¹.
- The optimum drain depth was 1.5 m. Depending on topography, the extreme values range from 0.8 m to 2.0 m.
- The minimum gradient of the field drains and field collectors were 1.0%.
- The feeder pipe diameter was 50 mm (internal diameter 43.9 mm).
- The pipe diameter of collector drains was DN 100, 125, 160, or 200, corresponding to the results of the hydraulic calculation.
- At the lower end of some farm plots, only a perforated collector DN 160 was executed.

A.1.3 Climate Condition

The climate of the project region is arid and reflected in the landscape of the desert. Rainfall is almost zero and therefore insufficient to satisfy crop water requirements. However, offshoots from wandering depressions may move from the northwest as far south as the project region, and clouds can bring some rain. Statistically, the average monthly rainfall is about 1 mm. Some years and many summers are reported to be without any rain and there are some years when

precipitation falls only during summertime. The average annual minimum and maximum temperature are 15.5 °C and 30.2 °C respectively. However, there are distinct divergences between winter (5.0 °C and 22.1 °C), and summer (23.2 °C and 40.0 °C) with short transitional periods in March (10.0 °C and 26.0 °C) and October (17.7 °C and 32.7 °C). During wintertime temperatures may fall below freezing point, so that the extremes of daily fluctuations, can be a limiting factor for plant growth. But also, maximum temperatures can reduce plant production either by direct influence or via high evapotranspiration requirements. The relative humidity amounts from 40 to 50 % in winter and falls to an average of 20 to 30 % in summer. The mean annual sunshine hours are 8.7 per day, ranging from 7.2 hours in December to 11.1 hours in July. Average annual wind speed is 269 km d⁻¹. There is no meteorological station at EAP and therefore the meteorological data shown in Table A-2 is from the nearest station to EAP (Sabha meteorological station). Sabha station located 50 km south of EAP and has been recording the daily weather data since the 1950s. The data in Table A-2 was obtained from CLIMWAT for CROPWAT (Smith, 1993).

Table A-2: Average monthly meteorological data from Sabha Station

Month	Tmin	Tmax	Humidity	Wind	Sun	ET0
	°C	°C	%	km d ⁻¹	hours	mm d ⁻¹
January	5.0	17.7	47	207	7.7	2.84
February	7.7	22.1	39	233	8.3	4.04
March	10.5	26.0	33	311	8.3	5.86
April	15.5	31.6	27	320	7.8	7.57
May	19.3	36.0	25	311	9.2	8.82
June	23.2	40.0	24	320	10.2	10.11
July	23.2	38.8	27	285	11.1	9.44
August	23.2	37.7	28	259	10.7	8.62
September	21.0	36.0	31	268	8.5	7.59
October	17.7	32.7	38	259	7.9	6.12
November	12.7	26.6	45	233	8.0	4.39
December	7.1	16.6	50	216	7.2	2.77
Average	15.5	30.2	34	269	8.7	6.51

A.1.4 Hydrogeology and Hydrology

The groundwater used for the supply of the EAP is contained in the sandstones of the Cambro-Ordovician formation. The Cambro-Ordovician aquifer represents the main aquifer, forms on a regional scale a large system, with the Devonian sand-stone representing a secondary aquifer. Groundwater stored in the two aquifers is mainly fossil water. Part of it may be water entrapped during the rock sedimentation, as the salt water in the carboniferous sandstones. Most of the groundwater has been attribute to the Pleistocene or perhaps to the latest Tertiary. Both aquifers are separated by intercalated Devonian shales representing a leaking aquiclude. In the Project Area the piezometric head of the two aquifers has been reported as approximately 20 m by Ital-consult (Tantawi, 2000).

The Devonian aquifer is confined by shales of the Upper Devonian and Carboniferous formation. The average head of the Cambro-Ordovician and

Devonian aquifer system in the Project Area was in 1970s about 30 to 40 m above ground level. It must be assumed that due to groundwater exploitation, the piezometric level has sunk considerably. This assumption was confirmed by the local authorities; however, quantitative data could not be obtained. The Carboniferous shales are covered by young, alluvial and/or aeolian sediments of varying thickness. The thickness of these beds may range from about 10 m to almost zero. Exact data on the thickness of these deposits are not available. These young sediments contain groundwater. According to information obtained locally, groundwater is reaching the ground surface in places (Al-Barouni, 2013).

Sabkhas lie in the east of the Eshkeda area. These Sabkhas may be related to the phreatic groundwater in the young sediment but exact origins are unknown. As mentioned previously the annual rainfall is almost zero. Statistically the average monthly rainfall is less than 1 mm, but occasionally once over many years significant downpours of up to 30 mm may occur. The average annual rainfall provides negligible groundwater recharge. Surface water from the northern hills (Jabal Al-Gharbi), sporadic heavy rainfall, infiltrating irrigation water from old schemes (before 1975) may have contributed to the recharge of the Sabkhas and the phreatic groundwater. Also, as mentioned earlier, leakage water from the Palaeozoic aquifer rising through fault zones may also have contributed to the Sabkhas.

No groundwater table has risen to such an elevation below ground level that it could have an effect on the agricultural production in the Project Area. However, since irrigation in the Project Area has started, the phreatic groundwater table has risen, already influencing the crop production. From this it must be concluded that the infiltrating irrigation water is liable for the rise of the water table. Even if a certain amount of the phreatic groundwater may be recharged from deeper aquifers by upward leakage, this volume of water could not be the only source contributing to the rising groundwater since the irrigation project started, because this leakage would have taken place already before the Project started. At that time, i.e. before groundwater extraction, the artesian head of the deep aquifer was definitely higher, which means that any leakage would have been higher than

after project start, i.e. after groundwater exploitation. Unfortunately, no regular observation of such a water table rise are available, for instance by piezometers. The proceeding statements, therefore, are based only upon verbal communications from the General Water Authority and some local farmers. However, they seem to be reliable. In order to draw down the phreatic water table, drainage is required. A typical profile of the entire geological sequence in the project area is shown in Table A-3.

Table A-3: Typical geological profile in Eshkeda agricultural project, reported by Italconsult in 1975

Hydrogeological characteristic	Depth (m)		Lithology	Formation
	From	To		
Phreatic aquifer	0	2	Sand, fine to coarse, quartzite, some sandstone, gravels, greyish to pinkish	Quaternary
	2	4	Silt (90%), brownish, soft to medium hard, sand (10%) very fine to fine, light brownish	Quaternary
Aquiclude	4	105	Shale and clay, dark grey with rare fine-grained sandstone interbedded	Carboniferous
Leaking Aquiclude	105	139	alternating clay, claystone, light grey to brownish and light grey fine-grained sandstone and siltstone	Devonian
Aquifer	139	185	sandstone, light grey, coarse grained with rare light grey clay interbedded	Awentwenin
	185	355	sandstone and quartzite, light grey, medium grained, hard to medium hard, kaolinitic	Cambro-Ordovician

A.2 Hammam Agricultural Project (HAP)

Hammam Agricultural Project (HAP) is located in the north-east part of Sokna Oasis in the Jufra District (29°04'01"N 15°47'05"E) at an elevation of circa 270 m above sea level (asl). The HAP covers 1,200 ha and is divided into 182 farms (6-8ha for each farm). Work on the project began in 1971, and the reclamation was completed in 1985. The irrigation system of the project is based on 14 artesian wells, drilled down to a reservoir at a depth of approx. 120 m. The potential of the

water is about 30 m above the surface. The water from the wells has a dissolved solids content of about 1500 ppm, and the content of NaCl is about 300 ppm. From the wells the water is sent by asbestos pipes to tanks on the individual farms. On the farms a surface irrigation system is used. The project has a system of open and covered drains. The covered drains are 4 inches (10.16 cm) concrete pipes placed with a distance between the lines of 40 – 50 m. These drains flow into 6- and 8-inch collector pipes connected to a system of 6 parallel open drain canals which guide the water to a main collector. The main collector runs to the lower parts of the valley where the water forms a 40 km long pool.

The first problem noticed is the saturation of the upper soils. The saturation may partly be caused by the fact that an impermeable layer is found at a depth of 0.5 to 2 m (Al-Khoja and Hamilla, 2007; Hamilla, 2018, 2005; van Aart, 1991). The water saturation gives rise to the following problems:

- Weak development of roots for plants causing low yield of crops.
- Evaporation of irrigation water causing raised concentration of salts in the soil.
- Serious damage of dwelling houses, pavements and installations as a result of soil soaking or swelling or even foundation failures.

According to the general Water Authority, it is estimated that the saturation of the upper soils is caused, not only by insufficient drainage, but also by excessive irrigation. The soil of the project has a high degree of salinity. If the estimates and test results we have received on the quantity and quality of drain water are correct however, this salinity must be managed. The salinity restricts the types of crops that can be cultivated as well as the yield of the crops. At the project we were given estimates of a water consumption around 25 to 30 million cubic metres per year. The consumption is not measured so there is no way to establish whether the estimate is correct or not. It is very important that a more accurate estimate of the consumption is found. A large amount of drainage water (estimated to be around 10 million cubic meters) is removed from the project to evaporation ponds located north east of HAP. The water cannot in the present situation be directly reused for irrigation as tests show contents of dissolved solids tenfold higher than

that of the water in the wells. However, it is important to minimise the amount of drainage water by reusing it (GWA, 2007).

The irrigation system at HAP consists of the following elements:

- Wells
- Distribution system
- Storage tanks
- Irrigation canals

As mentioned earlier, there are 14 artesian wells with a total discharge around $2500 \text{ m}^3 \text{ hr}^{-1}$. These numbers are estimated as most of the wells are not equipped with meters or meters no longer work. Therefore, it is difficult to estimate the total consumption for the entire project. Up to the 1990s the system used to operate without pumping and depended only at the artesian water level in the wells. The system currently changed and now the water is pumped from the wells to the storage tanks through the distribution system. The pipes installed to distribute the pumped water themselves leak. The leakages caused by corrosion and therefore some tanks do not get the estimated water volume. The General Water Authority reported that the pipe system needs to be replaced with a new system suited to the current system of wells (GWA, 2018, 2007, 2003).

The pumped water is stored at each farm in water tanks. Most of the tanks have volume capacity of 115 m^3 . Some tanks have overflow problems when filled during the night. The irrigation system at HAP has levelling problems, which has led to uneven distribution of the water in the fields. To overcome this issue farmers had to divide their fields into very small sections (10 to 30 m^2). These sections were constructed manually and are demolished every time (Al-Khoja and Hamilla, 2007).

According to the General Water Authority, during irrigation hours it is difficult to control the amount of water used for irrigation. Consequently, problems with deep percolation, waste of water, waterlogging, and extension of evaporation causing salt accumulation at the soil surface appears. Also, different undesired plants like

rush are growing and the agricultural crops are yielding badly. The General Water Authority reported that a correctly constructed irrigation systems of this type, run by well-educated and experienced farmers, could be expect to have an application-efficiency of the irrigation-water of about 50 %. Under the present conditions the efficiency is estimated to at a lower level, probably only 20 – 30% (GWA, 2018, 2007, 2005, 2003, 2001).

A.2.1 Background of Regional Development

Jufra is one of the districts of Libya. It is in the centre of the country. Its capital is Hon. Jufra is part of Fezzan, which is one of the three provinces of Libya; it is mostly full of deserts. A desert is a barren area of landscape where little precipitation occurs and consequently living conditions are hostile for plant and animal life. Deserts can be classified by the amount of precipitation that falls, by the temperature that prevails, by the causes of desertification or by their geographical location (United States Geological Survey, 2001). Jufra District is a broad region extending for about 117,000 Km² between the two mountains of Djebel Waddan and Djebel es-Soda. In this area, several smaller depressions reduce the surface height and caused water table rise. The consequent formation of a number of oasis, the three major ones being Waddan, Hun and Sokna plus the ancient oasis of Zellah, located in the eastern part of the District, and the oasis of Al Fugha located at south of Djebel es-Soda. In 2012 the total population in the region was 157,747.

Jufra due to its position represents one of the most interesting Libyan regions for date palm cultivation (*Phoenix dictalifera* - 2,700,000 tree) aimed at soft date production, which is practiced along with other types of cultivars such as vegetables and fruits suitable for a desert climate, the other important activity is pastoralism, the area contains 130,800 head (125,000 sheep, 5000 camels, and 800 cows). Consequently, this region was chosen for the integrated study of the palm dates cropping system. These studies were performed in 2009-2010 in the framework of the Italy - Libya cooperation project “Improvement and Valorisation of Date Palm in Al Jufrah Oasis”, carried out by Istituto Agronomico per

l'Oltremare (Italy) and the Board of Improving and Developing Olive and Palm Trees (Tripoli, Libya).

A.2.2 Current Drainage System

The drainage system of the area consists of one open main drainage ditch, located east of the project, 6 open main drains, and a number of field drains, most of them subsurface drains, but in a few parts of the project open drains. The condition, level, and hydraulic capacity of the main drain is reasonable for the project. However, blockages caused by rush or sand can be observed. The main drain has an average discharge around $0.25 \text{ m}^3 \text{ sec}^{-1}$ (GWA, 2007).

Six open drains are connected to the main drain. The slope of these drains is generally 1 – 2%. The drains are crossed by different roads and accesses to the farms. The culverts under these crossings are in some cases blocked, and at many locations, especially in the western part of the drains, the drain is blocked with sand or waste, thrown in the drain. The drains receive outlet from the field drains. The constructed erosion-protection at these outlets is concrete but of a very bad quality. Generally, the hydraulic capacity seems to be satisfactory, but the depth of the drains will in most of the area be insufficient to serve the surrounding fields in a proper way (Hamilla, 2005).

The field-drains are constructed from concrete-pipes, manufactured at the site. thickness varies from 14 mm to 23 mm and the inside diameter from 90 to 100 mm. The depth of the field drains ranged between 0.5 – 1.5 m. Generally, the depth of the drains is insufficient for satisfactory drainage of the area. Furthermore, the slop of the drains in many cases is constructed opposite to the natural slope of the area. The field drains generally are constructed with a distance of 30 – 60 m between the lines. Unfortunately, the smallest distance in most cases is used at places with the highest permeability. Also, most of the largest spacing between drains were installed without considering the permeability of the actual site. In a correctly designed drainage system, it is necessary to consider the permeability of the actual site (especially in areas with

highly varying soil-conditions) and to adapt the construction to the present conditions (van Aart, 1991).

A.2.3 Climate Condition

As there is no meteorological station at HAP, the meteorological data was obtained from the nearest station named Hon. Hon is located 15 km to the east of HAP. According the monthly average data obtained from CLIMWAT for CROPWAT (Table A-4), the lowest minimum air temperature has been registered in January with 2.7 °C and the highest maximum temperature was recorded for July and August with 38.2 °C. the humidity ranged between 33% to 59% with 45% as an average. The wind speed average in Hon station was 242 km d⁻¹. To estimate crop potential yield it is important to have information of light-conditions. The highest sunshine duration was registered in July with 10.9 hours and the lowest was in December with 6.4 hours. Finally, the ET₀ ranged from 2.72 in January to 8.28 in June (Smith, 1993).

Table A-4: Average monthly meteorological data from Hon Station

Month	Tmin	Tmax	Humidity	Wind	Sun	ET ₀
	°C	°C	%	km d ⁻¹	hours	mm d ⁻¹
January	2.7	20.0	59	225	6.7	2.72
February	5.0	22.1	53	242	7.5	3.50
March	7.1	26.0	47	294	7.3	4.97
April	10.5	30.5	39	294	6.5	6.33
May	15.0	33.2	37	277	8.6	7.25
June	18.8	37.7	33	277	8.2	8.28
July	19.3	38.2	37	225	10.9	8.03
August	19.3	38.2	40	207	10.5	7.46
September	18.2	36.6	45	216	8.7	6.45
October	14.3	32.1	52	216	7.2	4.91
November	9.3	26.0	55	199	7.3	3.49
December	5.5	21.0	50	233	6.4	3.08
Average	12.1	30.1	45	242	8.0	5.54

A.2.4 Hydrogeology and Hydrology

The Jufra area is located in the southern part of 2 groundwater provinces (Ghibla province and Hon graben province). The Ghibla province lies between the Hamada al Hamra and Jabal Nefusa to the north and the Hon graben to the east. The area is rolling to rough, the surface consisting chiefly of Cretaceous marine sediments; areas of sand dunes and basalt diversify the province.

A perched water underlies much of the Ghibla, but yields of wells tapping it are small and area distribution is erratic. Deep wells in the eastern and western parts of the province yield useful water by natural flow as do artesian springs in the west. The water is predominantly brackish except west of longitude 13° E and in some perched bodies. East of longitude 14°, chloride is the chief anion, whereas to the west, sulfate predominates. Sodium is the dominant cation. Winter precipitation recharges the upper aquifer to some extent most years, but underflow from the Hamada al Hamra may exceed local recharge. Natural and artificial discharges to the surface are small. Cretaceous rocks, especially the Ain Tobi Limestone and Garian Limestone and sand and sandstone of the Chiclo Formation, are the chief aquifers of the Ghibla (Hamilla, 2005).

The Hon graben groundwater province consists of a long fault-bounded valley underlain by rocks that are depressed relative to those adjacent to the valley. The nearly rhomboidal area consists of Tertiary rocks, at places overlain by Quaternary deposits. Water in the Hon graben is mostly brackish and not readily available to wells. In the southern part of the province wells, 450 m or more deep will tap aquifers containing poor water that is confined sufficiently to flow where land surface is low. Water in the graben is mostly the sodium sulphate type. Based on the general characters of the province it might be assumed, that the HAP area is related to the Ghibla groundwater province, but no general clue can be given to this (Al-Barouni, 2013).

As stated above, two aquifers can yield both potable water and irrigation water, the Mazuza limestone and the Chicla sandstone. Both aquifers are artesian. The water level of the Chicla sandstone in the area is approximately 30 m above

ground level, according to information obtained from the Furgan Project. No consumption takes place from the Chicla sandstone. In 1973, when water production from the Mazuza limestone aquifer started, a general water level of about 30 m was given for the Jufra area. This fell to about 14 m in the 1980s. Since the 1990s the water level has dropped below the surface, but the exact levels are unknown. This information leads to the conclusion that the consumption of water from the Mazuza limestone aquifer exceeds the possible recharge (Hamilla, 2018).

Appendix B Types of Data Used in The Analysis

This appendix includes the types of data used for the analysis in this research including data relating to soil physical properties, daily temperature, soil salinity, drainage design, and crop water requirement are discussed.

B.1 Soil Physical Properties

Due to the restrictions and agreement upon obtaining the data from the General Water Authority in Libya, the soil physical properties dataset cannot be published. The author obtained permission to use it for this research. However, the data is available from the author upon reasonable request and with permission of the General Water Authority in Libya.

B.1.1 Soil Texture and Physical Property in EAP

The texture and colour of the soils in EAP are almost uniform. The percentage of clay most of the time is <10%. Coarse fragments, gravel size, were occasionally found in the soils of the eastern region and in a few pits of the western area; the content of fines (< 0.05 mm) is slightly increased in the profiles of the eastern area. To measure the percentage of sand, silt and clay at EAP the hydrometer method described by Bouyoucos (1927) was applied. The total number of samples were around 450 samples (around one sample every 5 ha). 8 samples were eliminated because they were out of range in comparison to the rest of the data. Also, these samples represented only a very small area where the percentage of clay is very high (40 – 50%). In the remaining 442 samples, the

percentage of sand range between 66 – 98%. Silt in EAP ranges between 1 – 36%, and clay from 1 – 10%. The EAP dataset is associated with four soil texture classes dominated by sand (88.4%) with 8.0%, 3.4% and 0.2% of the set represented by loamy sand, sandy loam and loam, respectively (based on the USDA soil texture classification). Figure A-1 shows one of the samples of the soil data collected from EAP. The soil bulk density was measured following the methods described by Buckman and Brady, (1960). Field capacity and wilting point were determined by tensiometers, using the method reviewed by Richards (1949).

In EAP the auger hole method was adopted to measure the saturated hydraulic conductivity (K_{sat}). In accordance to the arranged investigation program boreholes were drilled on each farm in the project area. More than 500 drillings of 2.5 inches diameter with "Minute man" drilling equipment and accompanying soil profile descriptions have been executed. Because of the existing instable sandy soils in the Eshkeda area perforated tubes with diameters of 6.5 cm were inserted into the holes. After pumping out water and mud from the hole the rise of the water level was measured with the standard equipment for auger hole measurements (to measure K_{sat} at and below water table depth 'shallow groundwater'). In some farms no water table could be observed until 4 m depth below surface and therefore no measurement could be carried out. Where two hydrologically different layers were encountered, a second bore hole had to be drilled nearby to determine the hydraulic conductivity of the upper and lower layer. K_{sat} measurements for the selected 442 soil texture samples were used in this study. The range of K_{sat} values based on each subarea:

- Western area: 0.1 – 19.0 m d⁻¹
- Central area: 1.4 – 24.0 m d⁻¹
- Eastern area: 0.7 – 11.5 m d⁻¹

Based on the data, the K_{sat} ranges from 0.1 – 24.0 m d⁻¹. Generally, the topsoil in EAP has higher K_{sat} compared to the subsoil measurement. As mentioned above the topsoil at EAP has high percentage of sand compared to the subsoil. On some

farms of the project area field measurements were not possible (GWA, 2005). Either the groundwater table was not reached by the drilling or because of the quick entrance of mud into the holes despite using perforated tubes to stabilise and reduce silty and clayey soil material entering the well.

Wadi Shatti Drainage Project Cornelius - Brochier - Aqua Project ACI Date: June 1981				Surveyor: Petermann Area: Eshkeda settlement project Profile No: E 22				
Topography:		slightly undulating Serir south of Wadi Shatti depression						
Microrelief:						Surface Deposits: sand, slightly gravelly		
Land use:		irrigated agriculture				Vegetation: cereal alfalfa		
Depth	cm	0-20	20-100	100-190	190-200			
Horizon		Ap	B	C	G			
Color		7.5YR5/5	7/8	7/8	7/8			
Structure		sin 00	sin 00	sin 00	sin 00			
Consistence		0	0	0	0			
Plasticity		0	0	0	0			
Cementation		-	-	-	-			
Cutans		-	-	-	-			
Fe/Mn		-	-	-	-			
Gypsum		-	-	-	-			
Carbonates		-	-	-	-			
Texture		1'S	1'S	S(S)	S			
Wetness		2	2	3	4			
Roots		3	3	1	0			
Samples	cm	0-20	20-50	50-75	75-100	100-150	150-190	
Gravel %		0	0	0	0	0	0	
EC _{em} S/cm		0.86	0.73	1.42	0.40	0.80	1.10	
Salt %		0.01	0.01	0.01	< 0.01	0.01	0.01	
pH		7.7	7.7	7.6	8.5	8.4	8.1	
CaCO ₃ %		< 1	< 1	< 1	< 1	< 1	< 1	
Moist.Cap. %		17.5	16.5	15.5	19	19.5	19.5	
HC cm/d			> 600	1260	1300	1260	1260	
Texture	cs/ms/fs silt/clay	22 50 18 6 4	24 54 12 7 3	28 51 14 4 3	34 50 11 3 2	14 69 13 2 2	13 68 15 3 1	
Parent mat.		aeolian sand, quaternary				Groundwater		below 1.9 m g.l.
Remarks:						Soil type		yh 2/1-pa
						Land Class		S 3m

Figure B-1: Sample of soil survey for Eshkeda Agricultural Project (GWA, 2018; Cornelius-Brochier, 1981)

B.1.2 Soil Texture and Physical Properties in HAP

More than soil samples were collected from HAP to perform different physical and chemical properties analysis. All the laboratory work was done in Copenhagen, Denmark by Danenco company. The samples were collected from different layers across HAP. The physical properties analysis included the following:

- Geological description of all extracted samples for classification with regard to the laboratory tests required.
- Natural moisture contents were determined as the moisture content percentage of dry weight.
- Bulk density was determined as the density of undistributed samples given in g cm^{-3} .
- The void ratio (which is the volume of voids to the volume of solid particles).
- Saturated hydraulic conductivity (which is permeability of undisturbed samples is calculated from the amount of water penetrating a sample by a given pressure in a given time).
- Grain size distribution was determined by sieving and hydrometer analysis.
- Soil saturation, field capacity and wilting point.
- The Atterberg limit refers to the liquid limit and plastic limit of soil. These two limits are used internationally for soil identification, classification, and strength correlations. When clay minerals are present in fine-grained soil, the soil can be remoulded in the presence of some moisture without crumbling.
- pH was measured on saturated soil paste.

Based on the measurement, and according to the USDA textural classification the HAP dataset can be classified as, sand (22.3%), loamy sand (18.3%), sandy loam (31.4%), loam (0.6%), sandy clay loam (21.0%), clay loam (4.2%), sandy clay (1.8%) and clay (0.4%) (Soil Survey Division Staff, 1993). Bulk density ranges from 1.6 to 2.0 g cm^{-3} and saturated hydraulic conductivity ranges from 0.1 to 38.0 m d^{-1} . A total of 770 samples which have values of soil texture (percentage of sand, silt and clay), bulk density, field capacity, wilting point and saturated hydraulic conductivity were used in the analysis (the rest of the samples

have missing values of some properties). Figure A-2 shows a sample of the soil data obtained from HAP (GWA, 2018).

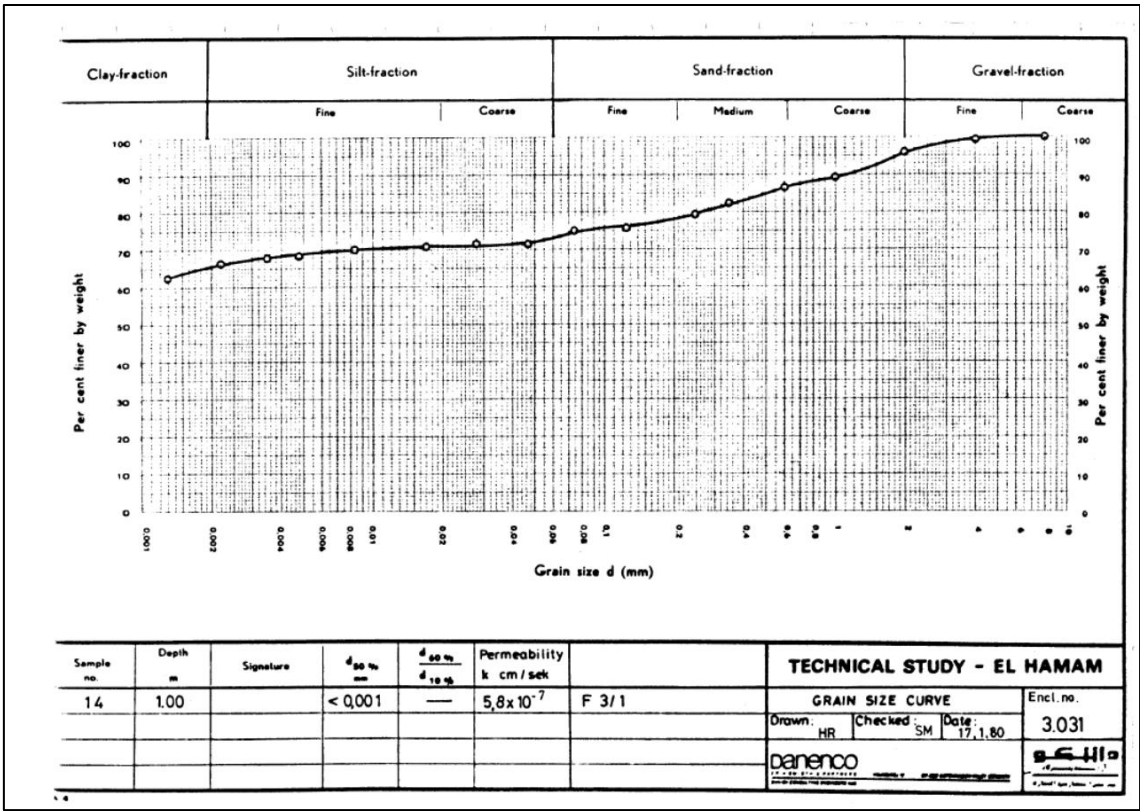


Figure B-2: Sample of the soil data was collected for HAP (GWA, 2018; Danenco, 1980)

B.2 Daily Temperature data

The temperature data used in this study is uploaded and freely available on Cranfield Online Research Data (CORD)

B.3 Soil Salinity and Remote Sensing Data

B.3.1 Salinity data in EAP

The content of easily soluble salts (mainly NaCl) is in the range of 0.5 thru 53 mS cm⁻¹ for the topsoil horizons (0 – 30 cm). The salinity level varies within the farm areas with regard to irrigation practices. Areas having a continued and uniform water application by sprinklers are less saline than areas where the water is distributed in furrows. The bare soil surface between the furrows has a slight

salinity ($4 - 8 \text{ mS cm}^{-1}$), due to the lateral through flow of water and solutes from the wet soil beneath the furrows.

The highest surface salinity level with an average of 11 mS cm^{-1} was analysed for the north-western part of the Central subarea. The eastern subarea shows an average slightly salinity level of $2 - 4 \text{ mS cm}^{-1}$ and 18 mS cm^{-1} for farm areas which were left uncultivated until the time when data was collected. Remaining farms in the western and central subareas are less saline and show EC values in the average range of 0.6 to 2 mS cm^{-1} . Occasionally a medium salinity of $5 - 10 \text{ mS cm}^{-1}$ was analysed for some farms; the deviations can be explained by variations of surface salinity between methods of irrigation, cropping pattern and preparation of land.

B.3.2 Soil Salinity in HAP

According to the ECe measurements for HAP, it can be noticed that salinity of the soil varies strongly in the project area (ECe in HAP ranges from $1.6 - 88 \text{ mS cm}^{-1}$). Generally, the highest salinity levels were found in the topsoil where an impermeable layer was found at a shallow depth ($1 - 2 \text{ m}$ for the surface). However, not all farms fall inside this hypothesis. Some farms at HAP and their salinity issues are described as following:

- **Farm 1:** In this farm a salinity of 67 mS cm^{-1} is found including a salt crust. With the salt crust excluded, the chloride content is 26 mS cm^{-1} dry soil. It can be seen on the farm, that excess irrigation is performed as the water table is situated only some 30 cm below the ground level. On this farm the high salinity must be attributed to excess irrigation combined with bad drainage.
- **Farm 2:** On this farm it has been demonstrated that the farmer irrigates with about 300 mm of water using surface irrigation. Combined overirrigation and insufficient drainage again causes increased salinity.
- **Farm 3:** The farm has a higher salinity than the surrounding farms. On this farm bad drainage conditions were demonstrated in the field, as an inspection showed both broken pipes, and no filter material.

- **Farm 4:** The salinity of this farm is found to be low, as the boring is performed close to a drain. Field investigations show that the effect of the drains is very local, concentrated to belts of only about 1-2 m along the drains, and that surface water is saline ($EC_e = 4.1 \text{ mS cm}^{-1}$).

Generally, the present situation is a result of uncontrolled irrigation in combination with bad drainage.

B.3.3 Remote Sensing Data in EAP and HAP

The remote sensing data used in this study was from Landsat 5 provided by Google Earth Engine (GEE). The remote sensing data was obtained for each location of soil salinity measurement. These data were then used to develop the Artificial Neural Networks to predict soil salinity. In this study, all of the satellite data pre-processing was conducted in GEE Code Editor (<https://code.earthengine.google.com>).

B.4 Drainage design data

In this section, other important parameters required to run DRAINMOD such as the depth and the thickness of the impervious layer as well as the initial depth of the shallow water table depth.

B.4.1 Drainage design data for EAP

- **Depth of the impervious layer:** The carboniferous shales of the Mrar formation covered by alluvial and aeolian sediments with thickness from about 10 m to almost zero must be regarded as a negative confining bed. The bottom of the phreatic water table mainly consists of clay and silty clay and is underlain by fine to coarse sand with interbedded gravels. The hydraulic conductivity of the layer ranges between ca. $0.006 - 0.02 \text{ m d}^{-1}$ and in comparison, with the upper soil horizons, the underlain layer is absolutely impermeable. The relief of the layer is rather undulated and does not coincide with the topography of the soil surface. In the western area the base is quite deep and the layer only rises to the soil surface in one plot. But in general, it lies at depths of more than 4 m below soil surface. In the western part of the

central area the layer is at a depth of between 1 – 2 m, whereas in the eastern part it only could be analysed on three plots. In the eastern area the depth of base is inhomogeneous changing from zero to more than four meters. In conformity with the relief of the impervious base the water table does reaching the soil surface. Recharge of this water table is given by surface water from northern hills, sporadic heavy rainfalls, infiltrating irrigation water and also by leakage water from the Paleozoic aquifer rising through fault zones of the layer.

- **Water table depth:** The project area is underlain by clay and siltstone of the Mrar formation, which has a thickness of 80 – 120 cm. The hydraulic conductivity of this formation is very low compared with the overlaying sands. From point of view of land drainage, the Mrar formation was considered as an "impervious layer". Applying irrigation water in excess of crop requirements resulted in a general rise of the water table. Where the water table has reached the root zone already, capillary rise of salt-loaded water and the removal of water by evapotranspiration, leave behind a greatly increased concentration of salts in the root zone and/or surplus of water. Investigations using a soil auger showed that the depth of the shallow water table varied between 0.5 m to about 4.0 m, depending on the elevation of soil surface and on the impervious Mrar formation. The field investigations were executed in August so that the results only can give instantaneous conditions of the actual situation and nothing can be said of the annual range of water table level. During winter months with reduced mean temperature, relative increase of rainfall and lower evapotranspiration the water table will rise. According to the local climatic conditions and the reduced evapotranspiration of plants the deepest water table in general can be expected during July and August. It can be stated, that in areas where the impervious layer is located at a depth of about 5 m the water table can be found at a depth of 1.0 - 1.5 m. In these areas the high-water table level is documented by soil surface salinity, mainly near windbreaks and channels with high evapotranspiration. In the upper areas of the western area where there is a deep impervious base, no water table was found, whereas in the central area even though there is greater

variations in the depth of the impervious layer, mainly in the eastern part, the water table is quite homogeneous till 2 m with only few exceptions. Contrary to the other areas the eastern area shows no shallow (0 – 1 m) water table but the values are mainly in range of 1 – 3 m and deeper. In areas where the impervious layer is less than 2.0 m, the water table was found at a depth of 0.6 – 0.9 m. In these areas' crops cannot be grown profitably because of yield reduction. Even some farm plots have been infested with reeds and have been taken out of production.

- **Irrigation water quality:** EAP has a total number of 25 wells, which are used to irrigate the growing crops in the project. A study was made in 2017 to measure the salinity levels in these well and the electrical conductivity (EC) ranges from 1 – 1.25 dS m⁻¹.

B.4.2 Drainage design data for HAP

- **Depth of impervious layer:** The topsoil is the more permeable layer in the project consisting mainly of alluvial deposits formed by erosion of cuesta ridges and deposited in the low laying areas. Also, the wind has deposited eolean sediments as intercalations in the alluvial deposits. On top of both a fine sand, and silty deposit a loess and an eolean sand forms the great sand-dune in the north-eastern part of HAP. As the top for these younger deposits has a very low permeability, and as the climate is hot and dry, some of the alluvial and eolean deposits are more or less cemented by gypsum and salt. The older deposits of the area most probably belong to the cretaceous Mizda Formation, the thickness of which is around 120 m. These deposits are followed by the Mizda Limestone member consisting of limestone, dolomitic limestone and dolomites forming the most important local aquifer in the area. The thickness of the permeable topsoil layer of the project varies from 0 m to approximately 2 m. The topsoil layers consist of soil types varying from sand and gravel to silt, sandy clay. As stated above the origin of the different topsoil layers are either alluvial or eolean. Generally, variation of topsoil thickness is great within the single farms because of the undulating character of the subsoil surface. The saturated hydraulic conductivity of the topsoil varies from

0.1 m d⁻¹ to 38.0 m d⁻¹. The layers of the Mizda Formation forming the impermeable layers under the topsoil consist of soils varying from clayey, to sticky clay with hydraulic conductivity as low as 8.64x10⁻⁵ m d⁻¹. The depth of this impervious layer ranges from 1.2 – 4.5 m, while most of the HAP has an average depth ranges from 1.5 – 2.0 m.

- **Water table depth:** irrigation combined with insufficient drainage led to water table increase in HAP. Water level observations were made in HAP for different locations during the soil survey. Weekly measurements of water table depth were recorded for around two months and the water table depth at most of the location ranges from 0.5 – 1.2 m from the soil surface. This shallow water table depth led to many problems in the project including salinity accumulation, and yield reduction.
- **Irrigation water quality:** as mentioned earlier, HAP has 14 artesian wells. These wells are used to irrigate all the crops in the project. The EC of the irrigation water ranges between 1.8 – 3.9 dS m⁻¹.

B.5 Crops and Crop Water requirement Data

B.5.1 Current crops growing and related issues

- **EAP:** the main cultivated crops are alfalfa, wheat, watermelon, tomatoes, onions, pepper, and fruit trees like pomegranate, grapes, and figs. There are no records on annual yield at EAP, which is the case in almost all of the agricultural lands in Libya. However, according to the general water authority in Libya, the areas that do not suffer from waterlogging and salinity have better yields (which is only 20% of the project), than the rest of the project.
- **HAP:** as a result of the present condition, especially the high water table depth and increased salinity, it is very difficult to grow any crop with satisfactory result. At the moment, the most important crops growing in Hap are alfalfa, date-palm trees, and different vegetables such as tomatoes, eggplant, cucumber, melon, watermelon, peppers, onions, figs, pomegranates, and few citrus trees. The current irrigation system and the levelling on the land make it difficult to secure a proper distribution of the water and difficult to control.

Furthermore, the project needs more manpower, which HAP lacks since operated. Therefore, around 60% of the project is currently cultivated and the yield in those areas is up to 50%.

B.5.2 Crop pattern and inputs for DRAINMOD

- **Crop pattern:** in DRAINMOD simulation for EAP and HAP, it was assumed that one crop was growing in the whole project at the same time (no geographical proportion of land acreage between various crops).
- **Crop rotation:** a rotation of four crops (wheat, beans, soybeans and maize) was applied in the 30-year simulation in EAP and HAP as described in the following table (Table B-1).

Table B-1: wheat, beans, soybeans and maize rotation in EAP and HAP

Crops	Simulated years	Season	Project
Wheat	1984, 1987, 1990, 1993, 1996, 1999, 2002, 2005, and 2008	Winter	EAP & HAP
Beans	1983, 1986, 1989 1992, 1995, 1998, 2001, 2004, 2007, and 2010	Winter	
Soybeans	1982, 1985, 1988, 1991, 1994, 1997, 2000, 2003, 2006, and 2009	Winter	
Maize	1981, 1984, 1987, 1990, 1993, 1996, 1999, 2002, 2005, and 2008	Summer	

- **Crops inputs for DRAINMOD:** DRAINMOD requires various crop input parameters such as the cropping window, planting date reduction parameters, and stress parameters related to excessive water and drought condition. Table B-2 summarised the values used for each crop as these values were calibrated and validated in arid areas in Egypt (similar climate condition to the one at EAP and HAP).

Table B-2: crops information for DRAINMOD simulations used in EAP and HAP

Input parameter	Wheat	Beans	Soybeans	Maize
Planting parameters				
Cropping window (Julian day)	265 – 72	258 – 58	265 – 72	73 – 264
Desired planting date (Julian day)	271	271	271	95
Growing days (days)	130	130	130	130
Last day of year to plant without yield loss (Julian day)	278	276	276	130
Days required to prepare seedbed and plant	5	1	1	1
First stage reduction factor	0.87	1	1	0.87
Days to use 1 st stage reduction factor	15	27	27	42
Second stage reduction factor	1.7	2	2	1.42
Excess water stress parameters				
Yield intercept for crop (%)	100	100	100	100
Slope for yield versus stress day index	0.71	0.65	0.65	0.71
Limiting water table depth (cm)	30	30	30	30
Deficit water stress parameters				
Yield intercept for crop (%)	100	100	100	100
Deficit slope	1.22	7.2	7.2	1.22
Factors for two successive periods of deficit soil water	1	1	1	1
Susceptibility period length (days)	1.26	130	130	130
Root depths (cm)	3 – 42	3 – 39	3 – 30	3 – 30
Lower limiting of water content in root zone (cm cm ⁻³)	0.09	0.09	0.09	0.09
Salinity stress parameters				
Soil salinity threshold (mg l ⁻¹)	3800	640	4000	1088
Slope for higher soil salinity values (% per mg l ⁻¹)	7.10×10 ⁻³	2.97×10 ⁻²	2.50×10 ⁻²	1.88×10 ⁻²

B.5.3 Crop water requirements

In 1999, the General Water Authority in Libya made a report on the irrigation water requirements for different crop across Libya. In this research 6 crops were used in EAP and HAP. Palm tree and alfalfa were applied in Chapter 3, and wheat, maize, soybeans and beans were applied in Chapters 4 – 6. The calculated crop water requirement was based on Sabha meteorological station for EAP and Hon meteorological station for HAP. The data is summarised in Table B-3 and B-4 and as following:

- Crop water requirement for all the crops (alfalfa, palm tree, wheat, maize, beans, and soybeans) are based on Sabha meteorological station (EAP area) and Hon meteorological station (HAP area)
- The planting date is expected to be on 1 March for **alfalfa** for both projects and the irrigation system is surface irrigation. The growing seasons is calculated as 360 days.
- The planting date for **palm tree** is 1 January and the season length are 360 days for both EAP and HAP.
- The **wheat** window season is between 1 November to 30 April with 180 days calculated as a growing season.
- **Maize** is expected to grow between 1 may to 31 October in both EAP and HAP. The season length is around 125 days.
- **Beans** is predicted to grow between 1 August to 28 February with total season length of around 170 days.
- **Soybeans** is expected to grow in EAP and HAP between 1 October to 30 April with total season length of 150 days.
- The irrigation system is surface irrigation with efficiency of around 60%. The leaching requirement ranges between 5 – 15%.
- Crop evapotranspiration (ET_c) is achieved by adding the effective rain (ER) to the net irrigation requirement (NIR). ET_c and ER are calculated using the following equations:

$$ET_c = ET_0 * K_c \quad (8-1)$$

$$ER = (P * 0.357) - 2.58 \quad (8-2)$$

Where: K_c crop coefficient and P is the monthly total precipitation mm month⁻¹.

- Gross irrigation requirement (GIR) is calculating by dividing NIR over 0.6 (the 60% irrigation efficiency).
- Total water requirement (TWR) is the sum of GIR and the leaching requirement (LR).

Table B-3: Irrigation water requirement for Alfalfa, palm tree, wheat, maize, beans and soybeans based on Sabha meteorological station (EAP area)

Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Yearly total
Crop: Alfalfa (surface irrigation)													
ETc (mm)	101.6	141.2	205.4	276.2	340.3	404.0	354.5	350.0	333.1	239.4	158.3	111.4	3015
ER (mm)	0.8	0.3	1.0	0.4	0.3	0.0	0.0	0.0	0.2	0.0	0.1	0.1	3
NIR (mm)	100.7	140.7	204.4	275.8	339.9	403.9	354.5	350.0	333.0	239.3	158.3	110.9	3011
GIR (mm)	167.8	234.5	340.7	459.7	566.5	673.2	590.8	583.3	555.0	398.8	263.8	184.8	5018
LR (%)	10	10	10	10	10	10	10	10	10	10	10	10	
TWR (mm)	184.6	258.0	374.7	505.6	623.2	740.5	649.9	641.7	610.5	438.7	290.2	203.3	5520
Crop: Palm tree (surface irrigation)													
ETc (mm)	93.8	132.6	184.9	252.4	319.9	390.5	347.5	343.1	326.4	232.9	151.3	105.2	2881
ER (mm)	0.8	0.3	0.1	0.4	0.3	0.0	0.0	0.0	0.0	0.2	0.0	0.1	3
NIR (mm)	92.9	132.2	183.9	251.9	319.6	390.5	347.5	343.1	326.4	232.6	151.1	104.9	2877
GIR (mm)	154.8	220.3	306.5	419.8	532.7	650.8	579.2	571.8	544.0	387.7	251.8	174.8	4795
LR (%)	5	5	5	5	5	5	5	5	5	5	5	5	
TWR (mm)	162.6	231.4	321.8	440.8	559.3	683.4	608.1	600.4	571.2	407.1	264.4	183.6	5034
Crop: Wheat (surface irrigation)													
ETc (mm)	119.8	169.4	227.3	237.0							63.1	94.9	912
ER (mm)	0.8	0.3	1.0	0.4							0.0	0.1	3
NIR (mm)	119.0	169.0	226.2	236.5							63.0	94.8	909
GIR (mm)	198.3	281.7	377.0	394.2							105.0	158.0	1515
LR (%)	5	5	5	5							5	5	
TWR (mm)	208.3	295.8	395.9	413.9							110.3	165.9	1590
Crop: Maize (surface irrigation)													

Continued Table													
ETc (mm)					175.6	392.4	421.8	385.1	54.3				1429
ER (mm)					0.3	0.0	0.0	0.0	0.0				0
NIR (mm)					174.2	392.3	421.8	385.1	54.3				1428
GIR (mm)					290.3	653.8	703.0	641.8	90.5				2380
LR (%)					15	15	15	15	15				
TWR (mm)					333.9	751.9	808.5	738.1	104.1				2737
Crop: Beans (surface irrigation)													
ETc (mm)	58.1							129.6	202.1	254.3	186.8	128.5	960
ER (mm)	0.8							0.0	0.0	0.2	0.0	0.1	1
NIR (mm)	57.4							129.6	202.1	254.1	186.7	129.4	959
GIR (mm)	95.7							216.0	336.8	423.5	311.2	215.7	1598
LR (%)	15							15	15	15	15	15	
TWR (mm)	110.0							248.4	387.4	487.0	357.8	248.0	1838
Crop: Soybeans (surface irrigation)													
ETc (mm)	119.8	145.4								83.8	91.2	116.1	556
ER (mm)	0.8	0.3								0.2	0.0	0.1	1
NIR (mm)	119.0	145.1								83.7	91.0	115.9	555
GIR (mm)	198.3	241.8								139.5	151.7	193.2	925
LR (%)	15	15								15	15	15	
TWR (mm)	228.1	278.1								160.4	174.4	222.1	1063

Where ETc is the crop evapotranspiration, ER is the effective rain, NIR is the net irrigation requirement, GIR is the gross irrigation requirement, LR is the leaching requirement, TWR is the total water requirement.

Table B-4: Irrigation water requirement for Alfalfa, palm tree, wheat, maize, beans and soybeans based on Hon meteorological station (HAP area)

Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Yearly total
Crop: Alfalfa (surface irrigation)													
ETc (mm)	80.5	110.6	145.7	207.2	246.3	275.7	264.3	259.5	214.6	160.1	110.4	86.5	2161
ER (mm)	2.1	1.0	1.9	1.9	1.9	0.2	0.0	0.2	1.2	1.4	3.4	1.2	16
NIR (mm)	78.5	109.6	143.7	205.2	244.5	275.4	264.3	259.4	213.4	158.7	107.0	85.5	2145
GIR (mm)	130.8	182.7	239.5	342.0	407.5	459.0	440.5	432.3	355.7	264.5	178.3	142.5	3575
LR (%)	10	10	10	10	10	10	10	10	10	10	10	10	
TWR (mm)	143.9	200.9	263.5	376.2	448.3	504.9	484.6	475.6	391.2	291.0	196.2	156.8	3932
Crop: Palm tree (surface irrigation)													
ETc (mm)	82.4	113.2	149.1	214.6	261.0	298.5	289.2	283.9	234.8	173.4	117.0	89.6	2307
ER (mm)	2.1	1.0	1.9	1.9	1.9	0.2	0.0	0.2	1.2	1.4	3.4	1.2	16
NIR (mm)	80.3	112.2	147.2	212.7	259.1	298.2	289.2	283.8	233.6	172.1	113.5	88.5	2290
GIR (mm)	133.8	187.0	245.3	354.5	431.8	497.0	482.0	473.0	389.3	286.8	189.2	147.5	3816
LR (%)	5	5	5	5	5	5	5	5	5	5	5	5	
TWR (mm)	140.5	196.4	257.6	372.2	453.4	521.9	506.1	496.7	408.8	301.2	198.6	154.9	4007
Crop: Wheat (surface irrigation)													
ETc (mm)	104.3	140.6	181.3	198.7							46.6	81.8	756
ER (mm)	2.1	1.0	1.9	1.9							3.4	1.2	12
NIR (mm)	102.1	142.1	179.3	196.6							43.3	80.7	744
GIR (mm)	170.2	236.8	298.8	327.7							72.2	134.5	1240
LR (%)	5	5	5	5							5	5	
TWR (mm)	178.7	248.7	313.8	344.1							75.8	141.2	1302
Crop: Maize (surface irrigation)													

Continued Table													
ETc (mm)					135.0	301.1	357.6	323.9	40.7				1158
ER (mm)					1.9	0.2	0.0	0.2	0.2				3
NIR (mm)					133.1	300.8	357.6	323.8	40.6				1156
GIR (mm)					221.8	501.3	596.0	539.7	67.7				1926
LR (%)					15	15	15	15	15				
TWR (mm)					255.1	576.5	685.4	620.6	77.8				2215
Crop: Beans (surface irrigation)													
ETc (mm)	50.2							100.7	141.0	189.5	145.4	111.7	739
ER (mm)	1.5							0.2	1.2	1.4	3.4	1.2	9
NIR (mm)	48.6							100.5	139.9	188.0	142.2	110.5	730
GIR (mm)	81.0							167.5	233.2	313.3	237.0	184.2	1216
LR (%)	15							15	15	15	15	15	
TWR (mm)	93.2							192.6	268.1	360.3	272.6	211.8	1399
Crop: Soybeans (surface irrigation)													
ETc (mm)	106.1	125.2								62.2	72.1	102.8	468
ER (mm)	2.1	1.0								1.4	3.4	1.2	9
NIR (mm)	104.0	124.2								60.8	68.6	101.7	459
GIR (mm)	173.3	207.0								101.3	114.3	169.5	765
LR (%)	15	15								15	15	15	
TWR (mm)	199.3	238.1								116.5	131.5	194.9	879

Where ETc is the crop evapotranspiration, ER is the effective rain, NIR is the net irrigation requirement, GIR is the gross irrigation requirement, LR is the leaching requirement, TWR is the total water requirement.

Appendix C Artificial Neural Networks

In this appendix, more details about the development of artificial neural networks (ANNs) are provided. The details include the pre-processing steps to prepare the data, the functions applied, the codes written, and other outputs related to each Chapter in this thesis.

C.1 Codes and Functions applied in this research

The following steps were applied to develop ANNs, specifically in Chapter 3 – 5.

C.1.1 Data preparation

- In this step, the collected data (which is available in comma separated values (CSV) format) was uploaded to the R (RStudio) environment using the following code:

```
data <- read.csv("Y:/PhD Murad Ellafi/year 2/KSAT analyses/Hammam  
ANN/SSC/training ksat hammam.csv", header = T)
```

- Creating a directory on the computer to save the outputs on the desired folder. The following code shows an example on how to create a directory in R (taken from Chapter 3):

```
setwd("C:/Users/s252409/OneDrive - Cranfield University/Ksat/WD")
```

- The following codes were applied to delete any missing data (the column in which has missing input or output variables will be deleted).

```
data <- na.omit(data_train)  
data <- data.frame(data_train)
```

C.1.2 Data processing

- Split the data to training and testing dataset. In Chapter 3 the split was 80% for training and 20% for testing. In Chapter 4, the split was 60% training and 40% testing and in Chapter 5, the split was 90% training and 10% testing. The following codes were applied in Chapters 3 – 5.

Chapter 3:

```
samplesize = 0.80 * nrow(data)  
index = sample( seq_len ( nrow ( data) ), size = samplesize )
```

Chapter 4:

```
samplesize = 0.60 * nrow(data)  
index = sample( seq_len ( nrow ( data) ), size = samplesize )
```

Chapter 5:

```
samplesize = 0.90 * nrow(data)
index = sample( seq_len ( nrow ( data) ), size = samplesize )
```

- Creating training and testing dataset. After splitting the data to training and testing the following codes allowed them to be associated with a new name.

```
trainset = data[ index, ]
testset = data[ -index, ]
The dataset needs to be scaled to simplify the mathematical process within the ANNs.
Therefore, all the values in the dataset were converted to a scale from -1 – 1.
max = apply(data, 2 , max)
min = apply(data, 2 , min)
scaled_training <- as.data.frame(scale(data, center = min, scale = max - min))
str(scaled_training)
train_ <- scaled_training[index,]
test_ <- scaled_training[-index,]
Identify the depended variable and the independent variables
n <- names(train_)
f <- as.formula(paste("KSAT ~", paste(n[!n %in% "KSAT"], collapse = " + ")))
```

C.1.3 ANN development

- The following codes show the process of training the ANNs and installing the required package. As mentioned in the thesis, the main package was applied to train and test the developed ANNs was neuralnet. The following example was taken from Chapter 5.

```
install.packages("neuralnet")
set.seed(123)
```

```
NN = neuralnet(EC ~ SI1+SI2+SI3+SI4+SI5+SI6+SI7+SI8+SI9, data = train_, hidden =
c(5,5), linear.output = T, algorithm = "rprop+", threshold=0.01, stepmax = 100000)
```

Where, the *set.seed* is a function in R used to create reproducible results when writing code that involves creating variables that take on random values. By using the *set.seed()* function, it guarantees that the same random values are produced each time you run the code. *Hidden* is showing the number of hidden layers and the number of neurons in each layer (for example, (5,5) means that two hidden layers were created with five neurons in each layer). *Linear.output = T* means that the required output from the model is linear. *algorithm = "rprop+"* algorithm is the activation function used in the development which is *rprop+*. *Rprop+* is short for resilient backpropagation. *Rprop+* was applied because it works well in many situations because it adapts the step size dynamically for each weight independently. *Threshold* by default in neuralnet requires the model partial derivative error to change at least 0.01 otherwise it will stop changing. *stepmax* controls how long your neural network trains. By default, it uses 100,000 iterations.

- To predict the accuracy of the developed ANN within the training set, the following codes were applied

```
predict_trainNN = compute(NN, train[,c(1:9)])
predict_trainNN = (predict_trainNN$net.result * (max(data $EC) - min(data $EC))) +
min(data $EC)
```

- To evaluate the accuracy of the developed ANN within the training set the following codes were applied

```
RMSE.NN_train = (sum((trainset$EC - predict_trainNN)^2) / nrow(trainset)) ^ 0.5
MSE.NN_train <- sum((predict_trainNN - trainset$EC)^2)/nrow(trainset)
Real_data = trainset$EC
cor(predict_trainNN, Real_data)
```

- To predict the accuracy within the testing dataset, the following codes were applied.

```
predict_testNN <- compute(NN, test[,c(1:9)])
predict_testNN <- (predict_testNN$net.result * (max(data$EC) - min(data$EC))) +
min(data$EC)
To evaluate the accuracy of the developed ANN against the testing dataset, the
following codes were applied.
RMSE.NN = (sum((testset$EC - predict_testNN)^2) / nrow(testset)) ^ 0.5
MSE.NN <- sum((predict_testNN - testset$EC)^2)/nrow(testset)
Real_data_test = testset$EC
cor(predict_testNN, Real_data_test)
```

C.1.4 K-fold cross validation

- The following codes were applied to get the cross-validation results

```
set.seed(50)
k = 10
RMSE.NN.cv = NULL
List = list()
# Fit neural network model within nested for loop
for(j in 10:360){
  for (i in 1:k) {
    index = sample(1:nrow(trainset),j)
    scaled = as.data.frame(scale(trainset, center = min, scale = max - min))
    trainNN = scaled[index,]
    testNN = scaled[-index,]
    datatest = trainset[-index,]
    NN.cv = neuralnet(KSAT ~ SAND+SILT+CLAY+BD, data = trainNN, hidden = 2,
linear.output = T, rep = 1, algorithm = "rprop+", threshold=0.01)
    predict_testNN = compute(NN.cv,testNN[,c(1:4)])
    predict_testNN = (predict_testNN$net.result*(max(trainset$KSAT)-
min(trainset$KSAT)))+min(trainset$KSAT)
    RMSE.NN.cv [i]<- (sum((datatest$KSAT - predict_testNN)^2)/nrow(datatest))^0.5
  }
  List[[j]] = RMSE.NN.cv
}
```

```

}
Matrix.RMSE = do.call(cbind, List)
Matrix.RMSE
mean(Matrix.RMSE[,350])
boxplot(Matrix.RMSE[,350], ylab = "RMSE", main = "RMSE BoxPlot (length of training
set = 360)")
install.packages("matrixStats")
library(matrixStats)
med = colMedians(Matrix.RMSE)
med
X = seq(10,360)
X
plot(med~X, type = "l", xlab = "length of training set", ylab = "median RMSE", main =
"Variation of RMSE with length of training set")

```

C.1.5 Neural networks tools package

Neural Network Tools (NeuralNetTools) are used for analysis and visualisation to help in the understanding of neural network models. These include functions for plotting, quantifying the importance of variables, running a sensitivity analysis, and producing a straightforward list of model weights.

The first function is the Plot Neural Network model function (plotnet). According to Ozesmi and Ozesmi (1999), this function plots a neural network as a neural interpretation diagram. Positive weights between layers are shown by default as black lines, and negative weights as grey lines. The line thickness is proportional to each weight's relative magnitude. The first layer contains solely input variables, with nodes randomly labelled I1 through In, for n input variables. Each node inside each hidden layer is labelled as H1 through Hn, and one or more hidden layers are shown. The output layer, with nodes designated O1 through On, is plotted last. Also shown are bias nodes related to the hidden and output layers. MLP-created neural networks do not have bias layers.

The second function is garson. garson function is applied to plot the relative importance of the input parameters. The weights that link parameters in a neural network are similar to parameter coefficients in a conventional regression model and may be used to characterise the connections between variables. The weights determine the proportional importance of information that is processed in the network, such that the weights mute input variables that do not correlate with a

response variable. Weights provided to explanatory factors have significant positive or negative connections with a response variable having the opposite impact. An obvious distinction between a neural network and a regression model is that a neural network has excessive weights. This trait is helpful since it makes neural networks particularly adaptable for modelling nonlinear functions with many interactions, but interpreting the effects of specific variables is, of course, challenging.

By deconstructing the model weights, an approach developed in Garson (1991) (also see Goh (1995)) finds the relative relevance of explanatory factors for a single response variable in a supervised neural network. By finding all weighted connections between the nodes of interest, one may establish the relative relevance (or strength of association) of a particular explanatory variable for the response variable. Thus, all weights linking the given input node to the response variable through the hidden layer are recognised. This is performed for all subsequent explanatory variables until a list of all input-specific weights is compiled. Each input node's connections are counted and scaled relative to the other inputs. One value is derived for each explanatory variable in the model that defines its connection with the response variable (see the appendix in Goh 1995 for a more detailed description). The initial approach presents relative significance as the absolute magnitude from zero to one, making it impossible to detect the direction of the reaction.

The last function applied is the Olden function. This approach is comparable to Garson's algorithm (Garson 1991, updated by Goh 1995) in that the connection weights between layers of a neural network serve as the basis for identifying the importance of an input parameter. In contrast, Olden et al. (2004) propose a connection weights approach that consistently outperforms Garson's technique in simulating the genuine variable significance in simulated datasets. This 'Olden' technique computes variable significance as the product of the raw input-hidden and hidden-output connection weights between each input and output neuron and the total of this product over all hidden neurons. The relative contributions of each link weight are preserved in terms of size and sign, which is an advantage

over Garson's technique, which only examines absolute magnitude. For instance, connection weights that change sign (e.g., from positive to negative) between the input-hidden and output-hidden layers would have a cancelling effect, but Garson's approach may provide deceptive findings based on the absolute magnitude. In addition, Olden's approach can evaluate neural networks with several hidden layers, while Garson's technique was designed for networks with a single hidden layer.

The relevance ratings given to each variable are expressed in units directly proportional to the total of the connection weights. Only the relative sign and magnitude between explanatory variables should be used to understand the actual results. There should be no comparisons between various models.

C.2 ANNs in Chapter 3

C.2.1 ANN1 results

ANN1 was developed for EAP to predict saturated hydraulic conductivity (K_{sat}) using the sand, silt and clay percentage, bulk density, field capacity and wilting point. Figure C-1 shows the structure of the developed ANN1 with the weights assigned to each neuron. Figure C-2 and Figure C-3 show the accuracy of ANN1 in predicting K_{sat} against the training and testing datasets, respectively. Figure C-4 illustrates the structure of ANN1 using the plotnet function. Figure C-5 and Figure C-6 show the importance of the input parameters using garson and olden functions, respectively.

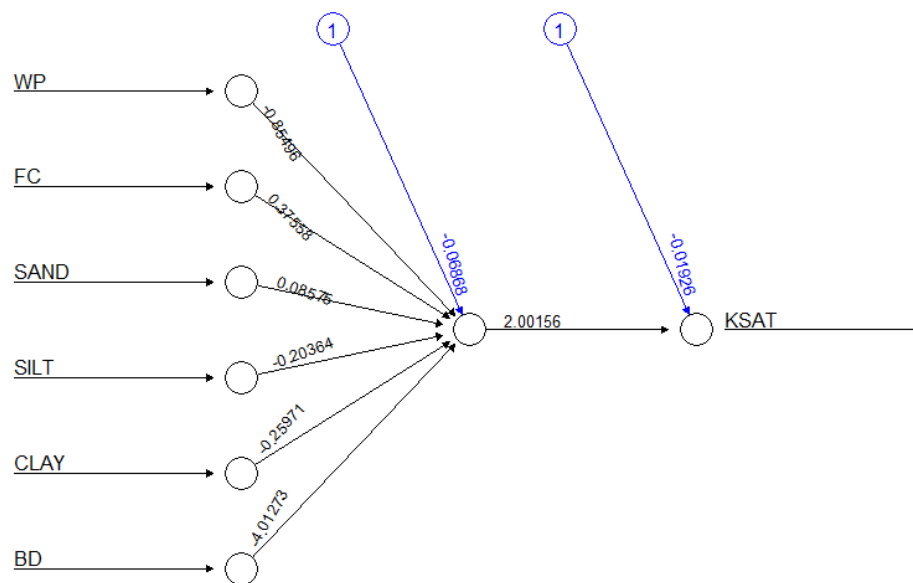


Figure C-1: ANN1 structure developed to predict K_{sat} in EAP

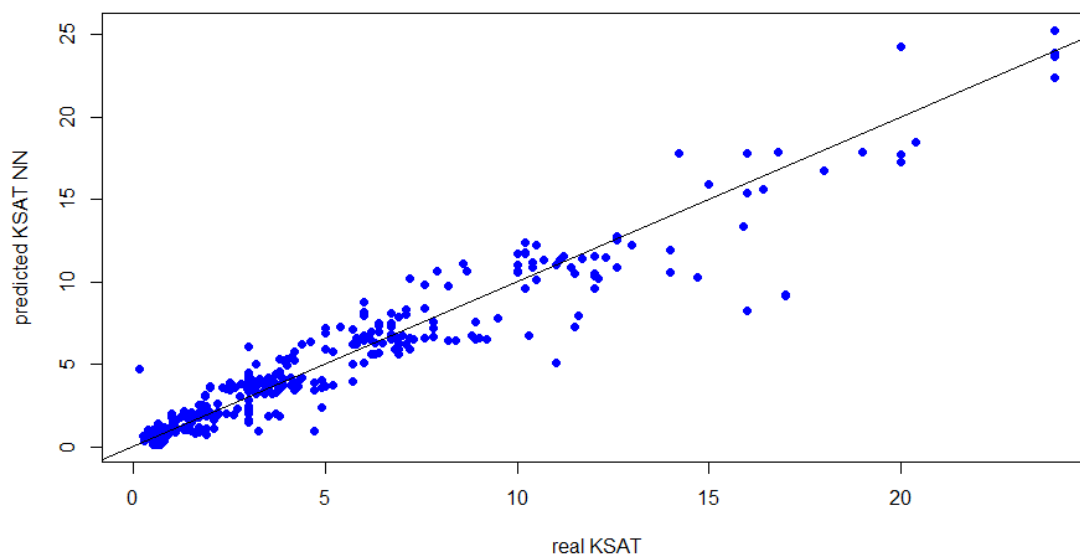


Figure C-2: the accuracy of ANN1 in predicting K_{sat} in EAP using the training dataset

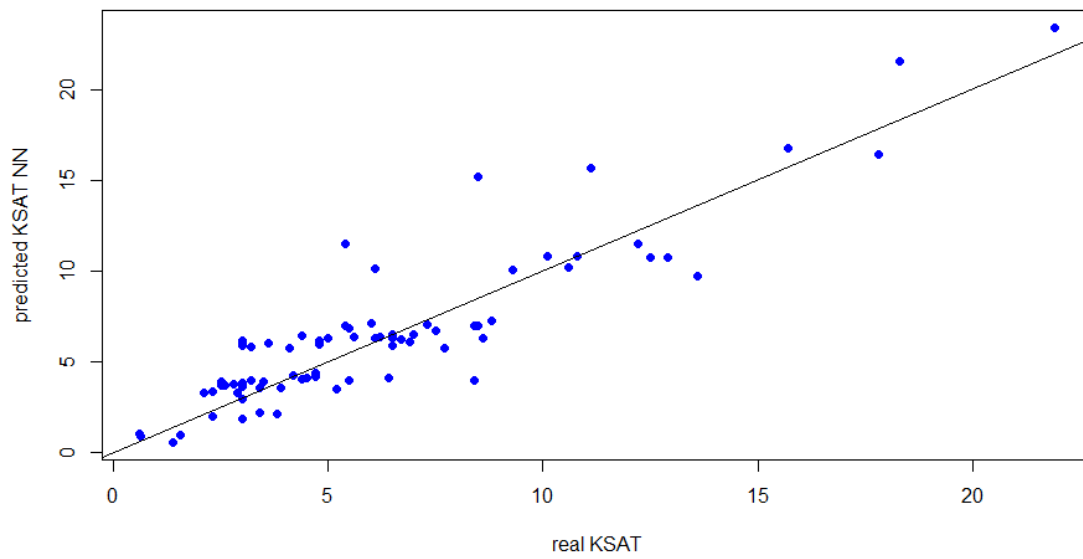


Figure C-3: ANN1 accuracy in predicting Ksat in EAP using the testing dataset

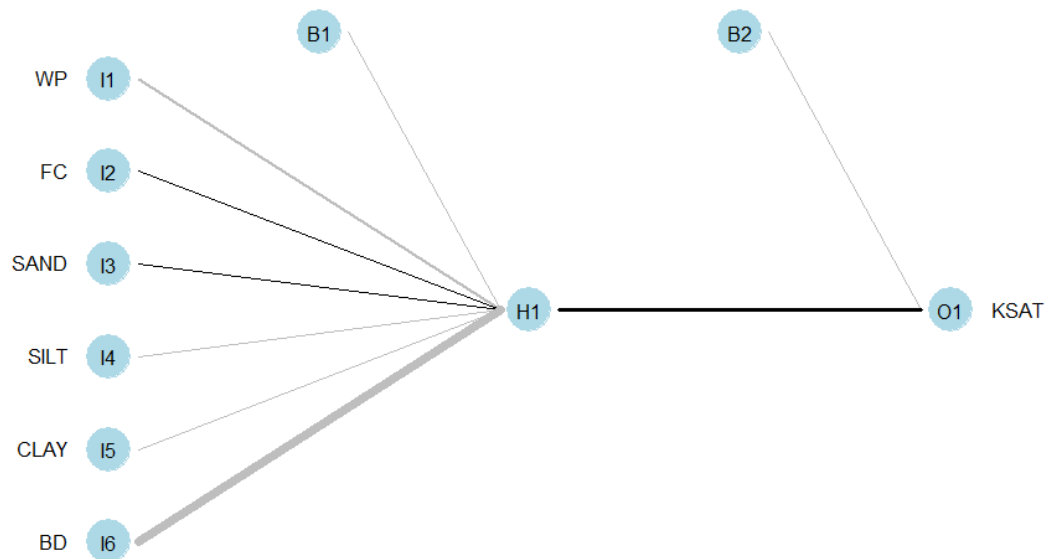


Figure C-4: ANN1 structure with weights depicted in the figure in different shades (the black shade represents the positive weights and the grey shade represents the negative weights, and the thicker shades represent the higher weights values)

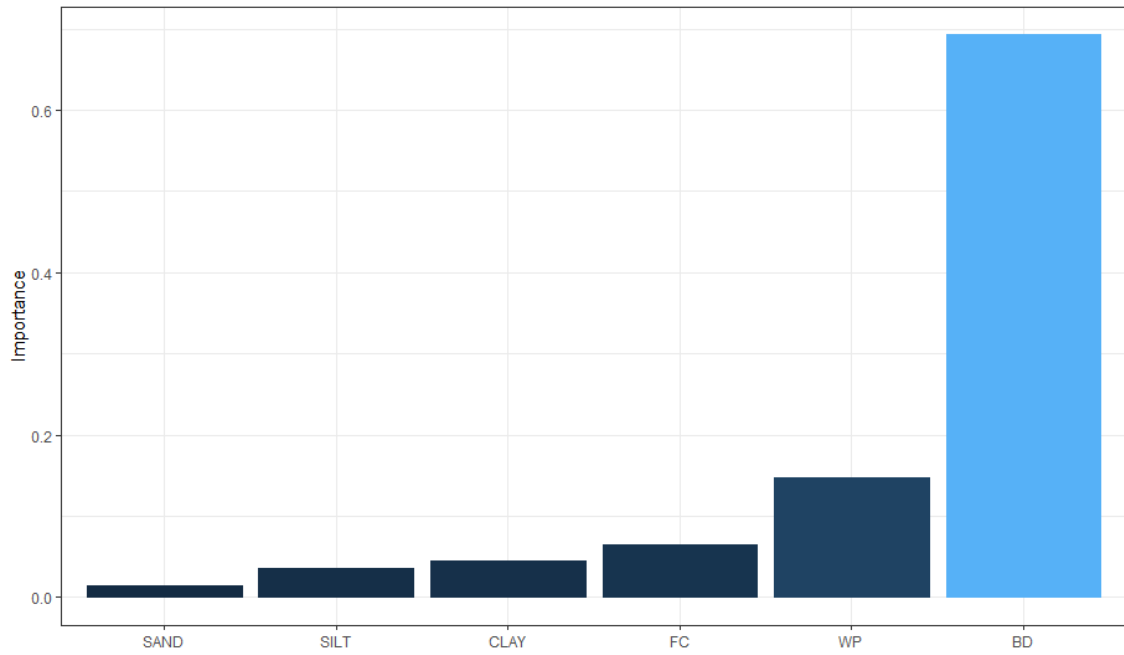


Figure C-5: The importance of each parameter applied in ANN1 based on garson method

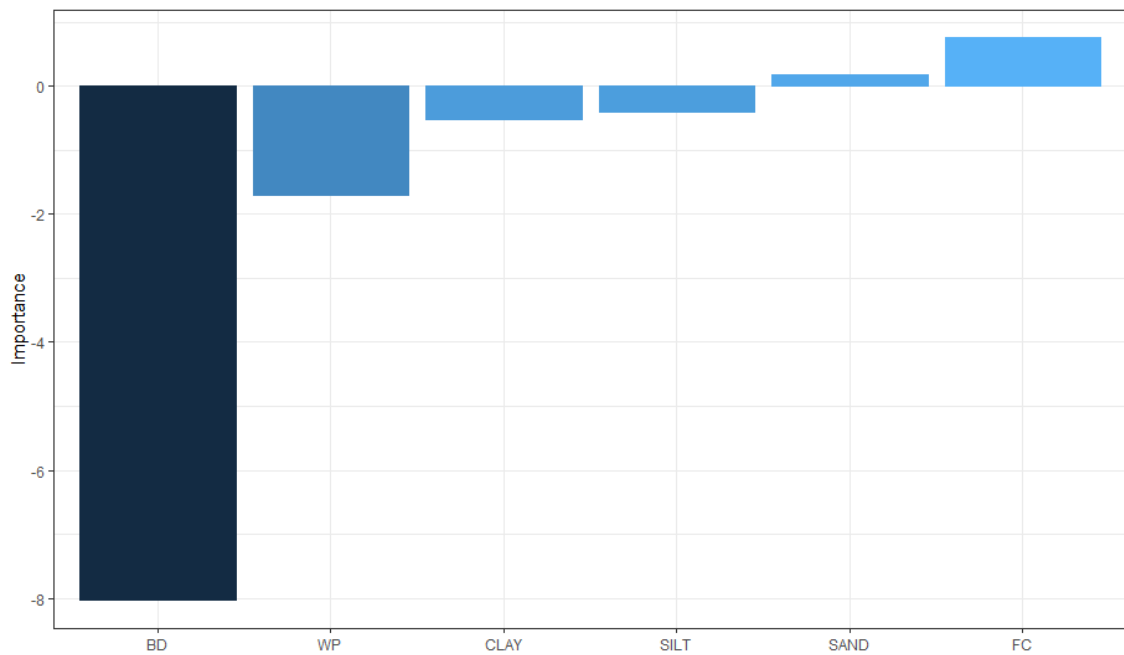


Figure C-6: The importance of the input parameters in predicting K_{sat} based on olden method

C.2.2 ANN2 results

ANN2 was developed for EAP to predict saturated hydraulic conductivity (K_{sat}) using the sand, silt and clay percentage, and bulk density. Figure C-7 shows the structure of the developed ANN2 with the weights assigned to each neuron. Figure C-8 and Figure C-9 show the accuracy of ANN2 in predicting K_{sat} against the training and testing datasets, respectively. Figure C-10 illustrates the structure of ANN2 using the plotnet function. Figure C-11 and Figure C-12 show the importance of the input parameters using garson and olden functions, respectively.

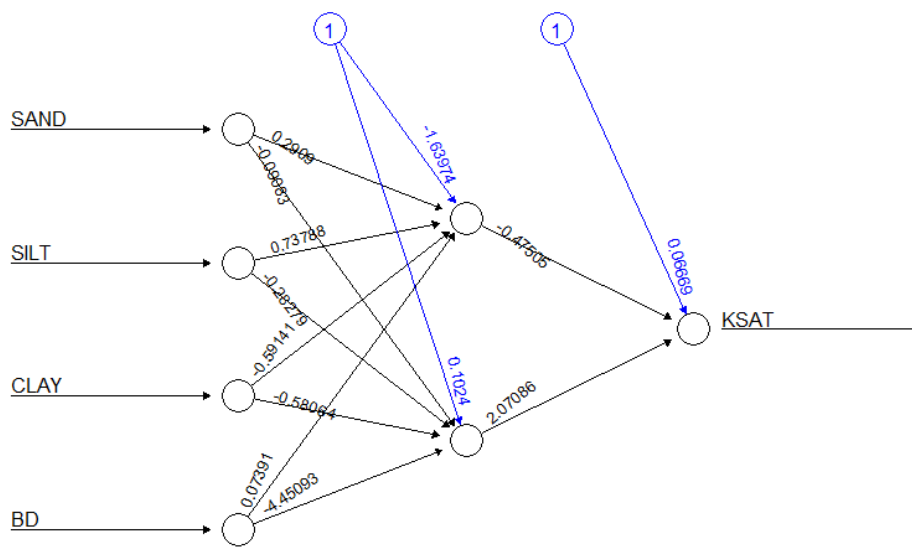


Figure C-7: The structure of ANN2 (developed to predict K_{sat} in EAP).

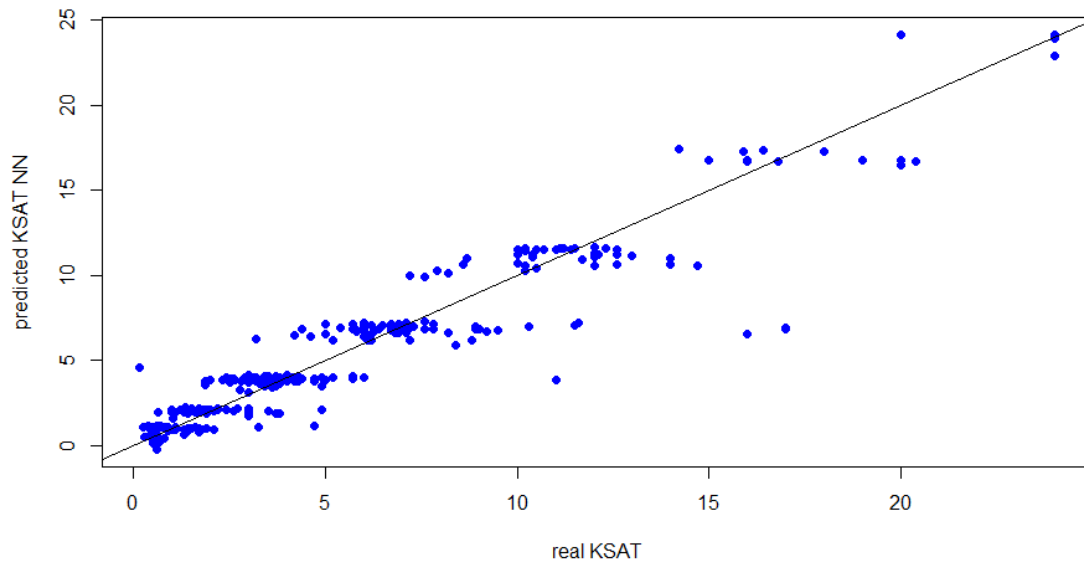


Figure C-8: ANN2 accuracy against training dataset to predict Ksat in EAP.

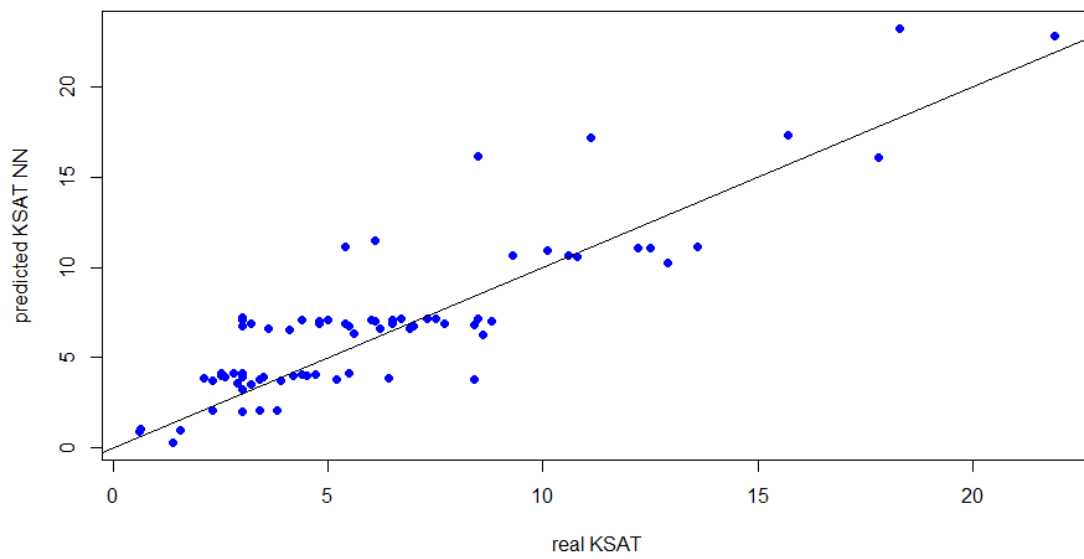


Figure C-9: ANN2 accuracy in predicting K_{sat} in EAP against the testing dataset

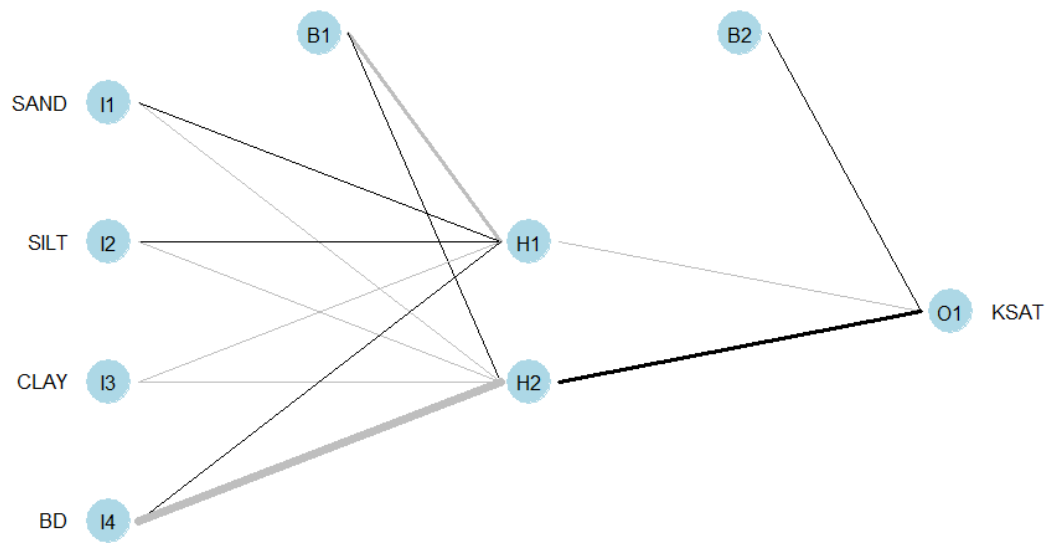


Figure C-10: ANN2 structure with weights depicted in the figure in different shades (the black shade represents the positive weights and the grey shade represents the negative weights, and the thicker shades represent the higher weights values)

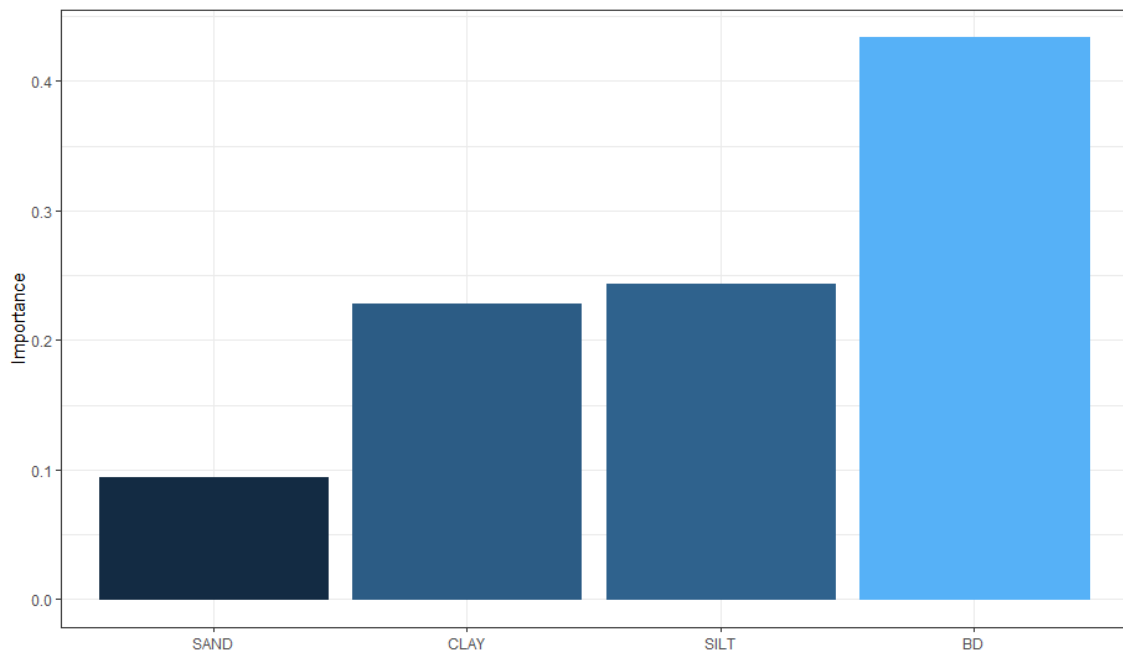


Figure C-11: the importance of the input parameters applied in ANN2 based on garson function

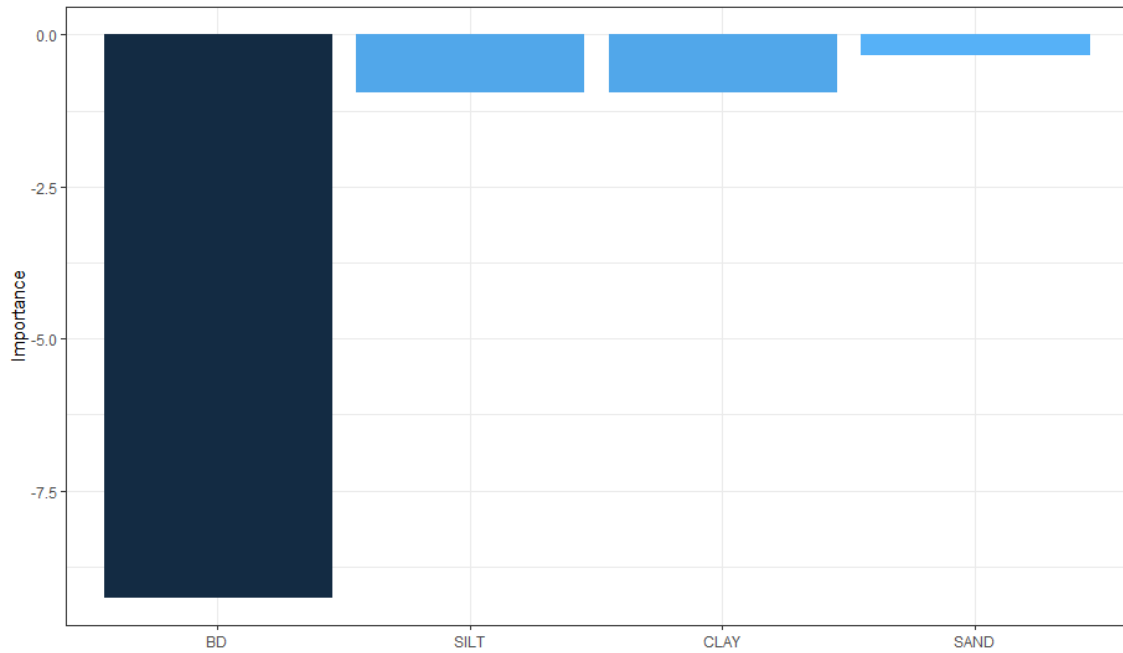


Figure C-12: the importance of the input parameters in ANN2 based on olden function.

C.2.3 ANN3 results

ANN3 was developed for HAP to predict saturated hydraulic conductivity (Ksat) using the sand, silt and clay percentage, field capacity, wilting point, and bulk density. Figure C-13 shows the structure of the developed ANN1 with the weights assigned to each neuron. Figure C-14 and Figure C-15 show the accuracy of ANN3 in predicting Ksat against the training and testing datasets, respectively. Figure C-16 illustrates the structure of ANN3 using the plotnet function. Figure C-17 shows the importance of the input parameters using olden functions. (note: garson function was not applied because the developed ANN has two hidden layers and the function only works with one hidden layer).

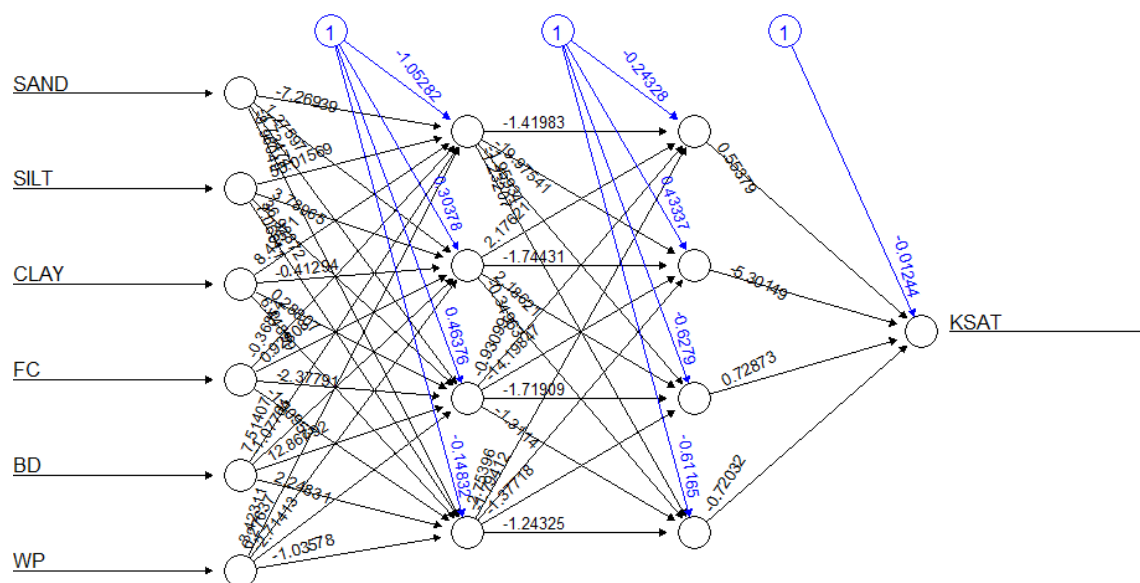


Figure C-13: ANN3 structure (developed to predict K_{sat} in HAP)

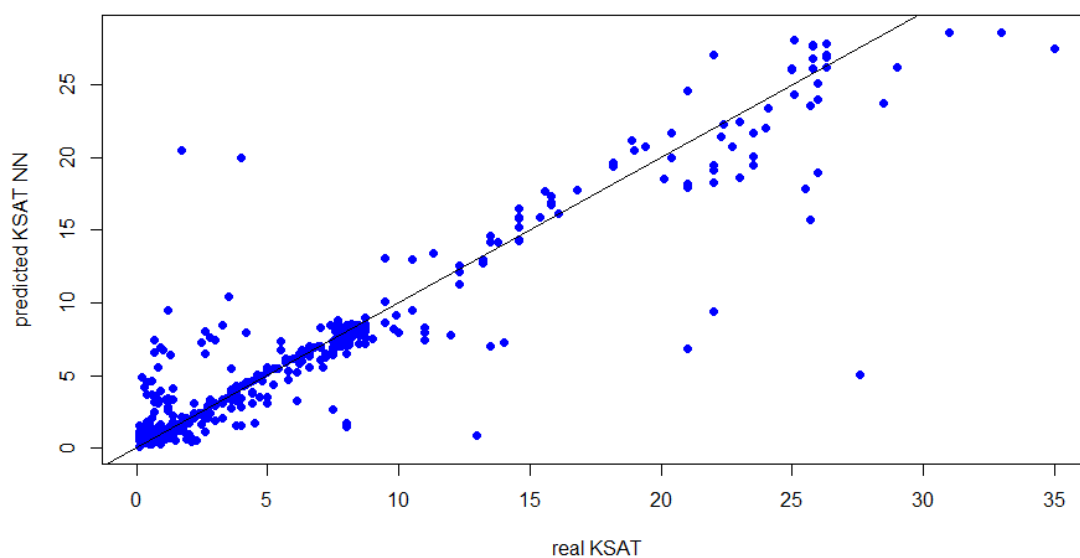


Figure C-14: The accuracy of ANN3 to predict K_{sat} in HAP against the training dataset.

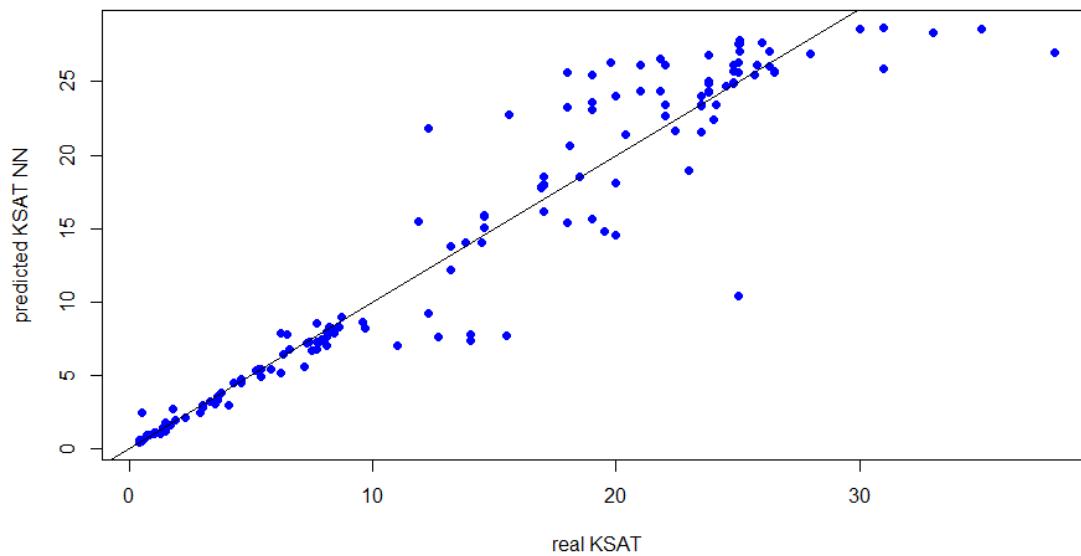


Figure C-15: The accuracy of ANN3 against testing dataset in predicting Ksat in HAP

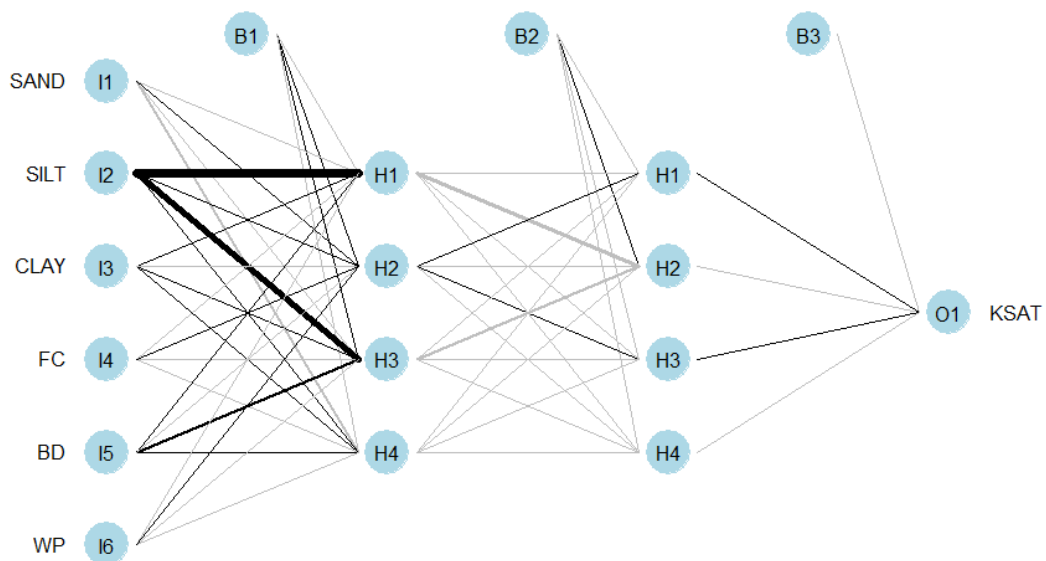


Figure C-16: The structure of ANN3 with weights depicted in the figure in different shades (the black shade represents the positive weights and the grey shade represents the negative weights, and the thicker shades represent the higher weights values)

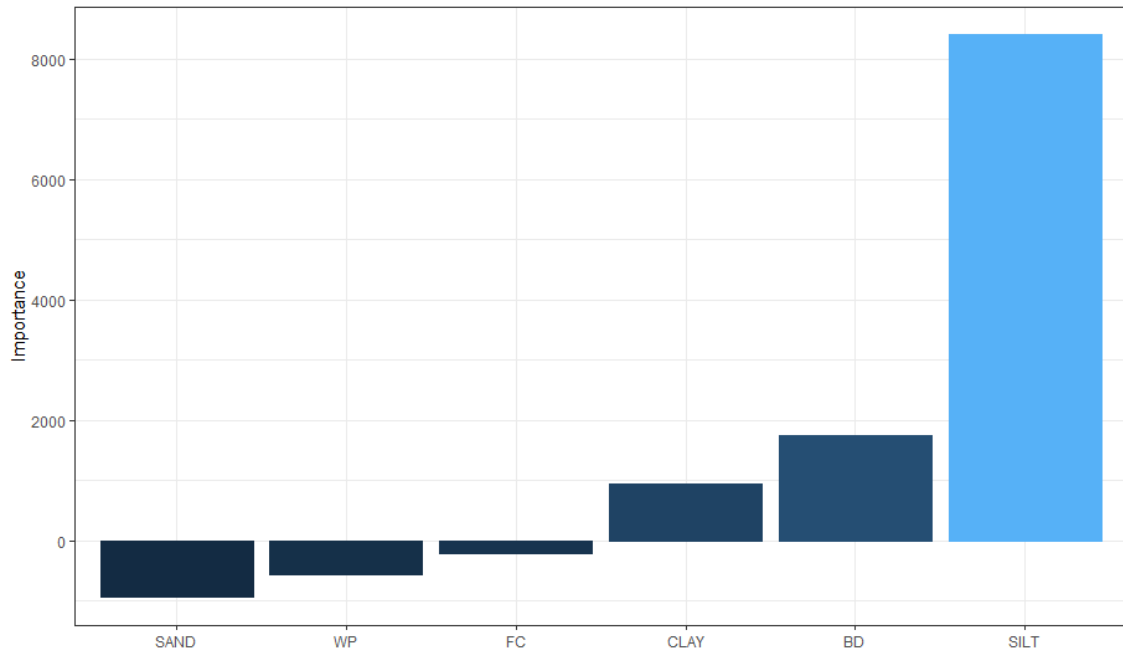


Figure C-17: The importance of the input parameters applied in ANN3 based on olden function.

C.2.4 ANN4 results

ANN4 was developed for HAP to predict saturated hydraulic conductivity (K_{sat}) using the sand, silt and clay percentage, and bulk density. Figure C-18 shows the structure of the developed ANN4 with the weights assigned to each neuron. Figure C-19 and Figure C-20 show the accuracy of ANN4 in predicting K_{sat} against the training and testing datasets, respectively. Figure C-21 illustrates the structure of ANN4 using the plotnet function. Figure C-22 and Figure C-23 show the importance of the input parameters using garson and olden functions, respectively.

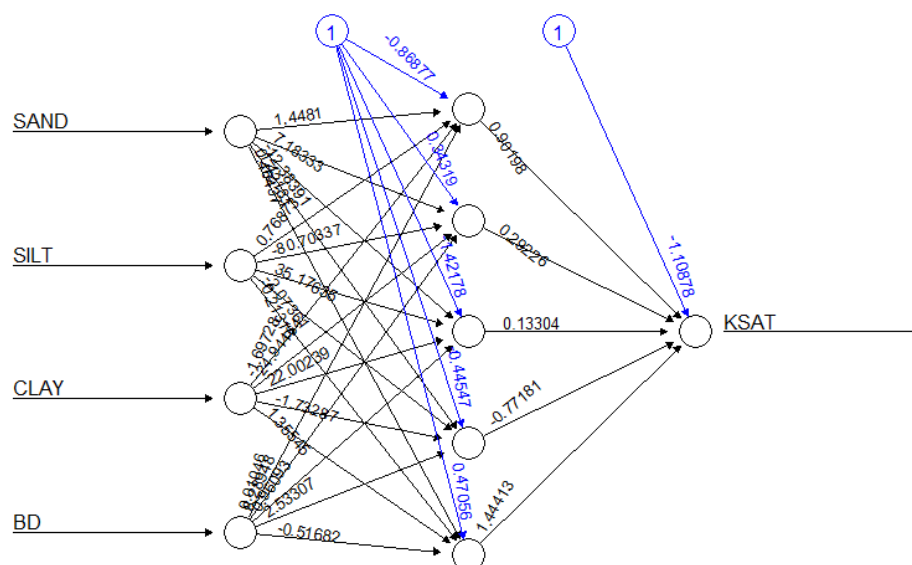


Figure C-18: The structure of the developed ANN4 to predict Ksat in HAP.

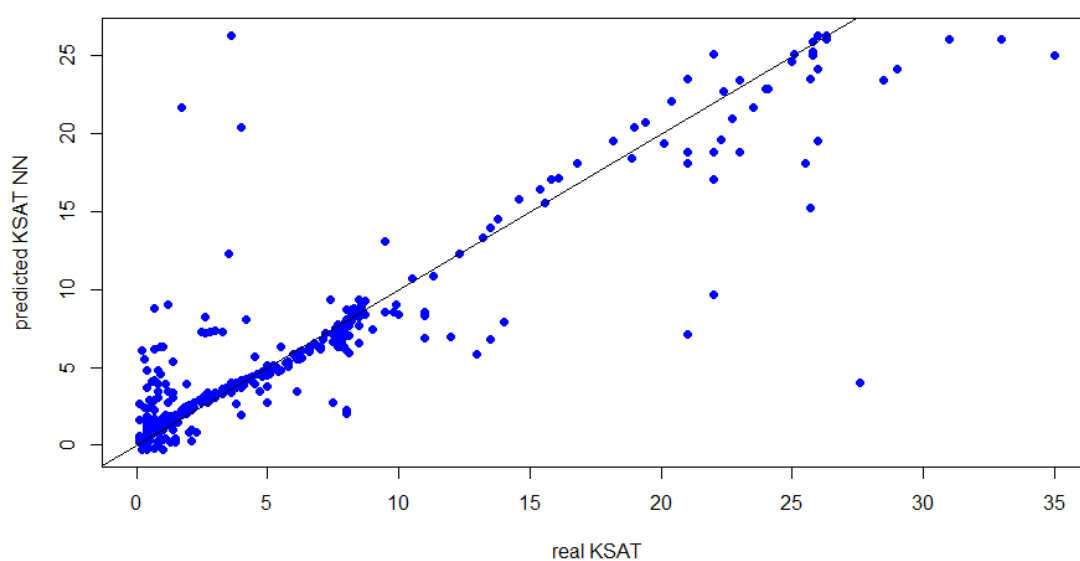


Figure C-19: The accuracy of ANN4 in predicting Ksat in HAP against the training dataset

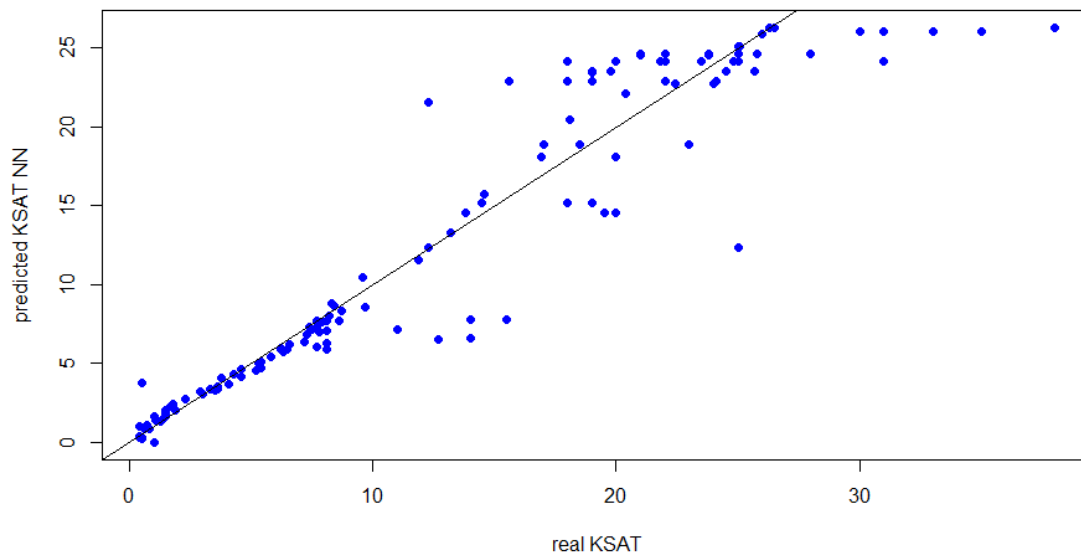


Figure C-20: The accuracy of ANN4 against the testing dataset (predicting Ksat in HAP)

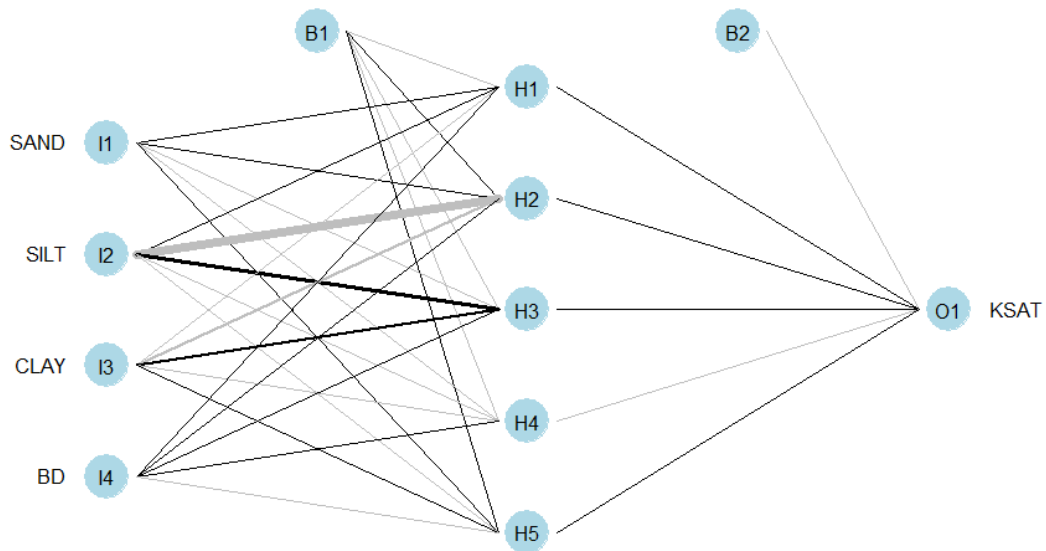


Figure C-21: ANN4 structure with weights depicted in the figure in different shades (the black shade represents the positive weights and the grey shade represents the negative weights, and the thicker shades represent the higher weights values)

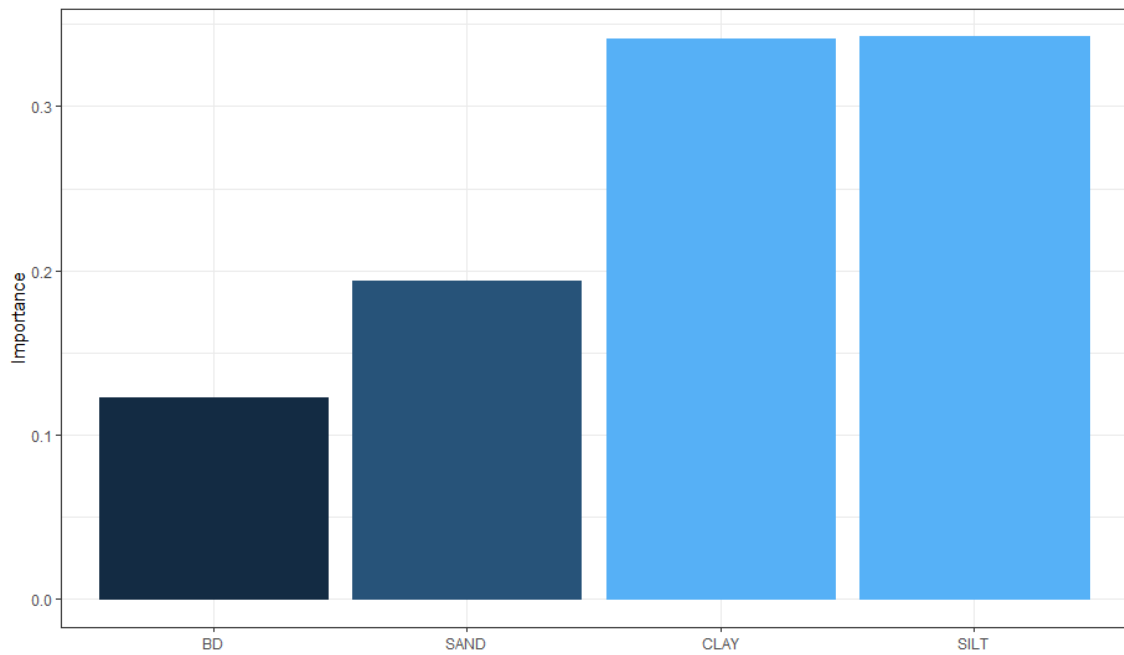


Figure C-22: The importance of the input parameters used in ANN4 based on garson function.

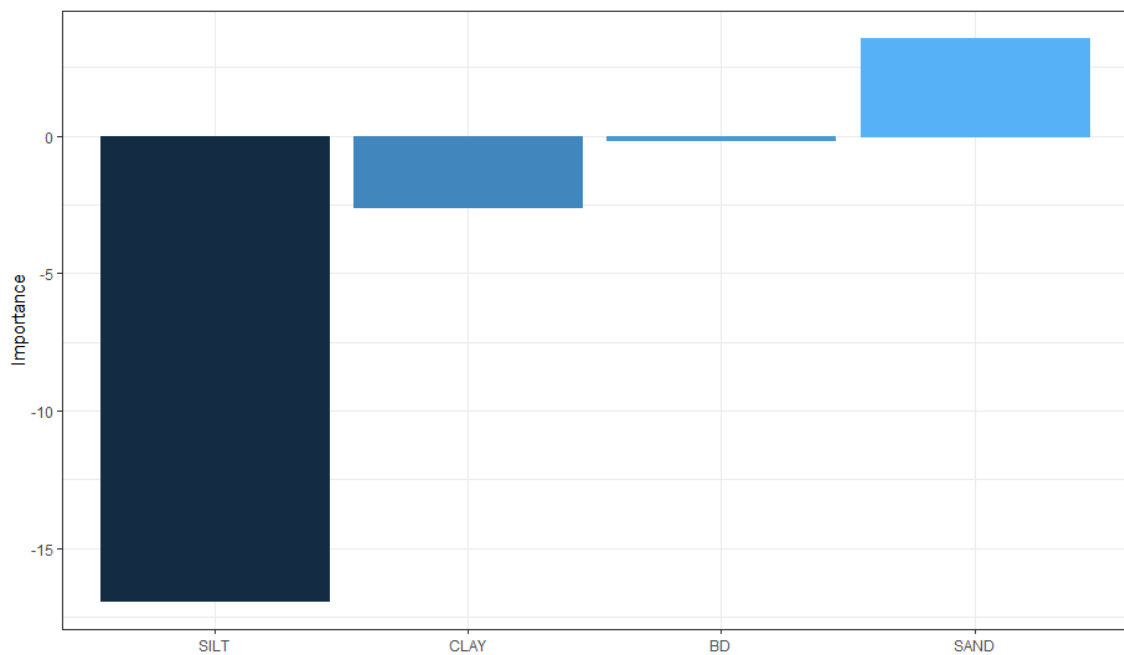


Figure C-23: The importance of the input parameters applied in ANN4 based on olden function

C.3 ANNs in Chapter 4

In these ANNs, 60% of the available DTmax and DTmin data were randomly selected as a training dataset, leaving 40% as a testing dataset. In Hon, the total available DTmax and DTmin values were available for 8390 days; 60% of these (5034 days) were randomly selected for the training dataset, and 3356 days' worth of DTmax and DTmin values utilised for testing the model. In Sabha, the total available DTmax and DTmin values were available for 9579 days; 60% of these (5748 days) were randomly selected for the training dataset, and 3831 days' worth of DTmax and DTmin values utilised for testing the model. Table C-1 shows the number of days for each month used to develop the ANNs (i.e. training and testing data).

Table C-1: the number of days for each month used to develop the ANNs

Month	Number of days in Sabha		Number of days in Hon	
	Training	Testing	Training	Testing
January	476	311	406	254
February	443	285	395	240
March	503	336	443	270
April	457	302	402	266
May	508	322	472	290
June	507	323	442	294
July	508	320	439	289
August	502	323	425	285
September	487	315	403	304
October	474	326	414	309
November	426	335	402	283
December	457	333	391	272
Total	5748	3831	5034	3356

C.3.1 ANN1S results

ANN1S was developed to predict the daily maximum and minimum air temperature (DTmax and DTmin) at Sabha meteorological station using input parameters including: day of the year (DOY), average month maximum air temperature (MTmax), average monthly minimum air temperature (MTmin), extreme maximum air temperature of the month (XMTmax), extreme minimum air temperature of the month (XMTmin), sunshine duration (SD), average daily

maximum air temperature calculated by the Global TempSIM (GTmax), and average daily minimum air temperature calculated by the Global TempSIM (GTmin). Figure C-24 shows the structure of the developed ANN with the input parameters. Figure C-25 – C28 show the accuracy of ANN1S in predicting DTmax and DTmin against the training and testing dataset respectively. Figure C-29 shows the structure of ANN1S based on plotnet function, and Figure C-30 shows the importance of the input parameters based on olden function. (Note: garson function cannot be applied because ANN1S has two outputs).

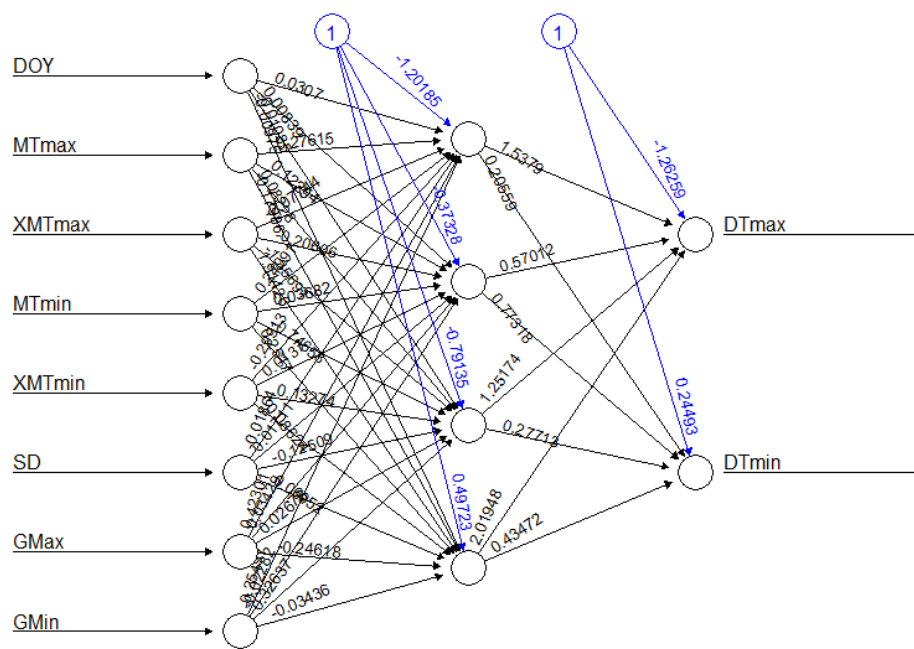


Figure C-24: The structure of the developed ANN1S to predict DTmax and DTmin at Sabha meteorological station.

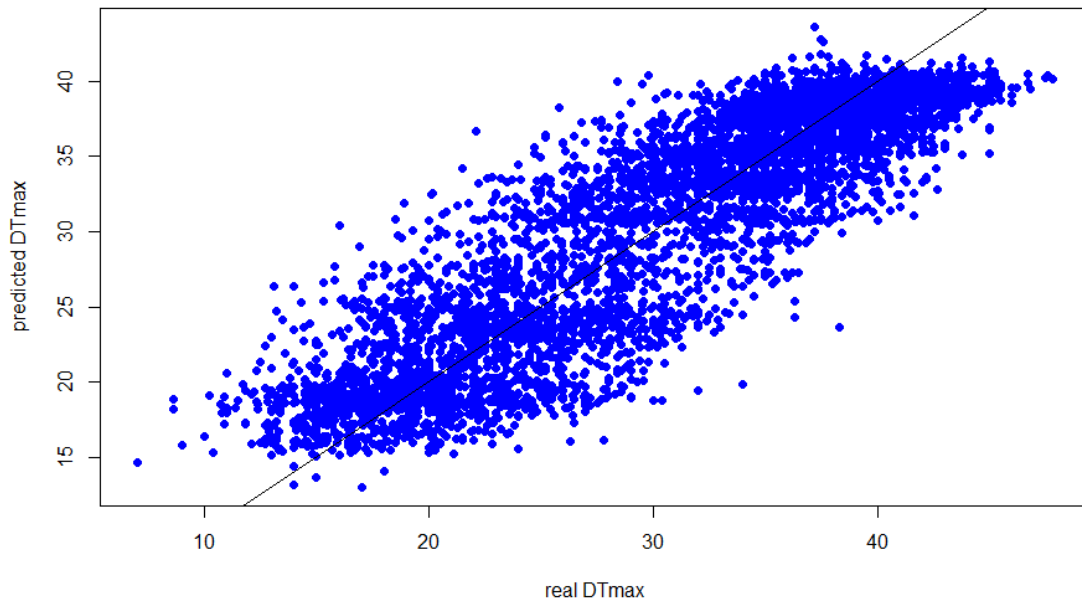


Figure C-25: The accuracy of ANN1S in predicting DTmax against the training dataset.

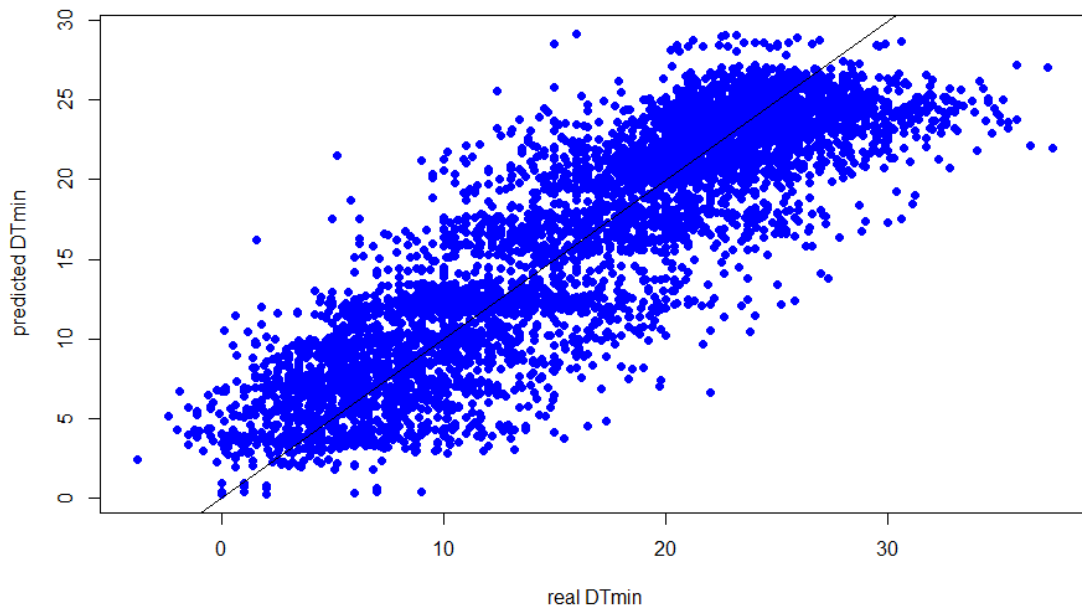


Figure C-26: The accuracy of ANN1S in predicting DTmin against the training dataset.

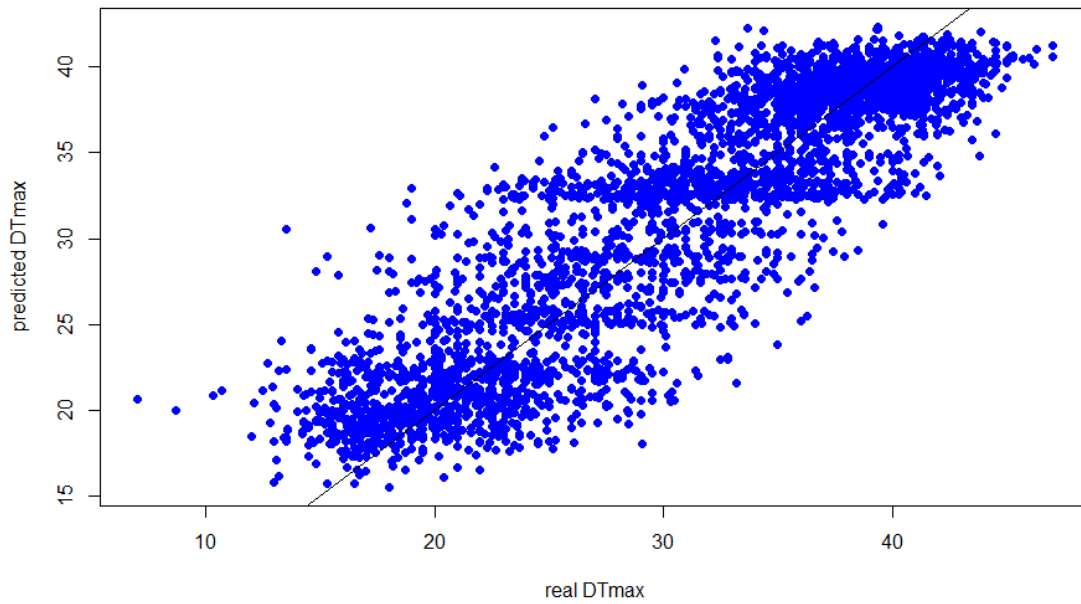


Figure C-27: The accuracy of ANN1S in predicting DTmax against the testing dataset.

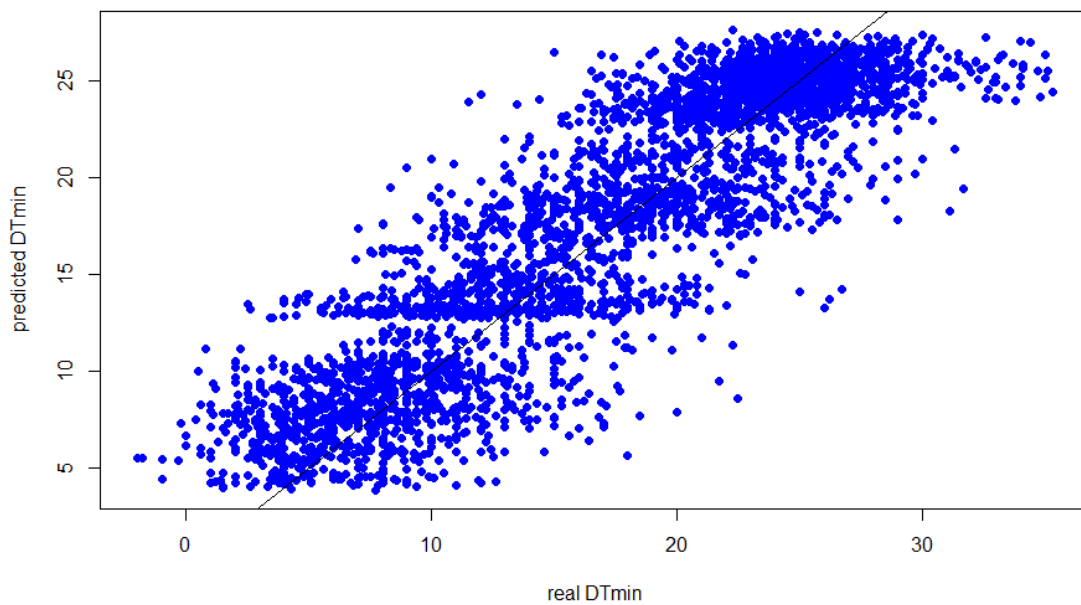


Figure C-28: The accuracy of ANN1S in predicting DTmin against the testing dataset.

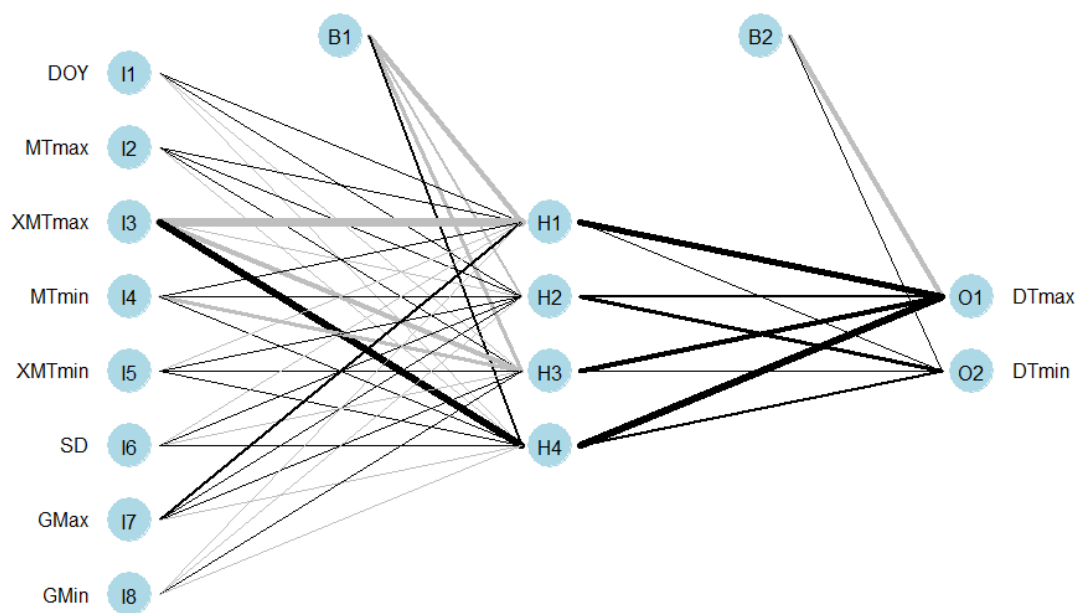


Figure C-29: ANN1S structure with weights depicted in the figure in different shades (the black shade represents the positive weights and the grey shade represents the negative weights, and the thicker shades represent the higher weights values)

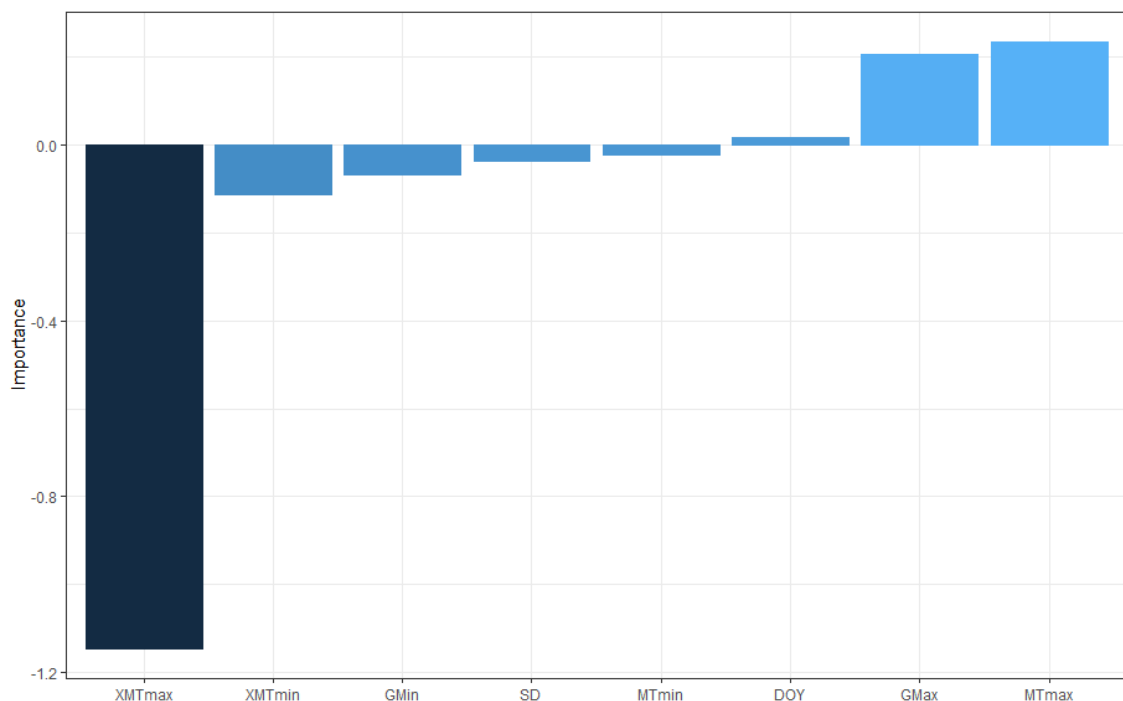


Figure C-30: The importance of the input parameters applied in ANN1S based on olden function.

C.3.2 ANN2S results

ANN2S was developed to predict the daily maximum and minimum air temperature (DTmax and DTmin) at Sabha meteorological station using input parameters including: day of the year (DOY), average month maximum air temperature (MTmax), average monthly minimum air temperature (MTmin), extreme maximum air temperature of the month (XMTmax), extreme minimum air temperature of the month (XMTmin), sunshine duration (SD), average daily maximum air temperature calculated by the Global TempSIM (GTmax), average daily minimum air temperature calculated by the Global TempSIM (GTmin), average daily maximum air temperature predicted by MODAWEK (ModTmax), and average minimum air temperature predicted by MODAWEK (ModTmin). Figure C-31 shows the structure of the developed ANN with the input parameters. Figure C-32 – C-35 show the accuracy of ANN2S in predicting DTmax and DTmin against the training and testing dataset respectively. Figure C-36 shows the structure of ANN2S based on plotnet function, and Figure C-37 shows the importance of the input parameters based on olden function. (Note: garson function cannot be applied because ANN2S has two outputs).

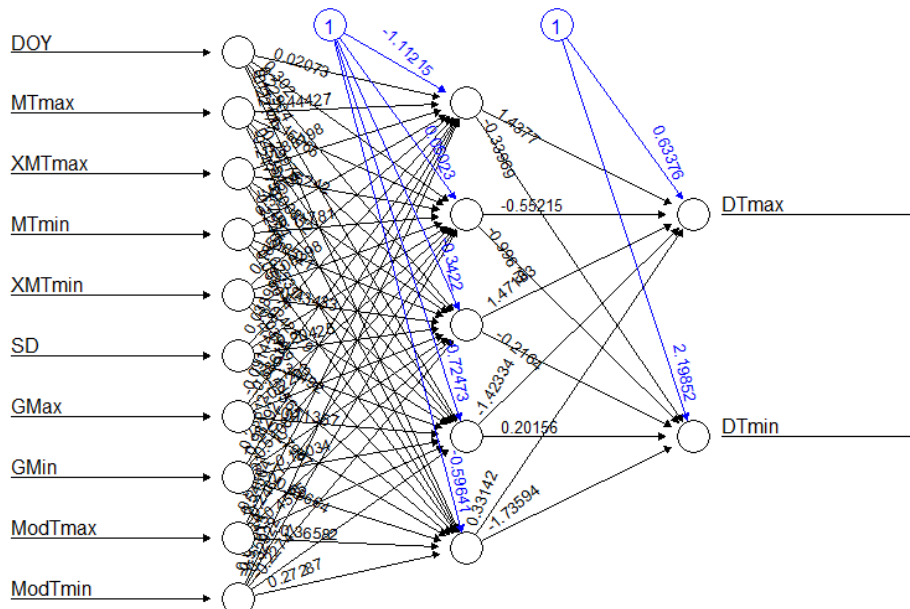


Figure C-31: The structure of ANN2S developed to predict DTmax and DTmin.

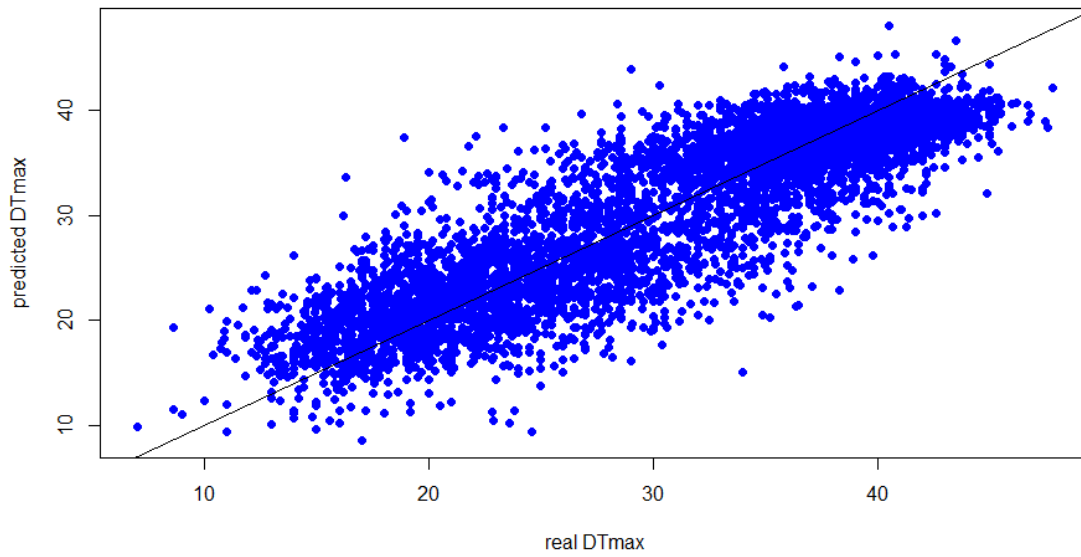


Figure C-32: The accuracy of ANN2S in predicting DTmax against the training dataset.

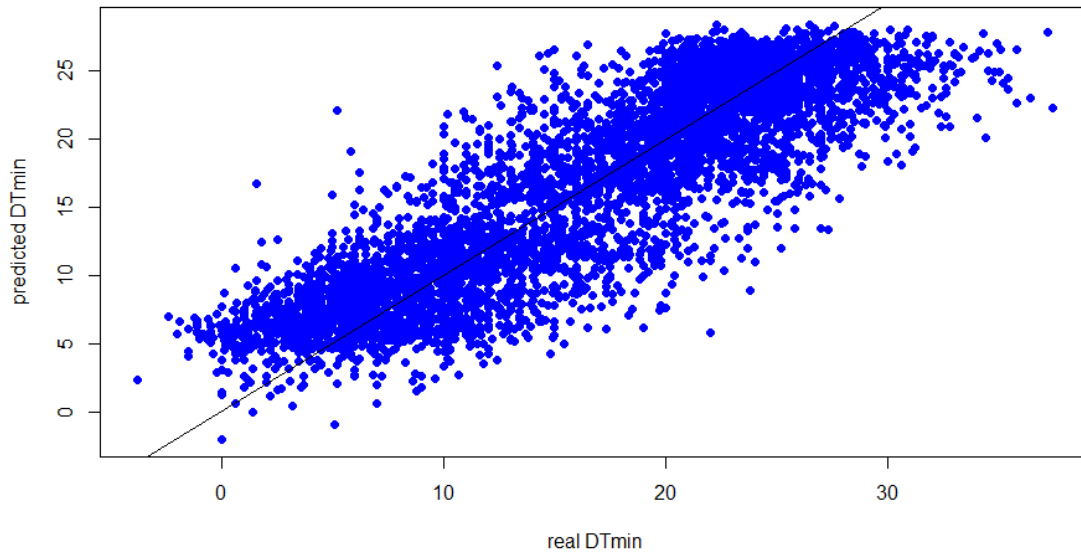


Figure C-33: The accuracy of ANN2S in predicting DTmin against the training dataset.

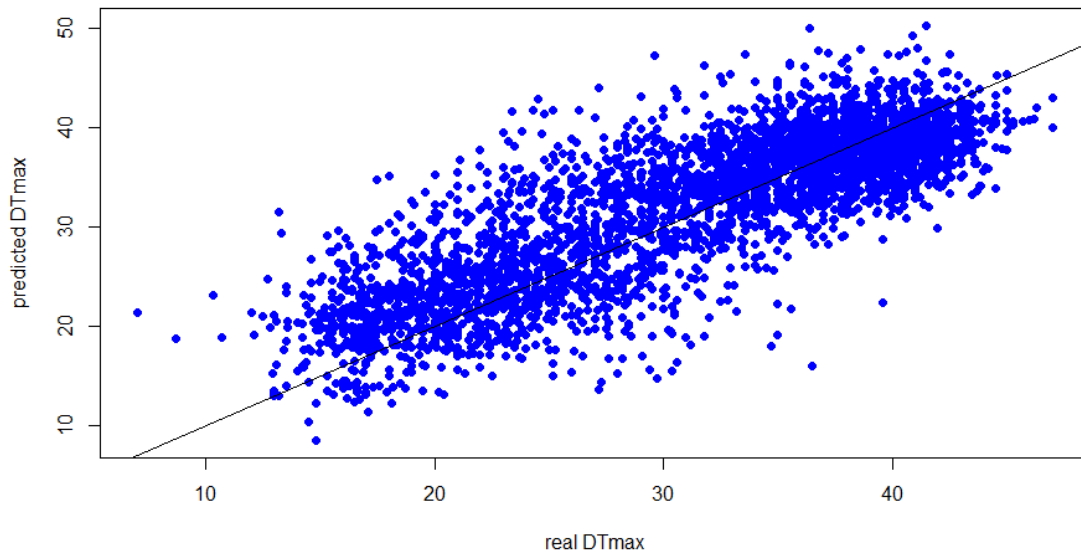


Figure C-34: The accuracy of ANN2S in predicting DTmax against the testing dataset.

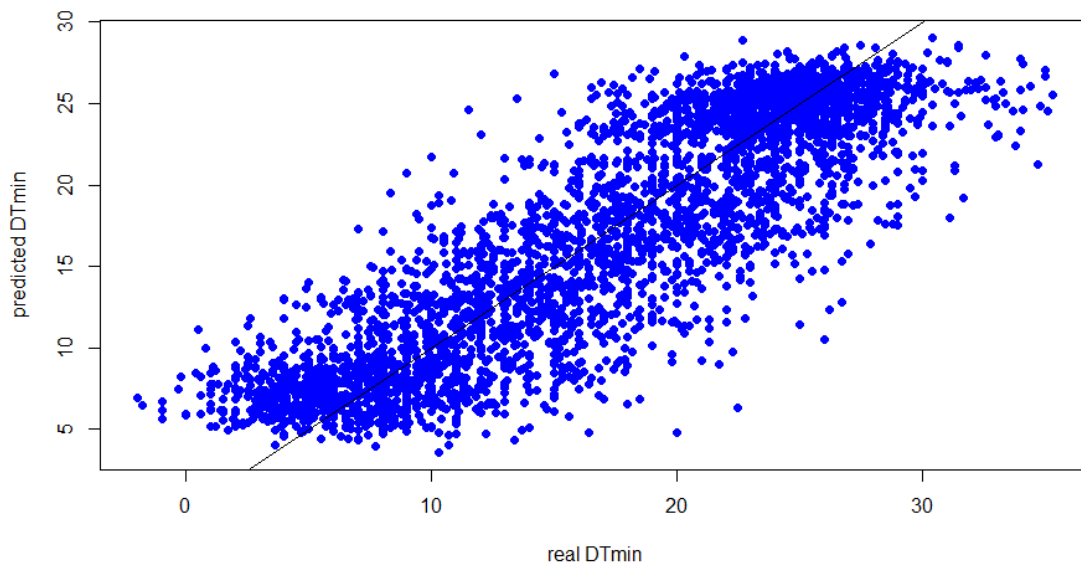


Figure C-35: The accuracy of ANN2S in predicting DTmin against the testing dataset.

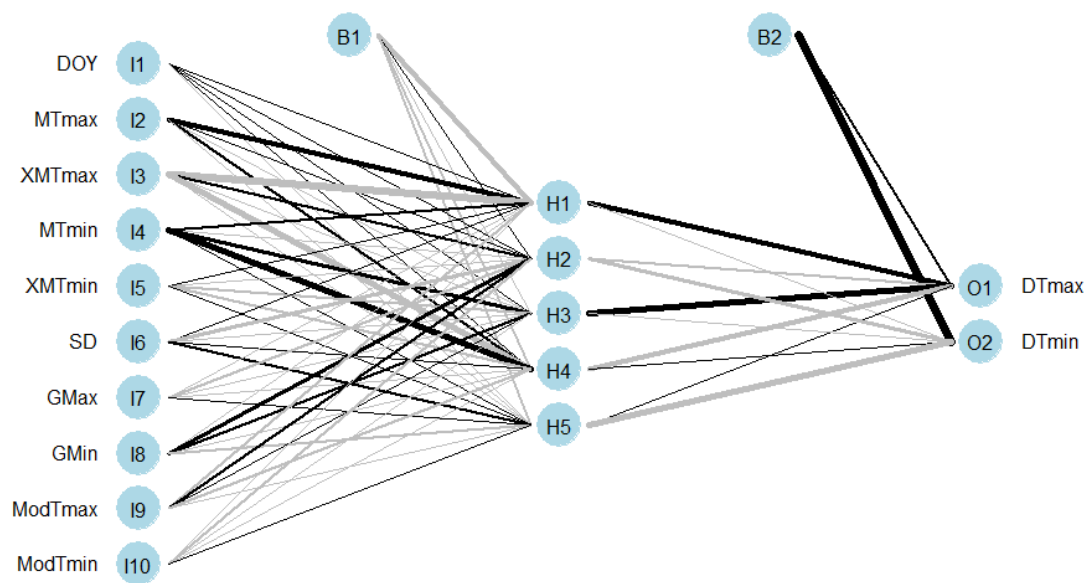


Figure C-36: ANN2S structure with weights depicted in the figure in different shades (the black shade represents the positive weights and the grey shade represents the negative weights, and the thicker shades represent the higher weights values).

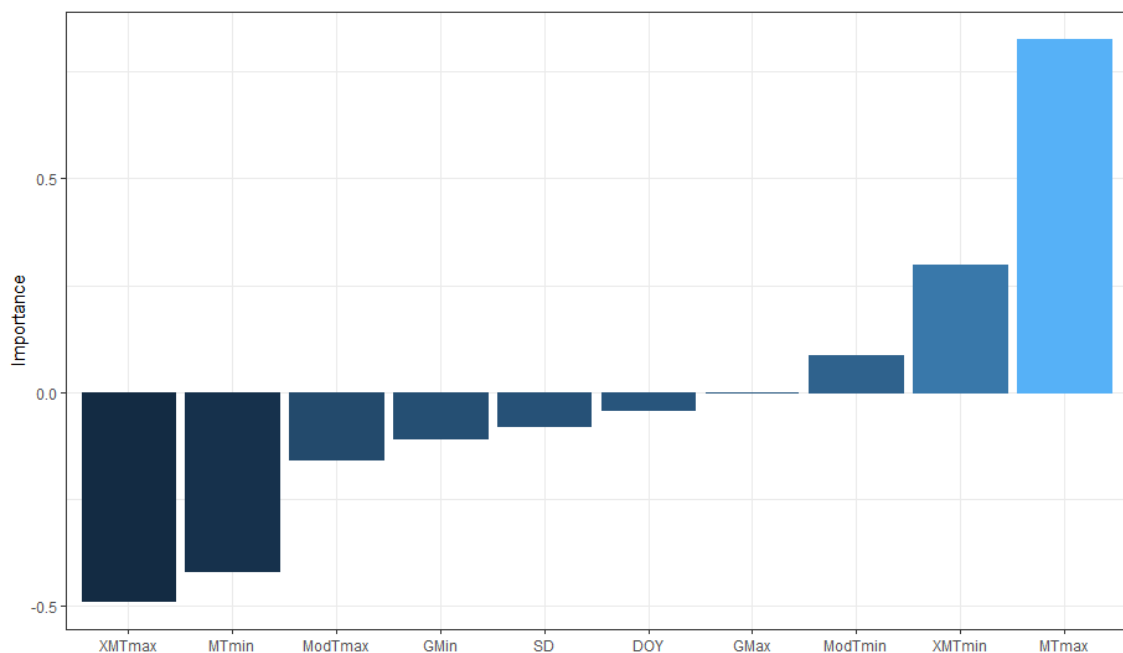


Figure C-37: The importance of the input parameters applied in ANN2S based on olden function.

C.3.3 ANN3S results

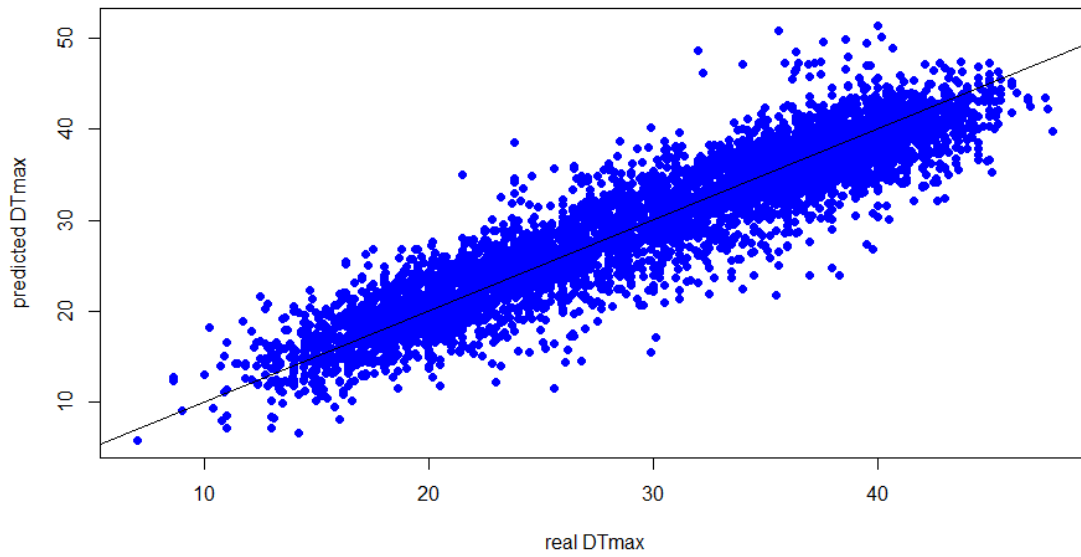


Figure C-39: The accuracy of ANN3S against the training dataset in predicting DTmax.

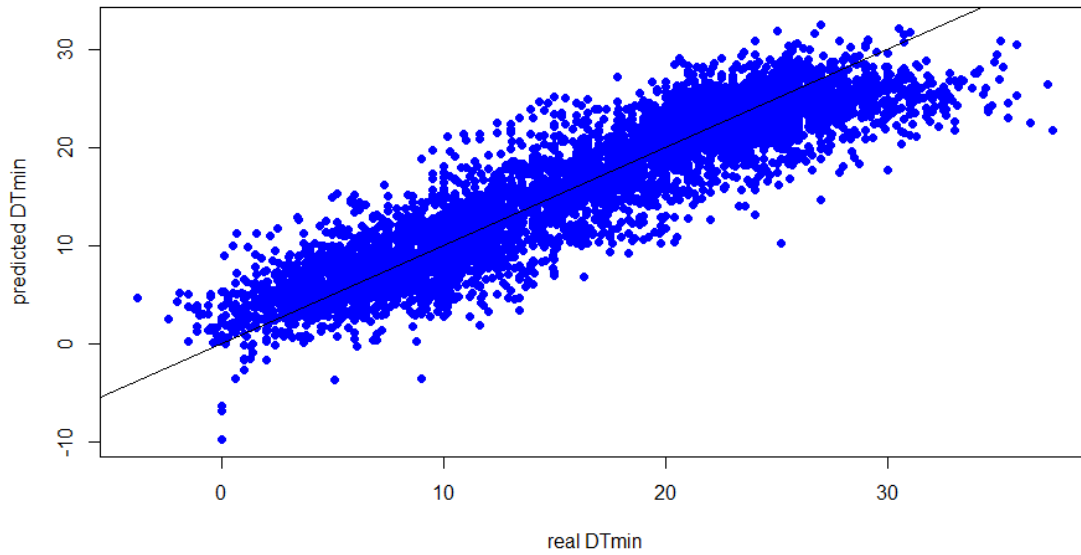


Figure C-40: The accuracy of ANN3S in predicting DTmin against the training dataset.

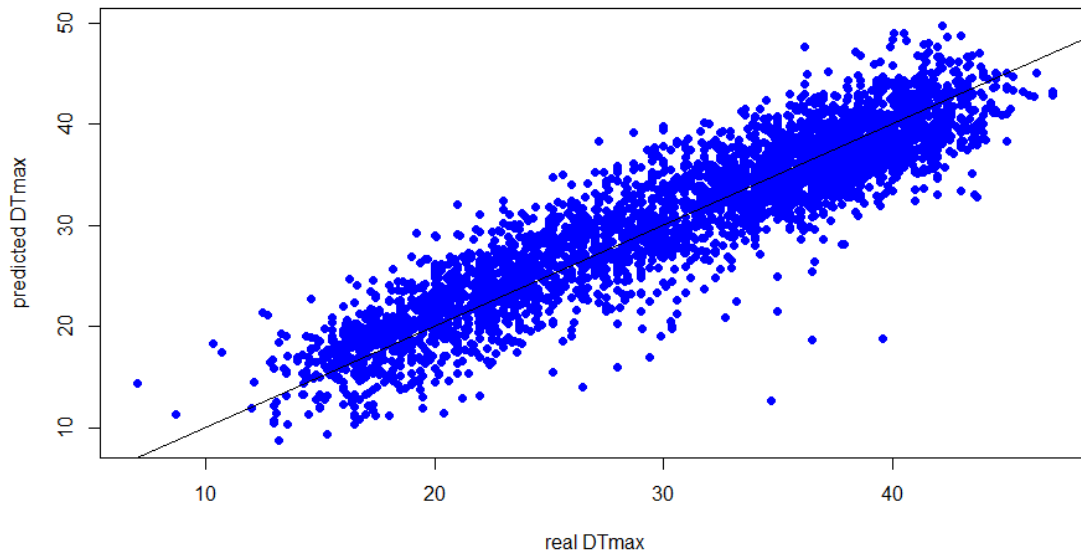


Figure C-41: The accuracy of ANN3S in predicting DTmax against the testing dataset.

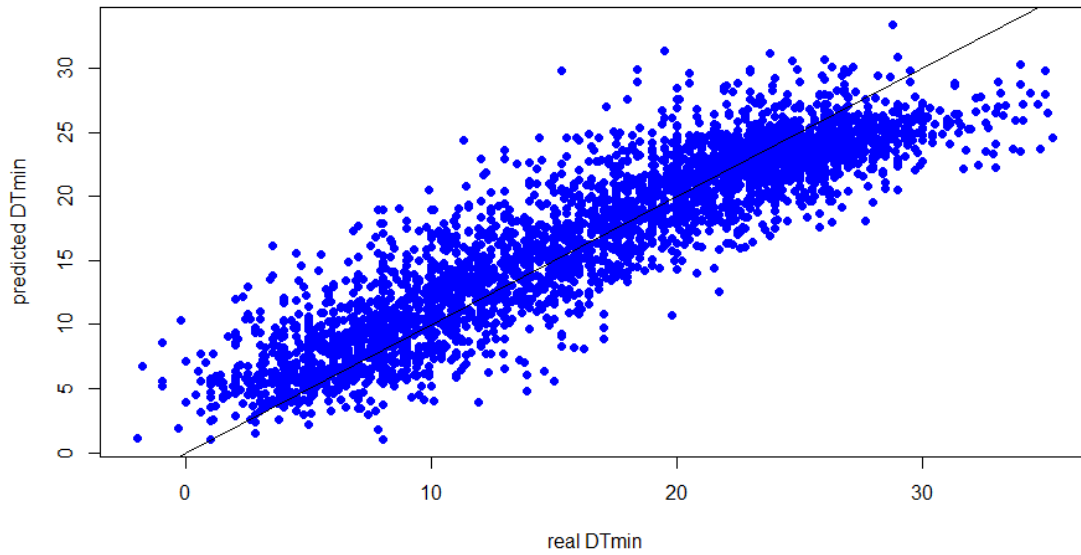


Figure C-42: The accuracy of ANN3S in predicting DTmin against the testing dataset.

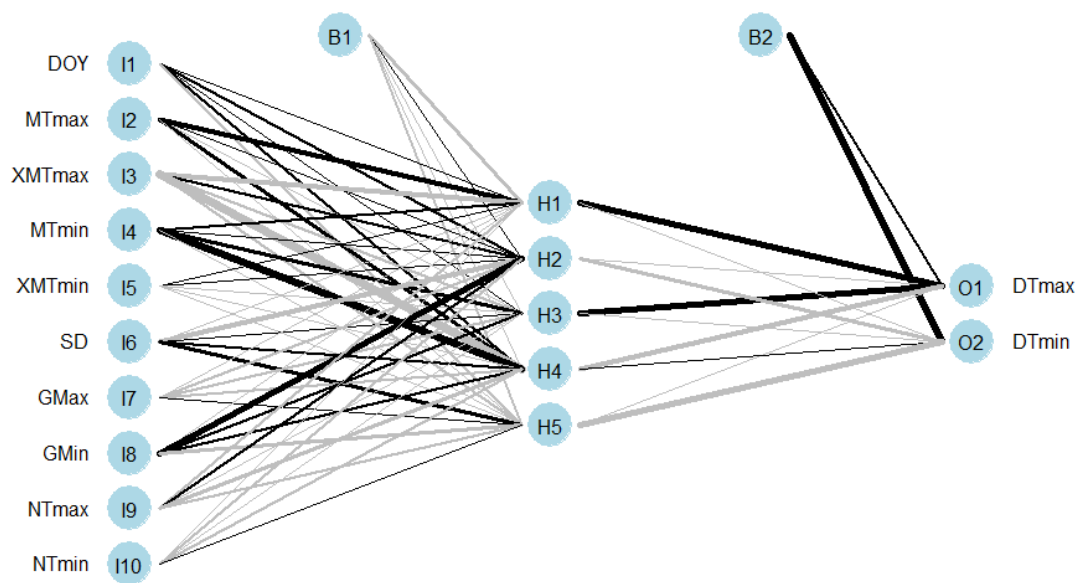


Figure C-43: ANN3S structure with weights depicted in the figure in different shades (the black shade represents the positive weights and the grey shade represents the negative weights, and the thicker shades represent the higher weights values).

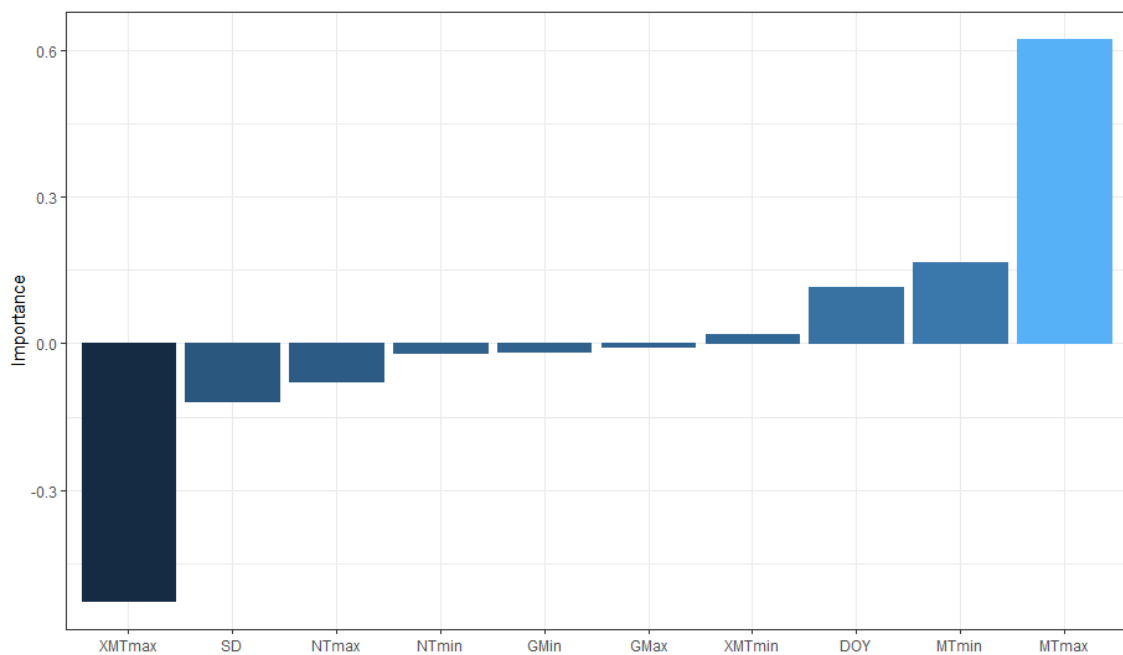


Figure C-44: The importance of the input parameters applied in ANN3S based on olden function.

C.3.4 ANN4S results

ANN4S was developed to predict the daily maximum and minimum air temperature (DTmax and DTmin) at Sabha meteorological station using input parameters including: day of the year (DOY), average month maximum air temperature (MTmax), average monthly minimum air temperature (MTmin), extreme maximum air temperature of the month (XMTmax), extreme minimum air temperature of the month (XMTmin), sunshine duration (SD), average daily maximum air temperature calculated by the Global TempSIM (GMax), average daily minimum air temperature calculated by the Global TempSIM (GMin), average daily maximum air temperature calculated by ERA5-Land (RSTmax), and average minimum air temperature calculated by ERA5_Land (RSTmin). Figure C-45 shows the structure of the developed ANN with the input parameters. Figure C-46 – 49 show the accuracy of ANN4S in predicting DTmax and DTmin against the training and testing dataset respectively. Figure C-50 shows the structure of ANN4S based on plotnet function, and Figure C-51 shows the importance of the input parameters based on olden function. (Note: garson function cannot be applied because ANN4S has two outputs).

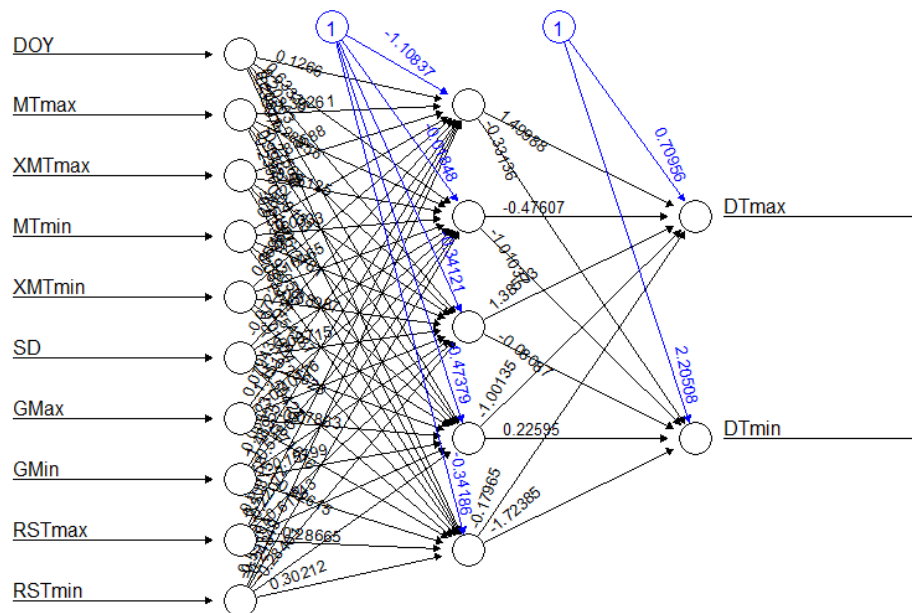


Figure C-45: The structure of the developed ANN4S to predict DTmax and DTmin.

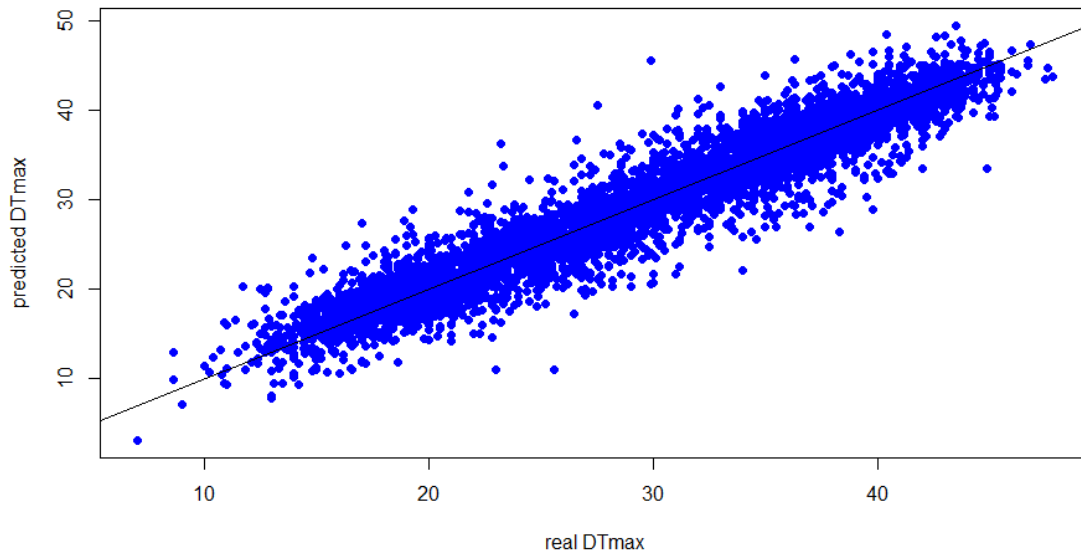


Figure C-46: The accuracy of ANN4S in predicting DTmax against the training dataset.

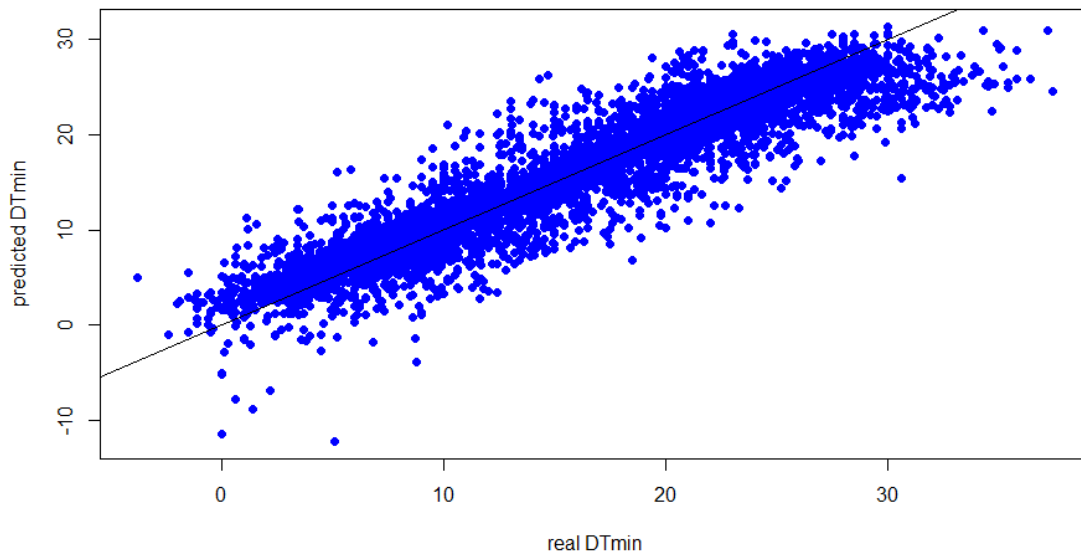


Figure C-47: The accuracy of ANN4S in predicting DTmin against the training dataset.

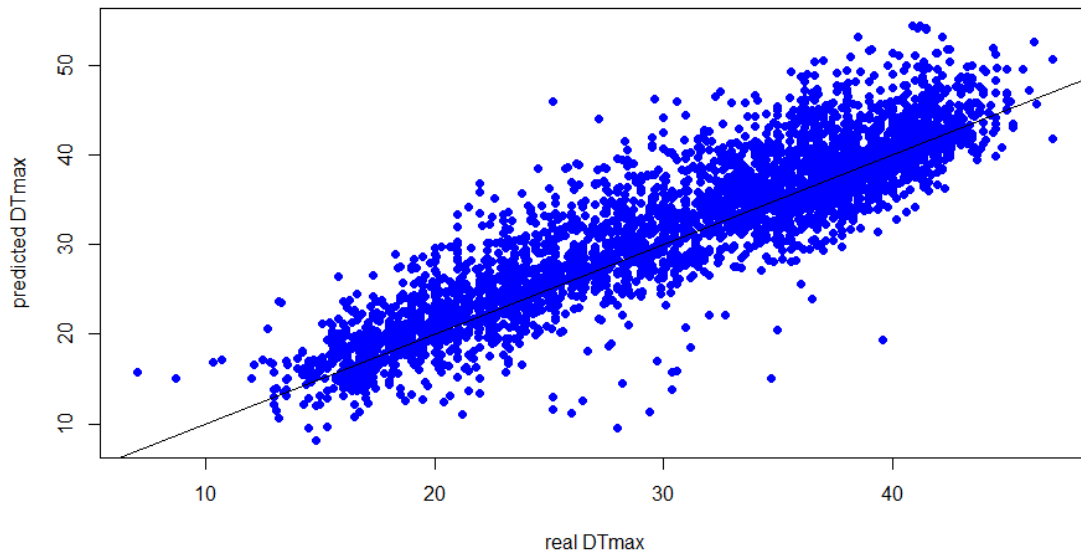


Figure C-48: The accuracy of ANN4S in predicting DTmax against the testing dataset.

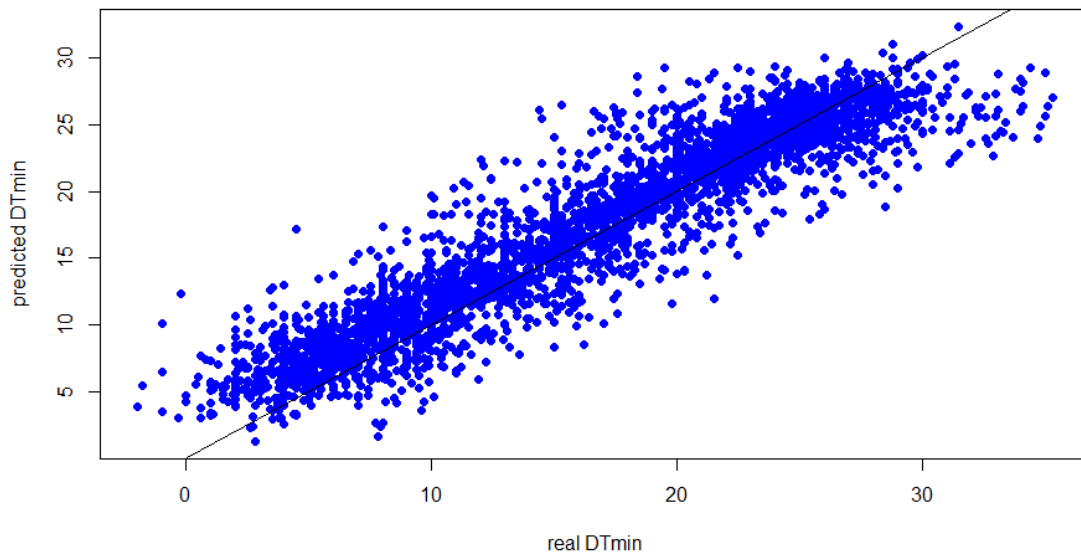


Figure C-49: The accuracy of ANN4S in predicting DTmin against the testing dataset.

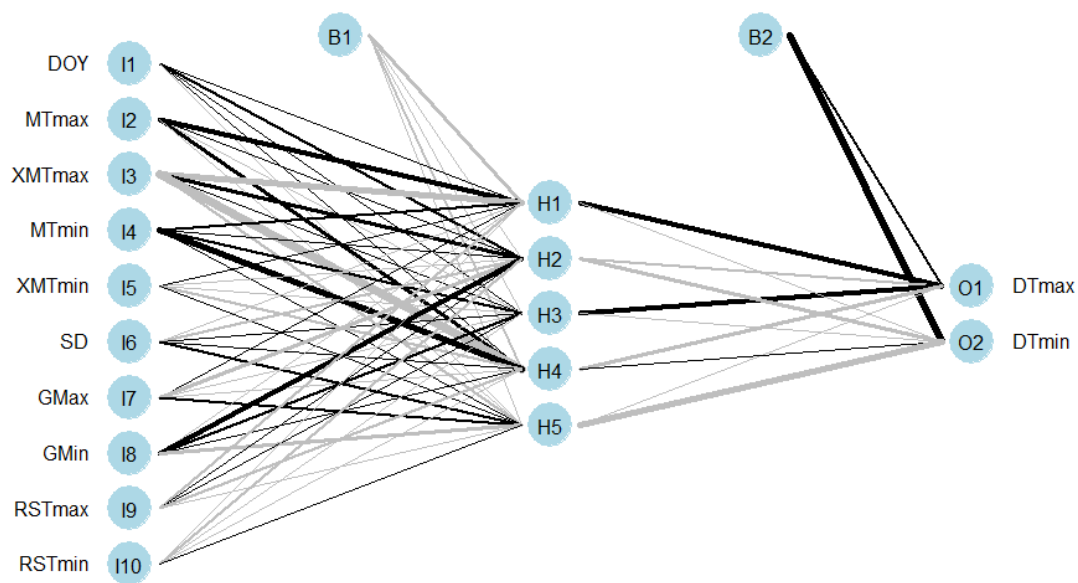


Figure C-50: ANN4S structure with weights depicted in the figure in different shades (the black shade represents the positive weights and the grey shade represents the negative weights, and the thicker shades represent the higher weights values).

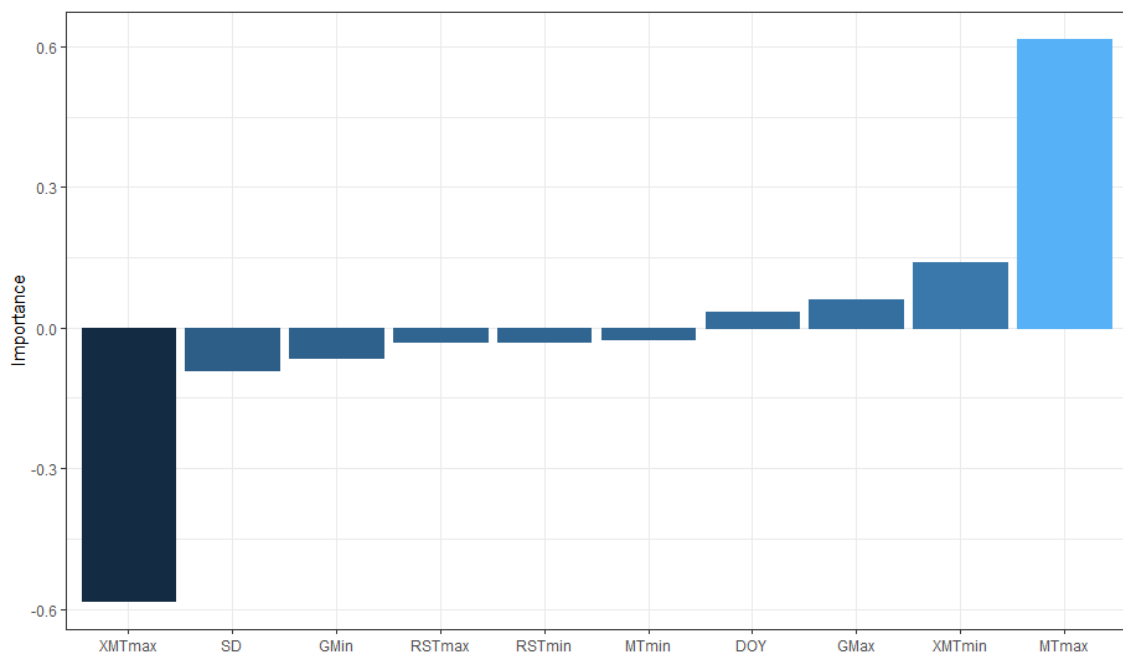


Figure C-51: The importance of the input parameters applied in ANN4S based on olden function.

C.3.5 ANN5S results

ANN5S was developed to predict the daily maximum and minimum air temperature (DTmax and DTmin) at Sabha meteorological station using input parameters including: day of the year (DOY), average month maximum air temperature (MTmax), average monthly minimum air temperature (MTmin), extreme maximum air temperature of the month (XMTmax), extreme minimum air temperature of the month (XMTmin), sunshine duration (SD), average daily maximum air temperature calculated by the Global TempSIM (GTmax), average daily minimum air temperature calculated by the Global TempSIM (GTmin), average daily maximum air temperature predicted by MODAWECC (ModTmax), and average minimum air temperature predicted by MODAWECC (ModTmin). average daily maximum air temperature at the neighbouring station (NTmax), and average minimum air temperature at the neighbouring station (NTmin). average daily maximum air temperature calculated by ERA5-Land (RSTmax), and average minimum air temperature calculated by ERA5_Land (RSTmin). Figure C-52 shows the structure of the developed ANN with the input parameters. Figure C-53 – C-56 show the accuracy of ANN4S in predicting DTmax and DTmin against the training and testing dataset respectively. Figure C-57 shows the structure of ANN4S based on plotnet function, and Figure C-58 shows the importance of the input parameters based on olden function. (Note: garson function cannot be applied because ANN4S has two outputs).

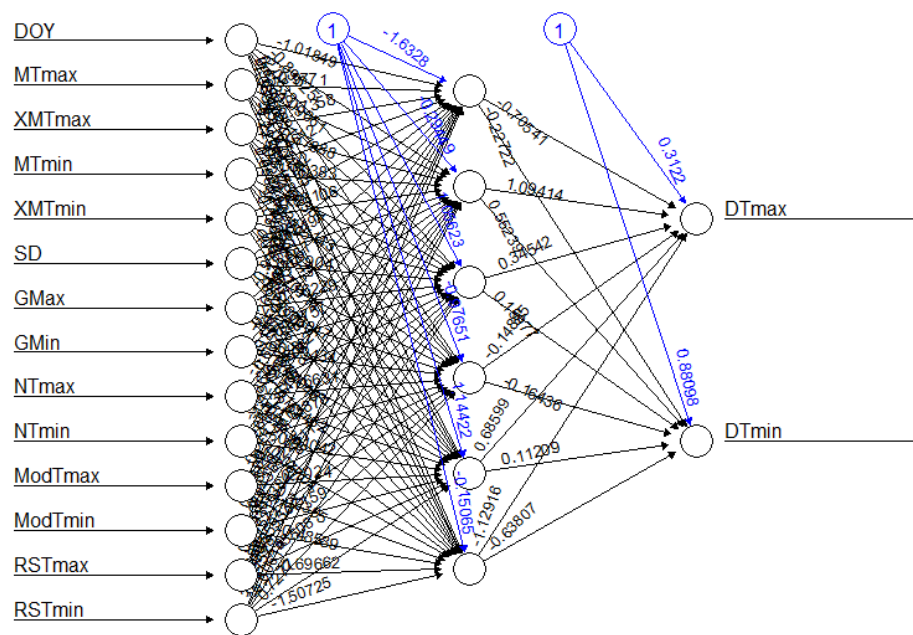


Figure C-52: The structure of the developed ANN5S to predict DTmax and DTmin

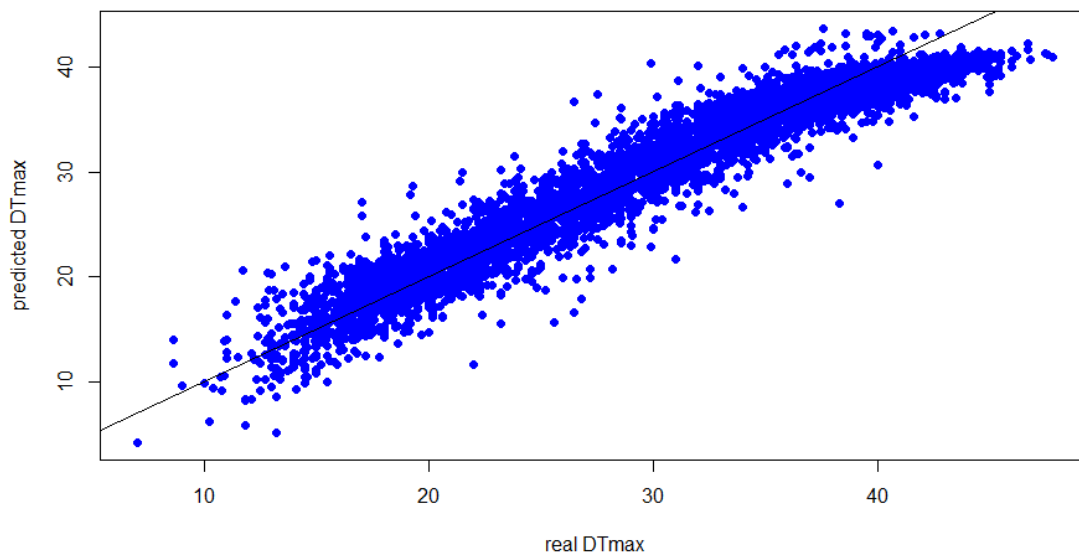


Figure C-53: The accuracy of ANN5S in predicting DTmax against the training dataset.

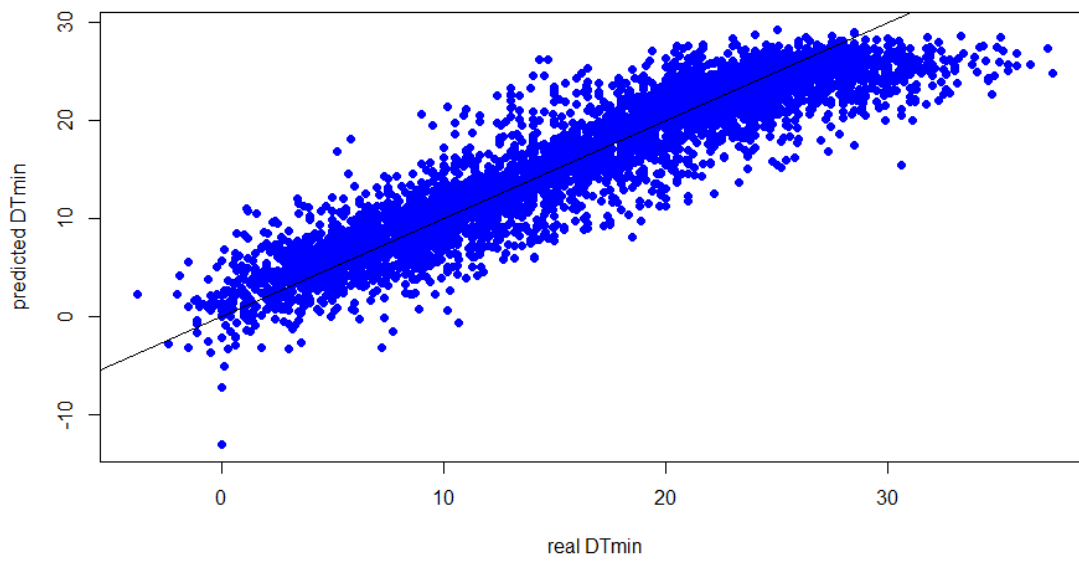


Figure C-54: The accuracy of ANN5S in predicting DTmin against the training dataset.

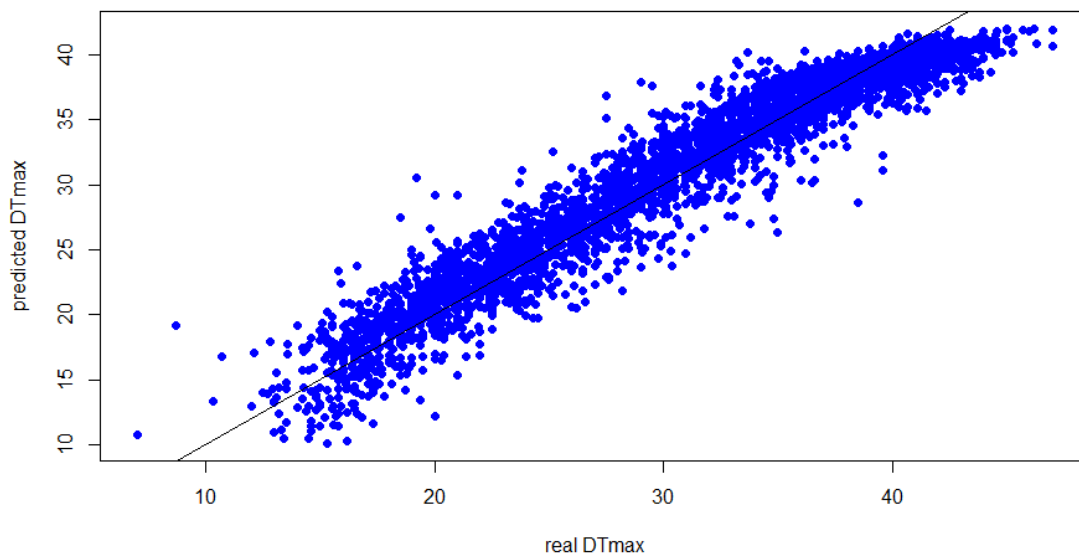


Figure C-55: The accuracy of ANN5S in predicting DTmax against the testing dataset.

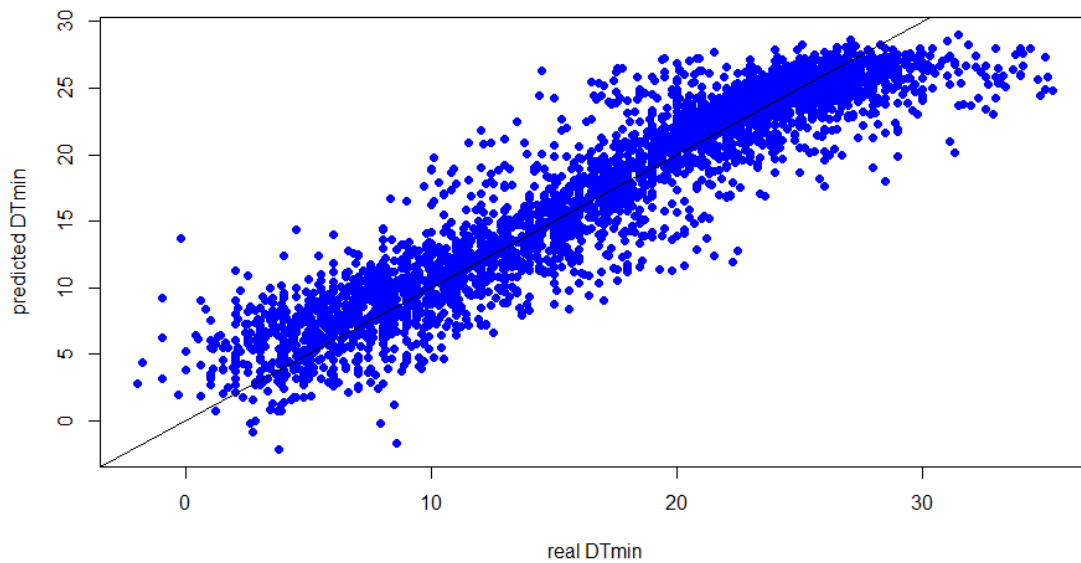


Figure C-56: The accuracy of ANN5S in predicting DTmin against the testing dataset

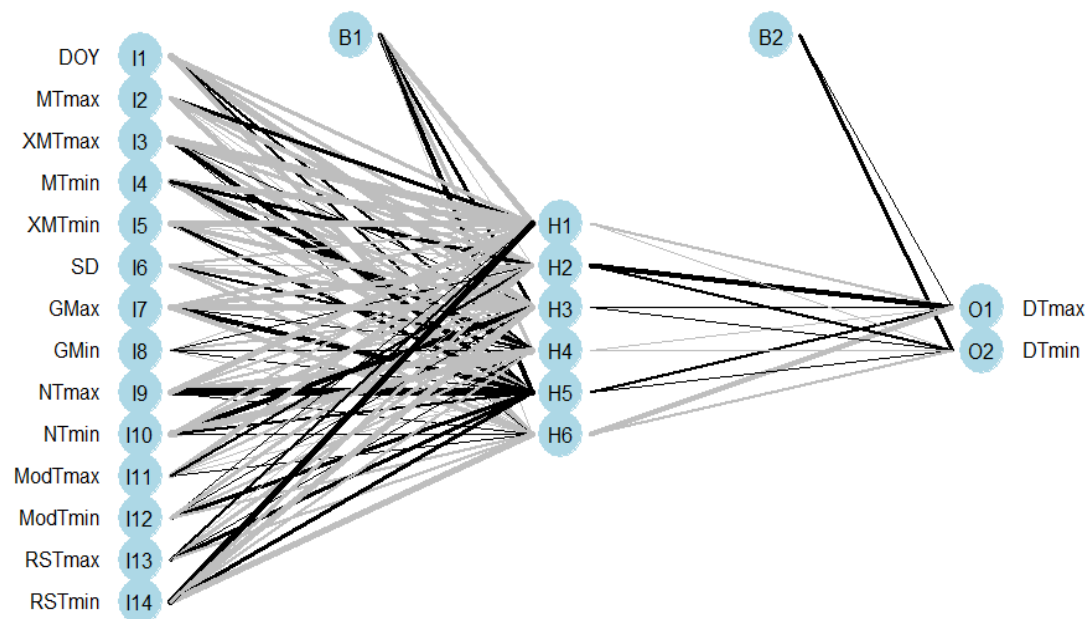


Figure C-57: ANN5S structure with weights depicted in the figure in different shades (the black shade represents the positive weights and the grey shade represents the negative weights, and the thicker shades represent the higher weights values).

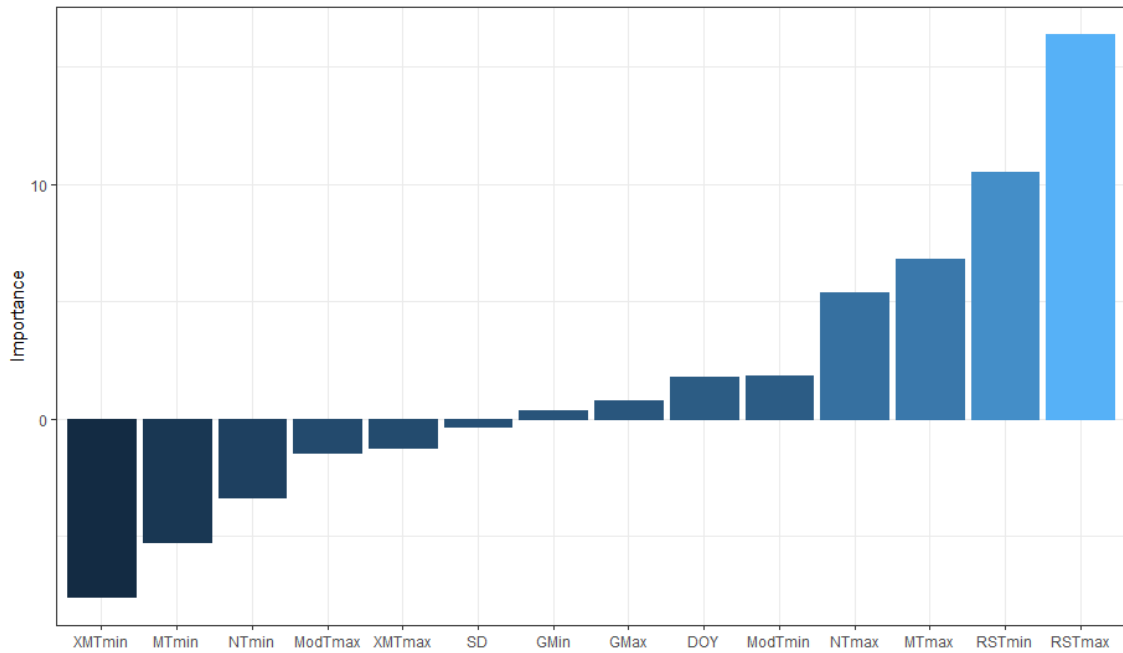


Figure C-58: The importance of the input parameters applied in ANN5S based on olden function.

C.3.6 ANN1H results

ANN1H was developed to predict the daily maximum and minimum air temperature (DTmax and DTmin) at Hon meteorological station using input parameters including: day of the year (DOY), average month maximum air temperature (MTmax), average monthly minimum air temperature (MTmin), extreme maximum air temperature of the month (XMTmax), extreme minimum air temperature of the month (XMTmin), sunshine duration (SD), average daily maximum air temperature calculated by the Global TempSIM (GTmax), and average daily minimum air temperature calculated by the Global TempSIM (GTmin). Figure C-59 shows the structure of the developed ANN with the input parameters. Figure C-60 – C-63 show the accuracy of ANN1H in predicting DTmax and DTmin against the training and testing dataset respectively. Figure C-64 shows the structure of ANN1H based on plotnet function, and Figure C-65 shows the importance of the input parameters based on olden function. (Note: garson function cannot be applied because ANN1H has two outputs).

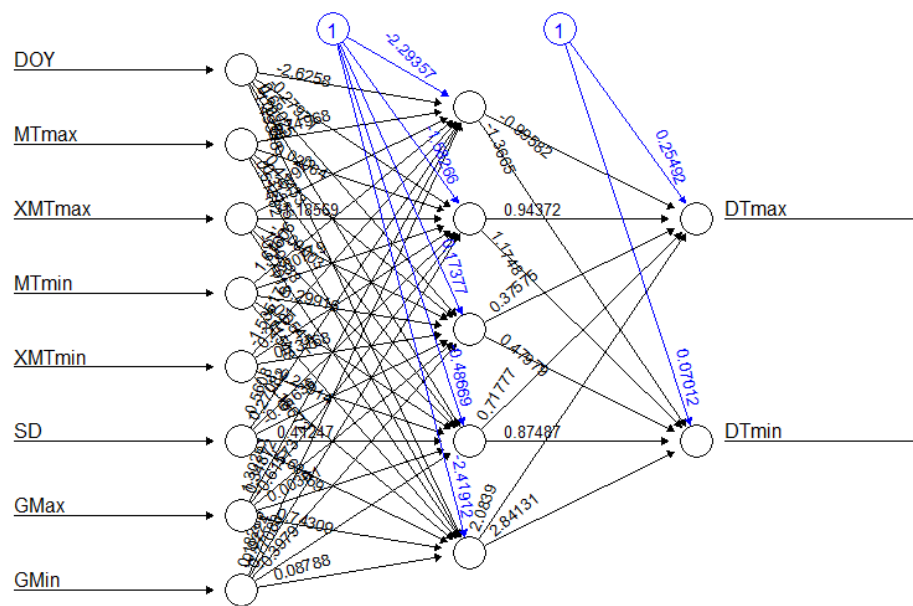


Figure C-59: The structure of the developed ANN1H to predict DTmax and DTmin

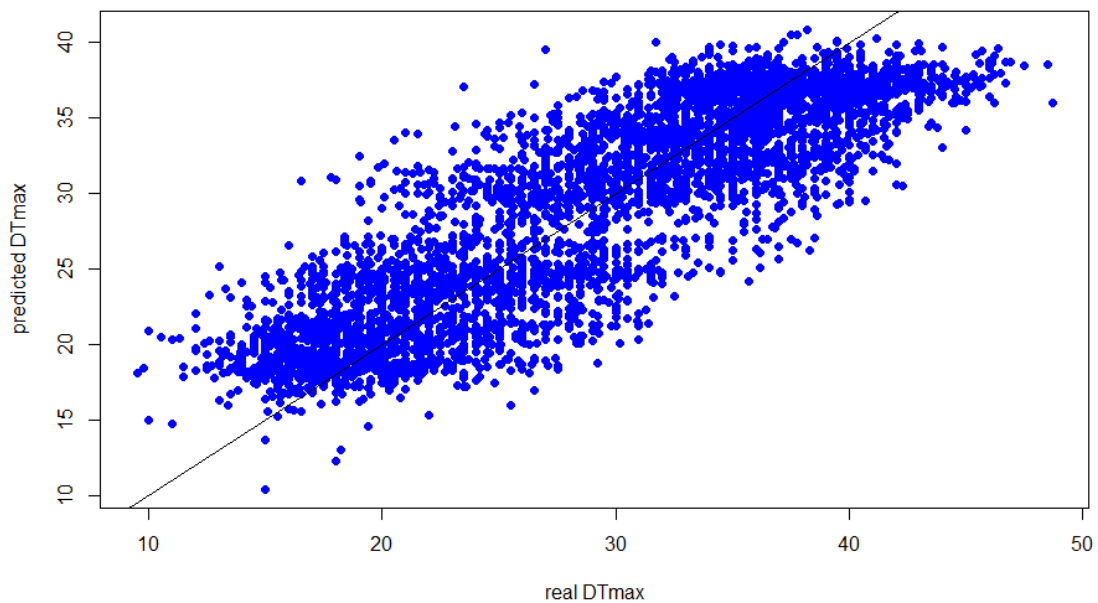


Figure C-60: The accuracy of ANN1H in predicting DTmax against the training dataset.

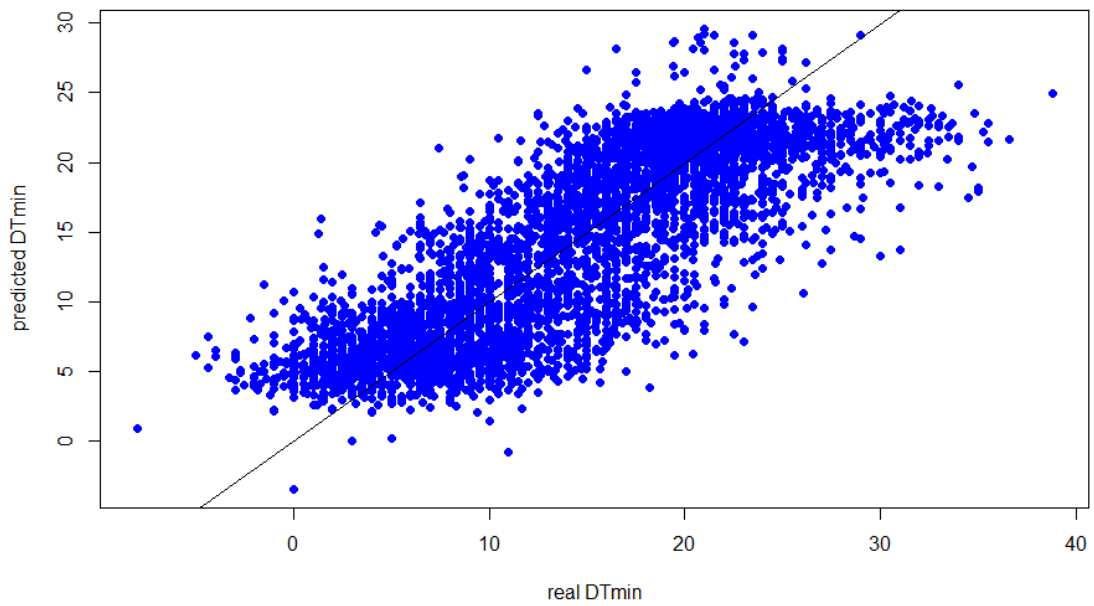


Figure C-61: The accuracy of ANN1H in predicting DTmin against the training dataset.

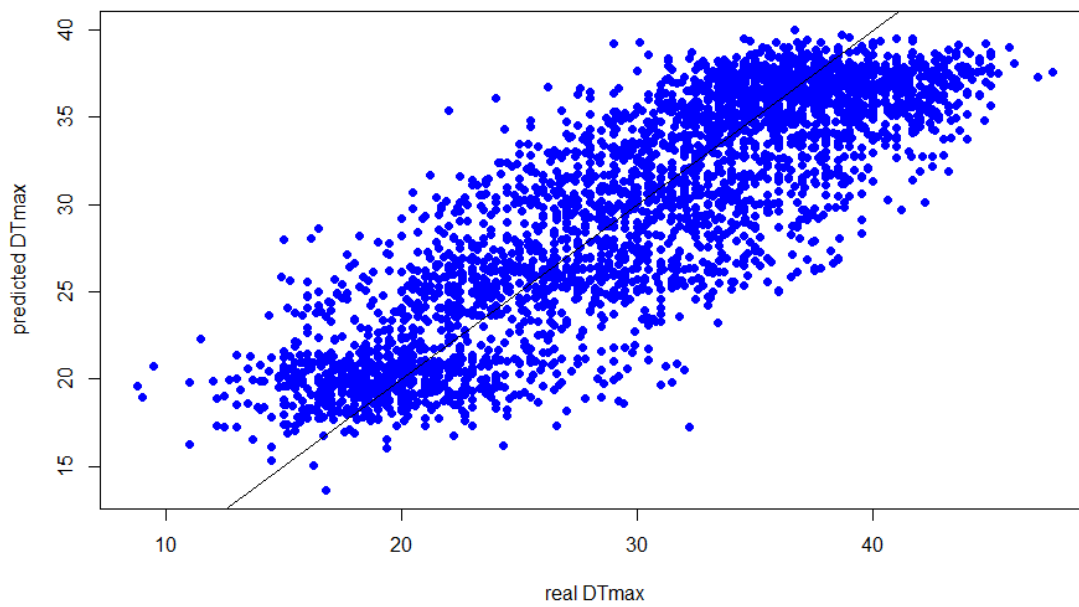


Figure C-62: The accuracy of ANN1H in predicting DTmax against the testing dataset

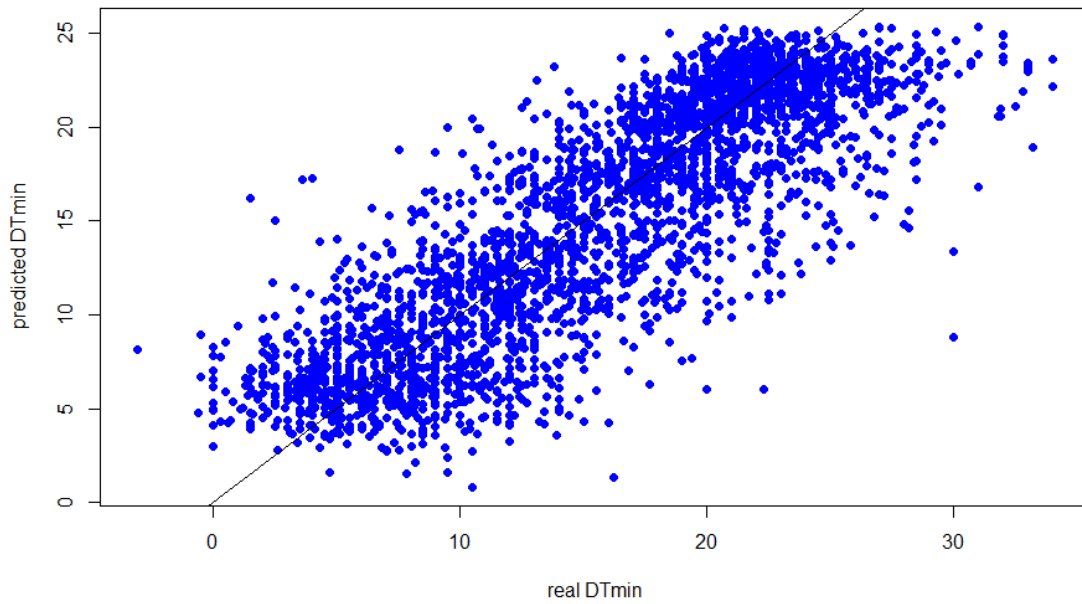


Figure C-63: The accuracy of ANN1H in predicting DTmin against the testing dataset.

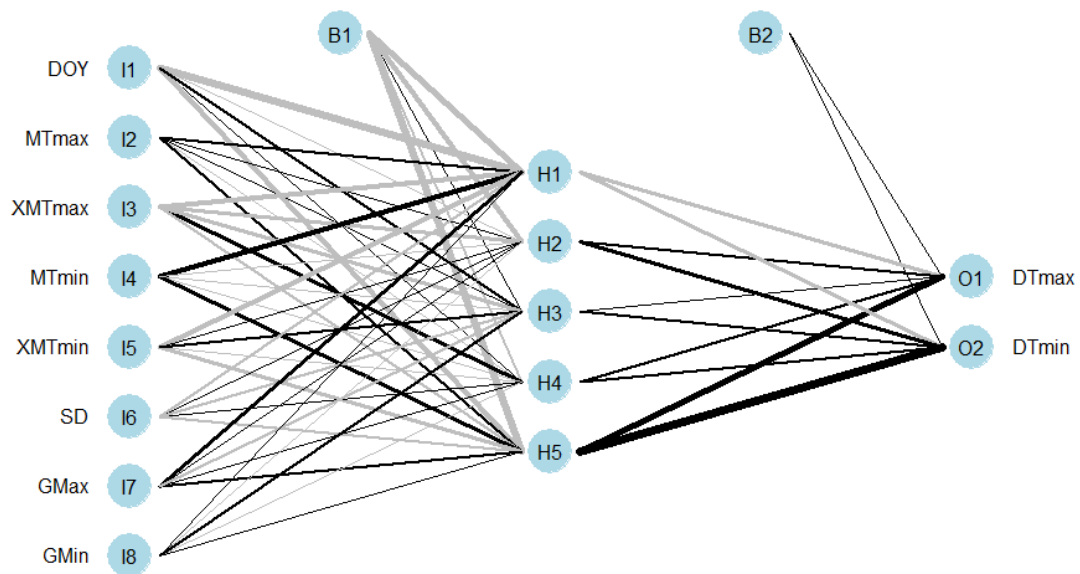


Figure C-64: ANN1H structure with weights depicted in the figure in different shades (the black shade represents the positive weights and the grey shade represents the negative weights, and the thicker shades represent the higher weights values).

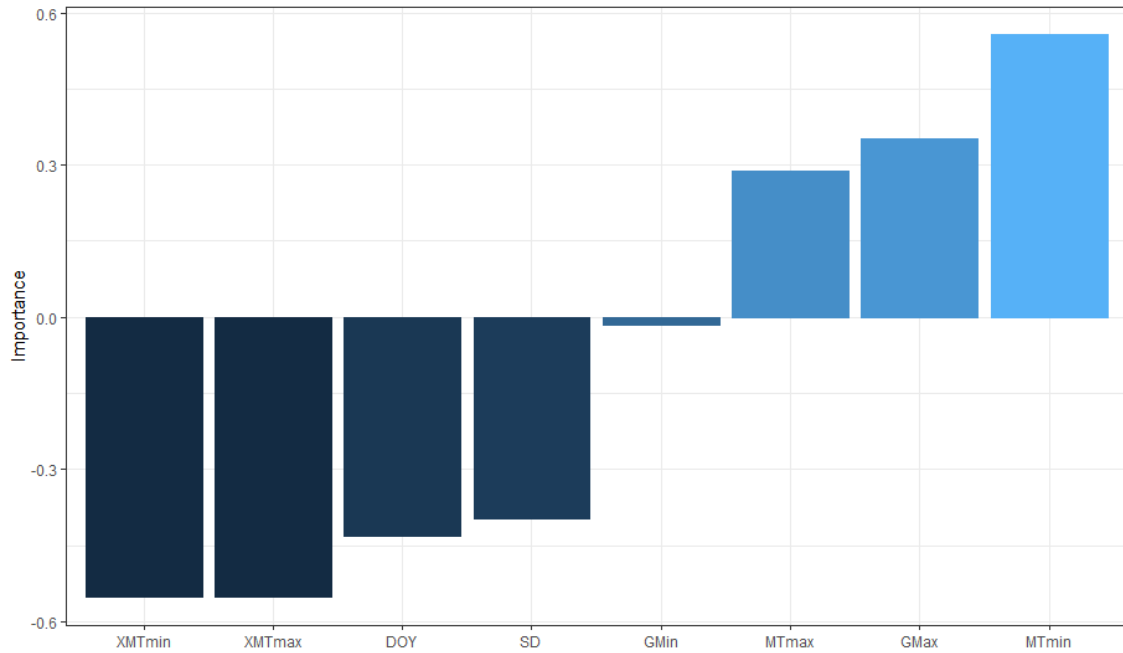


Figure C-65: The importance of the input parameters applied in ANN1H based on olden function.

C.3.7 ANN2H results

ANN2H was developed to predict the daily maximum and minimum air temperature (DTmax and DTmin) at Hon meteorological station using input parameters including: day of the year (DOY), average month maximum air temperature (MTmax), average monthly minimum air temperature (MTmin), extreme maximum air temperature of the month (XMTmax), extreme minimum air temperature of the month (XMTmin), sunshine duration (SD), average daily maximum air temperature calculated by the Global TempSIM (GTmax), average daily minimum air temperature calculated by the Global TempSIM (GTmin), average daily maximum air temperature predicted by MODAWEC (ModTmax), and average minimum air temperature predicted by MODAWEC (ModTmin). Figure C-66 shows the structure of the developed ANN with the input parameters. Figure C-67 – C-70 show the accuracy of ANN2H in predicting DTmax and DTmin against the training and testing dataset respectively. Figure C-71 shows the structure of ANN2H based on plotnet function, and Figure C-72 shows the importance of the input parameters based on olden function. (Note: garson function cannot be applied because ANN2H has two outputs).

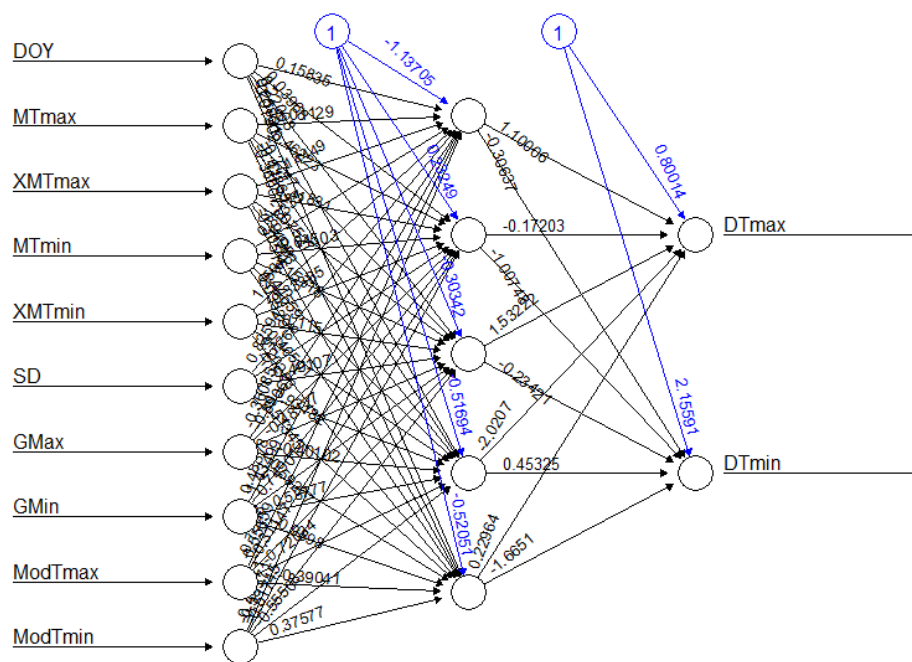


Figure C-66: The structure of the developed ANN2H to predict DTmax and DTmin

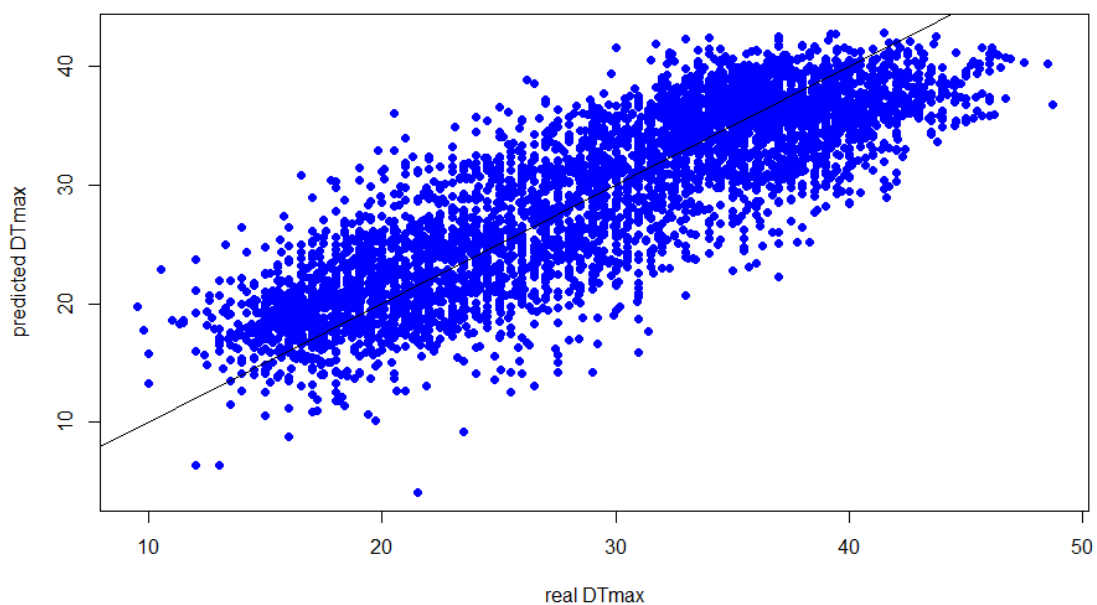


Figure C-67: The accuracy of ANN2H in predicting DTmax against the training dataset.

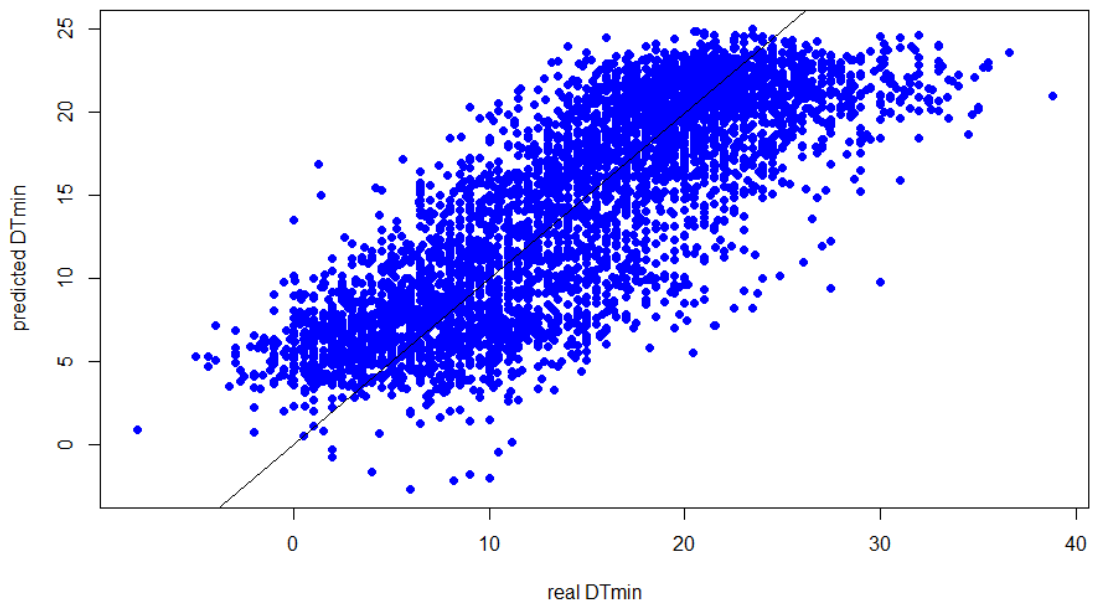


Figure C-68: The accuracy of ANN2H in predicting DTmin against the training dataset.

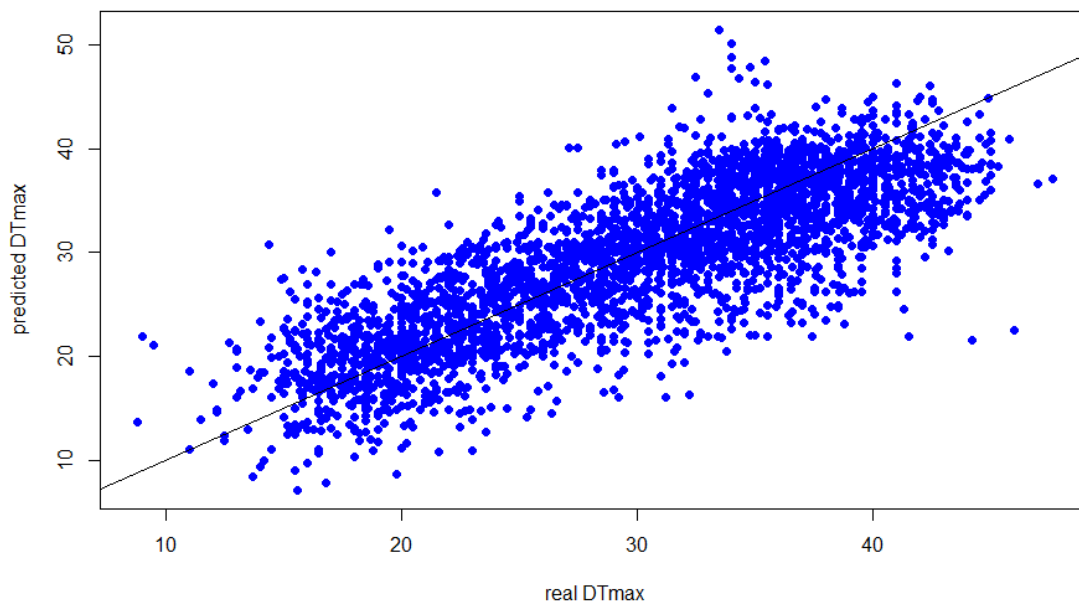


Figure C-69: The accuracy of ANN2H in predicting DTmax based on the testing dataset

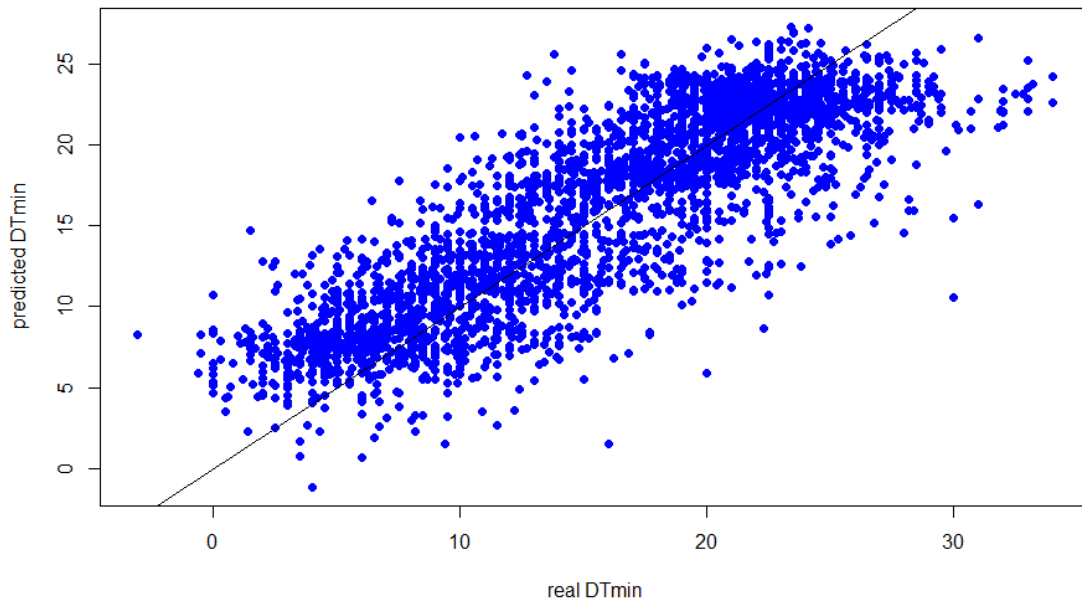


Figure C-70: The accuracy of ANN2H in predicting DTmin based on the testing dataset.

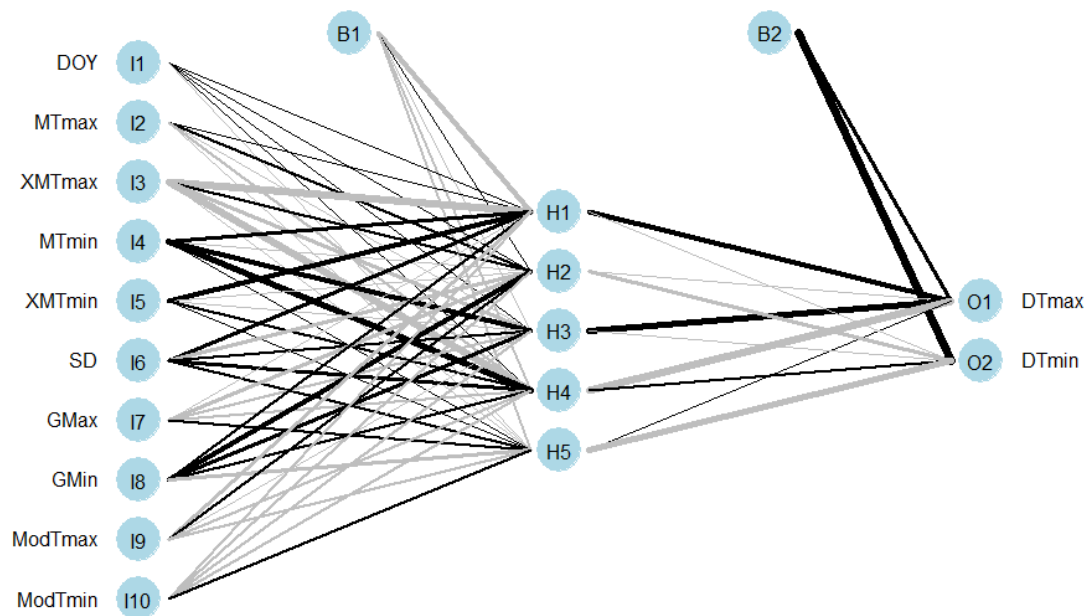


Figure C-71: ANN2H structure with weights depicted in the figure in different shades (the black shade represents the positive weights and the grey shade represents the negative weights, and the thicker shades represent the higher weights values)

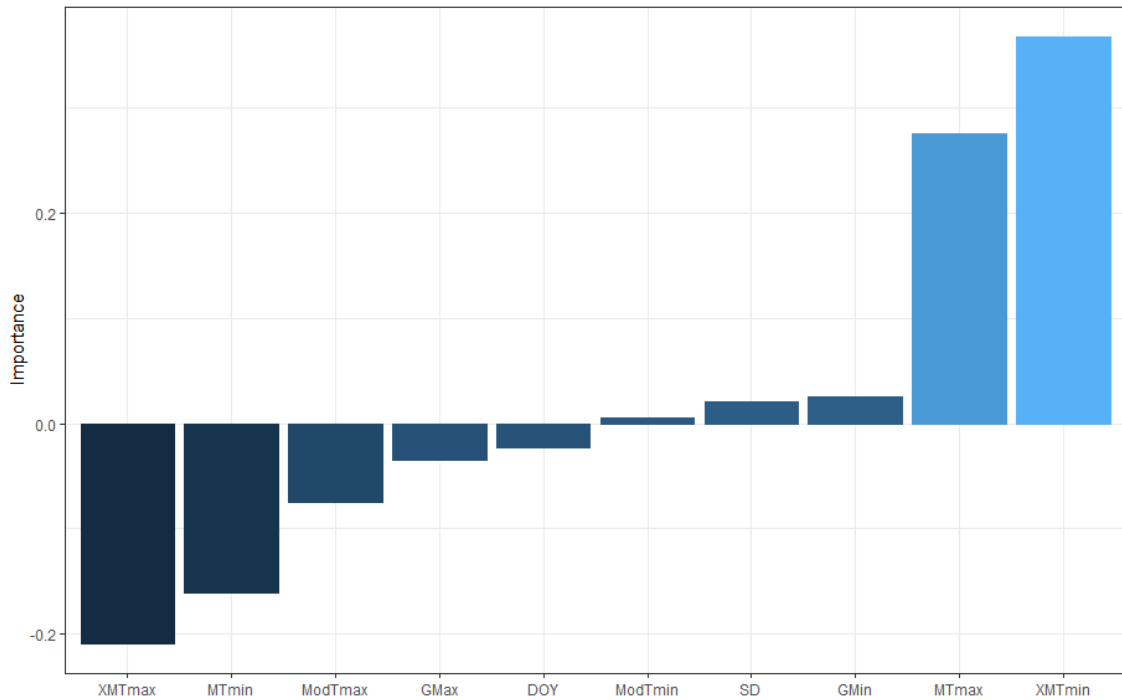


Figure C-72: The importance of the input parameters applied in ANN2H based on olden function.

C.3.8 ANN3H results

ANN3H was developed to predict the daily maximum and minimum air temperature (DTmax and DTmin) at Hon meteorological station using input parameters including: day of the year (DOY), average month maximum air temperature (MTmax), average monthly minimum air temperature (MTmin), extreme maximum air temperature of the month (XMTmax), extreme minimum air temperature of the month (XMTmin), sunshine duration (SD), average daily maximum air temperature calculated by the Global TempSIM (GTmax), average daily minimum air temperature calculated by the Global TempSIM (GTmin), average daily maximum air temperature at the neighbouring station (NTmax), and average minimum air temperature at the neighbouring station (NTmin). Figure C-73 shows the structure of the developed ANN with the input parameters. Figure C-74 – C-77 show the accuracy of ANN3H in predicting DTmax and DTmin against the training and testing dataset respectively. Figure C-78 shows the structure of ANN3H based on plotnet function, and Figure C-79 shows the

importance of the input parameters based on olden function. (Note: garson function cannot be applied because ANN3H has two outputs).

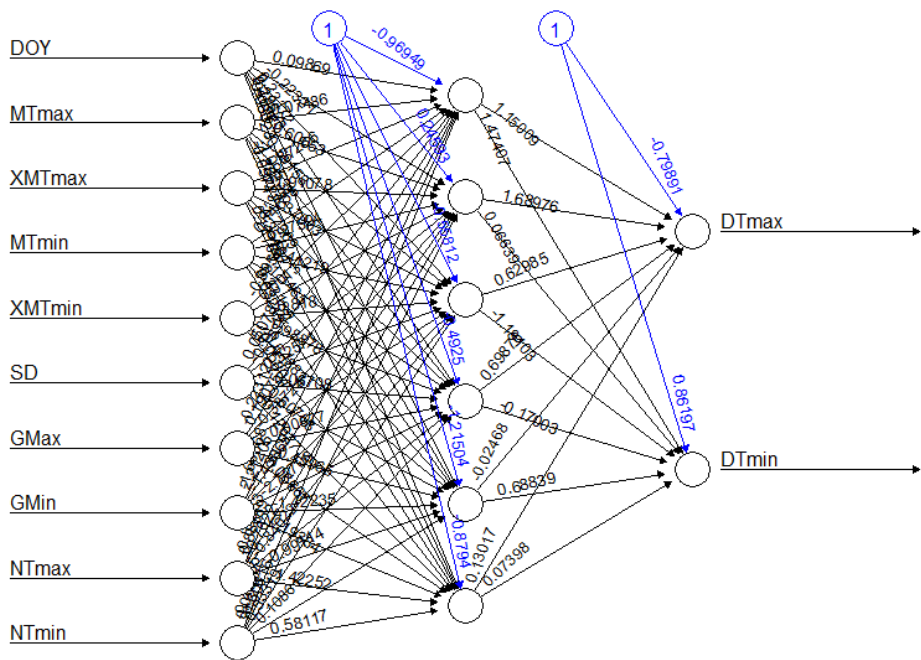


Figure C-73: The structure of the developed ANN3H to predict DTmax and DTmin.

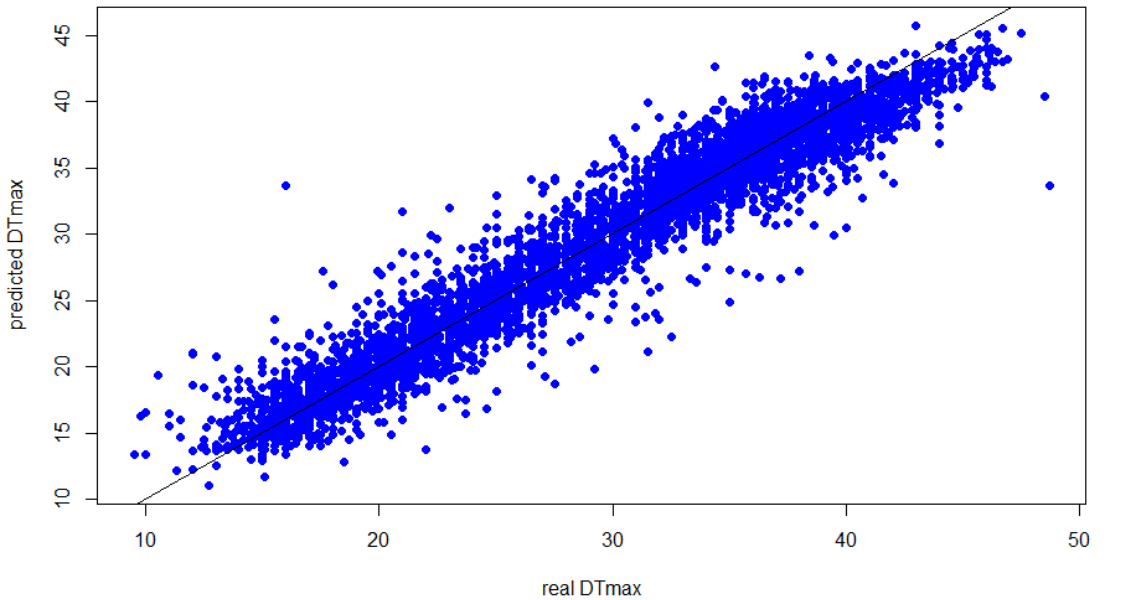


Figure C-74: The accuracy of ANN3H in predicting DTmax based on training dataset.

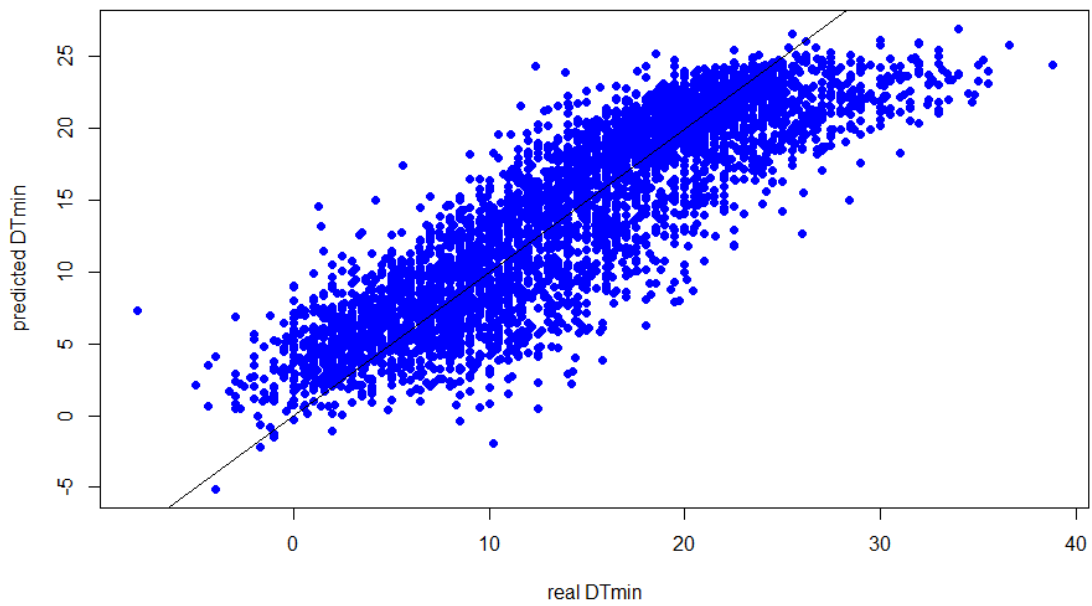


Figure C-75: The accuracy of ANN3H in predicting DTmin based on training dataset.

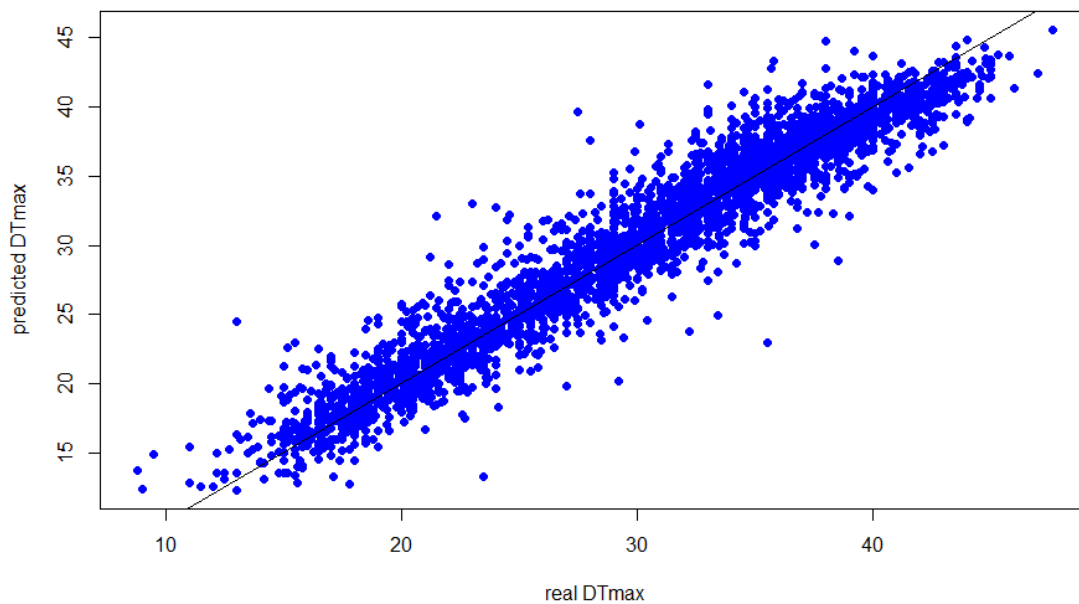


Figure C-76: The accuracy of ANN3H in predicting DTmax based on testing dataset.

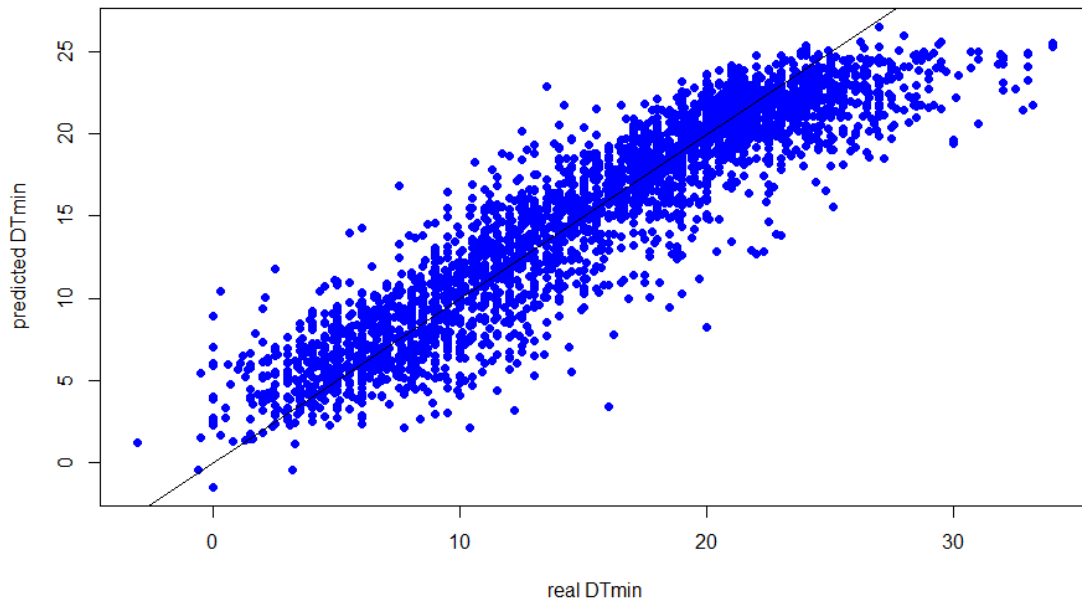


Figure C-77: The accuracy of ANN3H in predicting DTmin based on testing dataset.

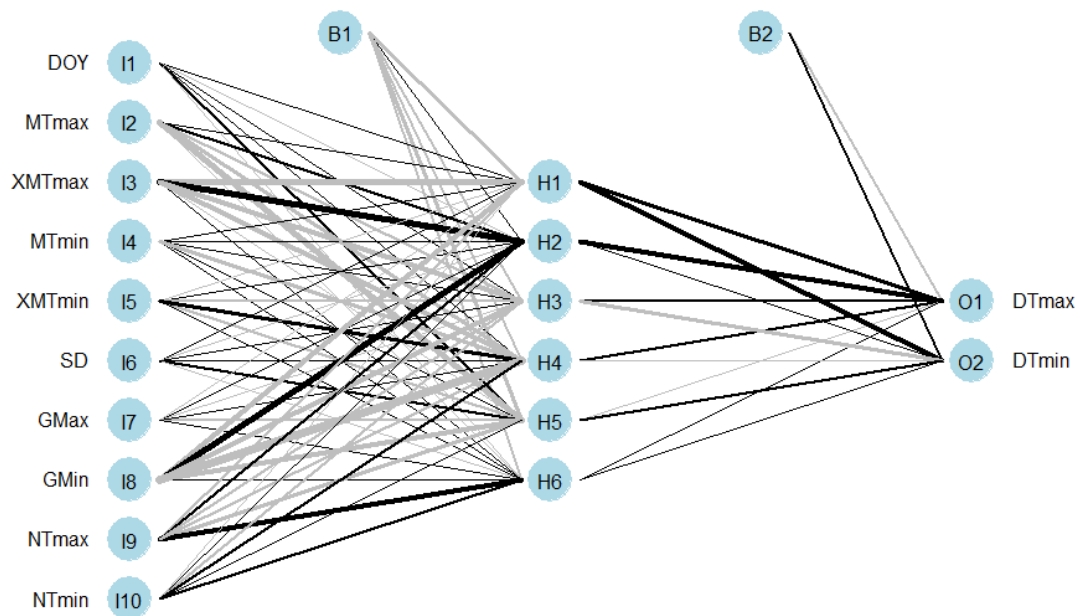


Figure C-78: ANN3H structure with weights depicted in the figure in different shades (the black shade represents the positive weights and the grey shade represents the negative weights, and the thicker shades represent the higher weights values)

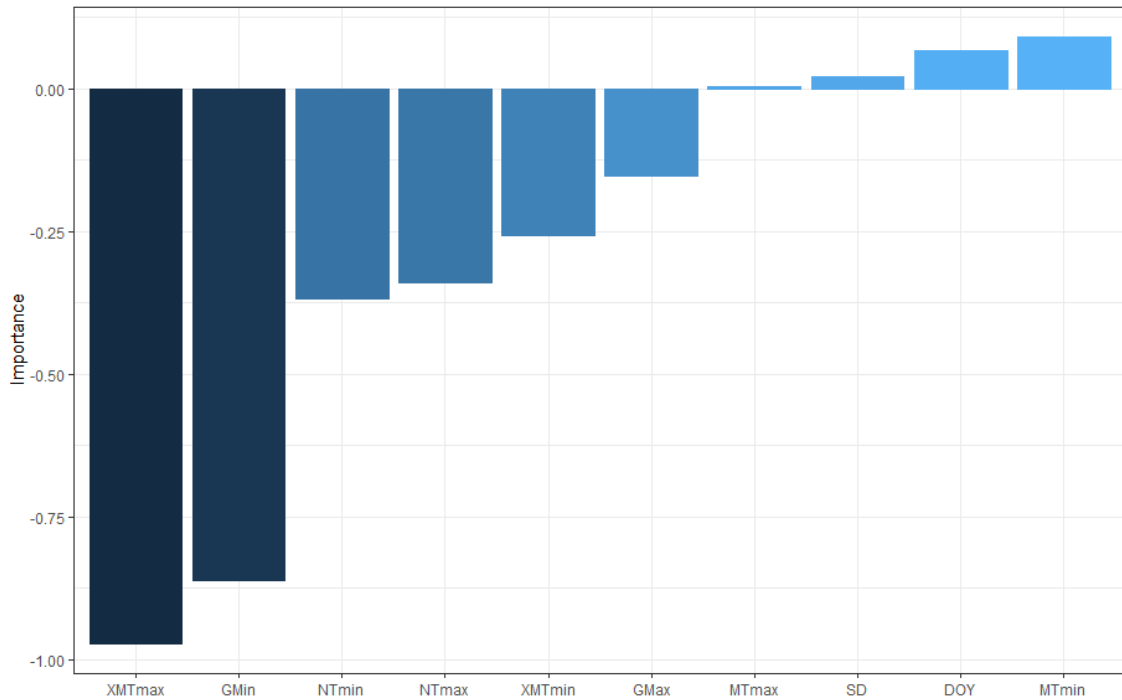


Figure C-79: The importance of the input parameters applied in ANN3H based on olden function.

C.3.9 ANN4H results

ANN4H was developed to predict the daily maximum and minimum air temperature (DTmax and DTmin) at Hon meteorological station using input parameters including: day of the year (DOY), average month maximum air temperature (MTmax), average monthly minimum air temperature (MTmin), extreme maximum air temperature of the month (XMTmax), extreme minimum air temperature of the month (XMTmin), sunshine duration (SD), average daily maximum air temperature calculated by the Global TempSIM (GTmax), average daily minimum air temperature calculated by the Global TempSIM (GTmin), average daily maximum air temperature calculated by ERA5-Land (RSTmax), and average minimum air temperature calculated by ERA5_Land (RSTmin). Figure C-80 shows the structure of the developed ANN with the input parameters. Figure C-81 – C-84 show the accuracy of ANN4H in predicting DTmax and DTmin against the training and testing dataset respectively. Figure C-85 shows the structure of ANN4H based on plotnet function, and Figure C-86 shows the

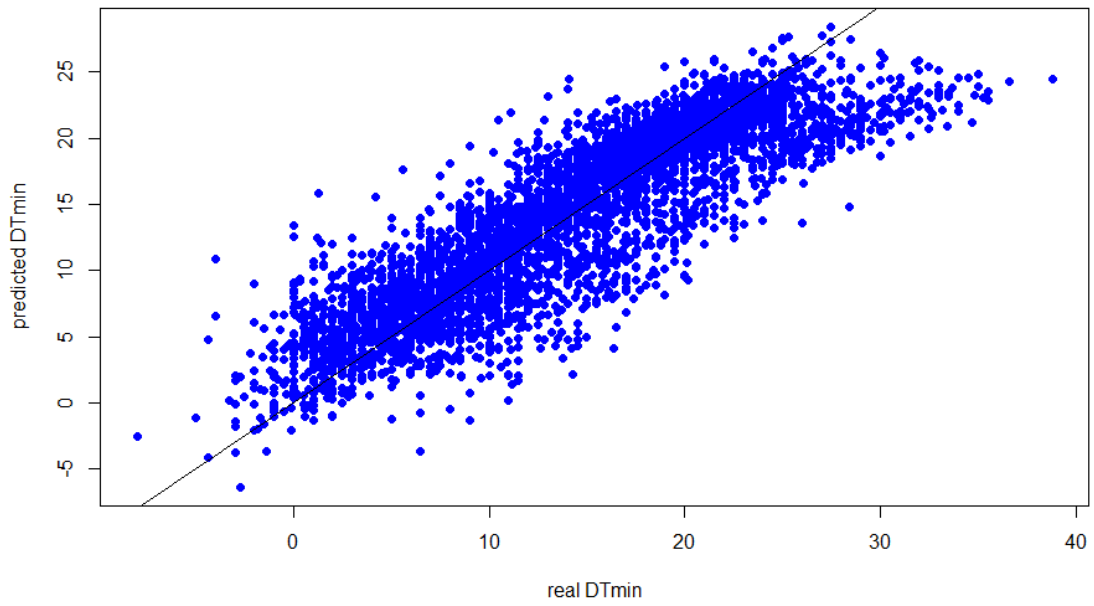


Figure C-82: The accuracy of ANN4H in predicting DTmin based on the training dataset.

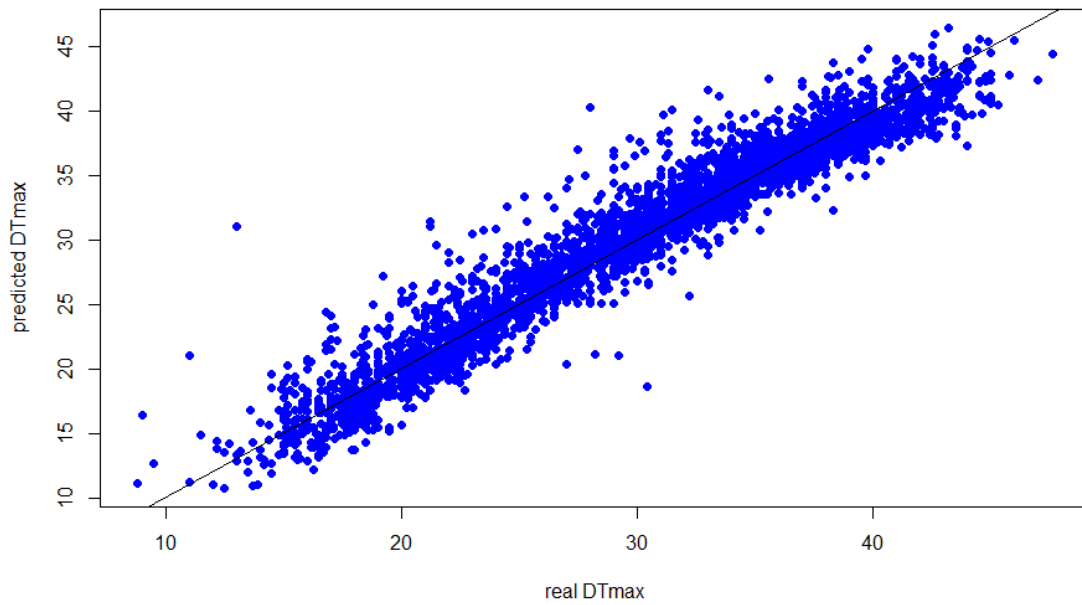


Figure C-83: The accuracy of ANN4H in predicting DTmax based on the testing dataset.

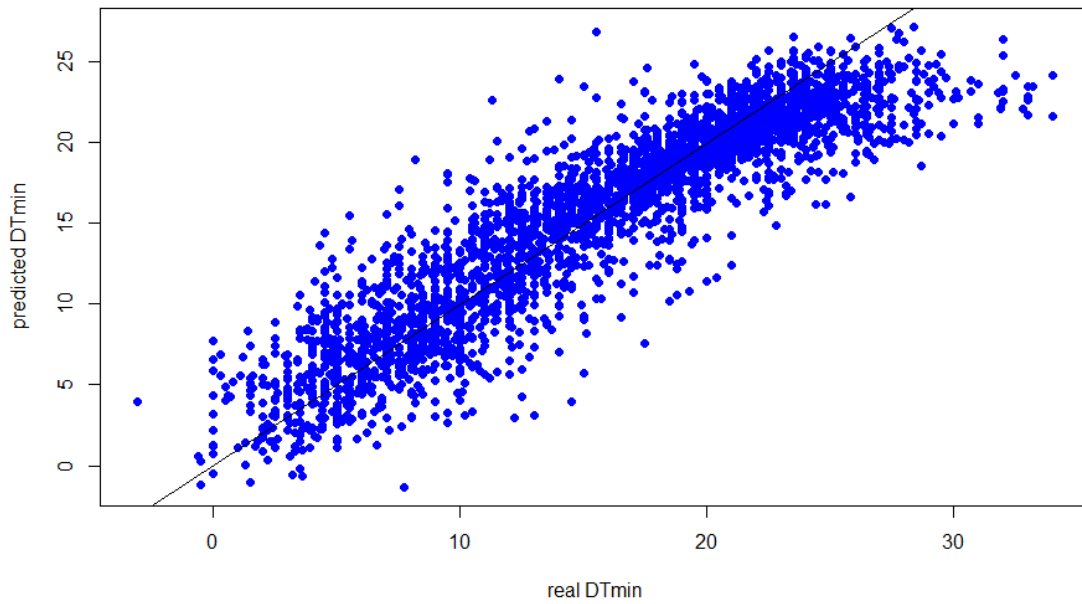


Figure C-84: The accuracy of ANN4H in predicting DTmin based on the testing dataset.

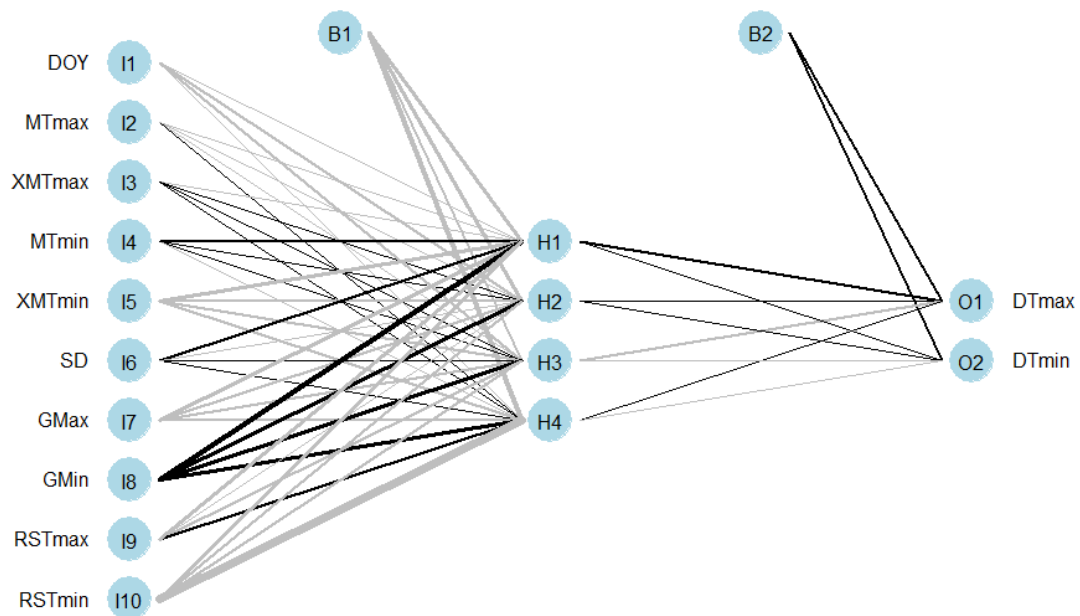


Figure C-85: ANN4H structure with weights depicted in the figure in different shades (the black shade represents the positive weights and the grey shade represents the negative weights, and the thicker shades represent the higher weights values)

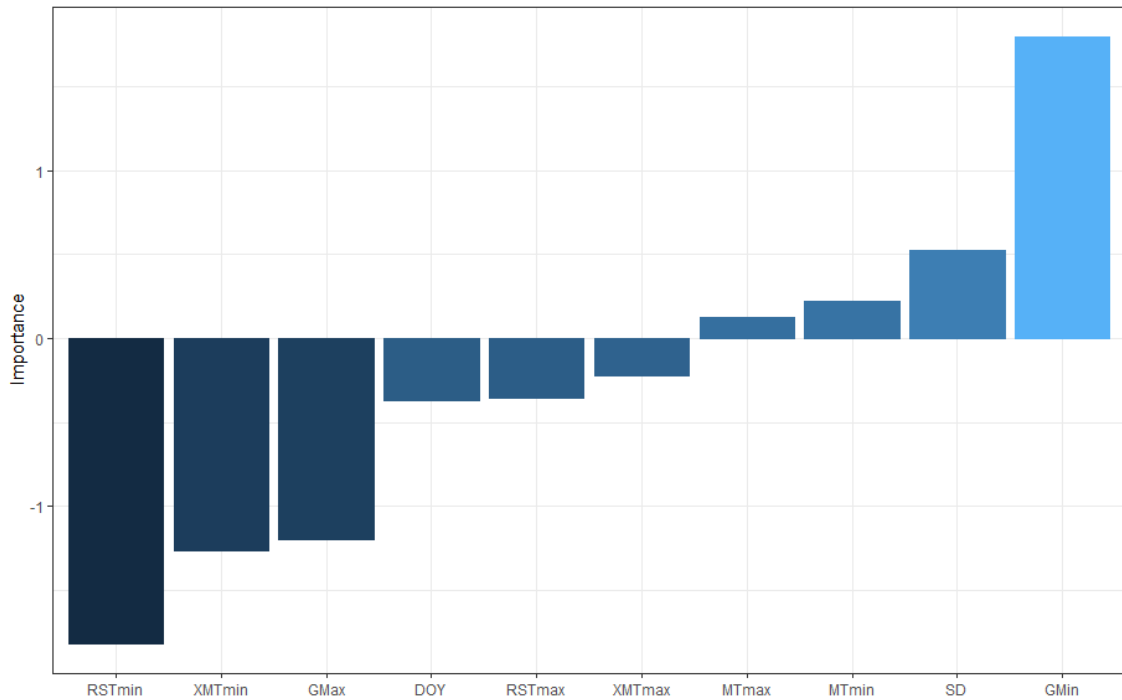


Figure C-86: The importance of the input parameters applet to develop ANN4H based on olden function.

C.3.10 ANN5H results

ANN5H was developed to predict the daily maximum and minimum air temperature (DTmax and DTmin) at Hon meteorological station using input parameters including: day of the year (DOY), average month maximum air temperature (MTmax), average monthly minimum air temperature (MTmin), extreme maximum air temperature of the month (XMTmax), extreme minimum air temperature of the month (XMTmin), sunshine duration (SD), average daily maximum air temperature calculated by the Global TempSIM (GTmax), average daily minimum air temperature calculated by the Global TempSIM (GTmin), average daily maximum air temperature predicted by MODAWECC (ModTmax), and average minimum air temperature predicted by MODAWECC (ModTmin). average daily maximum air temperature at the neighbouring station (NTmax), and average minimum air temperature at the neighbouring station (NTmin). average daily maximum air temperature calculated by ERA5-Land (RSTmax), and average minimum air temperature calculated by ERA5_Land (RSTmin). Figure C-87 shows the structure of the developed ANN with the input parameters. Figure

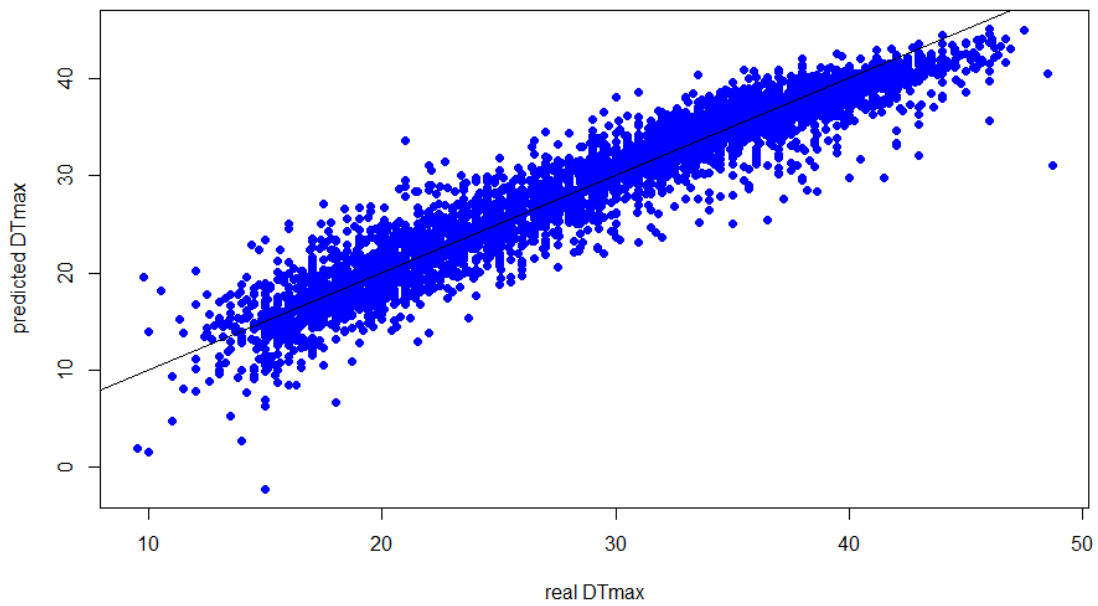


Figure C-88: The accuracy of ANN5H in predicting DTmax based on training dataset.

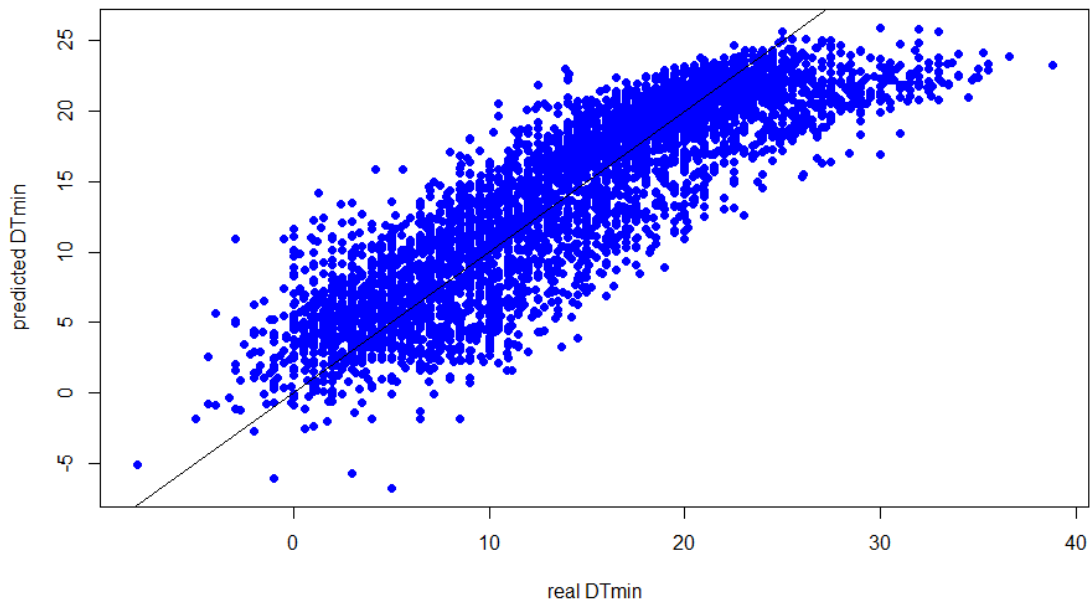


Figure C-89: The accuracy of ANN5H in predicting DTmin based on training dataset.

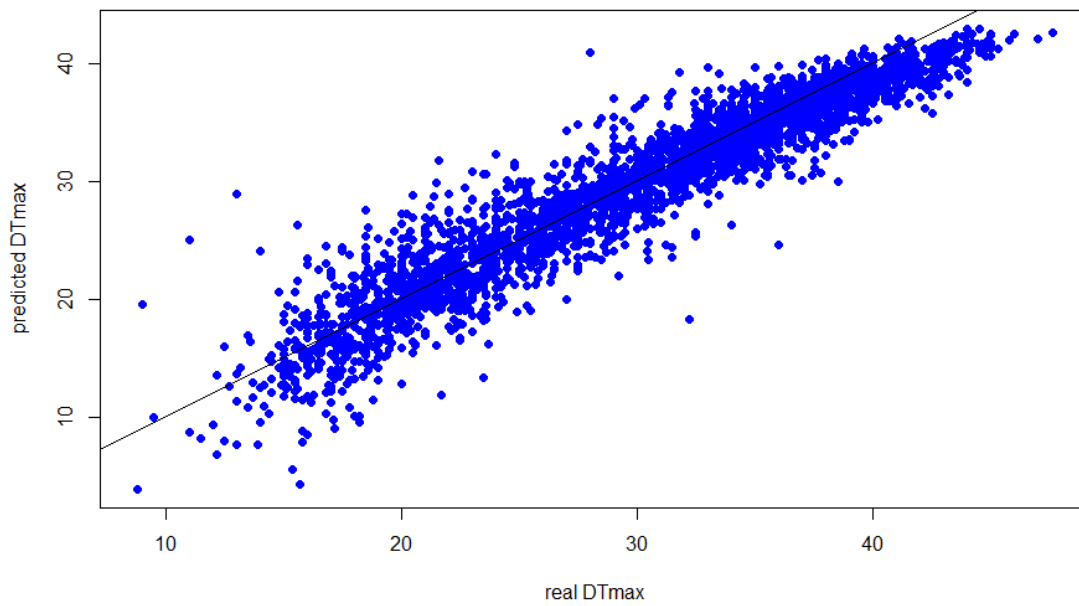


Figure C-90: The accuracy of ANN5H in predicting DTmax based on testing dataset.

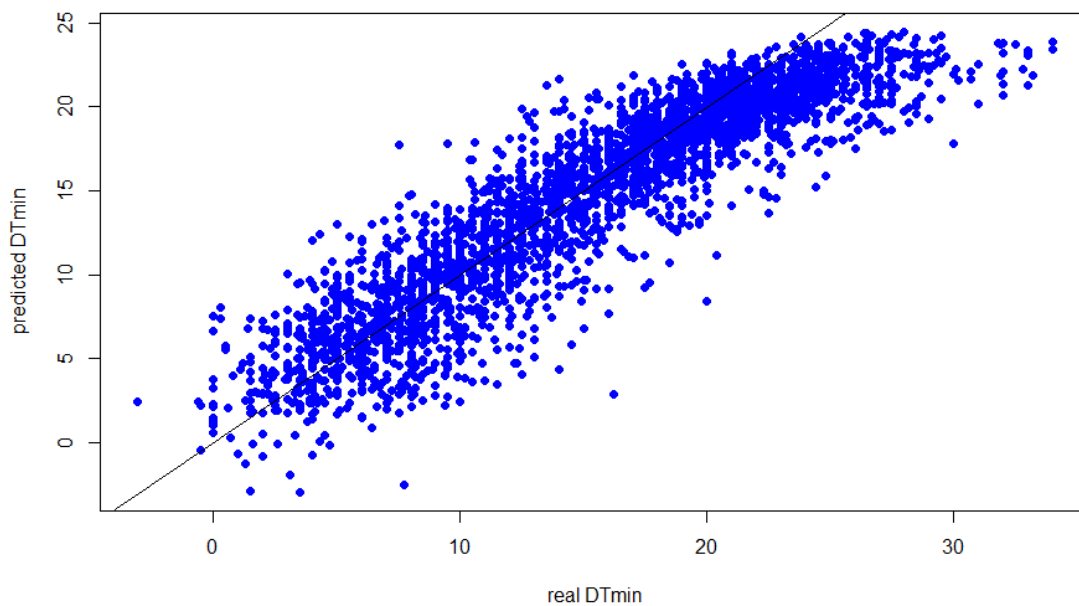


Figure C-91: The accuracy of ANN5H in predicting DTmin based on testing dataset.

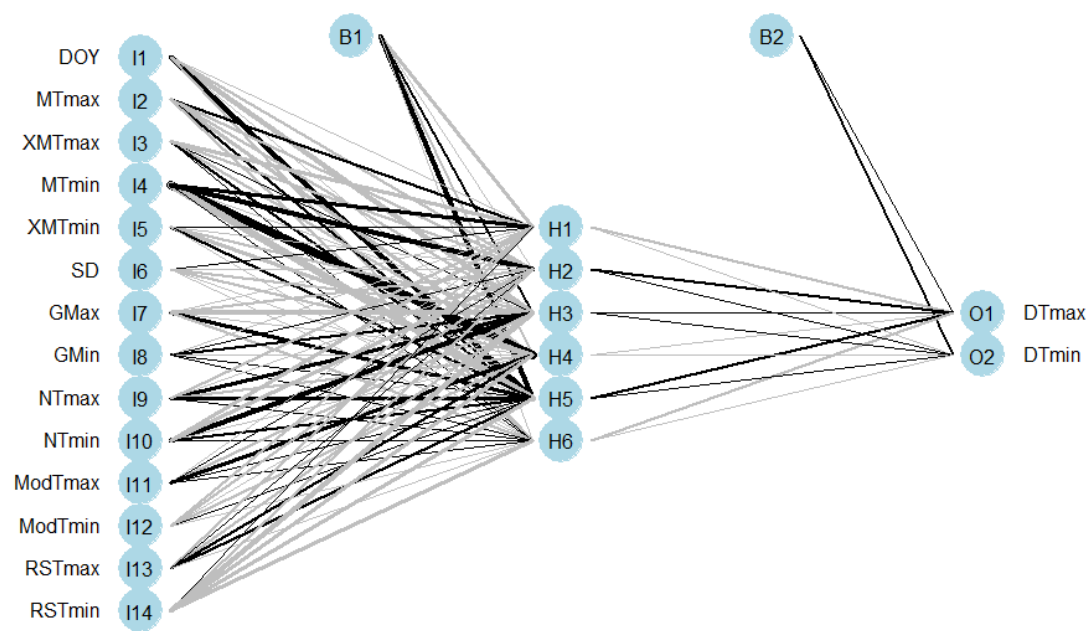


Figure C-92: ANN5H structure with weights depicted in the figure in different shades (the black shade represents the positive weights and the grey shade represents the negative weights, and the thicker shades represent the higher weights values)

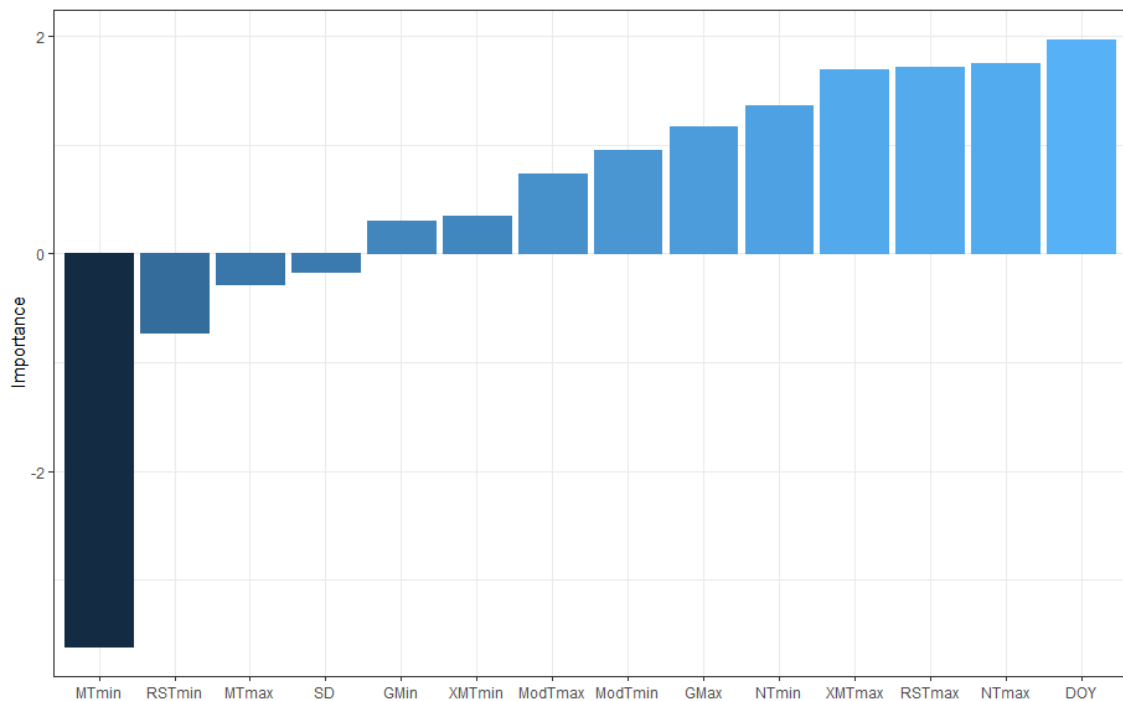


Figure C-93: The importance of the input parameters applied in ANN5H to predict DTmax and DTmin based on olden function.

C.4 ANNs in Chapter 5

C.4.1 ANN1 results

ANN1 was developed to predict soil salinity EC in EAP and HAP using six input parameters (i.e. Band 1 Visible (Blue), Band 2 Visible (Green), Band 3 Visible (Red), Band 4 Near-Infrared, Band 5 shortwave-infrared, and Band 7 shortwave infrared). Figure C-94 shows the structure of ANN1 which includes the input parameters the hidden layers and neurons and the output layer. Figure C-95 shows the structure of the developed ANN1 based on plotnet function and finally Figure C-96 illustrates the importance of the input parameters applied in ANN1. (Note: garson function cannot be applied because the developed ANN has multiple hidden layers).

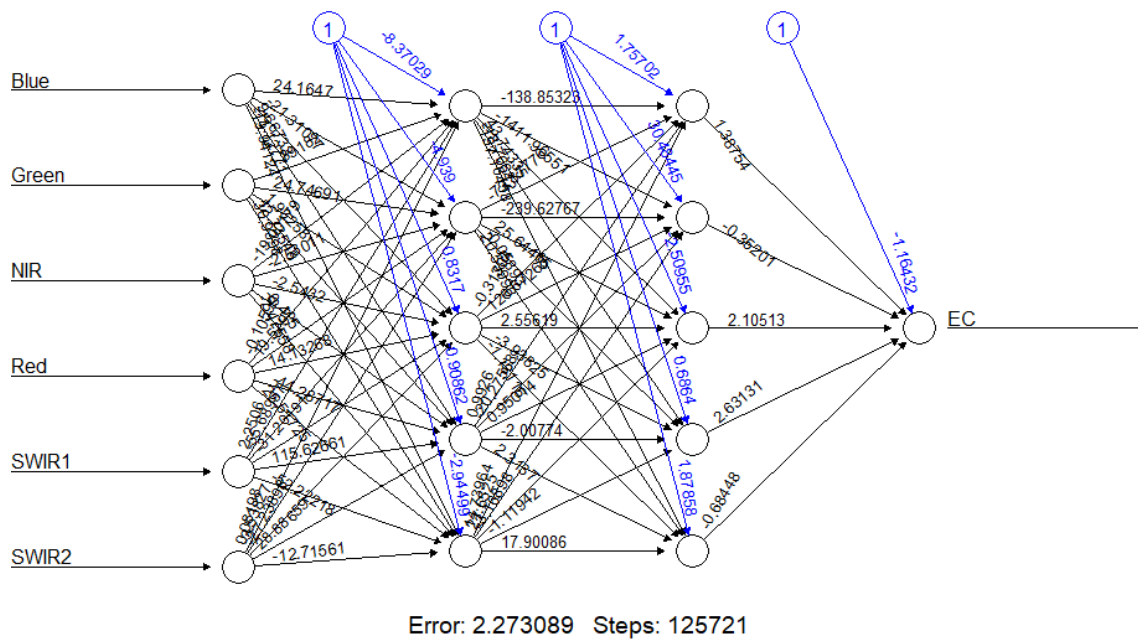


Figure C-94: The structure of the developed ANN1 to predict EC in EAP and HAP.

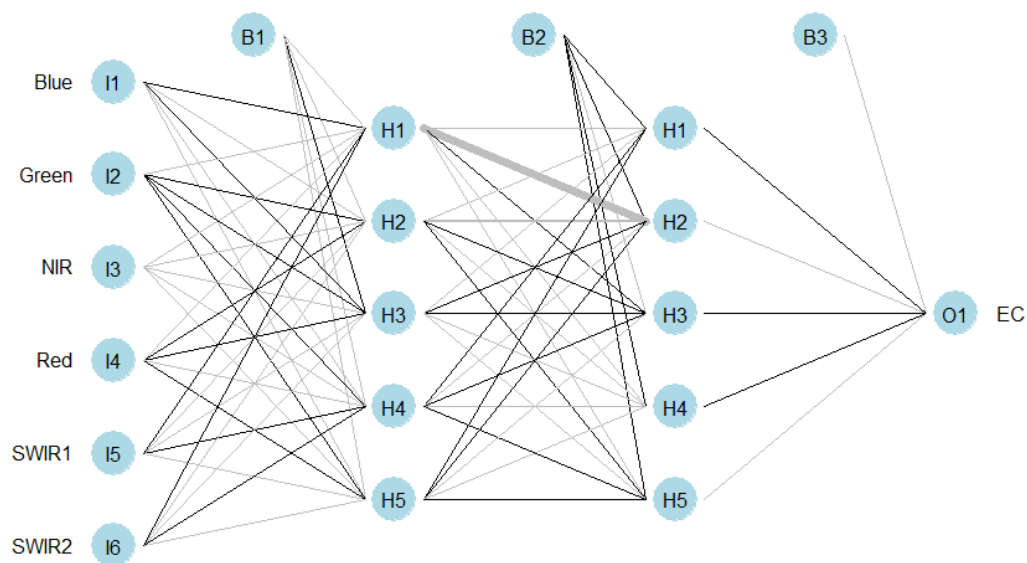


Figure C-95: ANN1 structure with weights depicted in the figure in different shades (the black shade represents the positive weights and the grey shade represents the negative weights, and the thicker shades represent the higher weights values).

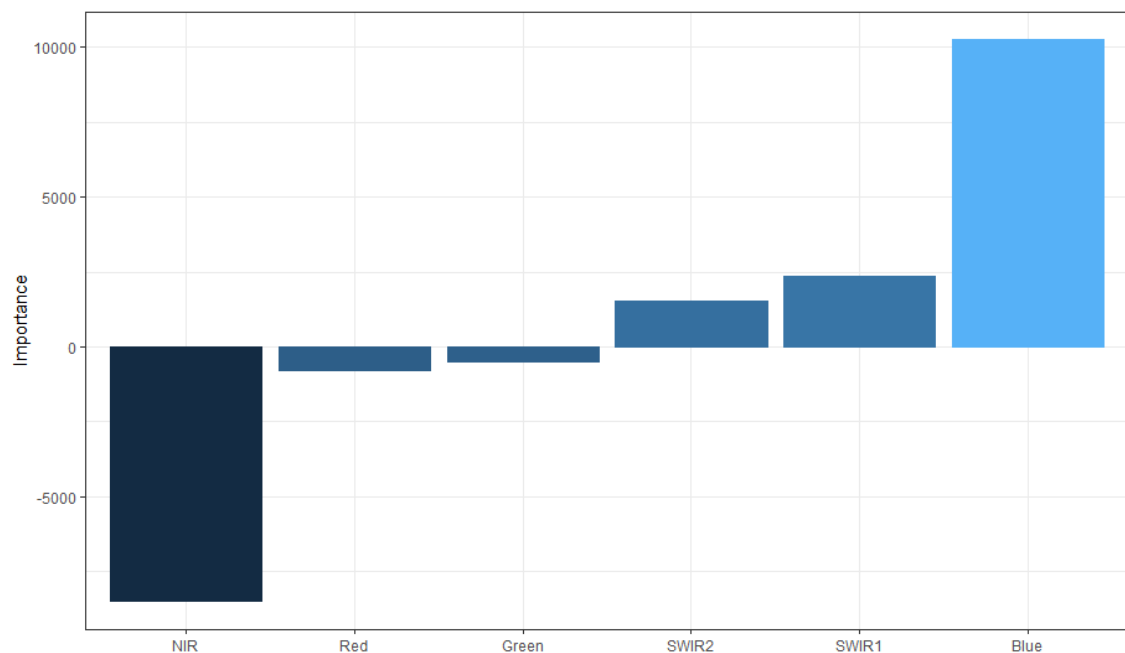


Figure C-96: The importance of the input parameters applied in ANN1 based on olden function.

C.4.2 ANN2 results

ANN2 was developed to predict soil salinity EC in EAP and HAP using nineteen input parameters included Band 1 Visible (Blue), Band 2 Visible (Green), Band 3 Visible (Red), Band 4 Near-Infrared, Band 5 shortwave-infrared, Band 7 shortwave infrared, Normalized difference salinity index, Brightness index, Salinity index 1, Salinity index 2, Salinity index 3, Salinity index 4, Salinity index 5, Salinity index 6, Salinity index 7, Salinity index 8, Salinity index 9, and Normalized difference vegetation index. Figure C-97 shows the structure of ANN2 which includes the input parameters the hidden layers and neurons and the output layer. Figure C-98 shows the structure of the developed ANN2 based on plotnet function and finally Figure C-99 illustrates the importance of the input parameters applied in ANN2. (Note: garson function cannot be applied because the developed ANN has multiple hidden layers).

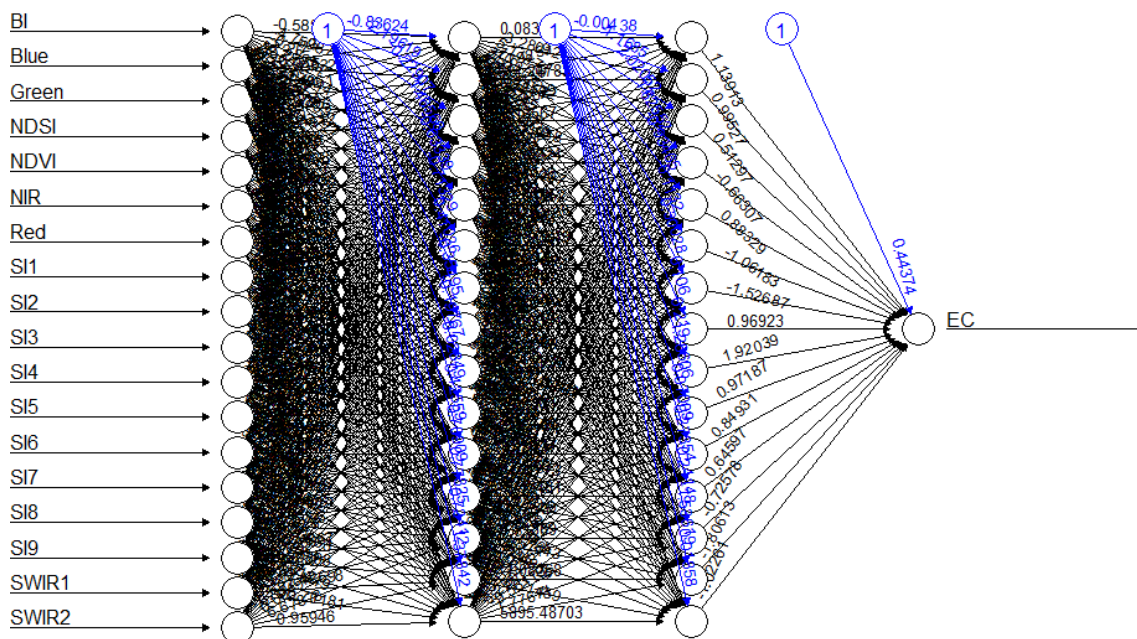


Figure C-97: The structure of the developed ANN2 to predict EC in EAP and HAP

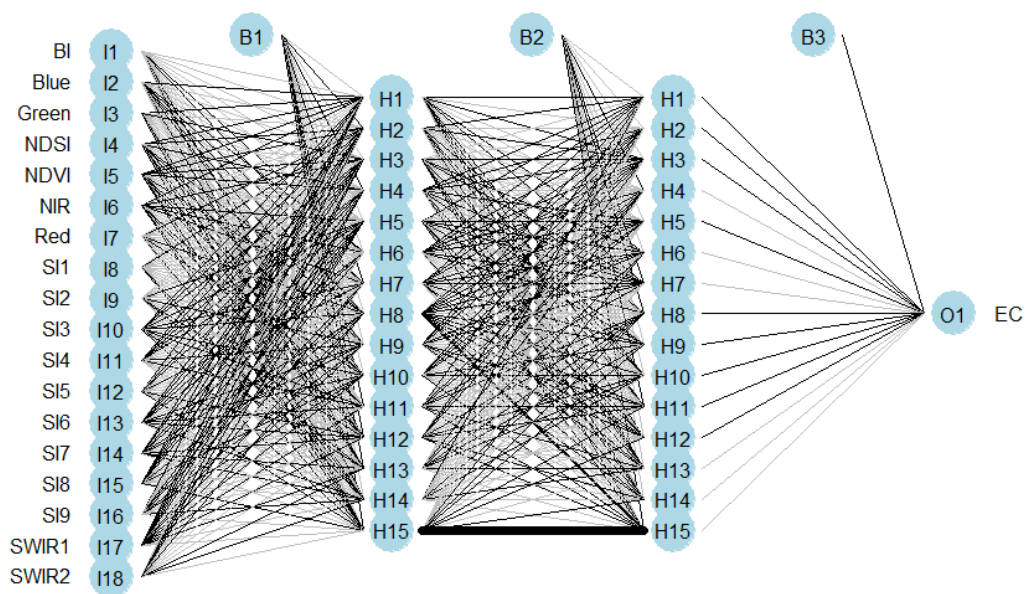


Figure C-98: ANN2 structure with weights depicted in the figure in different shades (the black shade represents the positive weights and the grey shade represents the negative weights, and the thicker shades represent the higher weights values)

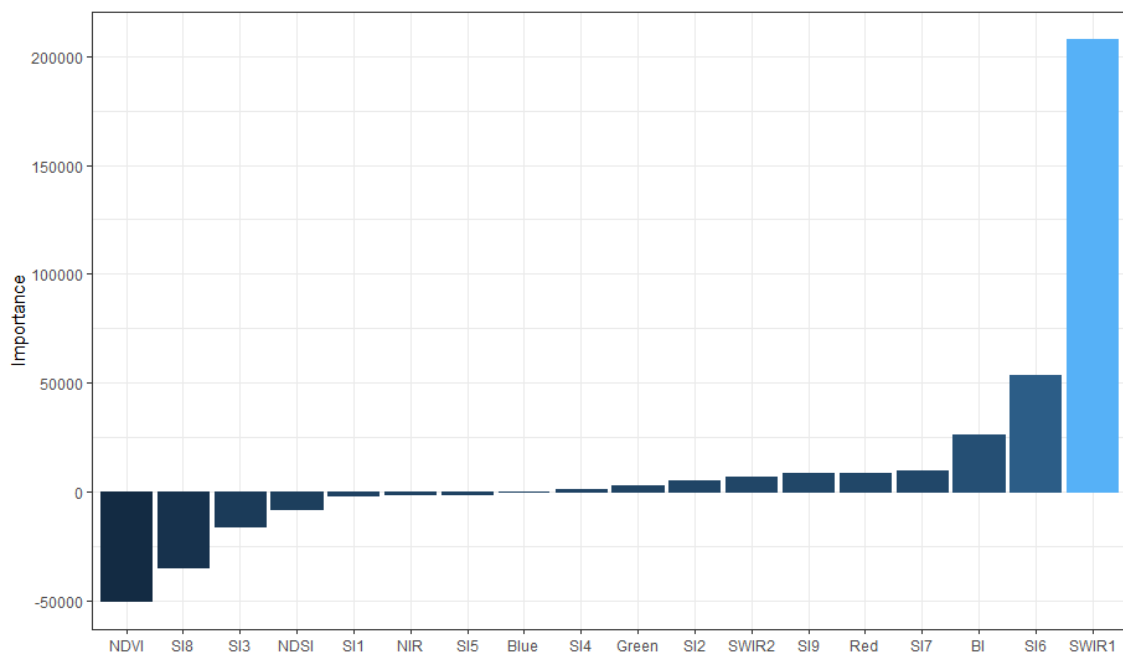


Figure C-99: The importance of the input parameters applied in ANN2 based on olden function.

Appendix D Drainage Optimal Design in Arid and Semi-Arid Areas

This appendix provides detailed information on the optimal drainage system and how the installed system can be operated in an optimal way. This appendix contains information on the current system installed in EAP and HAP compared to the optimal design. This appendix will focus on three aspects: irrigation system, crop pattern, and drainage design. Put simply, the optimal design is defined as that which provides the highest relative yield using the minimum irrigation amount.

In arid and semi-arid areas, irrigation and drainage management are the primary elements affecting the flow of water over and through the soil. As the majority of solute transport occurs via soil water fluxes, irrigation and drainage management have a significant role in determining solute fluxes through the soil. Timing in relation to crop water requirements and fertiliser and pesticide application is crucial in irrigation management for managing the quantity of soluble materials that will infiltrate below the root zone and be collected by drains. The timing of irrigation also impacts capillary rise into the root zone, which may lead to a build-up of salts in the root zone but decreases the amount of irrigation water required. Equally important to the time of irrigation is the quantity of water applied. Excess water, including precipitation that has been absorbed, percolates to deeper soil layers.

D.1 Optimal Irrigation System Vs irrigation systems at EAP and HAP

Not all the water drawn from a source (a river or well) makes it to the plants' root zone. During transit through the canals and in the fields, some water is lost. The remaining portion is subsequently utilised by the plants after being stored in the root zone. Just a portion of the water is effectively used, and the other portion is lost to the crops on the fields. As mentioned earlier, the groundwater aquifers used to irrigate crops in EAP, and HAP are non-renewable (i.e. the discharge rate is higher than the recharge). Therefore, the optimal irrigation system installed in

EAP and HAP should be the most efficient system that reduces any unwanted water loss. For example, surface irrigation systems have a low level of efficiency, averaging about 60 percent (Brouwer et al, 1989). This means that only 60 percent of the delivered water is stored in the top layer of the soil, where crop roots can extract it for beneficial use. The sprinkler irrigation and drip irrigation have higher average efficiency of 75% and 90% respectively (Brouwer et al, 1989). Many factors can cause irrigation water losses such as evaporation from the water surface, deep percolation to soil layers underneath the root zone, and runoff.

The annual water consumption at EAP is around 42 million m³ year⁻¹. In the wintertime the monthly peak demand in March is 3.7 million m³, and in summertime the highest values recorded in July/August show a total water consumption of around 4.6 million m³. However, not all the EAP are cultivated, and therefore the gross irrigation rate on cultivated area is measured as 5.52 mm d⁻¹ in wintertime and 11.23 mm d⁻¹ in summertime. The irrigation system as a whole shows considerable losses. Unfortunately, no records about exact pump hours or discharge rates from well pumps and irrigation pumps are kept. Also, no measurements relating to drainage water outflow from the project areas are available. Therefore, it is not possible to cross-check calculations, and the irrigation losses must be estimated. The monthly irrigation quantity measured for a year in the 1980s is illustrated in Table D-1.

Table D-1: Monthly irrigation quantity for EAP

Month	Irrigation quantities (per 1000 m ³)
January	2,032
February	3,087
March	3,665
April	2,790
May	4,095
June	3,960
July	4,595
August	4,595
September	3,330
October	3,330
November	3,220
December	2,970
Total	41,669

Where m³ is cubic meter

In HAP, it is estimated that the total annual water consumption ranges between 25 – 30 million m³ year⁻¹. This is equivalent to 2100 - 2500 mm year⁻¹ across the HAP area (1200 ha). However, when the total annual water consumption was estimated, there was no record of the total cultivated area in HAP. Also, these rates are within the net irrigation requirement for annual crops such as palm tree and alfalfa. However, not all the HAP area is used to grow palm tree and alfalfa. Other crops such as tomatoes, eggplant, cucumber, melon, watermelon, peppers, onions, figs, pomegranates, and some citrus trees are growing in HAP. As mentioned earlier, over irrigation occurs at HAP to overcome the levelling problems (some of the farms are not prepared for surface irrigation such as furrow irrigation and there is no slope to help the water flow). Also, the irrigation method applied in HAP is surface irrigation with up to 60% efficiency. As a result, the water table is shallow (average 50 cm from the surface), and a large amount of drainage water (more than 10 million m³ year⁻¹) is removed from the project.

The following actions should be considered for EAP and HAP to improve the irrigation system and achieve the optimal irrigation design:

- In order to obtain an efficient water distribution and water use efficiency, HAP as a whole project should be changed from surface irrigation to sprinkler irrigation system.
- Drip irrigation as the most efficient irrigation system should be adopted in EAP and HAP where possible to improve the water use efficiency.
- The pumped water from the groundwater aquifers at EAP and HAP should be monitored as well as the irrigation water used from the filled tanks.
- Drainage water in EAP and HAP should be regularly tested and evaluated to determine the viability of mixing it with irrigation water as an irrigation source for more saline tolerant crops (e.g. cotton).
- Upgrading the irrigation system surface irrigation to sprinkler irrigation or drip irrigation would help to improve the water use efficiency by 10 – 30%.

D.2 Optimal Drainage Design Vs Current Drainage Design at EAP and HAP.

An optimal drainage system is one that maximises the difference between the cost of the drains and increased gain in yields as a consequence of installing the drainage system. According to this definition, the optimal drainage system design comprises two very different factors. The first of them is the physical effects of installing drainage and predicting how the drainage affects the interactions between soil, water, and plants and, ultimately, crop yields. The cost of the drainage system and the value of the increased crop yields are the second factor to consider while selecting the optimal drainage system. Also, the optimum design should help to control the water table and manage the salinity levels at the root zone. In addition, the optimal design when installed at the right depth and spacing would maximise the water use efficiency by reducing the amount of drainage water. Therefore, the accuracy of predicting the key parameters influence the drainage system help to achieve the optimal design. The current drainage systems in EAP and HAP are far from being optimum. The current systems failed to control salinity and waterlogging problems as well as improving the crop yield. New drainage systems need to be constructed taking

into consideration the current situation in these projects such as the topography, the soil properties, the climate and the agricultural activities at regional level.

D.3 Crop Patterns and The Optimal Design

Cropping patterns have a significant impact on drain water quality in a variety of ways. First, crops take water from the root zone, causing an evapoconcentration of salts and other solutes in soil solution. This influences the chemical quality of the drainage water by changing the composition of the soil solution. Second, crop residues enrich the soil profile with organic matter. Soil organic matter content is important because it adsorbs metals and other solutes. Additionally, organic matter improves soil structure, which raises the soil's capacity to hold water. Third, crops use their root systems to absorb nutrients, and some have the ability to store huge amounts of certain salts and poisonous substances. Fourth, as crops vary in their tolerance to salt, the type of crop affects both the maximum tolerable salt concentration and the amount of water required to keep the root zone's salt balance within a manageable range. Finally, the addition of crops that fix nitrogen, such legumes, can help to lower nitrogen leaching. Legumes that live in association with bacteria that fix nitrogen are both nitrogen producers and consumers. In the crop rotation, they might take the place of chemical nitrogen fertiliser. By absorbing a lot of nitrogen, deep-rooted perennial crops like alfalfa can also aid in preventing nitrogen leaching (Blumenthal, et al., 1999).

Based on the results obtained in Chapter 6, improving the irrigation and drainage system in EAP and HAP will allow a wider range of crops to grow and improve the potential crop yield. However, the irrigation water quality in HAP is slightly higher than the one in EAP, and more restrictions should be applied on selecting a crop to grow in HAP. Also, 'with expected periods of prolonged water shortages', the optimal design should consider crops that are less sensitive to drought stress. Ideally, crops in irrigation schemes do not experience water shortages since irrigation water is delivered before the crops experience drought stress. However, it might not be possible to apply irrigation water precisely when it would be best to do so; for example, in a dry year, the tanks might not have

enough water to irrigate all the fields on schedule or the project management may decide to spread the available water over a large area, thus allowing more farmers to irrigate, although at less than the optimal amount. Table D-2 shows the salinity threshold and sensitivity of various field crops to drought stress.

Table D-2: Crops sensitivity to drought stress and salt tolerance as adopted from FAO (Brouwer et al, 1989).

Crop	Sensitivity to drought stress	Salinity threshold (dS m ⁻¹)	Slope (% per dS m ⁻¹)	Salt tolerance
Alfalfa	Low – medium	2.0	7.3	Medium sensitive
Beans	Medium – high	1.0	19.0	Sensitive
Soybeans	Low – medium	5.0	20.0	Medium tolerant
Wheat	Low – medium	6.0	7.1	Medium tolerant
Maize	Medium – high	1.7	12.0	Medium sensitive

D.4 DRAINMOD sensitivity analysis

Input data for soil properties, climatological data, crop information, and system parameters are necessary for simulation of a water management system. These inputs may be measured or approximated using a variety of techniques (see Chapters 3 – 5). Errors in the inputs will undoubtedly impact the results of simulations in terms of both daily predictions and objective function values (Chapters 3 – 6). Additionally, it is likely that certain input errors will have a greater impact on the outcomes than others. Therefore, it is necessary to determine the sensitivity of simulations to error in the various inputs to determine the order in which the required input data should be prioritised. This section will show how sensitive the objective functions are to input data error for various water management systems (this analysis was done by DRAINMOD developer and available with more detail in DRAINMOD manual (Skaggs, 1982)).

Sensitivity analyses were carried out by changing one input by a predetermined value while maintaining the values of the other inputs and conducting a simulation for 20 or 25 years of data. The values of the objective functions were then determined from the simulation results and shown as a function of input error over a 5-year recurrence interval. Hydraulic conductivity, water content at the lower limit (also known as the wilting point), upward flux and the depth of the water

table, drainage volume and the depth of the water table, root depth, and potential evapotranspiration (PET) were all examined. Simulations were run for each input parameter at the following values: $\pm 10\%$, $\pm 25\%$, $\pm 50\%$, $\pm 95\%$, $\pm 100\%$, and $+200\%$ of the correct value. For example, if the saturated hydraulic conductivity is $K_{\text{sat}} = 3.0 \text{ m d}^{-1}$, then $K_{\text{sat}} = 3.0 \text{ m d}^{-1}$, 3.3 m d^{-1} , 2.7 m d^{-1} , 3.75 m d^{-1} , 2.25 m d^{-1} , etc., simulations were run. The K_{sat} (or other soil parameter) was changed by the specified percentage error. For all levels of the independent variable, the specified percentage also increased or reduced functional connections, such as drainage volume vs water table depth (water table depth, in this case).

Irrigation depth, one of the objective functions, was tested in the sensitivity analysis and the results are showing in Figure D-1. The error in K_{sat} has the biggest impact on the predicted irrigation depth. An error of -50% in K_{sat} would have resulted in a predicted total annual irrigation depth of 86 cm, while the measured annual irrigation depth is around 132 cm. The second most sensitive input parameter is the depth to the impermeable layer. For the same error (-50%), the total predicted irrigation amount is 105 cm. Finally, the next most sensitive input parameter is PET with predicted 128 cm for the same error (-50%) (see Figure D-1). Therefore, if DRAINMOD is to be used to predict the irrigation depth, effort should be concentrated toward accurately predicting those input parameters (K_{sat} , depth to the impermeable layer, and PET).

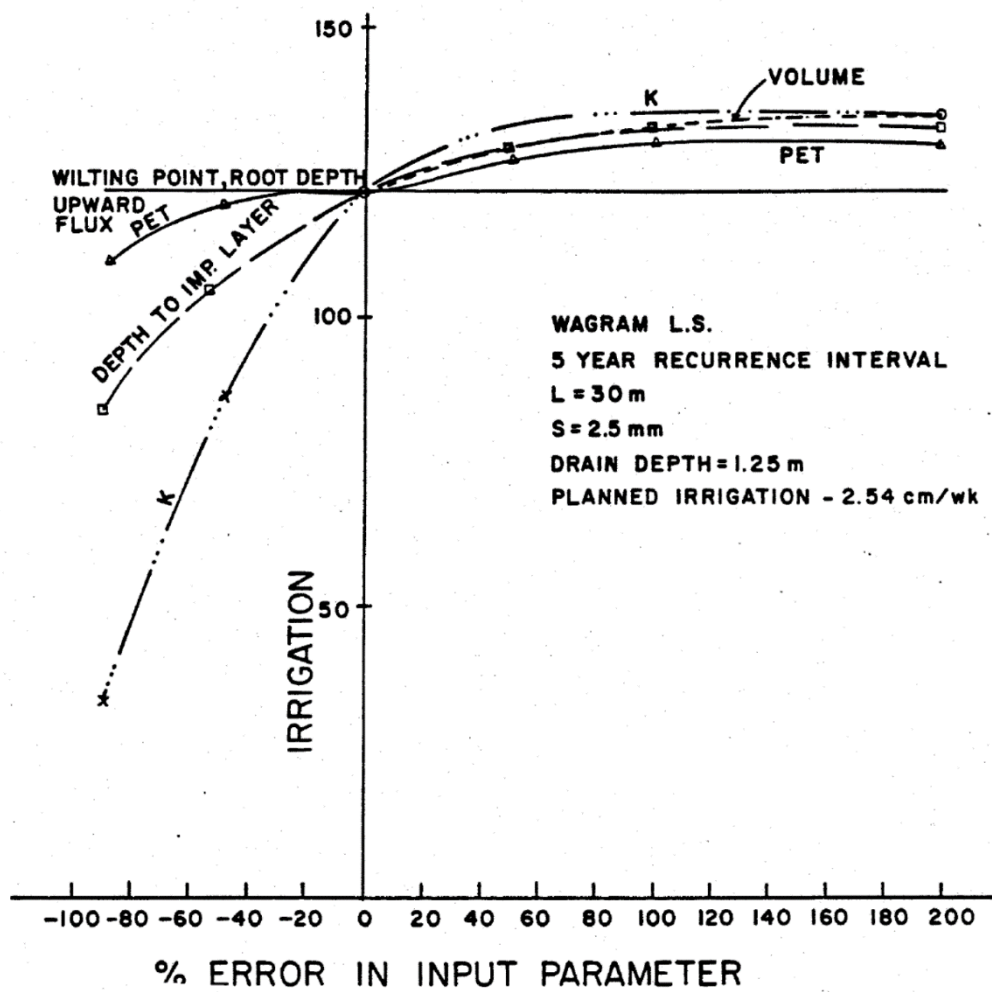


Figure D-1: Effect of errors in DRAINMOD inputs on predicting the total irrigation depth as adopted from Skaggs (1982).

Appendix E References

- Al-Barouni, 2013. The water situation in Libya. Tripoli, Libya.
- Al-Khoja, Hamilla, M., 2007. A report on irrigation and drainage in Al-Hamam and Al-Furjan Agricultural Projects General Administration of Irrigation and Drainage. Tripoli, Libya.
- Bouyoucos, G., 1927. The hydrometer as new method for mechanical analysis of soils. *Soil Sci.* 23, 343–353.
- C. Brouwer, K. Prins and M. Heibloem, "Irrigation Water Management: Irrigation Scheduling," Training Manual No. 4, 1989, Food and Agriculture Organization, Rome, 43 p.
- Buckman, H., Brady, N., 1960. *The Nature and Properties of Soil*, 6th ed. Macmillan company, New York, USA.
- Cornelius-Brochier J.V, 1981. Wadi Al Shatti: Drainage Design. Tripoli, Libya.
- Danenco, 1980. Technical Study for Jufra el Hamam Project. Copenhagen, Denmark.
- Garson, G., 1991. Interpreting neural network connection weights. *Artif. Intell. Expert* 6, 1–20.
- Goh, A.T., 1995. Back-propagation neural networks for modeling complex systems. *Artif. Intell. Eng.* 9, 143–151.
- GWA, 2018. Folder reports of the General Administration of Irrigation and Drainage. Tripoli, Libya.
- GWA, 2007. A field visit to Hammam Agricultural project to investigate the Sokna flood. Tripoli, Libya.
- GWA, 2005. The final report on agricultural drainage studies. Tripoli, Libya.

GWA, 2003. Report on the Hammam Agricultural Project and the current drainage system in Jufra district. Tripoli, Libya.

GWA, 2001. Folder reports of the General Administration of Irrigation and Drainage. Tripoli, Libya.

GWA, 1999. Water and irrigation requirements for the most important crops in Libya [unpublished report]. Tripoli.

Hamilla, M., 2018. Agricultural drainage in Libya. Tripoli, Libya.

Hamilla, M., 2005. Summary of the reports of the most important experts, teams and committees that visited the Hammam and Al Furjan projects. Tripoli, Libya.

Olden, J.D., Joy, M.K., Death, R., 2004. An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data. *Ecol. Modell.* 178, 389–397.

Ozesmi, S.L., Ozesmi, U., 1999. An artificial neural network approach to spatial habitat modeling with interspecific interaction. *Ecol. Modell.* 116, 15–31.

Richards, L., 1949. Methods of measuring soil moisture tension. *Soil Sci.* 68, 95–112.

Smith, M., 1993. CLIMWAT for CROPWAT : a climatic database for irrigation planning and management.

Tantawi, A., 2000. Water Resources in Libya. Egyptian Office for the Distribution of Publications, Cairo.

van Aart, R., 1991. An evaluation of irrigation & land drainage problem in some Settlement Project in West Libya. Tripoli, Libya.

van Alphen, J., Kor, G., 1984. The final report Wadi Shatti drainage Project & Discussion on the water logging & salinity problems in the Jufra Al Hamam & Furgan irrigation project. Tripoli, Libya.

