

CRANFIELD UNIVERSITY

JOHN E. P. BEALE

ESTIMATING FIELD-SCALE SOIL MOISTURE USING
SAR REMOTE SENSING AND THE COSMOS-UK
NETWORK

SCHOOL OF WATER, ENERGY AND ENVIRONMENT
Environment & Agrifood

PhD
Academic Year: 2020–2021

Supervisors: Dr Toby W. Waine, Prof Ron Corstanje
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requirements for the degree of PhD.

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Abstract

Soil moisture (SM) is one of the key parameters in the engineering, agronomic, geological, ecological, biological and hydrological functions of soil. Its needed to support decision making in agriculture for irrigation and trafficability, and is a key input to hydrological and meteorological models. Remote sensing has significant potential but there remains a challenge to improve the accuracy and usefulness of the data for end users. The objective of this thesis is to develop a field-scale soil moisture estimate from Sentinel-1 C-band synthetic aperture radar (SAR) data, that is sufficiently accurate to be useful to farmers and agronomists and the research community.

SAR is attractive as an all-weather remote sensing solution with potential to estimate soil moisture over large scales and at high spatial resolution. But because SAR backscatter is strongly affected by overlying vegetation and crops, and to some extent by soil surface roughness and soil texture, the process of SM retrieval from SAR is very complex. Among a number of potential solutions, one approach is to quantify the non-SM contributions by processing additional data alongside SAR data using models that are trained against *in-situ* SM observations. This is very resource intensive, with the results being limited in scope and accuracy by the ancillary and training data. The alternative change detection (CD) algorithm avoids the use of additional data or training sites by assuming, instead, that the effects of soil surface roughness and vegetation are relatively static on the timescale of soil moisture variation. This can be highly effective for estimating relative SM in many areas but not, crucially, in areas of farmland under arable cultivation where rapid changes in vegetation and soil surface roughness are common. This is mitigated in current published SM products by restricting their spatial resolution to around 1 km, averaging out the effects of anthropogenic change over a diversity of land uses. A 1 km pixel area is an order of magnitude larger than the average field size in the UK, for example. Such products do not satisfy the needs of farmers in arable areas and do not exploit the high spatial resolution available from SAR

sensors such as Sentinel-1 C-band (20 m). A key objective of this thesis is to achieve a better understanding of the capabilities of the change detection algorithm and enhance it to provide more accurate results for farming areas at field scale.

Whilst achieving field-scale resolution and better accuracy from the CD approach would be significant, the results would still not be very useful to farmers. The CD algorithm is not trained against ground measurements, so its output is a Soil Moisture Index (SMI) which is a relative estimate of SM within the boundaries of previous SAR measurements at each pixel. To obtain absolute values such as volumetric water content or soil moisture deficit (e.g. for irrigation management), the SMI is calibrated against the expected range of SM, often taken to be the difference between the soil's field capacity (FC) and permanent wilting point (PWP) predicted by the soil texture at each location. This study shows that a 10 to 20 vol.% mean absolute error may be introduced by uncertainties in selecting appropriate soil texture so the importance of using a reliable soil map is underlined. It is further shown that the highly dynamic nature of SM in the shallow surface layer penetrated by C-band SAR (1 to 2 cm) means that the Van Genuchten model parameters, θ_s and θ_r should be used as wet and dry references to define the expected range of SM. The common practice of using FC and PWP is shown to contribute an additional 2 to 10 vol.% error. Taken together, these errors are large compared to user requirements of 4 to 5 vol.% and a typical seasonal range of 20 to 40 vol.% depending on soil texture.

Validation is important for users to have confidence in the remote sensing of soil moisture from SAR. A further objective of this study was to address the issue of depth mismatch between the penetration of the SAR and the ground observations used for validation. The study concludes that C-band SAR SM estimates should not be validated directly against ground sensors at 5 to 10 cm depth. A novel validation method is proposed for validation of SAR SM estimates against simulated soil moisture profiles at 2 cm depth using a soil hydraulic model fitted to ground observations. In this thesis, the latter were obtained from the COSMOS-UK network of soil monitoring stations using Cosmic Ray Neutron Sensors with an approximately 200 m radius measurement zone and average measurement depth calculated to be around 10 cm. As a case study of using this improved method, the performance of the published Copernicus SSM soil moisture product across 13 COSMOS-UK test sites is shown to be in the range 8 to 20 vol.% mean error. It confirms, as expected, that the worst performance is in areas of arable agriculture, justifying the focus of the thesis in such areas.

As a stage to achieve the key objective, an SM estimate, spatially aggregated to field boundaries, is demonstrated by the first known implementation of the CD algorithm in Google Earth Engine. It was found that the increased speckle noise at this scale is typically balanced by reductions in noise from excluded clutter sources and increased sensitivity to SM. Periodic noise due to satellite orbit geometries (ascending versus descending) remains evident but temporal smoothing was shown to be effective against it. The performance, in terms of mean error, at field-scale varies from 8 vol.% in grass pasture to 20 vol.% in some arable fields during periods of rapid crop growth. To improve the accuracy in arable fields, a process has been developed to use multispectral remote sensing data to assign levels of confidence in the performance of the CD algorithm, to each field on every measurement date. An alternative method is proposed to achieve a more reliable soil moisture estimate by using two-dimensional interpolation using inverse distance and confidence weighting (IDCW) across a range of neighbouring fields within a local zone. By this method it is shown that, during the peak growing season, the mean absolute error in the soil moisture estimate for wheat fields is reduced from 20 vol.% to less than 5 vol.%, retaining field-scale resolution. This is the first time such levels of accuracy have been reported at field scale from Sentinel-1 SAR without the training of a model. The method is applicable anywhere where the remote sensing data is available alongside a suitable soil texture map. The output meets the operational requirements of farmers for 5 vol.% SM accuracy and is very close to research requirements of 4 vol.%. It may be used to create a mapping product for use by farmers and agronomists using to inform decision making in near real-time. For scientists, engineers, infrastructure engineers and environmentalists the data will be valuable for research into flooding, soil erosion, ground movement and landslip.

Keywords

Soil moisture, synthetic aperture radar, Sentinel-1, field-scale, COSMOS-UK

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List of Abbreviations

AMSR2	Advanced Microwave Scanning Radiometer 2
ANN	Artificial Neural Networks
ANOVA	Analysis of variance
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVIRIS	Airborne Visible InfraRed Imaging Spectrometer
BBSRC	Biotechnology and Biological Sciences Research Council
BS	Bare Soil
CAI	Cellulose Absorption Index
CD	Change Detection
CDT	Centre for Doctoral Training
COSMOS	Cosmic-ray soil moisture monitoring network
CRNS	Cosmic ray neutron sensor
DEM	Digital Elevation Map
EGU	European Geosciences Union
ESA	European Space Agency
FC	Field Capacity
GEE	Google Earth Engine
GIS	Geographical Information Systems
GRD	Ground Range Detected
HC	Hygroscopic Coefficient
H _{rms}	Root mean squared height difference
IDCW	Inverse Distance and Confidence Weighting
IDW	Inverse Distance Weighting
IW	Interferometric Wide (swath mode)
JPL	Jet Propulsion Laboratory
LAI	Leaf Area Index
LANDIS	Land Information System
LCPC	(UKCEH) Land Cover Plus:Crops
LIA	Local Incidence Angle
MAE	Mean Absolute Error
MIMICS	Michigan Microwave Canopy Scattering (model)
MODIS	Moderate Resolution Imaging Spectroradiometer
MSI	MultiSpectral Instrument (Sentinel-2)
m _v	Volumetric Soil Moisture
NASA	National Aeronautics and Space Administration
NATMAP	National Soil Map of England and Wales
NDVI	Normalised Difference Vegetation Index

NERC	Natural Environment Research Council
NIR	Near Infrared
NPV	Non-Photosynthetically Active Vegetation
NWFP	North Wyke Farm Platform National Capability
P	Porosity
PV	Photosynthetically Active Vegetation
PWP	Permanent Wilting Point
PYSMM	PYthon Sentinel-1 soil-Moisture Mapping Toolbox
R ²	Coefficient of Determination
RAW	Readily Available Water
RMSD	Root Mean Squared Difference
RMSE	Root Mean Squared Error
ROI	Region of Interest
RR	Random Roughness (of soil)
S1	Sentinel-1
S2	Sentinel-2
SAR	Synthetic Aperture Radar
SM	Soil moisture
SMAP	Soil Moisture Active Passive (mission)
SMD	Soil Moisture Deficit
SMI	Soil Moisture Index
SMOSAR	Soil MOisture retrieval from multi-temporal SAR data
SOC	Soil organic content/carbon
SRTM	Shuttle Radar Topography Mission
SSM	Surface Soil Moisture
STARS	Soils Training and Research Studentships
SVR	Support Vector Regression
SWIR	Short Wave Infrared
TDR	Time Domain Reflectometry
TDT	Time Domain Transmissometry
TIR	Thermal Infrared
UKCEH	United Kingdom Centre for Ecology and Hydrology
VV	Vertical-Vertical (polarisation)
VWC	Volumetric Soil Moisture
WCM	Water Cloud Model

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1 Introduction

1.1 Need for field-scale soil moisture

Soil moisture (SM) is one of the key parameters in the engineering, agronomic, geological, ecological, biological and hydrological functions of soil. For example, soil moisture is important to understand in the context of civil engineering and landslide risk assessment and mitigation. It is an important, but often unknown, input to meteorological models as the ability of the soil to exchange water and heat with the atmosphere has a strong effect on local weather. Soil moisture data is of particular value in agriculture to understand when the soil is approaching the wilting point of the crop (indicating that irrigation is required) (Adeyemi et al., 2017; Molden and James, 2000) in order to maximise yields whilst conserving water resources. This is important to global food security working towards the United Nations' Sustainable Development Goal 2 (SDG2) to "End hunger, achieve food security and improved nutrition and promote sustainable agriculture" (United Nations, 2021). At the local level it informs farmers in their decision making, not only for irrigation but to know when it is possible to move vehicles and when the soil can be worked effectively (Earl, 1997). Run-off is also an issue for farmers who should avoid spreading fertilisers on saturated soil to prevent nutrients polluting watercourses and causing algal blooms, killing fish by reducing the oxygen in the water. For flood risk analysis, it is important to know how close the soil is to being saturated (Alvarez-Garreton et al., 2014; Brocca et al., 2017a) to assess how much water runoff may result from forecast rainfall. Soil moisture varies between fields due to differences in the crops being grown, their state of development, soil texture, topography and irrigation and drainage.

The only direct method of measuring soil moisture is by collecting soil samples in the field and weighing them before and after drying them in a laboratory oven. Other methods estimate soil moisture by measuring electrical or optical properties

of soil, which includes sensors in and on the ground, remote sensing approaches, including optical, thermal and microwave. Satellites are the preferred platform from which to collect remote sensing data to achieve national and global SM coverage with regularly updated measurements.

1.2 Requirements

1.2.1 Practitioners

Practitioners who have a potential requirement for soil moisture data include farmers and those who manage grassland for recreation. These users need data to inform decision making in irrigation, the application of fertilisers and pesticides, and assessment of the firmness of the ground. Farmers need to assess whether the soil is trafficable and workable for their tillage and harvesting operations. Other users have similar needs, such as racecourses in assessing the "going" – an indication of turf conditions for horse racing.

Precision irrigation requires a closed-loop control system with soil moisture being monitored at around the level of 1% soil moisture by volume (vol.%) (Soulis et al., 2015) with, at least, daily updates. Satellite remote sensing is more likely to satisfy the needs of more common irrigation practices which use a crop-dependent maximum allowable depletion (MAD) level at which to trigger irrigation. The soil can be allowed to dry to MAD without causing the crop any water stress. MAD is typically about half of available water (AW), midway between the permanent wilting point (PWP) (Veihmeyer and Hendrickson, 1928) and the field capacity (FC) (Veihmeyer and Hendrickson, 1931) of the soil, which vary according to soil texture. To separate MAD and PWP successfully, the estimation error must be no more than a quarter of the AW. In Table 1.1 this error is calculated for five UK soil series which range from sand to clay. This is shown as error (a) and is in the range 3.75 vol.% to 5.3 vol.%. A review and survey by Moran (2000) and Moran et al. (1997) concluded that a once or twice weekly measurement of SM with 75% accuracy at a 20 m spatial resolution was desirable. Though not specified by the authors, the quoted accuracy target is assumed to relate to Soil Moisture Index (SMI) – the range of soil moisture conditions from driest to wettest. For the same five UK soil series, the maximum expected range of SM values was calculated to be between 28 and 52 vol.%. A 25% error equates to between 7 vol.% and 13 vol.%, depending on the soil texture, and is shown as error (b) in Table. 1.1. A third piece

of evidence is taken from Kerebel et al. (2010) who found, in a typical field, a SM noise level of around 5 vol.%, which suggests a more accurate measurement than this may not be achievable.

Table 1.1: Estimates of acceptable SM errors for irrigation scheduling. Calculated from soil hydraulic parameters for six UK soil series, representing typical soil characteristics in the upper (A) soil horizon under arable land use. Source of data is LANDIS (Proctor et al., 1998; Cranfield University, 2017). w_{wp} is permanent wilting point (PWP), w_{fc} is field capacity (FC), θ_s and θ_r are van Genuchten model parameters defining the upper and lower limits of soil moisture movement. Max error (a) is a quarter of AW available water, $0.25(w_{fc} - w_{wp})$. Max error (b) is $0.25(\theta_s - \theta_r)$

Soil Series	Type	w_{fc} vol.%	w_{wp} vol.%	Max error (a) vol. % $0.25(w_{fc} - w_{wp})$	θ_s vol. %	θ_r vol. %	Max error (b) vol. % $0.25(\theta_s - \theta_r)$
Wensum	Clay	55.5	35.7	4.95	73.98	21.51	13.12
Sollom	Sand	23.5	8.5	3.75	47.04	3.94	10.78
Munslow	Silt Loam	39.6	18.4	5.3	35.78	7.1	7.15
Grove	Clay Loam	42.8	24.4	4.6	41.93	10.25	7.92
Stixwould	Clay	50.6	31.4	4.8	59.69	16.35	10.84
Wyre	Clay	49.5	29.9	4.9	57.07	15.10	10.49

For trafficability and workability assessment, Earl (1997) concluded that some soils became trafficable at a root zone soil moisture deficit of 5 mm, and workable at 10 mm. To differentiate between these conditions a soil moisture estimation accuracy of around 5 vol% may be required.

For the spatial resolution requirement, though Moran et al. (1997) suggests 20 m, or better, there will be some homogeneity within fields as they are the normal management unit for farming operations. Other than for precision irrigation, a single soil moisture estimate per field parcel should be sufficient to permit effective management decisions. In UK, the average field area in the UKCEH Land Cover Plus:Crops 2018 (Morton et al., 2020) dataset is 5.9 ha. The subset of these that are arable fields have an average area of 8.53 ha, which is less than a tenth of the area covered by a 1 km square pixel (100 ha).

Another key requirement for farmers is to prevent runoff during irrigation, but this is especially important when applying fertilisers to prevent pollution of watercourses. There is no defined requirement for soil moisture other than, for example, UK government guidance that the surface of the soil must not be waterlogged (Environment Agency (UK), 2018), which is taken to mean it must be below saturation. How far the soil moisture should be below saturation is not specified and would be a function of the amount of water that the farmer expects to apply with the fertiliser.

The agricultural requirements, such as they are from limited published studies,

Table 1.2: Estimates of Soil moisture information requirements for agriculture

Agricultural application	Accuracy vol. %	Spatial resolution (m)	Depth	Temporal resolution (day)	Latency (day)	Reference
Precision Irrigation	1%	20 m	Root Zone	$\lesssim 1$	$\lesssim 1$	(Soulis et al., 2015)
Common Irrigation	5-7%	20 m to Field parcel ($\lesssim 300$ m)	Root Zone	4-7	$\lesssim 1$	1.1, (Moran et al., 1997; Moran, 2000; Kerebel et al., 2010)
Trafficability	5%	20 m to Field parcel ($\lesssim 300$ m)	Root Zone and Surface	< 4	$\lesssim 1$	(Earl, 1997)
Workability	5%	Field parcel ($\lesssim 300$ m)	Root Zone and Surface	< 4	$\lesssim 1$	(Earl, 1997)
Fertiliser application	No data	Field parcel ($\lesssim 300$ m)	Surface (5-10 cm)	$\lesssim 1$	$\lesssim 1$	(Torbert et al., 1999)

are summarised in Table 1.2. The majority of the requirements of farmers and agriculturalists would be satisfied by remote sensing product that would give them an estimate, to 5 vol.% accuracy, of in-field surface soil moisture, every 1-6 days, delivered by value-added web or mobile apps. The latency (delay between image capture and data availability) should be no more than 1-2 days. This would be of immediate benefit for decision making in managing crops, especially in avoiding pollution when spraying or spreading fertilizer and for workability assessment and livestock welfare. The estimation of root zone soil moisture could follow as a next step and would be valuable for selection of crops, rotation, and livestock.

1.2.2 Research

Soil moisture data from remote sensing is used for research purposes mainly as inputs to land surface models and numerical weather prediction to minimise drift and for data fusion. SMOS satellite sensor (European Space Agency, 2017) was specifically designed for this purpose. Its system specification is to achieve an accuracy of 4 vol.% in soil moisture estimation. This was chosen as an acceptable noise level suitable to enable soil evaporation models to be fitted to the satellite observations (Chanzy et al., 1995). Research teams now require higher temporal and spatial resolution SM estimates from satellites, but they would have to operate at similar levels of accuracy. For example, the spatial resolution of SMOS being 35 to 50 km, is not sufficient for catchment level modelling, and current ambitions are to achieve reliable SM estimation at 1 km resolution or better (Peng et al., 2021).

Though the research requirements may be satisfied by a gridded product, the advantage of a field-scale product is higher resolution allowing the exclusion of densely vegetated and wetland areas and most radar clutter sources (buildings, masts, roads) that are located outside field boundaries.

1.3 Retrievals of soil moisture

1.3.1 Ground sensors

Soil moisture sensors

In-situ soil moisture retrieval techniques include sensors, often in the form of probes, to measure the moisture by electrical means, such as resistivity or capacitance, frequency or time domain reflectometry (TDR). They are often used on a local basis to control irrigation. There are also a number of networks of in-situ sensors that are used for research purposes, including the validation of remote sensing soil moisture products. For example, the SMOSMANIA network (Calvet et al., 2007) in the south of France was installed to validate soil moisture retrievals from the SMOS passive microwave sensor. Another example is FLUXNET (Baldocchi et al., 2001), a global network of over 250 meteorological instrumentation sites that measure fluxes of trace gases between ecosystems and atmosphere by the eddy covariance method; a high proportion of these sites include direct soil moisture measurements. The International Soil Moisture Network (ISMN) (Dorigo et al., 2013) provides an accessible resource for accessing soil moisture networks such as these to inform scientific studies and validate remote sensing retrievals of soil moisture.

Soil moisture sensors can be impractical to install over large areas of land as their installation is costly and requires connectivity and power. They are also prone to uncertainty due to unreliable contact with the soil due to soil cracking, worm and root holes and air pockets. Such sensors only measure the soil moisture at a point, so are prone to uncertainty due to the heterogeneity of the soil. Several sensors are normally needed, spread across an area, to sample this diversity, addition to cost and complexity.

The relationship between soil electrical properties and moisture is also dependent on the soil texture, out of the box most sensors are calibrated for a typical soil and will have a quoted accuracy of around 5%. To obtain the maximum accuracy

of around 3% requires the sensor to be calibrated for the soil in which it is installed.

Ground sensor networks are not sufficiently dense to create a nationwide soil moisture map from them or provide field-scale information. The most scalable solutions tend to be based on modelling or remote sensing as they do not require the provision of sensors on the ground with their associated installation costs, connectivity and power provisioning challenges.

Cosmic ray neutron sensors (CRNS)

CRNS ([Andreasen et al., 2017](#)) were developed to overcome the disadvantages of point probe sensors. They exploit the absorption of fast neutrons, generated by cosmic rays, by hydrogen atoms in water molecules in the soil. The fast neutron counts from a volume of soil are inversely related to moisture content. The sensors are installed above ground, non-invasively, measuring the average soil moisture in a volume of soil contained in a radius of approximately 200 m ([Köhli et al., 2015a](#)), with average sensitivity depth of about 10 cm, both dimensions varying slightly with soil moisture. CRNS sensors are relatively expensive, in the region of £10k plus the site setup and calibration. Examples of CRNS networks are in the USA, Germany, Australia, India and South Africa ([Zreda, 2016](#)). The UK Centre for Ecology and Hydrology (UKCEH) has established a nationwide network of around 50 CRNS stations that comprise the COSMOS-UK network ([Evans et al., 2016](#); [Cooper et al., 2020](#)). An example of a COSMOS-UK site, at Cwm Garw in Wales, is shown in Fig. 1.1.

The COSMOS-UK network is important to the methodology of this thesis. The instrumentation at these sites ([Cooper et al., 2021](#)) includes the CRNS soil moisture sensor, a pair of wide angle cameras providing a 360 degree panorama of the site surroundings ("phenocams"), a number of soil moisture probes (which may include a soil moisture profile probe) and a meteorological station. Direct measurements are taken every 30 minutes of precipitation, absolute and relative humidity, air temperature, atmospheric pressure, incoming and outgoing long-wave and short-wave radiation, wind direction and speed, 3D wind speed, soil volumetric water content and temperature (at 5, 10, 15, 25, 50 cm depths), soil heat flux, snow depth, and, where fitted, profile soil volumetric water content.

The COSMOS network also reports the following derived data ([Cooper et al., 2021](#)) on a daily or hourly basis. These include the wider areas soil volumetric water content calculated from the CRNS output, the typical sensing depth of the

CRNS (D86), net radiation, and potential evaporation.

The primary soil moisture sensor at each site is the CRNS ([Andreasen et al., 2017](#)), which has a measurement footprint of approximately 200 metres in diameter ([Köhli et al., 2015b](#)). By mitigating against the spatial heterogeneity of soil hydraulic properties, CRNS data is more suited to validation of remotely-sensed soil moisture products without having to upscale the measurements from a densely spaced network of point sensors. The conversion of neutron counts to volumetric soil moisture is by a process described in [Ball et al. \(2020\)](#) with a reference soil moisture being obtained occasionally by soil sampling at each site. A large number of soil samples are taken in a spatial pattern up to 75 m from the CRNS sensor and at various depths ([Cooper et al., 2021](#)). The volumetric soil moisture of each sample is determined to high accuracy in the laboratory. The mismatch in scales between the CRNS and the installed TDR probes means that the latter are not suitable for calibration of the CRNS, notwithstanding the noise and errors that are also seen in the point probe data. The probes have not been calibrated to match the soil type at each site and will be less accurate as a result. The CRNS derived soil moisture content is expected to be a more accurate representation of the average soil moisture at the COSMOS site despite the uncertainties that will apply to the use of a model to derive it. These uncertainties are greatest where the soil might be exceptionally wet or dry or have a high organic matter content (such as peaty soils), or where the depth of soil is very shallow. The need to average noise means that soil moisture is not normally derived with less than 24 hours of counts.



Figure 1.1: Example of a COSMOS-UK soil moisture monitoring station at Cwm Garw, Wales. The Cosmic Ray Neutron Scattering (CRNS) soil moisture sensor is housed in the white tube on the right, vertically mounted, behind the solar panels. Image from COSMOS-UK website ([UK Centre for Ecology and Hydrology, 2021](#)).

1.3.2 Remote sensing solutions

Table 1.3 reviews a number of remote sensing technologies for soil moisture retrieval, and soil moisture products derived from them. These are also discussed, by type, in more detail in the following paragraphs.

Visible and near infrared (VNIR)

Multi-spectral optical imaging in the VNIR part of the electromagnetic spectrum is a long-established remote sensing technology for land-cover analysis at high spatial resolution (~30m). Satellites, such as the US Geological Survey's Landsat series (U.S. Geological Survey, 2021) being launched in the 1980's, have been joined more recently by the European Space Agency's Sentinel-2 (Drusch et al., 2012). These satellite sensors can achieve the highest spatial resolution (30 m for Landsat, 10 m for Sentinel 2, with future potential of 1 m) and would be very suited to field-scale or sub-field scale soil moisture estimation. The retrieval of soil moisture from such data (Periasamy and Shanmugam, 2017) exploits the dependence of the optical reflectance of bare soil on moisture content. However, the process is very complex with vegetation obscuring the soil, atmospheric effects, obscuration by clouds, and illumination (day/night) dependence. No operational soil moisture product has yet been established, although the optical trapezoid model (OPTRAM) (Sadeghi et al., 2017a) may be the first to achieve this. OPTRAM uses either Landsat8 or Sentinel-2 images and expects to provide soil moisture estimates at 120 m resolution every 2-16 days with a root mean square error (RMSE) of 4-5%. in volumetric water content (vwc) The prevalence of clouds in countries such as the UK is likely to be a severe limitation with large gaps in valid measurements being likely.

MARMIT for Soil Moisture Content (Bablet et al., 2018) is another example of a VNIR soil moisture retrieval algorithm that has been applied to data collected with drone-mounted cameras (Li et al., 2021) to achieve high-resolution soil moisture estimates with an RMSE of 3-5% vwc. The advantage of the drone platform is that they can fly under clouds and the atmospheric effects are significantly lessened. It would, however, be impractical to provided daily estimates by this method other than in very limited areas.

Thermal infrared (TIR)

TIR is also relatively mature as a satellite sensor technology, but the longer wavelength limits the spatial resolution; for the ASTER TIR sensor this is only 90 m resolution (Abrams, 2000). Soil moisture retrieval by TIR exploits the relationship between the thermal inertia of soil its moisture content (Hain et al., 2009). In common with VNIR remote sensing, vegetation obscuring the soil, atmospheric transmission, cloud cover and time of day are significant limitations and add complexity. A research level soil moisture retrieval experiment based on MODIS TIR data (Matsushima et al., 2018) demonstrated that an RMSE of 4-5% vwc was achievable at 120m spatial resolution, every 1-2 days. No operational soil moisture product is yet available based on TIR remote sensing.

Passive microwave remote sensing

Passive microwave sensors (microwave radiometers) (Drinkwater et al., 2009) exploit the relationship between the moisture content of bare soil and its microwave emission, which is biased towards the lower frequencies at L-band (~1.4 GHz, e.g. SMOS (European Space Agency, 2017)) or P-band (~750 MHz) (Ye et al., 2021). The effect of clouds and atmosphere is negligible compared to optical and infrared bands, and measurements may be equally well made at night. Vegetation is fully or partially transparent and has a small impact on estimation uncertainty. Soil moisture maps derived from passive L-band mi-

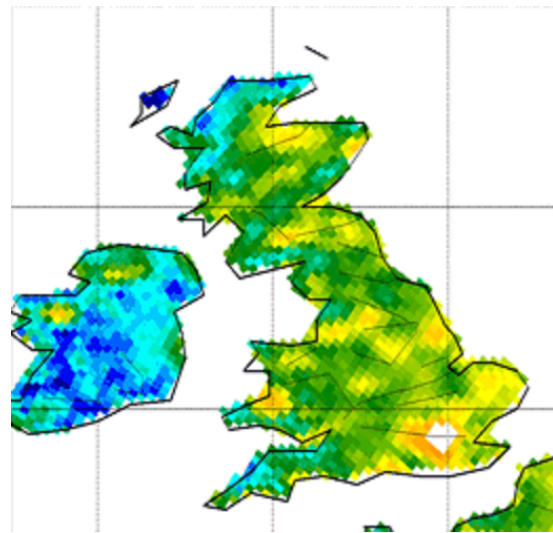


Figure 1.2: Example of a soil moisture product with 50 km pixel resolution based on the SMOS passive, L-band, sensor. The image indicates relative soil moisture across the UK in November 2001 (image credit ESA), colours indicating dry conditions (orange) to wettest (blue).

crowave satellite data such as SMAP (Entekhabi et al., 2010), SMOS (European Space Agency, 2017; Al Bitar et al., 2017) (see Fig.1.2) have been available for some years. Other products are available at other frequencies, such as AMSR2/GCOM-W1 surface soil moisture (Kim et al., 2015) (6.9, 7.3 & 10.7 GHz) and MWRI soil moisture (Parinussa et al., 2014) (X-band). Common to all of these passive microwave products is a low spatial resolution of 10 to 50 km (Petroopoulos et al.,

2015; European Space Agency, 2017), making them highly suitable for regional and national studies, but of little direct use to satisfy field-scale requirements. Though challenging to validate through ground measurement (Clewley et al., 2017), passive microwave soil moisture retrievals are regarded as relatively reliable and accurate across a broad range of land-cover and conditions, with the RMSE of L-band products of around 4-6% vwc (Li et al., 2020). The higher frequency products are less consistent due, probably, to vegetation effects and vary between an RMSE of 5-17% vwc.

Active microwave

Active microwave systems split into three types; scatterometers (Bartalis et al., 2007) are non-imaging sensors originally intended to detect wind speed through scattering, radar altimeters (Uebbing et al., 2017) are also non-imaging microwave systems designed to investigate ocean surfaces, and synthetic aperture radars (SAR) which form a high resolution image. In all cases they measure the backscatter of a microwave beam from the ground in terms of the radar backscatter coefficient, sigma nought (σ^0). The soil component, σ_{soil}^0 is related to its relative permittivity, which is a function of soil moisture (Oh et al., 1992) and soil texture. σ_{soil}^0 is also a function of the roughness of the soil surface, the isotropy of the scattering mechanism, and the local incidence angle of the microwave beam. If vegetation is present, it has its own backscatter signal, σ_{veg}^0 , and acts as an attenuating medium for both the microwave beam and backscatter from the soil (Bindlish and Barros, 2001), such that the received backscatter is approximately given by

$$\sigma^0 = \sigma_{veg}^0 + \tau^2 \sigma_{soil}^0 \quad (1.1)$$

where τ^2 is the vegetation transmission in two directions. This neglects the more complex interactions between the vegetation and the soil, which are relatively minor. Both τ^2 and σ_{veg}^0 are a function of the moisture in the vegetation, its density and the amount of soil covered by the vegetation. All active microwave systems are affected in their ability to measure soil moisture by enhanced backscattering due to surface roughness (on a scale comparable to the wavelength) and scattering by vegetation. Both effects are more significant as the wavelength reduces (Lang and Sighu, 1983; Martinez-Agirre et al., 2017). An operational soil moisture product is available derived from the ASCAT C-band scatterometer (Wagner et al., 2013; Brocca et al., 2017b) carried on the Metop satellites. This provides an estimate of

SM, almost daily, at 12.5 or 25 km resolution, with an RMSE less than 4% in vwc. Due to the wavelength being shorter than L-band, it is slightly more affected by vegetation, and would be expected to have lower performance in highly vegetated areas.

Synthetic aperture radar (SAR)

Synthetic aperture radar (SAR) sensors are imaging radar systems, whose large aperture produced high resolution images. Many L, C and X band SAR sensors are now available on platforms with data that is freely or commercially available. Their spatial resolution, frequency of measurement and all-weather performance most closely match the aspiration of near real-time field-scale soil moisture estimation. For example, since 2015 Sentinel-1 C-band data (Torres et al., 2012) has been available for free through ESA with spatial resolution of around 20 m. An example of Sentinel-1 imagery is shown in Fig. 1.3. Areas of dense vegetation (trees, and hedges) show as mid grey, clutter sources as bright white areas, and most cultivated fields are darker. Areas of water appear black.

Due to the problems with scalability of ground sensors, availability of cloud-free multispectral satellite images, and the low spatial resolution of the passive microwave systems, much of the recent research activity is focused on this type of sensor and Sentinel-1 in particular.

The Copernicus SSM product (Bauer-Marschallinger et al., 2019) has been available since 2018 with pre-operational status. It is understood that its accuracy of up to 8% vwc is not yet on a par with existing products, to be considered an operational. However, with a spatial resolution of 1 km and with a retrieval every 1-2 days over northern Europe, this is close to meeting the requirements of field-scale applications and is the focus of detailed study in this thesis.

Soil moisture products derived from multiple platforms

Among several emerging products based on the fusion of data from multiple sensors and platforms, two examples are the Copernicus Soil Water Index (SWI) and ESA Climate Change Initiative Soil Moisture (ESA CCI SM). Copernicus SWI fuses Copernicus SSM data with ASCAT-derived soil moisture to improve on the accuracy of the former whilst retaining its spatial and temporal resolution. An RMSE of 4-6% is reported (Bauer-Marschallinger et al., 2018). The objective of ESA CCI SM is rather different, it aims to provide a long time sequence of soil moisture

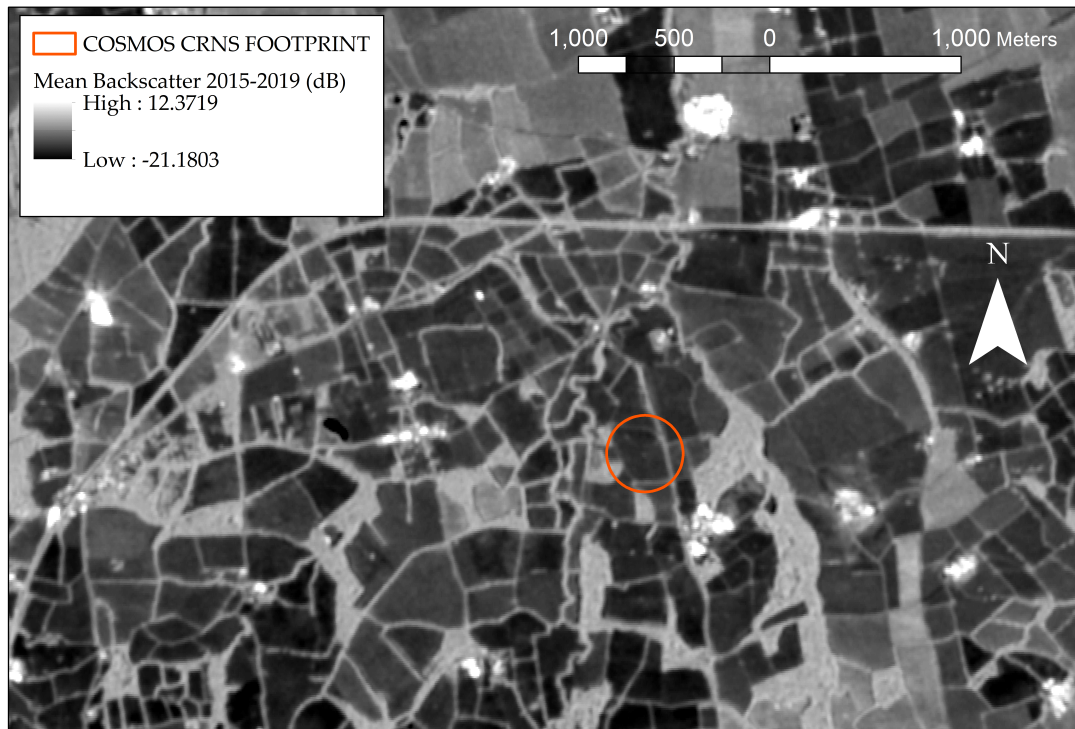


Figure 1.3: Greyscale image indicating mean C-band SAR backscatter from the Sentinel-1 satellites over 4 years, from 2015 to 2019. The area surrounds the test site at North Wyke, Devon, UK, which hosts a COSMOS-UK soil moisture monitoring station. The nominal 200 m soil moisture sensitivity footprint of its Cosmic Ray Neutron Sensor (CRNS) is shown as the red circle.

retrievals based on remote sensing for long-term studies, and combines passive and active sensors and their derived products. The spatial resolution is 0.25° with daily values reported to a reported accuracy of 6% vwc (EODC, 2021).

1.3.3 Influence of spatial heterogeneity

Higher resolution sensors and products are more likely to sample the field-scale spatial variability of land cover and soil moisture. The performance level will vary significantly between pixels according to that expected of the individual land cover types and conditions. Lower spatial resolution products will include, within each pixel, a mixture of responses according to the heterogeneity of land cover and land use. The SM estimation performance will be averaged and less variable. In the case of SAR there will also be a beneficial effect through the reduction of spatial noise due to speckle. For these reasons SAR products are often published at much lower resolution (1 km or over) than the sensor that collected the data. Beside the loss of higher spatial frequencies, this approach risks including persistent scattering

sources and significant areas of man-made landscapes, which may result in poor soil moisture retrieval performance.

1.4 Retrieval of soil moisture from SAR data

The retrieval of soil moisture analytically is very complex, requiring a number of physical and empirical models of microwave backscatter from soil and covering vegetation (Brown, 1985). The models were developed to predict soil backscatter from a range of input conditions, so soil moisture retrieval involves reversing the model to find a set of input conditions that produced the observed backscatter value. There will be a wide range of soil moisture amongst those possibilities, so the values of the other inputs have to be measured or estimated to reduce the solution space to a unique value. In general, the values of parameters such as soil surface roughness, vegetation biomass and even soil texture are not well known, and therefore a severe limitation.

Many semi-empirical models (Choker et al., 2017) and algorithms have been proposed. For example, machine learning techniques (Gupta et al., 2017; Bazzi et al., 2019), neural networks (Alexakis et al., 2017) and genetic algorithms (Davies et al., 2007) have been applied to this problem. They establish links between soil moisture and combinations of data from multiple sources including SAR. Some of these data will be proxies for the other contributing factors. For example, the data might include a soil texture map and a vegetation index from an optical sensor. Models and neural networks are trained against in situ soil moisture measurements and their performance will only be satisfactory within the range of parameters and geography on which they are trained (Jain and Singh, 2017; Padovano et al., 2017). This is a problem if such a solution is to be scaled to national coverage and beyond.

Statistical and temporal algorithms, such as change detection (CD) (Novak, 2013; Wagner et al., 1999; Hornacek et al., 2012; Pathe et al., 2009; Mattia et al., 2018), that do not require training or auxiliary data, are attractive for developing near real-time field-scale maps. The CD algorithm estimates soil moisture by calibrating the backscatter against the limits of all previously measured values at each location. It is the basis of the first public accessible soil moisture product at global scale (Copernicus Surface Soil Moisture (SSM) - (Bauer-Marschallinger and Paulik, 2019)). However, key assumptions, that soil surface roughness and vegetation vary slowly relative to soil moisture, contradict farming practice. Tillage and crop harvesting break these assumptions where arable crops are grown. The

Table 1.3: Status of soil moisture products derived from remote sensing

Type	Product	Technique	Reference	Platform(s)	Resolution	Repeat	RMSE	Status
VIS/NIR	Not yet available	MARMIT for SME	Li et al. (2021)	Short range/drone	n/a	n/a	3-5%	Research
VIS/NIR	Not yet available	OPTRAM	Sadeghi et al. (2017b)	Landsat8 & Sentinel-2	120m	16 days (L8); 2-5 days S2	4-5%	Emerging operationally
Thermal Infrared	Not yet available	Thermal Inertia	Matsushima et al. (2018)	MODIS	1km	1-2 days	4-5%	Research
Passive Microwave	Soil Moisture Active Passive (SMAP) SM	L-band; SCA-V	Entekhabi et al. (2010)	SMAP	3/9/36km	1-3 days	<4%	Operational
Passive Microwave	SMOS12 SM product	L-band Microwave Imaging Radiometer with Aperture Synthesis (MIRAS)	Al Bitar et al. (2017)	SMOS	25km	2-3 days	4-6%	Operational
Passive Microwave	AMSR2/GCOM-W1 surface soil moisture	Land Parameter Retrieval Model (LPRM). Data at 6.9; 7.3 & 10.7 GHz	Kim et al. (2015)	AMSR2	10km	Daily	6-10%	Operational
Passive Microwave	MWRI SM	X-band, single channel algorithm or LPRM	Parinussa et al. (2014)	Fenyung FY3B/C	25km	Daily	5-17%	Operational
Active Microwave	ASCAT SM	C-band Scatterometer	Wagner et al. (2013)	Metop	12.5km / 25 km	Daily (irregular)	<4%	Operational
Active SAR	Copernicus SSM	Change Detection	Bauer-Marschallinger et al. (2019)	Sentinel-1	1km	2-6 days	<8%	Available/Pre-operational
Active Microwave / SAR	Copernicus SWI	Fusion of Sentinel-1 C-band SAR and ASCAT. Two-layer water balance model	Bauer-Marschallinger et al. (2018)	Metop (ASCAT) and Sentinel 1	1km	2-6 days	4-6%	Operational
Fusion of several data sources	ESA CCI SM Passive / Active / Combined	Fusion of several products including some listed above	EODC (2021)	ESA-CCI	0.25°latitude and longitude	Daily	6%	Operational

Copernicus SSM product is published at a spatial resolution of only 1 km, which averages the SAR backscatter over, perhaps eleven fields and other non-cultivated areas. Any arable farming activity within a few of these fields will have a lesser overall impact at the pixel level. If an alternative solution can be found, the full spatial resolution of C-band SAR sensors, from which field-scale SM estimates should be possible.

Synergistic methods fuse multiple observations from different systems (Kuenzer et al., 2013) to provide a more accurate capability than any one system can provide. Examples include combining SAR with optical and thermal infrared sensors data (Hain et al., 2012) or passive microwave radiometers (Liu et al., 2012; Tomer et al., 2016). Statistical techniques such as triple collocation analysis (TCA) have been successfully attempted (Gruber et al., 2017). TCA estimates the random errors in three soil moisture datasets where accurate ground measurements are not available. Scaling parameters for each data set can be optimised to minimise uncertainty in the fused result. In-situ networks such as COSMOS-UK could be used in this context as a source of independent observation. Unfortunately, many of the remote sensing datasets are not field scale, or are prone to unavailability due to cloud cover. Spatial down-scaling is an alternative approach where a coarse resolution moisture map derived from ground measurements or from long-wavelength (e.g. L band) microwave and SAR sensors is refined into a higher resolution map by use of the higher frequency C-band SAR data (Peng et al., 2016; Peng and Loew, 2017; Schneider et al., 2014), but this assumes that the average intensity of the C-band data is correlated to soil moisture over a given area, which may not be the case.

1.5 Knowledge gaps

The use of active microwave (SAR) satellite imaging appears to be the only reliable route to achieving an unprecedented capability in field-scale soil moisture measurement in the UK. The freely available high-resolution C-band data from the ESA Sentinel-1 satellites (Torres et al., 2012) make this a highly attractive option even though C-band SAR is affected more by vegetation than, say, L-band Tsan Mo et al. (1984). The analysis of Sentinel-1 data to retrieve soil moisture has been the subject of intensive research recently with over 325 papers published on the topic since 2011 (4 years before launch). Despite this, there is not yet an operational published dataset at the field scale, the nearest being at 1 km resolution (Bauer-

Marschallinger and Paulik, 2019), where the pixels are an order of magnitude larger than the average UK arable field.

Several approaches have been reported that aim to derive field-scale soil moisture estimates from Sentinel-1. Among these are machine learning algorithms (Bazzi et al., 2019) which require training on ground observations and therefore challenge to scale up to national capability and beyond. The first field-scale results from the change detection type approach were not reported until 2020 (Mattia et al., 2020). This solution substituted 1 km scale data whenever the field-scale data was judged to be unreliable, so is actually of variable resolution. The first need was to establish which of these approaches was most likely to achieve a field-scale product.

In November 2018, the Copernicus Surface Soil Moisture (SSM) (Bauer-Marschallinger and Paulik, 2019) was published. As the first, global-scale, soil moisture product from Sentinel-1, based on the change detection (CD) algorithm. Though a product validated product at 1 km resolution, the particular performance of this product for agricultural areas had not been published.

Few of the established SAR SM retrieval algorithms take account of soil physics in two key respects. The effect of soil texture is often avoided by the use of relative units of soil moisture index (SMI) (Hunt et al., 2009), leaving the end user to convert the values to volumetric units or soil moisture deficit, as required. The uncertainties introduced at this stage were therefore neglected. Validation results are often reported with scale-independent metrics such as the coefficient of determination, R^2 , between the soil moisture index and ground observations (Filion et al., 2016; Alexakis et al., 2017; Millard et al., 2018). Thus representing an optimistic case of what may be achieved in practice. The other issue that has been neglected is the dynamics of soil moisture as sensed by the SAR at the soil surface compared to that observed by ground sensors installed at 5 to 10 cm depth. The penetration depth of a C-band SAR is only 0.5 to 2 cm into the surface (Nolan and Fatland, 2003) and will appear to have relatively more noise due to more variability in SM at this shallower depth.

The Copernicus SSM SM product, as an example, uses a nominal 1 km resolution pixel, which covers an area more than ten times larger than the average size of arable fields in the UK. It will also cover other land uses including non-cultivated areas where the SAR will not be sensitive to soil moisture, such as roads, hedges, trees and buildings. Some will generate high intensity clutter noise in the SAR image due to rocky areas (Pasolli et al., 2011), reflective objects and multiple path

reflections from buildings and structures (Tadono et al., 2000). Excluding these areas will provide a performance boost at field-scale. On the other hand, field-scale SM will be subject to a, generally, higher (field size dependent) level of speckle noise (Barber et al., 2012) and the full impact of in-field changes in vegetation density and soil roughness. This trade-off space has not been explored before.

Due to the assumptions behind the CD algorithm of largely static vegetation and soil roughness contributions to backscatter, relatively poor overall performance was anticipated for arable fields. This was very clear in the initial assessment of the Copernicus SSM product. It was observed that this was due to a period of very poor performance in the main growth period of the crops, and that performance was better at other times. A research gap was identified to exploit this observation and to create a mitigation measure which aimed to provide an acceptable level of performance, at between 5 and 10 vol.% accuracy throughout the cropping cycle, whilst retaining field-scale resolution.

The temporal resolution of the soil moisture retrieval is also important for agricultural applications to allow timely interventions such as irrigation. The issues include both the frequency of SAR image collection and the latency between acquisition and actionable data being available to the end user.

1.6 Aims, objectives and thesis structure

The aim of the thesis was to establish **whether C-band synthetic aperture radar data from satellites can be used to map soil moisture (SM) at the field-scale**, particularly addressing the needs of agriculture in the UK. The objectives were set to achieve incremental progress towards meeting this aim, and are summarised as follows:

Objective 1 was to **evaluate and select from state-of-the-art SAR satellite SM retrieval algorithms for their potential to create field-scale resolution products**. This included a review of the capabilities and issues surrounding the retrieval of soil moisture from SAR backscatter.

Objective 2, to **assess the performance of existing Copernicus SSM product for agricultural fields**, arose from the timely publication of this product, based on a change detection algorithm, at the start of this research study. This objective was further sub-divided, with Objective 2a to **develop a validation method for C-band SAR derived surface soil moisture products at COSMOS-UK ground stations**. This was to produce a generic method for validation of C-band SAR-derived surface

soil moisture retrievals using the COSMOS-UK network specifically, but extendable to other in-situ monitoring networks. Objective 2b was then to **use this method to quantify the performance of Copernicus SSM in the context of agricultural land uses in the UK.**

Having established a baseline performance of a change detection algorithm at 1 km resolution through the Copernicus SSM product, Objective 3 was to **increase the spatial resolution of the change detection algorithm to achieve field scale output by using field parcel boundaries and to compare the performance levels to the 1 km gridded product.**

Finally, Objective 4 was to **demonstrate an improvement in performance of the field scale algorithm by correcting for the influence of crop cover and anthropogenic change and identify a route to scale this to UK national coverage with acceptable temporal resolution.**

Figure 1.4 sets out the structure of the thesis and how the paper format chapters (2 to 5) link to the objective and the overall aim. Chapter 2 investigates the significance of soil properties to the estimation of soil moisture from C-band synthetic aperture radar and sets the scene for the choice of change detection algorithm for focus in the thesis. This addresses Objective 1. Chapter 3 then addresses the first half of Objective 2 by proposing a new method for assessing the performance of SAR-derived surface soil moisture products. This methodology will be used throughout the remaining chapters and builds on the output of the first chapter by including the effect of soil texture in the assessment, and in the conversion of relative soil moisture indices to volumetric units. Chapter 3 uses this methodology to assess the performance of the Copernicus SSM produce in arable fields, partly satisfying the second part of Objective 2. In Chapter 4, the field scale implementation of the change detection algorithm is completed and this product is then used to complete the assessment of performance at arable field, completing Objective 2(b). The production of a prototype field-scale SM product that was of an improved noise level satisfied Objective 3. Finally, in Chapter 5, Objective 4 was met by the proposed method to produce an improved field-scale soil moisture estimate by spatial interpolation that would yield acceptable accuracy at all stages of arable crop development. Overall, this satisfied the aim of the thesis by demonstrating that it is, indeed, possible to develop a field-scale soil moisture product from Sentinel-1 C-band SAR data. The final chapters, 6 and 7 discuss the findings in detail, draw final conclusions and present ideas for future work. The references are listed at the end of each chapter.

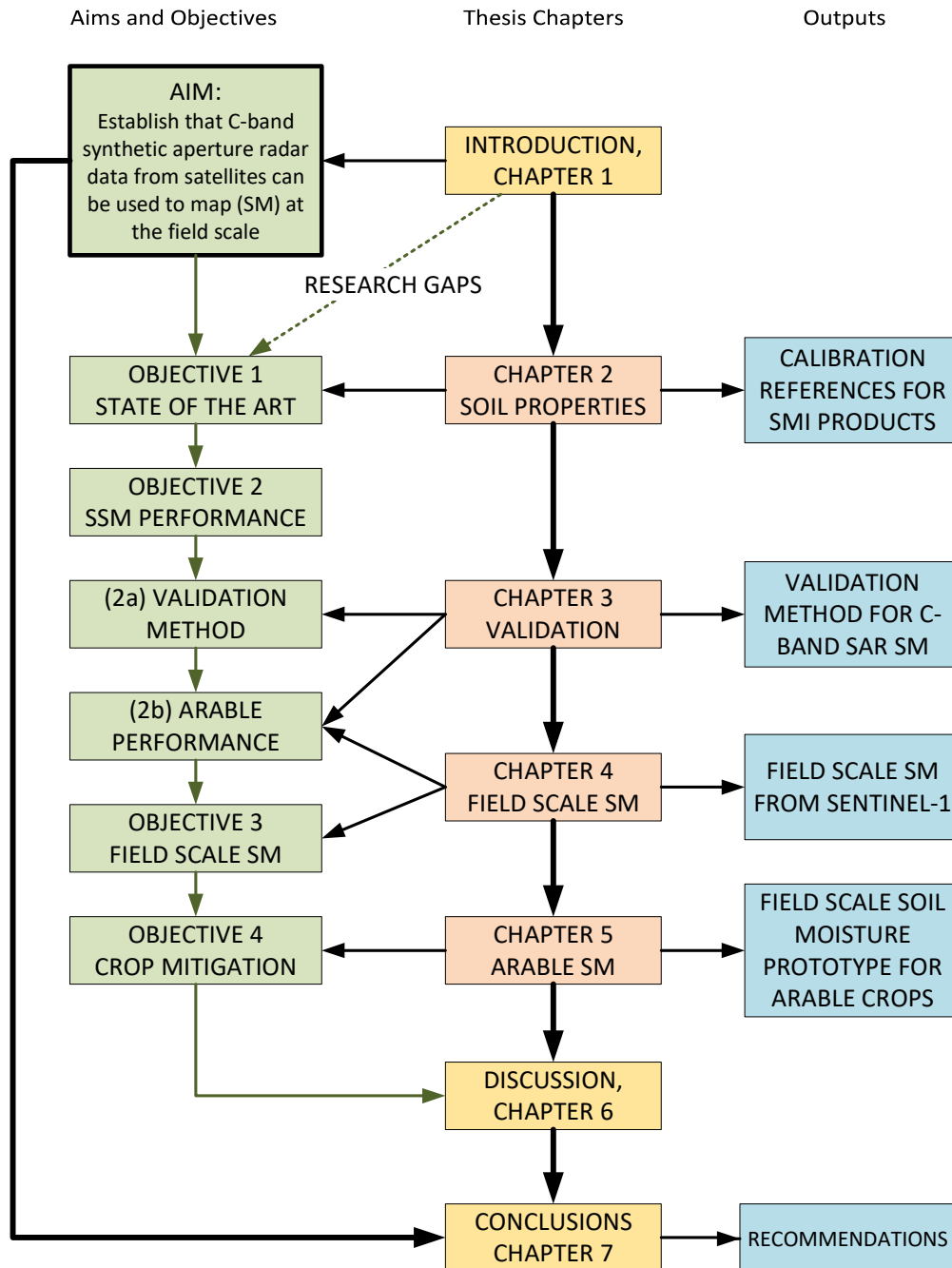


Figure 1.4: Thesis structure showing how the paper format chapters (2-5) in orange map to the aim and objectives (in green), and the main outputs (in blue).

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2 Significance of soil properties to C-band SAR estimation of soil moisture

This paper format chapter examines the role and significance of soil texture and other factors in the retrieval of soil moisture from C-band SAR. It concludes that soil texture is crucially important to the conversion of data supplied in relative, index form to absolute values, and should be considered holistically as part of the problem. The freezing of soil is a key issue to be addressed and soil roughness parameters might be predictable, to some extent, by soil texture where the land is under arable cultivation.

Abstract

Soil Moisture is a key variable in agriculture, hydrology, weather and climate modelling. Satellite-based remote sensing, particularly C-band SAR (such as Sentinel-1), has the potential to provide wide area soil moisture estimation at the field scale that many agricultural applications require. However, many current data products are aggregated to a spatial resolution of at least 1km and/or provide soil moisture in terms of soil moisture indices to mitigate the effects of unknowns such as soil roughness, soil hydrological properties and vegetation. Despite the existence of geospatial datasets of soil properties and land use, such data is rarely exploited as the impact of soil texture on soil moisture retrieval is assumed to be relatively minor. Using a modelling approach, we demonstrate here that soil properties, and in particular soil texture, can contribute significantly to the relative permittivity of the soil. This is equivalent to a 10 to 20 vol.% range in retrieved soil moisture by model inversion, and up to 7.5 vol.% range due to soil organic matter. In the conversion of soil moisture indices to volumetric soil moisture, soil texture contributes to a range in SM values of between 18 vol.% and 38 vol.%. Additionally, we show that soil texture is correlated with soil surface roughness for agricultural fields. This could provide a basis for estimating soil roughness parameters following farming operations such as primary tillage. The change in relative permittivity of the soil when it freezes leads to a significant underestimate of the soil moisture. This error is proportional to soil texture could be corrected for rather than flagging or masking the affected areas. The results of this study show that soil properties are important to soil moisture retrieval, especially when considering field-scale resolution over arable agricultural areas.

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2.1 Introduction

Soil Moisture (SM) is a key input to decision making in agriculture and a key variable in hydrology, weather and climate models (Alvarez-Garreton et al., 2014; Brocca et al., 2017; Dorigo and de Jeu, 2016; Entekhabi et al., 1996). Demand for regional and national SM estimation is being addressed through a combination of modelling, in-situ measurement (Andreasen et al., 2017; Evans et al., 2016) and remote sensing (Petropoulos et al., 2015). For agricultural purposes, such as control of irrigation (Adeyemi et al., 2017; Molden and James, 2000), knowledge of SM variability at the field scale is important due to differences in land use, soil properties, drainage, tillage, vegetation and other factors. Synthetic aperture radar (SAR) is favoured as a remote sensing solution for its ability to image through clouds, penetrate vegetation (Doerry, 2004) and for its high spatial resolution. C-band, 5.4 GHz SAR (Torres et al., 2012) data is now freely available through the Copernicus Open Access Hub (ESA, 2019) from the European Space Agency's Sentinel-1 (S1) satellites.

A common method to retrieve SM from SAR data is to analyse polarised backscatter, which is also driven by other factors, as illustrated by Fig. 2.1; the S1 backscatter image (σ_{VV}^0) shows a number of agricultural fields in eastern England, where the main sources of contrast in backscatter between adjacent fields will be vegetation (Lang and Sighu, 1983), soil surface roughness (Álvarez-Mozos et al., 2009; Martinez-Agirre et al., 2017) and soil moisture.

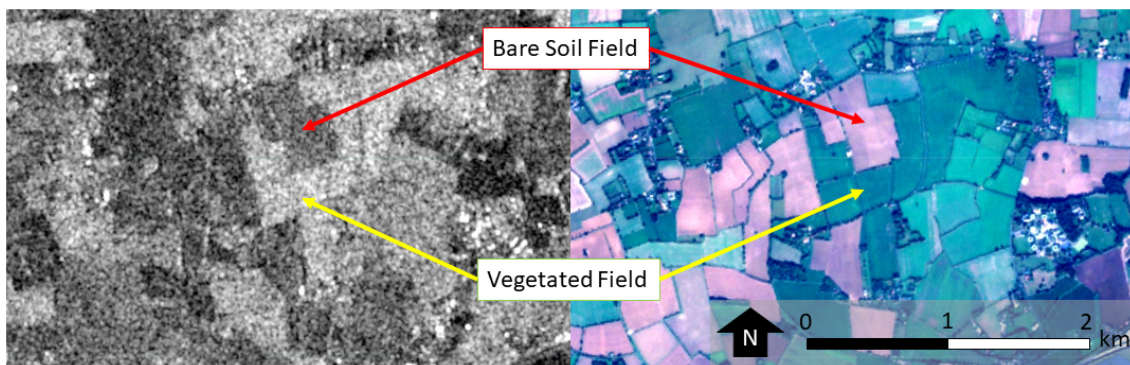


Figure 2.1: Example of Sentinel-1 SAR σ_{VV}^0 image (left) of agricultural fields at Morley in East Anglia, UK contrasted with natural colour imagery from Sentinel-2 (right). Date 11th October 2018. At this scale SM would be assumed to be similar for both bare and vegetated fields and yet the backscatter contributions are highly contrasting, demonstrating the potential impact of vegetation, surface roughness after tilling, and soil properties. Copyright European Space Agency - ESA, produced from ESA remote sensing data.

Unknowns such as the amount and condition of vegetation and the soil surface

roughness manifest as errors in SM estimation from SAR backscatter; these may be minimised by spatial averaging (Álvarez-Mozos et al., 2009) and temporal filtering (Mattia et al., 2009), or a mask may be applied to identify areas where SM is unreliable due to the land use (such as forested areas) or insensitivity to SM (such as urban and rocky areas and steep slopes) (Pasolli et al., 2011). Other sources of error are often not considered, including soil texture (Jackson and O'Neill, 1986), temperature (Rodionova, 2017) and the presence of man-made objects (Tadono et al., 2000). The effect of soil properties on soil moisture retrieval from SAR has not previously been quantified.

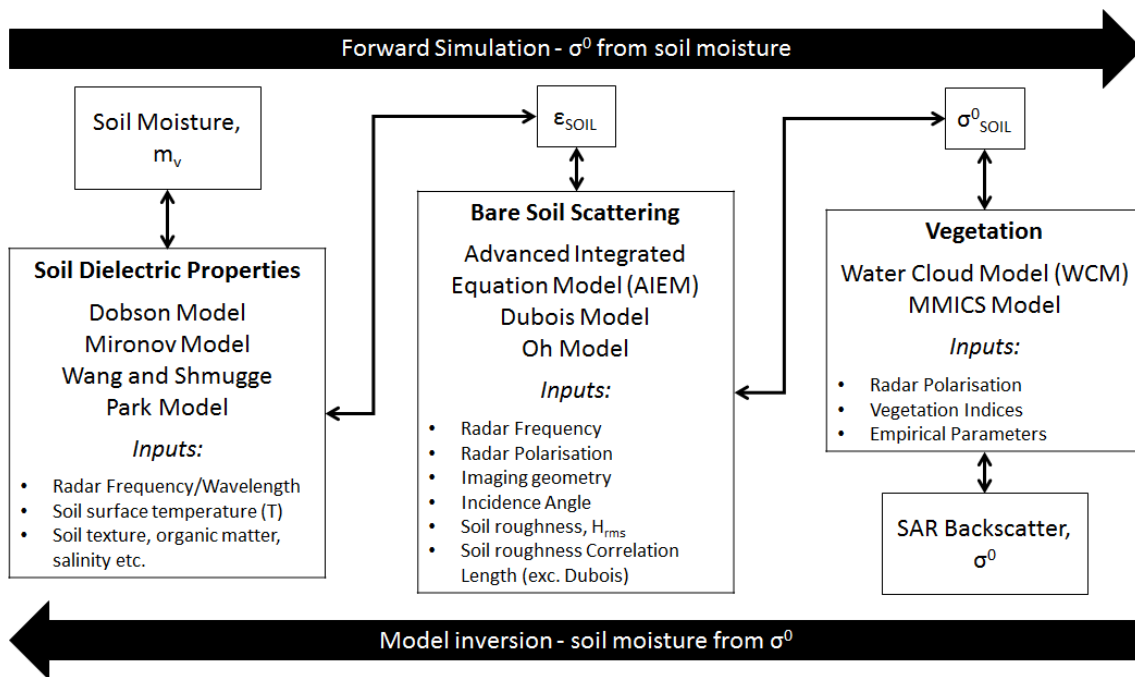


Figure 2.2: Process of estimation of soil moisture (SM) by volume (m_v) from SAR backscatter coefficient (σ^0) through inversion of models (Dobson et al., 1985; Mironov et al., 2004; Wang and Schmugge, 1980; Park et al., 2017; Tzong-Dar Wu and Kun-Shan Chen, 2004; Dubois et al., 1995; Oh, 2004; Attema and Ulaby, 1978; Ulaby et al., 1988; McDonald and Ulaby, 1991)

This study considers two common methods for retrieving soil moisture from SAR backscatter coefficients. The first of these is model inversion. Figure 2.2 shows examples of semi-empirical models that combine in a forward direction to predict the radar backscatter (σ^0_{soil}) of the land surface. Going in the reverse direction, starting with backscatter and fixing the other factors, soil moisture may be estimated. The models on the left of the Figure 2.2 predict the relative complex permittivity of the soil (ϵ_{soil}), as a function of frequency, soil moisture by volume (m_v), texture, composition and surface temperature. Among these factors, this study looks at the scale of the effect that soil texture and organic

matter content has, to understand how important accurate information on these parameters is to the inversion process. Though temperature effects are generally insignificant, there is a known issue caused by frozen soil (Baghdadi et al., 2018). The study investigates whether this effect is linked to soil texture. The models in the middle of Figure 2.2 predict a radar backscatter coefficient (σ_{soil}^0), by adding in scattering due to the SAR imaging geometry, polarisation and frequency, and surface topography (quantified by the correlation length and root-mean-square height difference, H_{rms}). The surface roughness of the soil is a major unknown, but it is commonly observed that tillage introduces soil roughness that appears to depend on soil texture (Zobeck and Onstad, 1987). For example, Figure 2.3 contrasts the cloddy nature of a ploughed clay soil with a ploughed sandy soil. Models on the right of the Figure 2.2 are among those used to predict the effects of a vegetation layer to estimate the radar backscatter coefficient that the SAR actually measures.



(a) Clay soil (Kent, UK)
Nikki Mahadevan CC BY-SA 2.0



(b) Sandy soil (Suffolk, UK)
Bob Jones CC BY-SA 2.0

Figure 2.3: Contrasting soil surface roughness for two ploughed fields

The determination of empirical parameters for the models of Figure 2.2 is typically achieved by fitting a sample of satellite observations and ground measurements (for example, by minimising a cost function as described by Bai et al. (2017)). When analytical model inversion is not possible, it is common to use look up tables or machine learning approaches. Look-up tables are generated from forward modelling using a range of expected input values, one of which will be soil moisture. The inversion is performed by selecting the closest set of input values that would generate the observed output. This method becomes impractical if the range of possible inputs are not constrained. The alternative is to use a machine learning approach to invert the model using forward modelled data as a training

data set (El Hajj et al., 2016). A good example of this was recently published by Hajj et al. (2017).

The second method of SM retrieval from SAR that we will consider is the use of temporal processing algorithms which attempt to overcome the difficulty in choosing realistic soil surface roughness and vegetation parameters. A particular example of this approach is a change detection algorithm (Wagner et al., 1999; Hornacek et al., 2012; Pathe et al., 2009) which assumes that the contributions to radar backscatter due to soil moisture, surface roughness and vegetation have different temporal characteristics. In particular, on bare to moderately vegetated, non-arable land, short timescale changes in backscatter coefficient are assumed to be due to changes in SM. A long time-series of SAR data is initially normalised to a local incidence angle. Assuming the range of radar backscatter values represents a complete range of soil moisture conditions, a sensitivity raster is calculated. This is used to calibrate new SAR backscatter images to provide an estimate of the soil moisture as an SM index (SMI) value at each pixel. A SMI is a normalised value relative to local reference wet and dry conditions. SMIs are commonly used in SM products derived from remote sensing or modelling. Recent examples of SMI products based in whole or part on change detection algorithms and Sentinel-1 data include the Copernicus SSM (Bauer-Marschallinger and Paulik, 2019) and Copernicus SWI (Doubkova et al., 2016). For applications requiring volumetric water content (VWC) or soil moisture deficit (SMD) the SM at the wet and dry conditions must be independently measured or estimated at each site. The latter involves estimating soil hydrological properties from soil texture, uncertainty about which will contribute to the error in retrieving SM from SMIs derived from SAR - the significance of which has not previously been quantified.

For decades, soil scientists have been collecting information on soil properties such as texture, density, organic matter content and hydrological properties, much of which is now readily accessible as geospatial data. This paper seeks to discover whether this valuable resource could contribute to a reduction of the errors in soil moisture estimation from C-band SAR satellites. In particular, we address the following questions:

- How significant is the contribution of (a) soil texture and (b) soil organic carbon to soil moisture retrieval by model inversion?
- To what extent can soil properties influence soil surface roughness and the magnitude of roughness change as a result of anthropogenic change in arable

agriculture?

- How is backscatter change during the freezing of soil influenced by soil properties?
- What is the magnitude of the error introduced when deriving volumetric water content without reference to the correct soil properties?

2.2 Materials and methods

2.2.1 Model

To investigate the contribution of soil texture to soil moisture retrieval from SAR by model inversion, the study investigated the dependence of soil reflectivity on its texture through a model. Reflectivity is a function of refractive index, which is linked to the relative permittivity (or dielectric constant) of the soil, ϵ_{soil} , through the Fresnel equations (Breon et al., 1995) and Kirchoff's Law (Kelly, 1965). The soil relative permittivity is modelled by multi-phase mixing of the relative permittivity values of the constituent parts of soil, including the solid matter ($\epsilon_{sand,clay,silt}$), air (ϵ_{air}) and the soil water (ϵ_{water}). ϵ_{water} depends on the fraction of water that is "bound" to the soil particles by Van der Waals or capillary forces (ϵ_{bound}) (Park et al., 2017; Wang and Schmugge, 1980) rather than "free", within the large soil pores (ϵ_{free}). Clay particles bind more water molecules than an equivalent mass of sand particles due mainly to increased surface area.

The soil dielectric mixing model by Park et al. (2017) (hereafter referred to as the Park model) was selected in preference to its predecessors proposed by Hallikainen et al. (1985), Dobson et al. (1985) and Mironov et al. (2004) for its ability to simulate the widest range of soil moisture conditions. Within the shallow surface soil layer which C-band SAR penetrates (Nolan and Fatland, 2003) and in high rainfall regions, the soil will routinely saturate with additional water on its surface. Conversely, in warm and dry weather conditions the surface layer will attain very low moisture values.

According to the Park model, ϵ_{soil} is a function of the following parameters:

- Soil moisture by volume, m_v
- Soil texture (proportions of sand, silt, clay), $v_{sand}, v_{silt}, v_{clay}$
- Soil permanent wilting point m_{wvp} and porosity, p

- Soil temperature, T
- Soil water salinity, S

$v_{sand}, v_{silt}, v_{clay}$ and p may be obtained from soil texture maps and m_{vwp} is obtained or derived from soil hydrological data and pedotransfer functions. The model used in this study does not account for soil organic carbon.

The Park model considers three regimes; the first (equation 2.1) is when the SM is below the Permanent Wilting Point (PWP), where all of the water is assumed to be in the bound state, the second (equation 2.2) is when the SM is above PWP but below saturation level, where there is a mixture of bound and free water, the third (equation 2.3) when the soil is above saturation point, there is excess free water that cannot be held by the soil which is generally held on the surface but cannot immediately drain away. This third regime is a new consideration when compared to previous models, but one that is important for flood prediction. The following equations from the Park model were used to calculate the real part of the relative permittivity of the soil (ϵ'_{soil}) as a function of SM (w), porosity (p), permanent wilting point (w_{wp}), the volume fractions of sand, silt and clay ($v_{sand}, v_{silt}, v_{clay}$) and the relative permittivities of the soil constituents ($\epsilon'_{sand}, \epsilon'_{silt}, \epsilon'_{clay}, \epsilon'_{bound}$ (water), ϵ'_{free} (water) and ϵ'_{air}):

For $w \leq w_{wp}$:

$$\epsilon'_{soil} = 0.8((1-p)(v_{sand}\epsilon'_{sand} + v_{silt}\epsilon'_{silt} + v_{clay}\epsilon'_{clay}) + m_v\epsilon'_{bound} + (p-m_v)\epsilon'_{air}) \quad (2.1)$$

For $w_{wp} < w \leq p$:

$$\epsilon'_{soil} = 0.8((1-p)(v_{sand}\epsilon'_{sand} + v_{silt}\epsilon'_{silt} + v_{clay}\epsilon'_{clay}) + m_v \left(\left(\frac{p-m_v}{p-m_{vwp}} \right) \epsilon'_{bound} + \left(\frac{m_v-m_{vwp}}{p-m_{vwp}} \right) \epsilon'_{free} \right) + (p-m_v)\epsilon'_{air}) \quad (2.2)$$

For $w > p$:

$$\epsilon'_{soil} = 0.8((1-m_v)(v_{sand}\epsilon'_{sand} + v_{silt}\epsilon'_{silt} + v_{clay}\epsilon'_{clay}) + m_v\epsilon'_{free}) \quad (2.3)$$

The values for ϵ'_{free} and ϵ'_{bound} were determined as a function of radar frequency (f), temperature (T) and salinity (S) using the Debye relaxation formula by the method set out by equations 25-31 in Park et al. (2017), setting both ϵ'_{free}^{min} and ϵ'_{bound}^{min}

to the value 4.9. The frequency, f was set to 5.4 GHz, the salinity, S , was set to zero, and the soil temperature, T set to 10°C (this is a typical value in the UK).

The Park model was implemented in a Microsoft Excel spreadsheet from equations in the authors' published manuscript (Park et al., 2017). In the process of doing so some minor errors and omissions were identified and resolved by correspondence with the lead author. Having arrived at a model implementation that replicated the results in the published manuscript, example soil properties were input, as listed in Table 2.1. The model then was inverted (using the Excel goal seek feature) to determine soil moisture from relative permittivity (which may be calculated from SAR backscatter). A number of soil types representing the full range of the soil textural triangle were modelled to estimate the errors in volumetric SM estimation due to soil texture.

2.2.2 Data

Soil texture

The soil-related parameters required to run the Park model and determine the soil texture impact for conversion of SMI to VWC were obtained from the LANDIS Horizon Hydraulics and Fundamentals data sets (Hallett et al., 2017). LANDIS covers England and Wales and is based around soil series and land use; the Horizon dataset tabulates soil texture and hydraulic properties for typically observed soil horizons. Six example soil series were chosen to represent a range of soil texture types, as listed in Table 2.1. To simulate the surface soil layer in an agricultural context, the A soil horizon under arable land use was selected. The van Genuchten

Table 2.1: Input parameters used for simulation in the Park et al. (2017) model, plus selected Van Genuchten model parameters θ_s and θ_r used to assess errors in SMI to VWC. Data is from six UK soil series, representing typical soil characteristics in the upper (A) soil horizon under arable land use. Source of data is LANDIS (Proctor et al., 1998; Cranfield University, 2017). m_{vwp} is permanent wilting point, m_{vfc} is field capacity, p porosity, v_{sand} , v_{silt} and v_{clay} are volume fractions of sand, silt and clay in the soil. Note that for Wensum $\theta_s > p$ is counter to expectations. θ_s is derived from model fitting rather than direct measurement and is more likely to be in error at such high values.

Soil Series	Type	$m_{vwp} vol. \%$	$m_{vfc} vol. \%$	$p vol. \%$	$v_{sand} \%$	$v_{silt} \%$	$v_{clay} \%$	$\theta_s vol. \%$	$\theta_r \%$
Wensum	Clay	35.7	55.5	66.6	3	26	71	73.98	21.51
Sollom	Sand	8.5	23.5	57.7	94	5	1	47.04	3.94
Munslow	Silt Loam	18.4	39.6	51	4	80	16	35.78	7.19
Grove	Clay Loam	24.4	42.8	54.1	32	34	34	41.93	10.25
Stixwould	Clay	31.4	50.6	62.2	18	27	55	59.69	16.35
Wyre	Clay	29.9	49.5	61.1	20	32	48	57.07	15.10

(1980) model parameters θ_s and θ_r were selected as estimates of the wettest and driest soil moisture conditions likely to be found at the surface. These were used to simulate conversion of SMI to VWC values.

Soil organic carbon (SOC)

Previous studies were contradictory, some show that microwave relative permittivity increases slightly with humus and organic carbon (Jackson, 1987; Chaudhari, 2015), whilst others suggest the opposite trend (Bobrov et al., 2005; Manns et al., 2015). This apparent conflict is resolved by measurements on 12 soil samples at a slightly higher frequency than C-band (6.925 GHz) carried out by Liu et al. (2013), who also explored a range of soil moisture conditions. Two soil samples were selected that have similar soil texture but very different organic matter content (4.15% and 17.8%). The PWP, FC and saturation values of SM have been estimated from the fractions of clay and sand in each soil using the method of Saxton et al. (1986). The soil properties are shown in Table 2.2.

Table 2.2: Soil properties for the two soils selected from Liu et al. (2013) which have similar clay content but contrasting levels of SOC. Note that the volume fractions of clay, silt and sand, v_{clay} , v_{silt} , and v_{sand} relate to the mineral content excluding SOC. Values of w_{wp} , w_{fc} and p values are estimated from the soil texture by the method of Saxton et al. (1986).

Property	Soil 2	Soil 5
v_{clay} %	17.56	15.87
v_{silt} %	41.42	29.16
v_{sand} %	41.02	54.97
SOC %	17.84	4.15
w_{wp} vol.%	11.6	11.2
w_{fc} vol.%	25.5	22.7
p vol.%	46.1	44.5

Soil surface roughness

To investigate the potential impact of soil texture on soil surface roughness, work by Evans (1980) and Martinez-Agirre et al. (2016) explored the step changes in soil roughness induced by tillage operations such as ploughing, harrowing, drilling and rolling. Data was also obtained from the review paper by Zobeck and Onstad

(1987) compared the measurements of soil Random Roughness (RR) (Romkens and Wang, 1986) as a function of tillage operations and soil texture. These data sources demonstrate an evolution over time of a series of farming operations in their study locations.

To complete a regression analysis of soil roughness versus texture, other data points were extracted from soil surface profiles published by Currence and Lovely (1970), Evans (1980) and Martinez-Agirre et al. (2016) (where a clay content of 35% has been estimated from the textural triangle for silty clay-loam). The data points were converted into pairs of random roughness values (in cm) with the corresponding clay fraction from the soil texture, then categorised according to the type of tillage operation as Primary, Secondary or No Till.

Soil Freezing

Most approaches to soil moisture estimation from Sentinel-1 do not account for the effect of soil temperature variations as is assumed insignificant compared to the other factors discussed earlier. The soil properties and conditions where this assumption could break down are when the temperature is low enough to freeze the soil surface.

When soil freezes there is a sharp decrease in the real part of the relative permittivity (ϵ'_{soil}) of the soil, as documented by Zhang et al. (2003), Mironov and Lukin (2009), and Mironov et al. (2017). This is easily detectable in Sentinel-1 imagery and can be used as a method for mapping of frozen soil (Baghdadi et al., 2018; Park et al., 2011). The problem for soil moisture estimation is that frozen soil will appear to have a much lower soil moisture content than it actually has. In the case of overnight and early morning frost there may be patches of frozen and unfrozen soil within a field. Correction for this effect would firstly require mapping of the frozen areas (using a method such as that of Baghdadi et al. (2018)), then selective application of a correction factor to certain pixels, or masking them out as frozen and indeterminable.

To investigate the potential impact of soil texture on the change in backscatter from the soil when it freezes, data was obtained from previously published results in Zhang et al. (2003). The data was adapted to show, as an example, the variation of the real part of the relative permittivity with temperature for pure sand, silt and clay at a fixed SM value of $m_v=30$ vol.%.

2.2.3 Method for assessing impact of soil texture on SMI to VWC conversion

The conversion of an SMI value to VWC involves scaling the SMI to the range of expected VWC values (wet and dry references). For SMIs that purport to describe soil moisture at depth it is typically suggested that the Field Capacity (FC) (Veihmeyer and Hendrickson, 1931) and Permanent Wilting Point (PWP) (Veihmeyer and Hendrickson, 1928) are used. However, for surface soil layers these references do not define the limits the variability in SM (Koorevaar et al., 1983). For the purpose of illustration, this study selected the saturated soil-water content (θ_s) and residual soil-water content (θ_r) relating to the van Genuchten (1980) model. Six example soil properties were chosen, as listed in Table 2.1 above. The VWC values were calculated, using these references, for each soil series for the full range of SMI from zero to the maximum.

2.3 Results

2.3.1 Soil texture and relative permittivity

The relationship between soil relative permittivity and SM from the reverse Park model is shown in Figure 2.4, revealing inflexion points at PWP and FC. The six plots were generated using the soil series texture and hydraulic properties from Table 2.1. Of these, the Grove soil series sits approximately in the middle of the the soil textural triangle and represents a default case. High clay-content soils are predicted to have a lower relative permittivity than sandy soils. When using a model inversion approach to retrieve soil moisture from SAR, the relative permittivity of the soil would be estimated prior to conversion to SM. The range of potential SM values for a particular relative permittivity is shown by the dashed line in Figure 2.4, which varies between approximately 20 vol.% near the PWP, and 10 vol.% at saturation.

2.3.2 Soil organic matter and relative permittivity

Microwave measurements at 6.925 GHz for the two soil samples in Table 2.2 (Liu et al., 2013), were transposed to obtain Figure 2.5, a plot of SM as a function of relative permittivity. The difference in equivalent SM values between the two soils

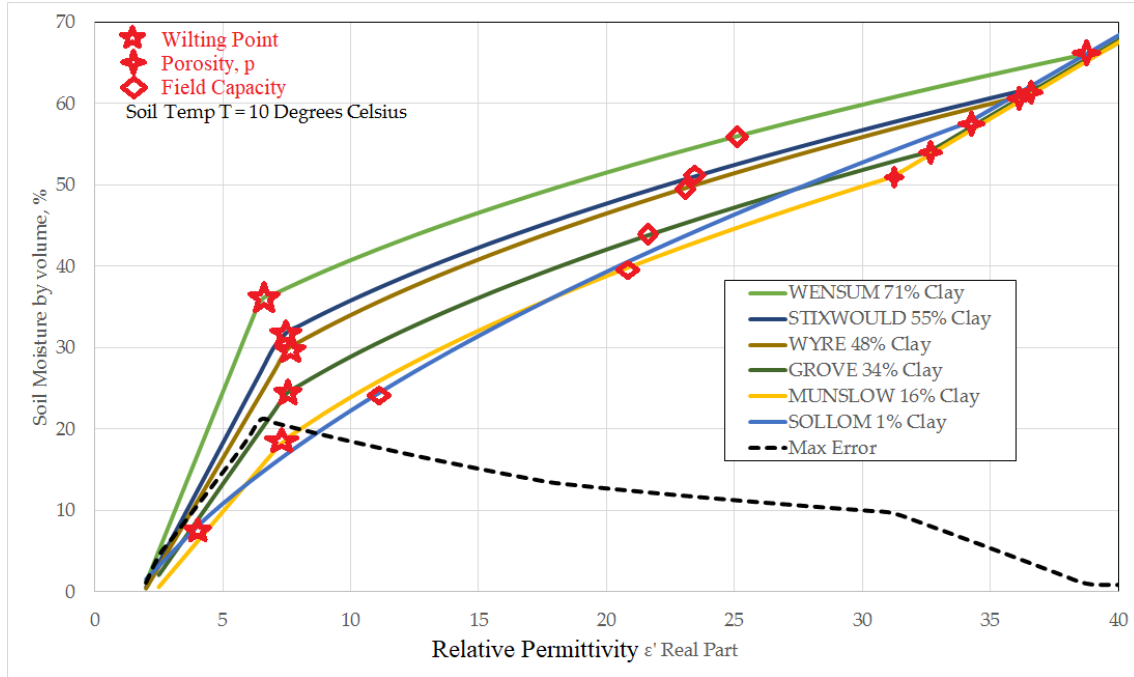


Figure 2.4: Soil moisture, m_v , as function of the real part of the relative permittivity, ϵ' at 5.4 GHz, for six UK soil types, as predicted by inverting the model of [Park et al. \(2017\)](#). The spread of SM values is shown by the dashed line, which reaches a maximum near the permanent wilting point of the soil.

is plotted against relative permittivity as a dashed line.

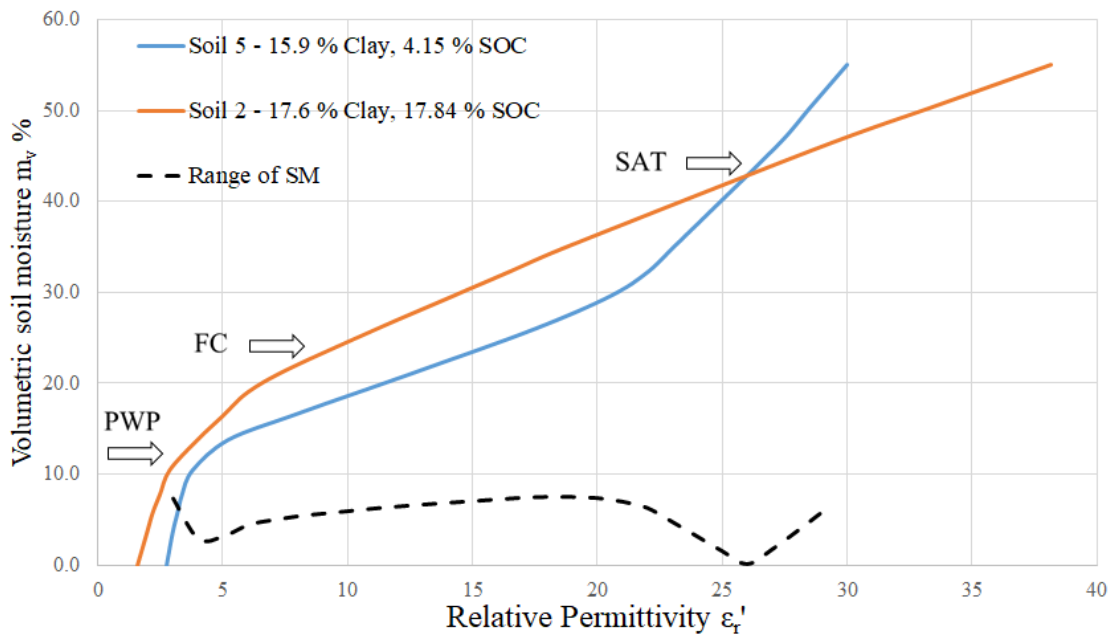


Figure 2.5: Dependence of soil moisture on relative permittivity for two soils with significantly different organic matter content. This is a simplified version of data presented by [Liu et al. \(2013\)](#) of measurements on soil samples from Heilongjiang Province, northeast China.

Both soils exhibit similar relationships between SM and relative permittivity

as predicted by the Park model in Figure 2.4, with the high SOC "Soil 2" (orange curve) appearing to behave like a higher clay content soil, and the low SOC "Soil 5" behaving as expected according to its soil texture. This suggests that the high SOC sample has a greater proportion of bound water and a higher soil moisture at saturation (above 55 vol.%). The dashed line in Figure 2.5 shows that the potential error in retrieving soil moisture by model inversion is small near the soil PWP and near saturation. The maximum potential error due to SOC in retrieved m_v occurs between FC and saturation, and is about 7.5 vol.% based on these two soil samples, which is about half of that attributable to soil texture.

2.3.3 Soil surface roughness

To illustrate the changes in soil surface roughness that occur as a result of tillage operations, and how this differs between soils of different textural categories, Figure 2.6 plots several temporal profiles obtained from published results. The description of Morgan and Nearing (2013) is consistent with this data, which shows that primary tillage (ploughing) results in a rough, sometimes cloddy surface with H_{rms} values of up to 6 cm. Secondary tillage (harrowing) reduces this to 1-3 cm, which is often further reduced by drilling and rolling. There is potential for roughness changes of up to 5 cm in H_{rms} between image acquisitions due to anthropogenic influences, apparent texture dependency.

The results of the regression analysis of random roughness (RR) versus clay fraction carried out on the extended set of published data is shown in Figure 2.7, using a best fit linear regression approach. It provides evidence of a correlation between RR after primary tillage and soil clay content, with an R^2 value of 0.32. There is no apparent correlation between the soil texture and RR after secondary tillage operations. This is probably because farmers are aiming to achieve the same tilth in all cases and work the soil with appropriate implements to achieve this. Of particular interest is the apparent, but weak, correlation for No Till with $R^2 = 0.37$. Knowledge of the expected sequence of farming operations in conjunction with soil texture information could, therefore, assist in estimating soil roughness (RR or H_{rms}) in the absence of an actual measurement, as follows:

- $H_{rms} \approx 0.5 - 1.0$ cm for all soil types under zero tillage;
- $H_{rms} \approx 1 - 2$ cm for all soil types after secondary tillage and drilling or after weathering;

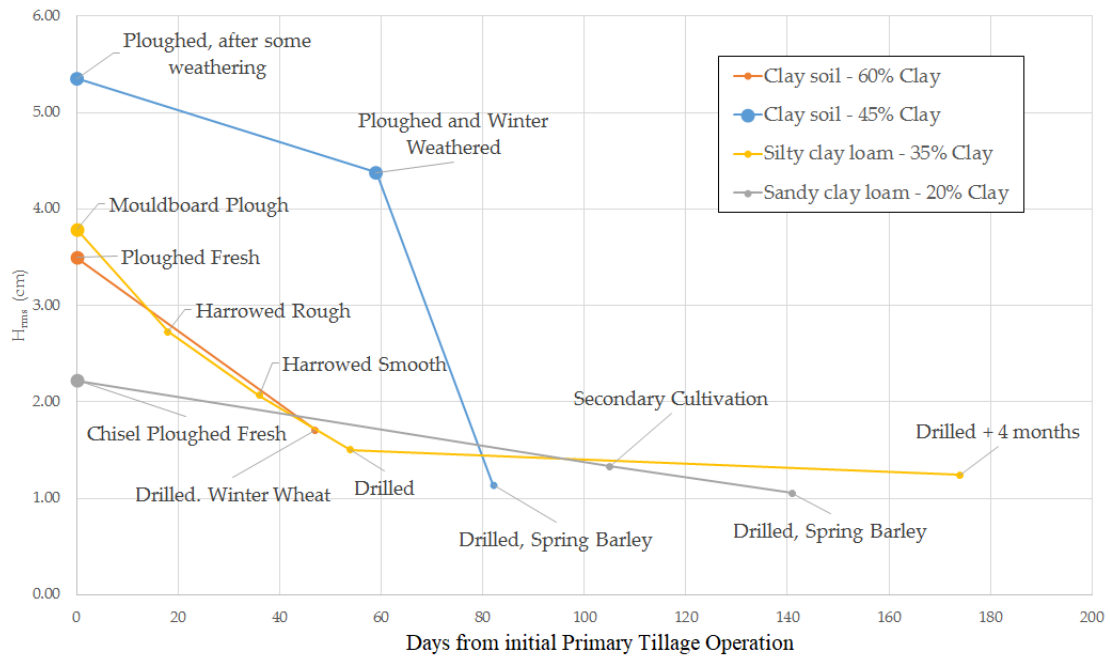


Figure 2.6: Evolution of soil roughness over time and due to tillage for several soil textures. Larger dots are primary tillage operations, small dots secondary tillage. Data taken from [Evans \(1980\)](#) and [Morgan and Nearing \(2013\)](#).

- $H_{rms} \approx 2 - 6$ cm depending on % clay content after ploughing;

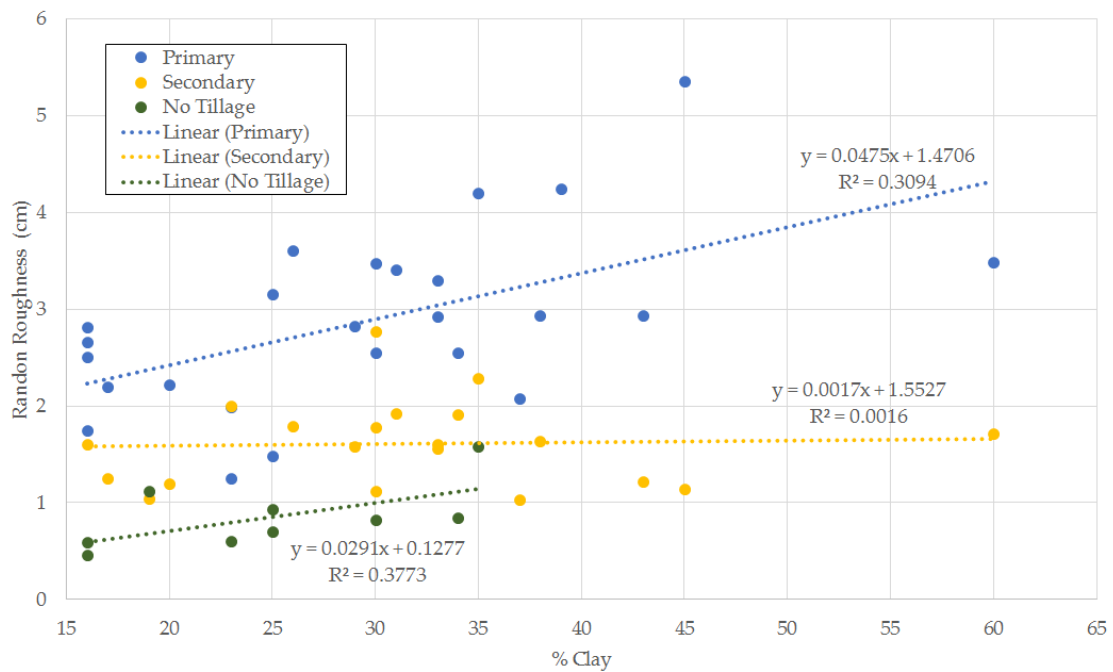


Figure 2.7: Soil surface roughness (H_{rms}) as a function of clay content for tillage operations. Data from [Currence and Lovely \(1970\)](#); [Evans \(1980\)](#); [Martinez-Agirre et al. \(2016\)](#); [Zobeck and Onstad \(1987\)](#).

2.3.4 Soil freezing

A typical relationship between soil relative permittivity, ϵ'_r , and temperature, through the freezing point, for sand, silt and clay, is shown in Figure 2.8. The relative magnitudes of ϵ'_r invert at the freezing point. The decrease in relative permittivity caused by freezing is shown, in this example, to be equivalent to a drop in volumetric moisture content from over 30 vol.% to under 15 vol.%.

2.3.5 SMI to VWC conversion

The relationship between SMI and VWC using the Van Genuchten model parameters θ_s and θ_r as wet and dry references is shown in Figure 2.9. The various lines represent surface soil layers (A horizon) for six example UK soil series covering a range of potential soil texture extremes. Also plotted in this figure is a line showing the range of VWC values for each value of SMI. This shows that using an assumed and potentially incorrect soil texture can lead to a maximum error in VWC estimation of between 18 vol.% and 38 vol.%.

2.4 Discussion

This study set out to quantify the impact of soil properties on the retrieval of SM from C-band SAR data. The two cases of direct model inversion and temporal change algorithms were considered, also the conversion of SMI data to VWC.

For model inversion soil texture is a parameter of the models that link the soil relative permittivity to SM. Using a variety of UK soils as input the Park model has demonstrated that soil texture contributes to a variability of between 10 vol.% and 20 vol.% in the retrieved soil moisture. The greatest variability occurs at SM values close to the PWP, when accurate measurement of soil moisture would be most advantageous. Most soils have significant SOC which has been shown to emulate the effect to a higher clay fraction. In the cases studied, a further variability of up to 7.5 vol.% was found due to SOC, with the greatest variation predicted in wet soils with SM above FC. Other models within the inversion process simulate the contribution of soil surface roughness. In the absence of knowledge of this parameter by independent means, the correlations identified between soil surface roughness and soil texture for ploughed and zero-till soil may be useful in setting realistic estimates for this parameter. It has also been discovered that secondary

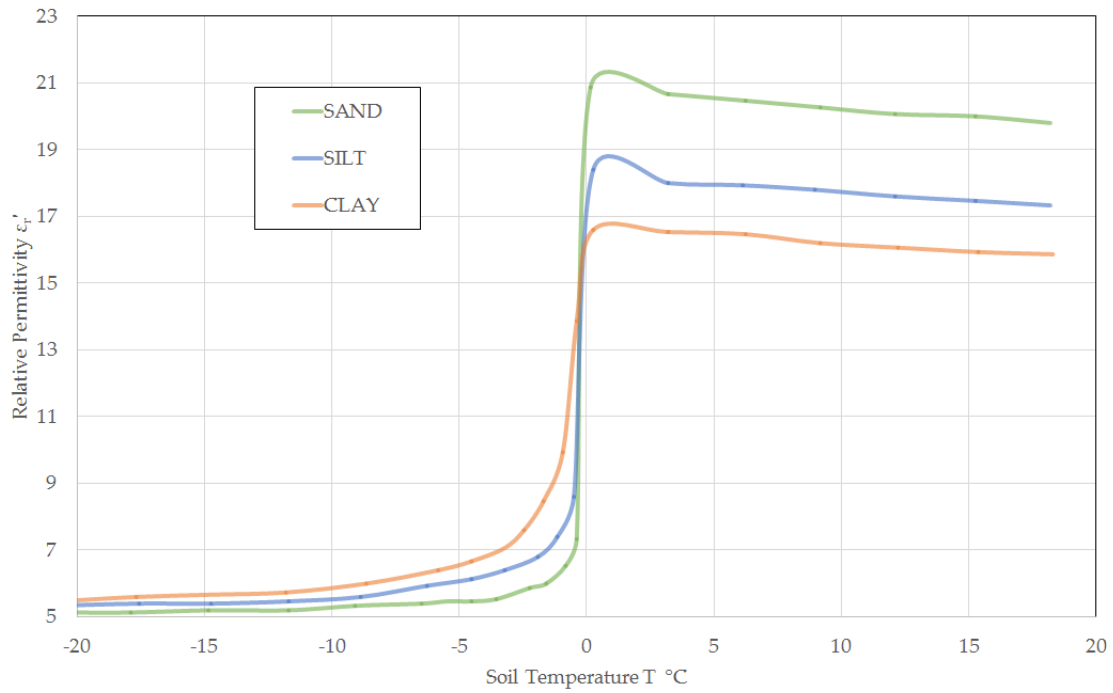


Figure 2.8: Variation of real part of relative permittivity with temperature for sand, silt and clay at $m_v=30$ vol.%, adapted from Zhang et al. (2003).

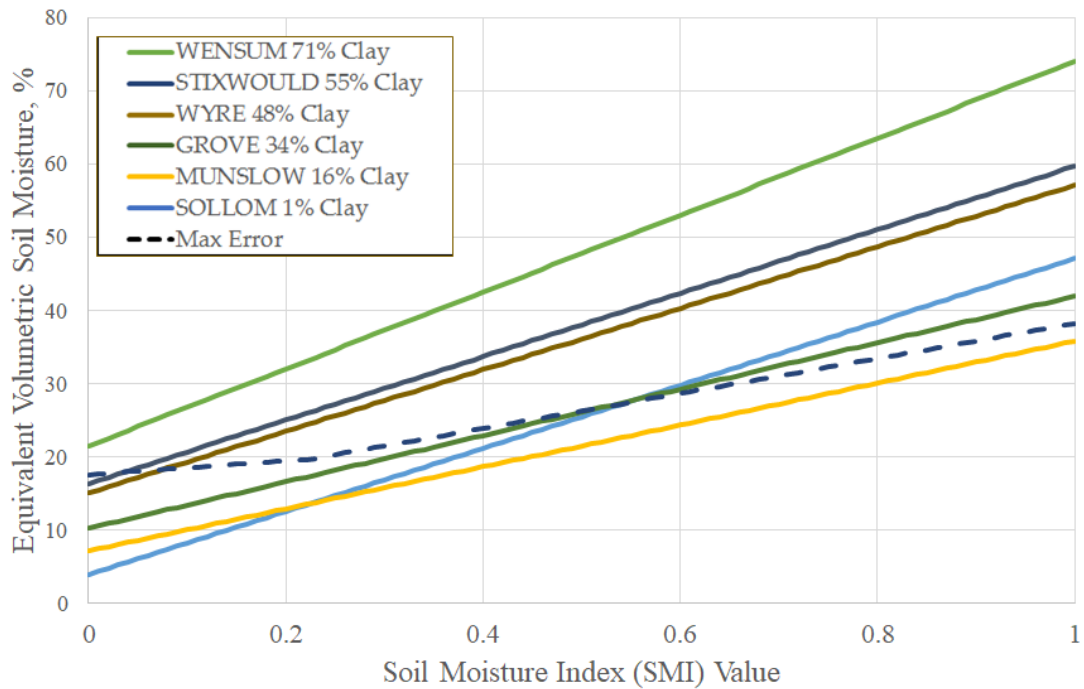


Figure 2.9: Volumetric Water Content (VWC) as a function of Soil Moisture Index (SMI) for surface soil layers of six UK soil series (arable land use). Also showing the range of potential values for a given SMI value.

tillage and seed drilling seems to produce soil of uniform roughness that does not depend on soil texture. The relative paucity of data suggests that further experimental studies, perhaps under laboratory conditions, would be needed to develop an empirical model to predict soil surface roughness as a function of soil texture across a wide variety of sites and conditions. It may then be possible to detect tillage events by sudden changes in backscatter and introduce a correction based on the crop-cycle context and soil texture.

Another factor related to soil roughness is depression storage or ponding of standing water when the soil is saturated or immediately after heavy rainfall. The smooth surface of the ponded water will act as a specular reflector for microwaves, so the backscatter coefficient for any area including ponded water will be significantly reduced. Whilst larger areas of standing water may be detected and masked in a SAR image, small pools of water will be sub-pixel, and contribute to an underestimated soil moisture. The depression storage capacity of clay soils is 1.6 to 2.3 times that of sandy soils according to [Morgan and Nearing \(2013\)](#), and is also linked to surface roughness, slope and furrow orientation ([Edwards et al., 1994](#)). This is therefore another soil texture-dependent variable.

Temporal processing, such as the change detection algorithm ([Wagner et al., 1999](#); [Hornacek et al., 2012](#); [Pathe et al., 2009](#)), assumes that factors such as surface temperature are negligible, and that vegetation and surface roughness effects are relatively stable over time. Both should be questioned in the context of arable fields. This study has confirmed that significant step changes in soil roughness are induced by tillage operations such as ploughing, harrowing, drilling and rolling. The magnitude of this change can be estimated using soil texture. So, whilst the algorithm assumptions would not apply to agricultural fields under tillage, it is conceivable that an improved algorithm could take account of it. Whilst the impact of vegetation has not been addressed by this study, the growth and ripening of crops is also quite rapid — over a scale of weeks to months — and harvesting will cause a step change in vegetation cover over a very short time. For example, wheat and barley crops can show a change in normalised difference vegetation index (NDVI) from 0.3 to 0.8 in around 100 days during growth, declining rapidly before and during harvest ([Nasrallah et al., 2018](#)). According to [Farrar et al. \(1994\)](#) and [Demattê et al. \(2017\)](#) an increase of NDVI over time following rainfall is dependent on soil texture and chemical composition, with clay soils and aluminium-rich soils showing the greatest rate of increase in NDVI. Similarly, [Dewaele et al. \(2017\)](#) found that maximum leaf area index (LAI) observations were correlated with the

maximum soil water holding capacity for rainfed croplands over France. It may be possible to exploit these findings in developing a model to correct for vegetation changes after rainfall.

In most situations, soil temperature has a minor influence on the microwave dielectric properties of soil (Jackson, 1987) though the effect is observable in Sentinel-1 data (Rodionova, 2017). Generally, the effect is insignificant compared to variability introduced by the other factors discussed. This assumption breaks down when the temperature is low enough for some or all of the soil water to freeze. When this happens it is accompanied with a sharp decrease in the real part of the relative permittivity (ϵ'_r), as documented by Zhang et al. (2003), Mironov and Lukin (2009) and Mironov et al. (2017). This is easily detectable in Sentinel-1 imagery and has been used as a method for mapping of frozen soil, as demonstrated by Baghdadi et al. (2018); Park et al. (2011). When retrieving SM from SAR, areas of frozen soil will appear to have anomalously low SM content. Mitigation of this effect often involves detecting and masking the frozen areas (using a method after Baghdadi et al. (2018)), but selective application of a correction factor that is soil texture dependent may be a viable and more useful approach.

This study has also considered how users would convert recently published SM products that are agnostic of soil texture to a usable volumetric water content (VWC) or soil moisture deficit (SMD) from an SMI. To do the conversion the SM representing wettest and driest conditions must be independently measured or estimated. The latter involves estimating soil hydrological properties from soil texture. For the first time it is now demonstrated that using an assumed and potentially incorrect soil texture for conversion can lead to a maximum error in VWC estimation of between 18 vol.% and 38 vol.% . This is unsatisfactory for practical uses as an accuracy of close to 5 vol.% is likely to be required.

Soil properties may be obtained from existing soil maps and databases, chosen to match the field scale where possible. Whilst the Harmonized World Soil Database (Fischer et al., 2012) has a resolution of 1km, national and regional maps are often available at higher resolution, especially in agricultural areas. As a basis on which to estimate vegetation cover or soil roughness, land cover maps may be useful. As an example, the Corine land cover map of Europe (European Environment Agency, 2006) has a minimum feature size of 25 hectares, and limited cover classes, but higher resolution local maps are often available. For example, the UK Centre for Ecology and Hydrology (UKCEH) has published its *Land Cover plus: Crops* product (Jarvis et al., 2019), which categorises two million land parcels into annual

crop types for every field in Great Britain. Potential agricultural stakeholders in soil moisture estimation by remote sensing are likely to have accurate soil type and land use information for their areas.

2.5 Conclusions

The error contribution of soil texture in soil moisture retrieval from remote sensing of soil dielectric properties (by model inversion or by conversion of a Soil Moisture Index) is assessed for the first time. Mineral soil texture contributes a potential error of 10-20 vol.%, which is greatest when the soil is near its permanent wilting point and least near saturation. Soil organic matter adds a further 7.5 vol.% uncertainty, in the case studied, such that the overall error due to use of inaccurate soil properties is between 18 vol.% and 38 vol.%.

In arable farming, soil surface roughness following primary tillage operations, or under no tillage, has been discovered to be correlated to soil texture. Secondary tillage produces a consistent soil roughness across all soil textures. The conclusion is that further work could establish a model to predict soil roughness from land use, soil properties and knowledge of the timing of tillage operations in the field.

As soil freezes, the reduction in relative permittivity manifests as an underestimation of soil moisture by up to 15 vol.%. The magnitude of this error is predictable from the soil texture and may be corrected for.

Soil properties are important to soil moisture retrieval, especially when considering field-scale resolution over arable agricultural areas. Any assessment of remote sensing SM estimation processes should include the use of soil properties to derive absolute values. The use of accurate soil properties and the correction for changes in soil roughness and on freezing will inform future algorithm development and improve the accuracy of direct SM retrieval through model inversion or change detection algorithms, especially in agricultural areas. Machine learning algorithms should always include soil properties as input data.

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3 A Method to Assess the Performance of SAR-derived Surface Soil Moisture Products

This chapter in paper format introduces a new method to quantitatively assess the performance of surface soil moisture estimates from C-band Synthetic Aperture Radar. It solves the problem of depth mismatch in existing validation methods which compare remotely sensed estimates of SM against *in situ* measurements at a greater depth of soil than the SAR can penetrate. This is important to accurately evaluate, potentially small, improvements in accuracy as a result of algorithm developments.

Abstract

Synthetic Aperture Radar (SAR) is a remote sensing technique for mapping of soil moisture with high spatial resolution. C-band SAR can resolve features at field scale, or better, but responds to moisture only within the top 1 to 2 cm of the soil. When validating SAR-derived soil moisture products against standard in-situ measurements at 5 to 10 cm depth, the greater moisture variability at the soil surface may be inaccurately categorised as measurement error. An alternative method was developed where the C-band SAR product is validated against soil moisture simulated at 2 cm depth by the HYDRUS-1D model. This reproduces soil moisture depth profiles from daily meteorological observations, leaf area index and soil hydraulic parameters. The model was fitted at 13 COSMOS-UK sites so that the model output at 10 cm depth closely reproduced the cosmic ray neutron sensor data. At 10 of the sites studied there was an improvement of up to 8 vol.% in RMSD by validating the Copernicus SSM product at 2 cm compared to 10 cm. This suggests that Copernicus SSM and other C-band SAR surface soil moisture algorithms may be more accurate than have hitherto been acknowledged.

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3.1 Introduction

Soil moisture remote sensing is of significant interest to agriculture, hydrological modelling and weather forecasting. Satellite active microwave systems have the ability to operate over wide areas in almost all weather conditions, with C-band synthetic aperture radar (SAR) systems being able to achieve field-scale resolution or better. Soil moisture estimation by SAR exploits the dependence of radar backscatter on soil water content, but there are other dependencies on factors that are often unknown. These include soil texture, surface roughness, topography and the effect of vegetation. A number of advanced algorithms have been and are being developed to address this problem.

The quantitative assessment, or validation, of SAR-based soil moisture retrieval algorithms (Gruber et al., 2020) is commonly undertaken by statistical comparison to in-situ soil moisture measurements. The instruments used include soil moisture probes (Paulik et al., 2014; Dorigo et al., 2015; Greifeneder et al., 2017; El Hajj et al., 2018; Al-Yaari et al., 2019) and Cosmic Ray Neutron Sensors (CRNS) (Andreasen et al., 2017; Montzka et al., 2017; Evans et al., 2016). A review of the International Soil Monitoring Network (ISMN) (Dorigo et al., 2013) reveals that probes are generally installed at a nominal depth of at least 5 cm and have a sample volume extending 5-6 cm in depth. This measurement depth is appropriate for validation of L-band SAR-derived soil moisture products, where it matches the microwave penetration depth (Nolan and Fatland, 2003) in bare soil. CRNS have an effective measurement depth of at least 10 cm (depending on soil moisture). Due to the practical problems of measuring soil moisture with probes at 1-2 cm (Tsegaye et al., 2004; Schmutz and Namikas, 2011), there is no established measurement network that matches the penetration depth of C-band SAR.

Reliable soil moisture measurements very near the surface can be achieved by soil sampling and laboratory analysis, as in a previous study by Boisvert et al. (1997). Gravimetric soil moisture was measured at 1 cm depth increments from the surface to 10 cm depth in various sample plots of bare soil subjected to a range of irrigation and drying profiles. The statistics of these measurements (converted to volumetric soil moisture) are summarised in the box plot of Fig. 3.1, annotated with the sample standard deviation, σ . This shows that the variability of soil moisture decreases significantly with depth. It is very high at the surface where the soil is subject to rapid wetting and drying due to rainfall, irrigation and evaporation (Moghadas et al., 2013), whilst drainage to lower layers is a much slower process.

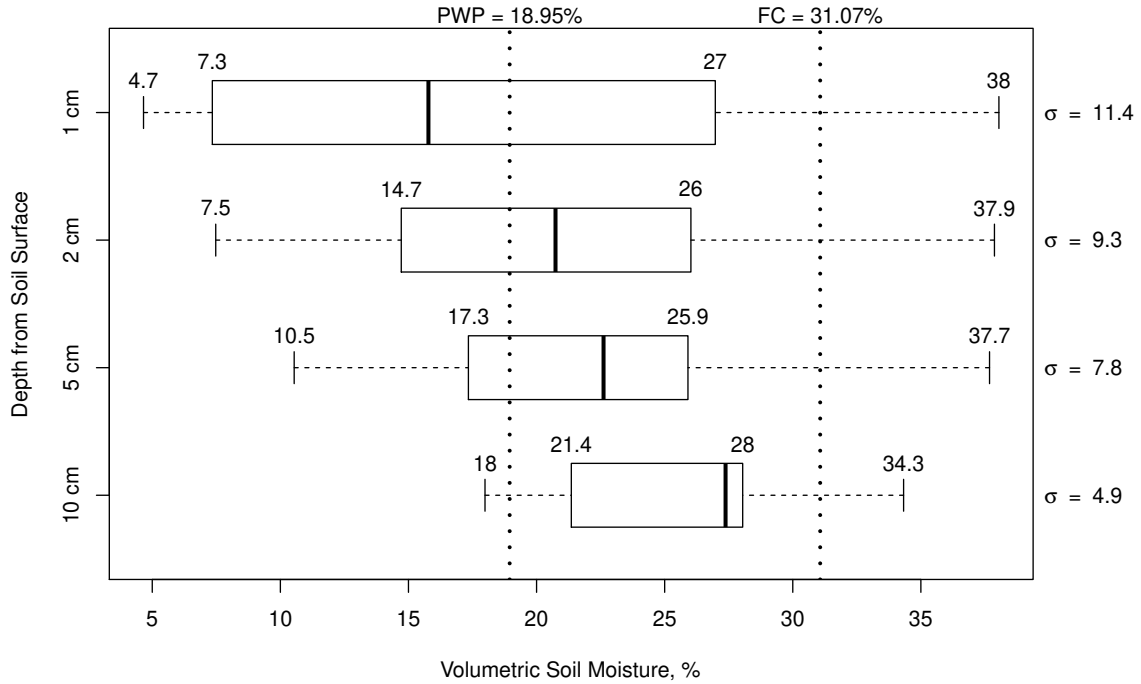


Figure 3.1: Boxplot of soil moisture variability at shallow depths, in a Dark Brown Chernozemic soil (41% sand, 34% clay) at Lethbridge, Alberta, Canada over 9 days of various wetting and drying regimes, analysis of data from Boisvert et al. (1997). The whiskers define the extremes of the data, the thick bars the median, and the box ends represent the first and third quartile values. The standard deviation, σ , at each depth is shown on the right, with estimates of Field Capacity (FC) (Veihmeyer and Hendrickson, 1931) and Permanent Wilting Point (PWP) (Veihmeyer and Hendrickson, 1928) by the method of Saxton et al. (1986) as vertical, dotted lines

At deeper levels soil moisture varies more slowly and over a smaller range. It cannot be assumed that soil moisture measured at 5 or 10 cm is similar to that at 1 to 2 cm depth. The consequence of doing so as part of a validation process of any soil moisture estimates derived from C-band SAR has not previously been quantified.

The speed and range of movement in soil moisture at the surface also challenges the interpretation of soil moisture products that are published as a dimensionless and relative Soil Moisture Index (SMI) (Hunt et al., 2009). An example is the Copernicus Surface Soil Moisture (SSM) product (Bauer-Marschallinger and Paulik, 2019), based on C-band Sentinel-1 data. For applications, such as irrigation scheduling, absolute soil moisture values will be derived by site specific scaling. The Field Capacity (FC) (Veihmeyer and Hendrickson, 1931) and Permanent Wilting Point (PWP) (Veihmeyer and Hendrickson, 1928) of the soil are commonly used for this purpose, to define the range of possible soil moisture values. Fig.

3.1 shows that, whilst this may be acceptable at 10 cm depth, FC and PWP do not define the limits of soil moisture at very shallow depths. This issue is overlooked in the performance assessment of SMI-based products using scale-independent metrics, such as the coefficient of determination (R^2). This study uses, for the first time, alternative scale-sensitive metrics in an assessment of the Copernicus SSM product. The SMI values are scaled to VWC, having first identified the *van Genuchten* (1980) parameters, Saturated Water Content (θ_s) and Residual Water Content (θ_R), as suitable alternative limits of soil moisture content at the surface.

Modelling is an alternative to in-situ measurement of soil moisture where the latter is impractical. HYDRUS 1-D (v4.17) (J. Simunek et al., 2012) is a public domain Windows-based model for analysis of water flow and solute transport in variably saturated porous media, such as soil. It is available for free download from PC-Progress (<https://www.pc-progress.com/en/Default.aspx?hydrus-1d>) and has been found to be accurate to $< 0.12 \text{ vol.}\%$ in soil moisture prediction Kanzari et al. (2018). The model has been successfully used in previous work (Negm et al., 2017; Silva Ursulino et al., 2019) to simulate soil moisture profiles near the surface. It is a finite element model which simulates the one-dimensional movement of water in porous media by numerically solving the Richards equation (Richards, 1931) for water flow. Soil hydraulic parameters are key inputs to the model, but they are not static and vary with soil texture, land use and management. Values obtained previously by laboratory measurements or indirectly from soil maps may not reflect contemporary conditions or local heterogeneity. They need to be optimised by an iterative process using in-situ measurements of soil moisture as the benchmark.

The aim of this study was to establish, for the first time, a scalable method for generating soil moisture time-series at 2 cm depth or less, that may be used for objective assessment of C-band SAR-derived surface soil moisture data. The study evaluates the impact of this on the apparent performance assessments of an example product, compared to assessment at a greater depth of measurement. Having identified new limits on soil moisture variability at the surface, the additional errors due to scaling were estimated, contrasting the use of the new limits with the common choice of FC and PWP.

3.2 Study sites and time period

The COSMOS-UK network (Evans et al., 2016) comprises a total of 50 soil moisture monitoring stations across the UK, operated by the UK Centre for Ecology and Hydrology (UKCEH). The primary soil moisture sensor at each site is a Cosmic Ray Neutron Sensor (CRNS) (Andreassen et al., 2017), which has a measurement footprint of approximately 200 metres in diameter (Köhli et al., 2015a). By mitigating against the spatial heterogeneity of soil hydraulic properties, CRNS data is more suited to validation of remotely sensed soil moisture products without having to upscale the measurements from a densely spaced network of point sensors.

The COSMOS-UK sites are also instrumented to measure a range of meteorological and environmental parameters. COSMOS-UK sites were selected for this study for their ability to supply high quality daily time-series measurements of soil moisture from the CRNS sensor, with co-located measurements of potential evapotranspiration and rainfall. Thirteen sites were selected for this study, as shown in Fig. 3.2. They represent agricultural sites as opposed to forested sites where the vegetation canopy would be too dense for C-band SAR to be able to sense soil moisture. The land uses are permanent grass, ley grass, and arable crops, where farmers and agronomists would hope that SAR remote sensing would be of benefit to them in monitoring soil moisture. The chosen sites also vary in soil textures, as shown by Table 3.1.

During 2018 the UK experienced a very cold and wet spring followed by a prolonged heatwave and drought. Using this year in the study made it probable that the soil moisture would vary between the wettest and driest conditions - well outside the range between FC and PWP - posing the greatest challenge to fit the model to in-situ data.

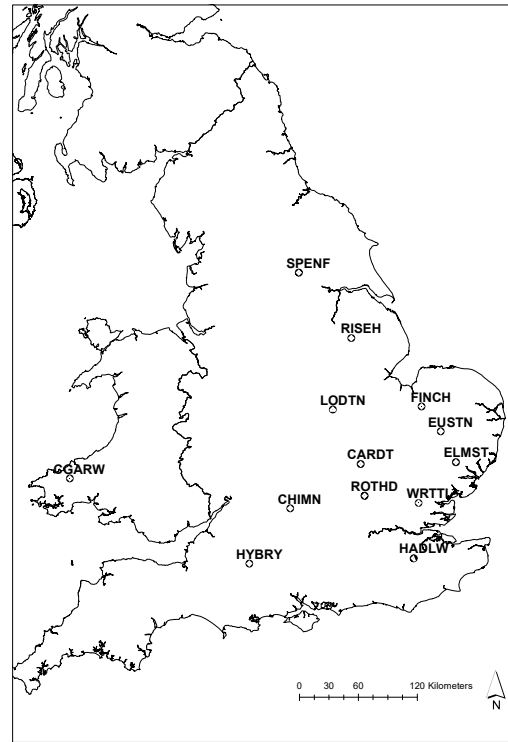


Figure 3.2: Locations of the subset of COSMOS-UK sites selected for this study. The labels are the site identifiers

Table 3.1: Subset of COSMOS-UK sites selected for this study

Site identifier	Site name	Soil type	Land cover	Dominant soil series
CARDT	Cardington	Loam to Silt Loam	Permanent Grass	Efford
CHIMN	Chimney Meadows	Clay Loam	Permanent Grass	Kelmscot
CGARW	Cwm Garw	Peaty Mineral Soil	Permanent Grass	Hafren
ELMST	Elmsett	Loam	Arable	Beccles
EUSTN	Euston	Sandy loam	Permanent Grass	Newport
FINCH	Fincham	Sandy loam, lime-rich	Arable	Swaffham Prior
HADLW	Hadlow	Clay Loam	Ley Grass	Wickham
HYBRY	Heytesbury	Shallow silt loam, lime-rich	Permanent Grass	Andover
LODTN	Loddington	Clay	Arable	Denchworth
RISEH	Riseholme	Humose Clay loam	Permanent Grass	Elmton
ROTHD	Rothamsted	Silty Loam	Arable	Batcombe
SPENF	Spen Farm	Clay loam	Arable	Aberford
WRTTL	Writtle	Loam with impeded drainage	Arable	Hornbeam

3.3 Data

The HYDRUS-1D model requires a number of input parameters and time series data in order to predict soil moisture profiles over time, and in situ soil moisture measurements for model fitting:

3.3.1 CRNS soil moisture

CRNS soil moisture measurements were obtained from the COSMOS-UK network for model fitting. The effective measurement depth of a CRNS sensor is defined by its 86% cumulative sensitivity depth, $D_{86}(\theta, r)$ (Zreda et al., 2008) where θ is the soil moisture and r is the radius from the sensor. It may be calculated by the methods proposed by Köhli et al. (2015b) who also define a sensitivity weighting as a function of depth

$$W(d, \theta, r) \propto e^{-2d/D_{86}(\theta, r)} \quad (3.1)$$

where d is the soil depth in cm. A cumulative sensitivity depth function $S(d, \theta, r)$ can be derived by integrating this function and setting the constant value so that $S(d_{\infty}, \theta, r) = 1$:

$$S(d, \theta, r) = 1 - e^{-2d/D_{86}(\theta, r)} \quad (3.2)$$

To find the depth equivalent to 50% of the cumulative response, setting $S(d_{50}, \theta, r) = 0.5$:

$$d_{50}(\theta, r) = -0.5.D_{86}(\theta, r).ln(0.5) = 0.3466.D_{86}(\theta, r) \quad (3.3)$$

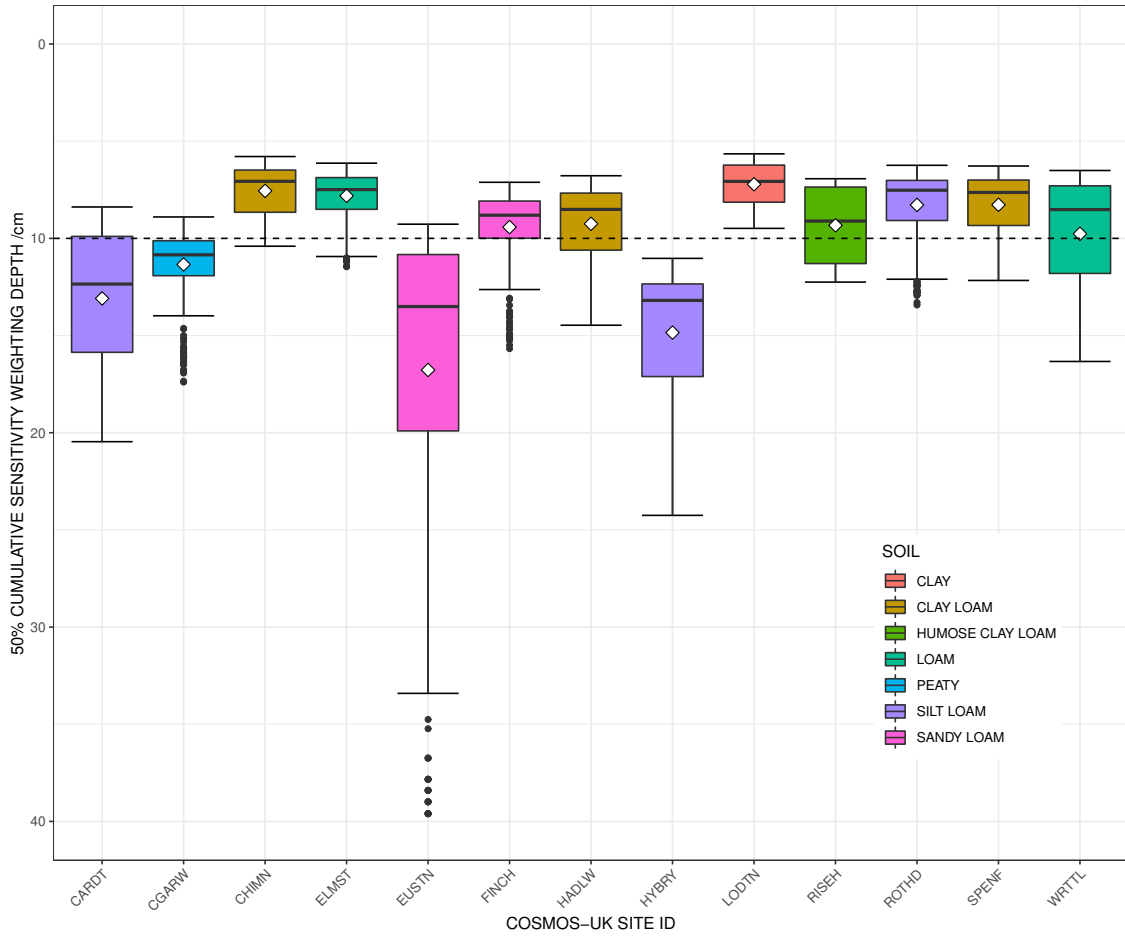


Figure 3.3: Boxplot representing the variation in the 50% cumulative sensitivity depth d_{50} (weighted by radius) during 2018 at the COSMOS-UK sites used in this study. The whiskers define the extremes of the data, the thick bars the median, and the box ends represent the first and third quartile values. The mean for each site is plotted as the white diamond. The box colours represent the site soil classification for the surface layer. 10cm soil depth, as used for model fitting, is shown as a dashed line.

Values of $d_{50}(\theta, r)$ were calculated for each daily COSMOS-UK CRNS measurement of 2018 at all thirteen sites for $r = 1, 5, 25$ and 75 m. They were then weighted by the factors $w = 1.89\text{E}5, 2.45\text{E}4, 8.22\text{E}3$ and $4.9\text{E}3$ respectively, these weightings used by the COSMOS-UK team based on Köhli et al. (2015b). Fig. 3.3 summarises the statistics of d_{50} in the form of a boxplot. For most sites the mean of d_{50} is close to 10 cm and the mean across all sites is 10.27 cm. This result agrees with a recent study in China (Tian and Song, 2019), that found that CRNS measurements were more highly correlated with soil moisture at 10 cm from the surface than at any other depth.

A depth of 10 cm is within the upper mineral soil layer (A Horizon) for all of the sites chosen for this study. According to a recent review (Hartemink et al., 2020),

the coefficient of variation of clay content in a typical A horizon is low (8%). This allows us to assume that the soil hydraulic properties are approximately the same at 10 cm and 2 cm, and to perform the model fitting at 10 cm against COSMOS UK data using a single layer model. A multi-layer configuration of the model would have been impractical to optimise due to the number of variables this would introduce.

3.3.2 Soil hydraulic properties

The soil hydraulic properties required by HYDRUS-1D are the water retention parameters of the van Genuchten-Mualem model (van Genuchten, 1980; Mualem, 1976); water content at quasi-saturation (θ_s), residual water content (θ_R), saturated hydraulic conductivity (K_s) and model fitting parameters (n , α). Initial values were obtained from the National Soil Map of England and Wales (NATMAP) (Thomson et al., 1983) as follows: At each site, the dominant soil series was identified in a GIS system (ArcMap v10.6) by overlaying a shapefile representing the nominal 200 m radius sensitivity footprint of the CRNS sensor over the vector soil map and finding the largest intersection. The main land use within the same 200 m radius was estimated by visual inspection of the COSMOS-UK phenocam images and other site metadata to be either permanent grass (PG), ley grass (LE), arable (AR) or other (OT). The depth of the upper soil horizon, its soil texture and bulk density were looked up in the LANDIS Horizon Fundamentals (Cranfield University, 2021a; Hollis et al., 2015) spreadsheet using the dominant soil series and land use. In the same way, the soil hydraulic properties were obtained from the LANDIS Horizon Hydraulics table (Cranfield University, 2021b; Hollis et al., 2015); these are summarised in Table 3.2. For the Cwm Garw site, which has a very peaty soil, the LANDIS hydraulic parameters were incomplete. The initial soil hydraulics parameters were taken from a previous study of a site with peat soil by Fields et al. (2017).

If the LANDIS or equivalent data were not available, at some new site, outside the UK, for example, a set of van Genuchten-Mualem model water retention parameters may be estimated using the Rosetta Lite v1.1 (Schaap et al., 2001) pedotransfer function provided within the HYDRUS-1D model, by supplying it with the soil texture and bulk density. If that information is also unavailable, basis soil texture classes can also be used. In these cases, the parameters predicted may be further from the actual values and it would take more time to optimise them.

Table 3.2: HYDRUS-1D initial soil hydraulic properties obtained from LANDIS Horizon Hydraulics data (Hollis et al., 2015) for the 13 study sites. These are parameters of the van Genuchten-Mualem model (van Genuchten, 1980; Mualem, 1976); water content at quasi-saturation (θ_s), residual water content (θ_R), saturated hydraulic conductivity (K_s) and model fitting parameters (n , α).

Site identifier	Soil hydraulic parameters				
	$\theta_s(\text{vol.}\%)$	$\theta_R(\text{vol.}\%)$	α	n	$K_s(\text{cm/day})$
CARDT	48.36	9.59	0.0492	1.2438	109.3
CGARW	90.00	9.00	0.1158	1.3830	6540.5
CHIMN	54.56	11.36	0.0540	1.2326	101.4
ELMST	32.50	7.32	0.0591	1.2488	76.4
EUSTN	45.21	7.31	0.0908	1.3480	115.5
FINCH	36.98	7.71	0.0784	1.2984	92.05
HADLW	57.47	12.22	0.0441	1.2229	105.3
HYBRY	69.09	13.47	0.0406	1.2321	117.6
LODTN	44.09	11.35	0.0384	1.2131	71.5
RISEH	72.30	14.59	0.0468	1.2247	107.3
ROTHD	33.90	7.46	0.0406	1.2385	107.3
SPENF	40.33	9.34	0.0510	1.2387	76.4
WRTTL	35.38	7.65	0.0489	1.2483	76.4

The end result should be equally accurate.

3.3.3 Vegetation properties

The drying mechanisms of the soil near the surface are drainage to a lower soil layer, direct evaporation, E_E , and transpiration through plant roots, E_T . The drainage element is modelled by HYDRUS-1D, but the aggregate of the other two is dependent on weather conditions. This is the potential evapotranspiration ($E_0 = E_E + E_T$) and is a standard component of the COSMOS-UK site data. The HYDRUS-1D model requires E_0 to be partitioned into E_E and E_T ; this is driven by the state of the vegetation. A common approximation is to assume that areas of bare soil are subject only to evaporation and areas covered by vegetation subject only to transpiration. Leaf Area Index (LAI) is a vegetation parameter that is inversely related to the proportion of bare soil, so a form of Beer's Law (Ritchie, 1972; Savabi and Williams, 1995), may be used for the partitioning: $E_E = E_0 e^{-\alpha \text{LAI}}$ where the default extinction coefficient, $\alpha = 0.463$. HYDRUS-1D includes the option to perform this calculation automatically if daily time series of E_0 and LAI are supplied.

For this study, LAI estimates were obtained from the MODIS optical instrument on the Terra and Aqua satellites. This MODIS dataset (MCD15A3H V6 level 4)

(Myneni et al., 2015) suffers, especially over the UK, from unreliability due to cloud cover. To minimise the impact of this, the 4-day time series was smoothed by weighting according to the confidence values ("SCF_QC" bits) provided with the product, by the following equation,

$$LAI_{i+1} = LAI_i + \Delta_{i+1} / (1 + C_{i+1}) \quad (3.4)$$

where LAI_i, LAI_{i+1} represent the time series of LAI, C is the confidence level (0 = High to 4 = No Data) and Δ is the change in the LAI value between the previous time-step and the MODIS measurement. The data was then aligned to the COSMOS-UK data time-series by linear interpolation.

HYDRUS 1-D uses rooting depth and the root density profile to calculate the transpiration profile with depth. For the purposes of this study, these parameters were set the same for each site, with the root density decreasing linearly with depth over the upper 15 cm only. This is an estimate typical of many grass species, and will be suitable for many of the sites used in this study. For others, this assumption could introduce a small error in the model fitting.

3.3.4 SAR-derived soil moisture

To illustrate the effectiveness of the method through a case study, a remote sensing soil moisture product based on C-band Sentinel-1 SAR data, Copernicus SSM (Bauer-Marschallinger and Paulik, 2019), was selected. This product estimates soil moisture by the change detection method (Hornacek et al., 2012), and presents it as an SMI value between 0% and 100% relative to the range of historically observed values at each geospatial location. The spatial resolution of the Copernicus SSM product is nominally 1km, and the temporal resolution is governed by the orbital coverage of Sentinel-1, being approximately once every 2-6 days within the UK. A time series was obtained by averaging the SMI values of the pixels overlapping the CRNS 200m radius footprint (weighted by their intersection) at each of the 13 monitoring stations selected. For the purposes of comparison to the HYDRUS model output, the predicted values (P_i) are the remote sensing predictions and the HYDRUS-1D modelled soil moisture at 2cm are the independent observations (O_i). Prior to analysis the remotely sensed soil moisture values (S_i) were converted from an SMI to volumetric water content (VWC) by scaling, as shown in Equation 3.5, where θ_{wet} and θ_{dry} are the selected wet and dry soil moisture references as

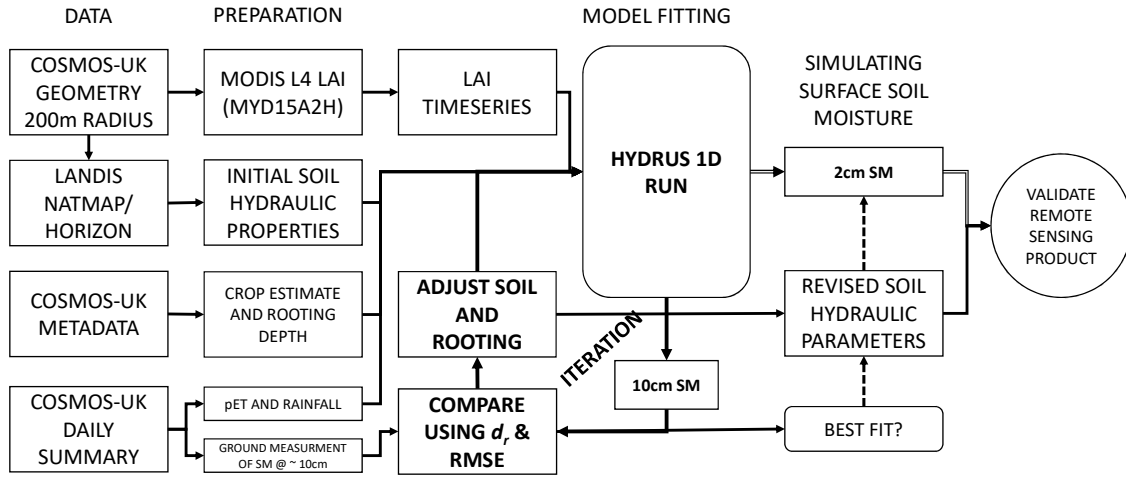


Figure 3.4: Block diagram of the method for Model fitting of HYDRUS-1D and using the fitted model to generate a time series of soil moisture at 2 cm soil depth.

determined in Section 3.4.2:

$$P_i = \theta_{dry} + S_i(\theta_{wet} - \theta_{dry}) \quad (3.5)$$

3.4 Methods

3.4.1 Simulating soil moisture at shallow depth

The method for generating a soil moisture time series at 2 cm is depicted in Fig. 3.4. The HYDRUS-1D model was configured for a single soil layer the same thickness as the upper horizon using the initial soil hydraulic properties derived from LANDIS data (Hollis et al., 2015) as described in 3.3.2. Excess water at the surface was set to run off and free drainage to a lower soil layer was defined at the lower interface. The daily time series of potential evapotranspiration, rainfall and Leaf Area Index were imported into the HYDRUS-1D model as time-varying boundary conditions.

The soil hydraulic parameters were optimised by iteration until the model predictions at 10 cm depth (P_i) matched in situ soil moisture observations, (O_i) from the COSMOS-UK CRNS, as closely as possible. The approach of Harmel et al. (2014) was used; selecting an index of agreement based on the Willmott Index (Willmott, 1981), d , which quantifies the relative co-variability of the predictions about the mean of the observations. The refined version, d_r (Willmott et al., 2012), is reported to be less sensitive to extreme values and better suited for model evaluation than R^2 (Legates and McCabe, 1999). It is a dimensionless number,

calculated according to Equations 3.6 and 3.7 that varies between -1 (no fit) and +1 (ideal fit) and is particularly suitable where a 1:1 relationship between prediction and observation is expected. The mean absolute percentage difference (MAPD), as defined by Equation 3.8, and the Root Mean Squared Difference (RMSD), as defined by Equation 3.9, were also calculated. The RMSD was further decomposed into bias (b) and unbiased RMSD (ubRMSD) according to equations 3.10 and 3.11. The p -value at 95% confidence intervals was calculated using the two-tailed Student's t -distribution, with the value of t calculated by dividing the regression slope by its standard error. The recommendation of (Harmel et al., 2014) is that the model optimisation sought to maximise d_r but without allowing RMSD to increase significantly, so this approach was adopted here.

$$d_r(P, O) = 1 - \frac{\sum_{i=1}^n |P_i - O_i|}{2 \sum_{i=1}^n |O_i - \bar{O}|}, \text{ when } \sum_{i=1}^n |P_i - O_i| \leq 2 \sum_{i=1}^n |O_i - \bar{O}| \quad (3.6)$$

$$d_r(P, O) = \frac{2 \sum_{i=1}^n |O_i - \bar{O}|}{\sum_{i=1}^n |P_i - O_i|} - 1, \text{ when } \sum_{i=1}^n |P_i - O_i| > 2 \sum_{i=1}^n |O_i - \bar{O}| \quad (3.7)$$

$$MAPD(P, O) = \frac{100}{n} * \sum_{i=1}^n \frac{|P_i - O_i|}{O_i} \quad (3.8)$$

$$RMSD(P, O) = \sqrt{\frac{\sum_{i=1}^n (P_i - O_i)^2}{n}} \quad (3.9)$$

$$b(P, O) = \frac{\sum_{i=1}^n (P_i - O_i)}{n} \quad (3.10)$$

$$ubRMSD(P, O) = \sqrt{Var(P, O)} = \sqrt{RMSD^2(P, O) - b^2(P, O)} \quad (3.11)$$

To optimise the fit of the HYDRUS-1D model to CRNS data, d_r and RMSD were calculated as a function of each soil hydraulic parameter (θ_R , θ_S , α , n , K_s) to locate a value close to a maximum in d_r and a minimum in RMSD. Some interdependence between the parameters was evident, so the whole process was repeated several

times for each study site until no further improvement could be achieved. Having established an optimum set of values of the soil hydraulic parameters that appear to describe the local soil properties well, the HYDRUS-1D model output at the desired simulation depth of 2 cm was then obtained using these values.

3.4.2 Identifying soil moisture limits at the surface

A review was conducted to identify soil moisture parameters that are candidates for natural limits on the movement of soil moisture due to drying or wetting processes. These are all related to soil physics or attributes of the drying mechanisms. Starting at the highest value of soil moisture:

1. Porosity (P) defines the total pore space available to be filled with water and sets an effective upper limit for soil water content, probably achieved only if the soil surface is under water for some time.
2. Water Content at Quasi-Saturation (θ_S) is one of the [van Genuchten \(1980\)](#) fitted model parameters, and is typically 5-15% below P , due to entrapment of

Table 3.3: Candidate wet and dry references for the surface soil layer at COSMOS-UK sites used in this study, based on LANDIS HORIZON Hydraulics Data. Optimised values of θ_{SX} and θ_{RX} were derived from model fitting as shown in Table 3.4. Values are in volumetric water content (vol.%). In the case of ELMST, FINCH and ROTHHD $\theta_{FC} > \theta_S$ which is not logical. θ_S is derived from model fitting and is likely to be in error, and actually much closer to the value of P in these cases.

Site Label	Wet References			Dry References		
	P	θ_S	θ_{FC}	θ_{PWP}	θ_{HC}	θ_R
CARDT	53.2	48.36	44.2	21.1	17.66	9.59
CGARW	>90	90.00	53.0	26.4	6.70	9.00
CHIMN	56.2	54.56	47.0	23.4	19.58	11.36
ELMST	44.2	32.50	36.7	19.9	15.21	7.32
EUSTN	52.9	45.21	41.4	17.1	11.33	7.31
FINCH	47.7	36.98	38.2	19.9	13.61	7.71
HADLW	56.9	57.47	48.2	24.2	21.02	12.22
HYBRY	60.8	69.09	51.4	23.7	21.15	13.47
LODTN	50.7	44.09	44.5	26.1	21.34	11.35
RISEH	62.2	72.33	52.5	25.1	22.18	14.59
ROTHD	44.7	33.86	38.5	19.7	16.17	7.46
SPENF	49.2	40.33	41.6	22.8	17.88	9.34
WRTTL	46.0	35.38	38.8	19.9	15.77	7.65

air during wetting. Soil is unlikely to wet above this value, excess water will run off. After wetting to this point, the soil will dry rapidly due to drainage (mostly) and evapotranspiration.

3. Field Capacity (FC or θ_{FC}) (Veihmeyer and Hendrickson, 1931) is the point below which soil will no longer drain to a lower layer under gravity. Further drying is by evapotranspiration only.
4. Permanent Wilting Point (PWP or θ_{PWP}) (Veihmeyer and Hendrickson, 1928) is a point at which transpiration by plants falls to zero and evaporation becomes the only drying mechanism.
5. Hygroscopic Coefficient (θ_{HC}), or natural air-dried moisture value, defines the water content of soil that has dried by evaporation then allowed to reach equilibrium in a saturated atmosphere. Most of the pore water has been removed. Further drying is possible in very hot conditions by evaporating some capillary water, but this requires significantly more energy. When the temperature falls, the soil moisture will tend to return to this value naturally, without rainfall, provided there is sufficient humidity in the air.
6. Residual Water Content (θ_R) is another of the van Genuchten (1980) model parameters, and is an approximate lower limit of the soil drying process in natural conditions rather than at the much higher temperature of an oven.

To identify which, if any, of these candidates are suitable as wet or dry reference points, values of P , θ_S , θ_{FC} , θ_{PWP} and θ_R were obtained from the LANDIS Horizon data for each of the 13 COSMOS-UK sites, as shown in Table 3.3. θ_{HC} was calculated using the van Genuchten (1980) model, Equation 3.12, where $h = 3,100$ kPa and n and m were obtained initially from the LANDIS Horizon Hydraulics data (Hollis et al., 2015).

$$\theta_{HC} = \theta_R + \frac{(\theta_S - \theta_R)}{(1 + (\alpha h)^n)^m} \quad (3.12)$$

The HYDRUS-1D model fitting process also generated optimised values for θ_S and θ_R which will be referred to as θ_{SX} and θ_{RX} respectively.

Pairs of candidate references were evaluated by using them to scale the remotely sensed SMI time series of the Copernicus SSM product to volumetric water content. The results were compared to the 2 cm depth soil moisture simulation of the model. As previously discussed, scale-independent statistical measures of accuracy, such

as the coefficient of determination (R^2), are inappropriate as they are not sensitive to scaling errors introduced in the conversion of SMI to VWC. Scale-dependent measures, such as *RMSD* (Equation 3.9) are also unsuitable because the scaling process serves to amplify or attenuate any systematic noise in the time-series, affecting the *RMSD* value independently of the trend. Alternative metrics were identified based on range and offset. Linear regression was used to find the best-fit straight line to describe the relationship between the calibrated volumetric soil moisture from remote sensing (y) and the model output at 2 cm (x). This line was expected to be of the form $y = a + bx$ where a is the offset and b is the slope. Since the ideal scaling has no offset ($a = 0$) and unity slope ($b = 1$), metrics in the form of $|a|$ and $|1 - b|$ were used, in addition to d_r and *RMSD*, to find the most effective combinations of candidate references for each site.

3.5 Case study

To assess the relative benefits of validating a C-band SAR derived surface soil moisture product against the modelled soil moisture at 2 cm, a limited performance assessment of the Copernicus SSM product (Bauer-Marschallinger and Paulik, 2019) was undertaken. This product is based on data from ESA's Sentinel-1 satellites (Torres et al., 2012) and processed with a change detection algorithm (Hornacek et al., 2012). Using the methods described earlier, daily soil moisture model predictions for 2018 were generated at 2, 5, 10 and 15 cm soil depth for each of the study sites. SSM-derived volumetric water content estimates were obtained by calibrating the SMI values against wet and dry soil moisture references, θ_{wet} and θ_{dry} respectively. As the SSM data does not provide a daily time series at any particular location, values for the days within the SSM time series were paired with the equivalent days in the model output for comparison.

Inspection of the SSM data showed that it was characterised by significant, apparently random, errors, that were much larger in magnitude than the soil moisture variation. To mitigate this, a simple exponential filter, defined by Equation 3.13 was implemented. The decay constant, α_i , is a function of the time interval between measurements in days, $\Delta T = T_i - T_{i-1}$, according to Equation 3.14. The values of $\alpha_0 = 0.8$ and $\lambda = 0.1$ were chosen to reduce the noise level without significantly reducing the data sensitivity to short term changes in soil moisture. The time constant of this filter is $\lambda^{-1} = 10$ days, which is similar to the 12-day repeat cycle of each Sentinel-1 satellites. A significant component of the noise that

the filter is attenuating may be artefacts of multiple platforms and overlapping orbit image footprints that are otherwise beneficial in enabling more frequent measurements. A full optimisation of such a filter, or an alternative mitigation strategy is outside the scope of this study, and is not necessary to achieving the objectives.

$$P'_i = (1 - \alpha_i)P_i + \alpha_i P_{i-1} \quad (3.13)$$

$$\alpha_i = \alpha_0 e^{\lambda(1-\Delta T)} \text{ where } \alpha_0 = 0.8, \lambda = 0.1 \quad (3.14)$$

The performance of the SSM derived VWC was assessed against that modelled by HYDRUS-1D using the refined Willmott Index of Agreement, d_r (Willmott et al., 2012), $RMSD$, linear regression slope error ($|1 - b|$) and offset ($|a|$). For the purpose of calculating d_r , the HYDRUS-1D model output is used in place of the more usual ground observations (O) against which to test the estimates from the SSM product, which are 'predictions' (P) in the context of the Willmott Index. A good level of performance is characterised by a high value of d_r , and low values of $RMSD$, $|1 - b|$ and $|a|$.

3.6 Results

3.6.1 Model fitting

Results of the model fitting at 10 cm depth to the CRNS data for all 13 selected COSMOS-UK sites and the whole of 2018 are presented in Table 3.4. This shows the final values of the soil hydraulic parameters after optimisation and the values of d_r , $RMSD$ and other metrics achieved. The p -values are very small and show that the model fits are statistically significant at the 95% confidence level ($p \ll 0.05$). The Cwm Garw site (CGARW) is a slight outlier in terms of d_r and $RMSD$, but here the soil depth is relatively shallow so the free drainage assumption for the bottom of the A Horizon may not be valid. The models used may also not work as well for peat soils with a high organic matter content. Across the other sites the d_r value ranges from 0.774 to 0.862 and the $RMSD$ from 2.52 to 5.78 vol.%. An example of the time series fit at the Fincham (FINCH) site is shown in Appendix 3.A; the optimisation process is very effective in matching the prediction to the observations. Remaining variance may be due, to some degree, to the effective

Table 3.4: Optimised van Genuchten-Mualem soil hydraulic parameters and model fit statistics (HYDRUS-1D at 10 cm versus CRNS) for 2018 at 13 COSMOS-UK sites. θ_{SX} is the water content at saturation and θ_{RX} is the residual water content. α and n are parameters of the water retention function and K_s is the saturated (vertical) hydraulic conductivity. The model fit statistics are the Willmott Index (d_r), MAPD, RMSD, Bias, ubRMSD and the p value. Where no units are shown, the metric or parameter is dimensionless.

SITE ID	Optimised Soil Hydraulic Properties				
	$\theta_{SX}(\text{vol.}\%)$	$\theta_{RX}(\text{vol.}\%)$	$\alpha(\text{cm}^{-1})$	n	$K_s(\text{cm.day}^{-1})$
CARDT	47.0	5.20	0.0008	1.66	6.0
CGARW	90.0	9.00	0.0990	1.23	8580
CHIMN	61.4	3.50	0.0070	1.27	95.0
ELMST	48.5	0.05	0.0015	1.19	7.0
EUSTN	49.7	0.01	0.0140	1.61	95.0
FINCH	40.4	1.00	0.0120	1.29	38.0
HADLW	64.3	4.50	0.0032	1.49	15.0
HYBRY	61.2	4.30	0.0070	1.42	50.0
LODTN	69.8	10.00	0.0030	1.30	15.0
RISEH	73.0	12.00	0.0235	1.46	265
ROTHD	37.9	2.20	0.0080	1.27	3.0
SPENF	41.1	4.00	0.0010	1.29	10.0
WRTTL	57.5	1.90	0.0020	1.62	1.5

SITE ID	Model Fit Metrics					
	d_r	MAPD	RMSD (vol.%)	Bias (vol.%)	ubRMSD (vol.%)	p value
CARDT	0.779	15.90%	4.62%	3.42%	3.11%	6.31E-105
CGARW	0.659	12.72%	7.75%	5.96%	4.96%	1.26E-59
CHIMN	0.827	7.75%	3.68%	2.66%	2.53%	1.16E-139
ELMST	0.829	6.90%	3.17%	2.45%	2.01%	9.58E-156
EUSTN	0.866	60.47%	2.52%	1.89%	1.67%	2.02E-166
FINCH	0.775	9.32%	2.93%	2.22%	1.90%	5.84E-119
HADLW	0.832	9.20%	4.23%	3.19%	2.78%	8.47E-112
HYBRY	0.762	13.02%	5.35%	4.24%	3.26%	3.57E-88
LODTN	0.834	6.95%	4.62%	3.19%	3.34%	8.23E-135
RISEH	0.837	7.85%	3.20%	2.39%	2.14%	1.18E-152
ROTHD	0.774	10.02%	4.30%	2.95%	3.13%	4.13E-100
SPENF	0.855	7.13%	2.76%	1.96%	1.94%	5.25E-128
WRTTL	0.807	14.20%	5.78%	4.52%	3.60%	2.84E-152

measurement depth of the CRNS sensor, which is a function of soil moisture.

Having established an optimised set of soil hydraulic properties for each site, the candidates for use as reference soil moisture values (θ_{wet} and θ_{dry}) for converting SMI's to volumetric water content may be revised also.

3.6.2 Predicting soil moisture at 2 cm

The HYDRUS-1D model with its optimised soil hydraulic parameters were used to simulate soil moisture at each of the 13 selected COSMOS-UK sites, for the whole of 2018. Observation nodes were set at soil depths of 2, 5, 10 and 15 cm from the surface. An example of the prediction at the Chimney Meadows (CHIMN) site is shown in Fig. 3.5, which plots about four months of data in the summer, which was a drought and heatwave period. In such conditions, the profile of soil moisture is expected to vary significantly with depth. The modelled time series demonstrates this, with the simulation at 2 cm depth showing the greatest range of soil moisture values and the simulation at 15 cm showing the least. The 2 cm time series demonstrates rapid reaction to short rainfall events and longer dry spells.

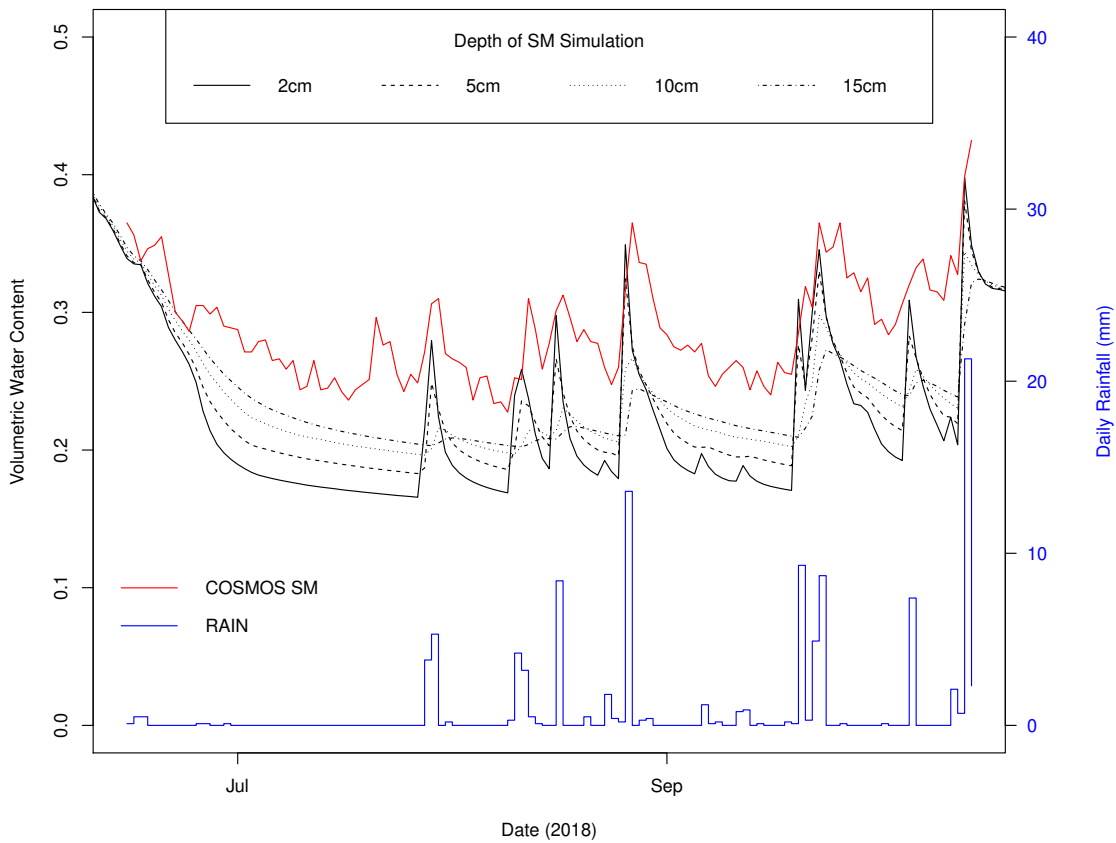


Figure 3.5: HYDRUS 1-D (Simunek et al., 2008) HYDRUS 1-D modelled soil moisture at the Chimney Meadows COSMOS-UK site at various depths from the surface from mid-June to mid-October 2018. The period is selected to include a drought period at the start followed by separated rainfall events, illustrating that the soil moisture at the surface is much more responsive to drying and wetting than at greater depths. Shown for comparison is the daily rainfall total (blue) and the soil moisture estimate (at around 10cm depth) from the CRNS sensor (red).

Table 3.5: Analysis of wet and dry reference choices for CHIMN site in 2018. First choice combinations are shown in **bold**, second choice underlined.

Metric	<i>RMSD</i> , (vol.frac.)				Slope error, $ 1 - b $				Offset, $ a $, (vol.frac.)			
	Wet References				Wet References				Wet References			
Dry References	<i>P</i>	θ_S	θ_{SX}	<i>FC</i>	<i>P</i>	θ_S	θ_{SX}	<i>FC</i>	<i>P</i>	θ_S	θ_{SX}	<i>FC</i>
<i>PWP</i>	0.12	0.11	0.14	0.09	0.61	0.63	0.55	0.72	0.25	0.25	0.26	0.25
<i>HC</i>	0.11	0.11	0.13	0.1	0.57	0.58	0.5	0.67	0.22	0.22	0.22	0.21
θ_R	0.13	<u>0.12</u>	0.14	0.12	0.47	<u>0.49</u>	0.41	0.58	0.14	<u>0.14</u>	0.14	0.13
θ_{RX}	0.15	0.15	0.16	0.16	0.37	0.39	0.31	0.48	0.07	0.07	0.07	0.06

3.6.3 Identifying wet and dry reference values for converting SMI to absolute VWC

At each of the 13 selected COSMOS-UK sites, the 2018 time-series of SSM-derived volumetric SM, y_i , was determined by the intersection-weighted average of the pixels overlapping the 200 m CRNS sensitivity footprint. The volumetric soil moisture was calculated from the published soil moisture index values using four each wet and dry references. The wet references chosen were *P*, θ_{SX} , θ_S and *FC*. The dry references were θ_{RX} , θ_R , *HC* and *PWP*. θ_{SX} and θ_{RX} were the optimised values established in the HYDRUS-1D model fitting process, all the others were taken from LANDIS Horizon Hydraulics data. For the same acquisition dates, the fitted HYDRUS-1D model predictions of soil moisture at 2 cm were used as the best available proxy for a daily soil moisture measurement, x_i . A linear relationship of the form $y_i = a + bx_i$ was expected, where, ideally, $a = 0$ and $b = 1$. For each of the sixteen combinations of references, the regression coefficients a and b were found by linear regression analysis in R, and the slope error ($|1 - b|$) and offset ($|a|$) calculated, along with the *RMSD*. An example of these results for the Chimney Meadows (CHIMN) site is shown in Table 3.5. For each site, first and second choice wet and dry references were identified by inspection of these tables, the primary focus being to achieve a low value of *RMSD*, slope error and offset.

A summary of these recommendations for all 13 sites given by Table 3.6. The additional error estimate for using second choice over first choice reference recommendations was calculated as the mean of the differences between the first and second choice references at each site. In most cases this is less than 5 vol.% except for LOTDN, HYBRY and SPENF sites where the error is up to 10 vol.%. A similar estimate was calculated for using the common choice of *FC* and *PWP* as references compared to the first choice recommendations. The error in this case is generally larger. It should be noted that these are estimates of the average error, the actual

error will be soil moisture dependents and will be greatest towards the extremes of the range, where the error could be up to 20 vol.%.

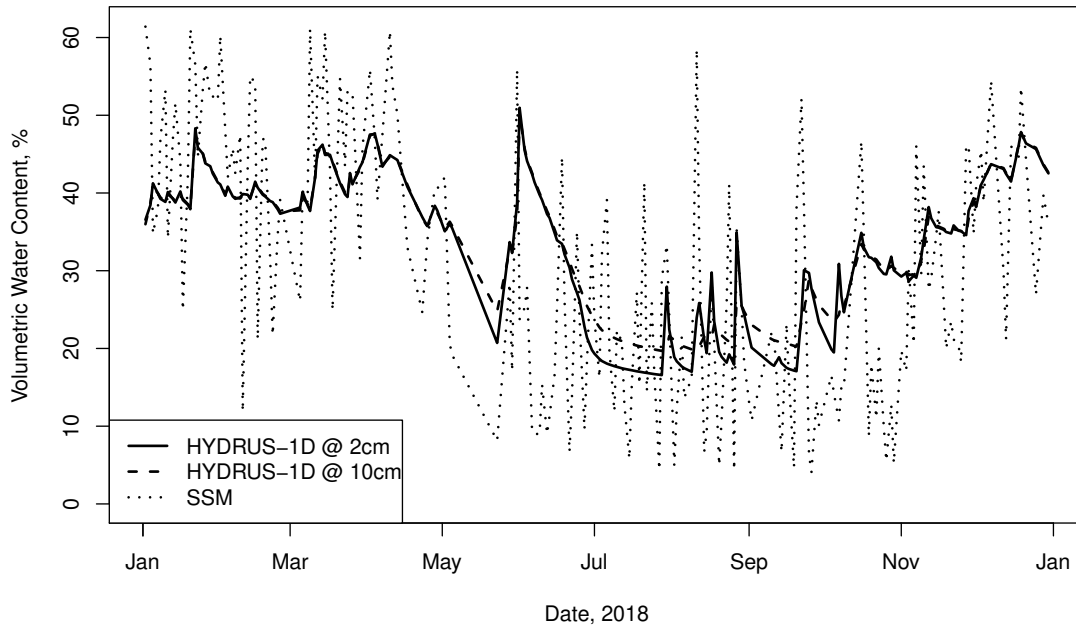
Table 3.6: Recommended choices of wet and dry reference parameters for conversion of Copernicus SSM SMI to VWC at 13 COSMOS-UK sites, based on 2018 data, and comparison with HYDRUS-1D modelled soil moisture at 2 cm depth. The additional error estimate for using 2nd choice over 1st choice or FC/PWP is the mean of the differences between the pairs of wet/dry references at each site.

Site identifier	Wet Reference		Dry Reference		Error Est. vol. %	
	1st Choice	2nd Choice	1st Choice	2nd Choice	1st vs. 2nd	1st vs. FC/PWP
CARDT	θ_{SX}	θ_S	θ_{RX}	θ_R	2.9	6.6
CGARW	θ_{SX}	θ_S	θ_{RX}	θ_R	0	9.8
CHIMN	θ_{SX}	P	θ_{RX}	θ_R	1.3	2.8
ELMST	θ_{SX}	P	θ_{RX}	θ_R	1.5	4
EUSTN	P	θ_{SX}	θ_{RX}	θ_R	2.1	2.8
FINCH	θ_{SX}	θ_S	θ_{RX}	θ_R	1.6	8.4
HADLW	θ_{SX}	θ_S	θ_{RX}	θ_R	0.4	1.8
HYBRY	θ_{SX}	θ_S	θ_{RX}	θ_R	8.5	4.8
LODTN	θ_{SX}	P	θ_R	θ_{RX}	10.2	5.3
RISEH	P	FC	θ_{RX}	θ_R	3.6	1.7
ROTHD	P	FC	θ_{RX}	θ_R	0.5	5.7
SPENF	θ_{SX}	P	θ_{RX}	θ_R	6.7	9.7
WRTTL	θ_{SX}	P	θ_{RX}	θ_R	2.9	0.4

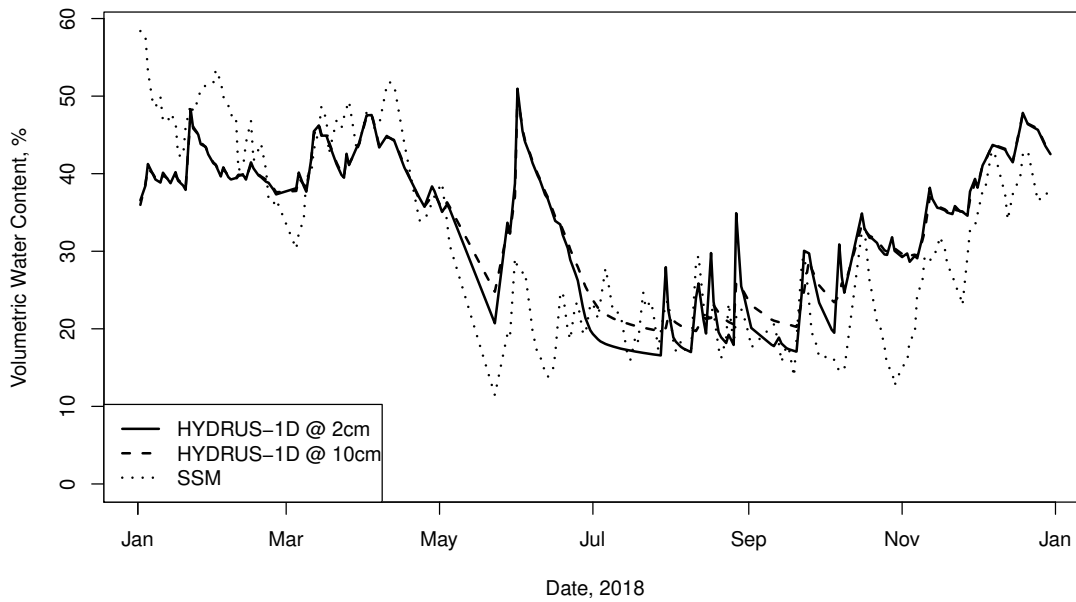
3.6.4 Case study - assessment of the Copernicus SSM derived VWC

Fig. 3.6 illustrates, for one site, the beneficial impact of the exponential smoothing filter that was applied to the Copernicus SSM derived soil moisture data. Similar benefits were seen at all other sites. In this example, the remotely-sensed time series in Fig. 3.6(b) is much better matched to the HYDRUS-1D model output, but retains a similar dynamic range and responsiveness to soil moisture changes. The maximum deviation is between May and July, which may be due to vegetation effects in the remotely sensed data, and is currently subject to further study by the authors.

Appendix 3.B summarises the performance metrics for the SSM-derived volumetric soil moisture assessed against modelled soil moisture at 2 and 10 cm, at all 13 of the selected COSMOS-UK sites. The assessment was repeated for SSM data with and without the smoothing by exponential filter.



(a) Non-smoothed Copernicus SSM data



(b) Exponentially smoothed Copernicus SSM data

Figure 3.6: HYDRUS 1-D (Simunek et al., 2008) Copernicus SSM derived VWC time series for 2018 compared to the HYDRUS-1D model output at 2 cm and 10 cm depths. The site is Chimney Meadows (CHIMN).

3.7 Discussion

3.7.1 Model fitting

The optimised soil hydraulic properties model fit in Table 3.4 is characterised by an RMSD value of less than 5 vol.% in almost all cases, which is a significant achievement in light of the fact that the CRNS sensor has a variable depth sensitivity. The results provided enough confidence in the model to use it at a shallower soil depth.

Comparing the optimised to initial soil hydraulic properties (Tables 3.4 and 3.2), the deviation is quite large at some sites. Generally, the fitted values of θ_R are lower than the initial values from the soil maps, in some cases very close to 0 vol.% SM. For some sites the value of θ_S is much higher than the starting value (CHIMN, ELMST, LODTN, WRTTL) which might suggest that the soil texture is not as expected from the soil map. Some of the optimised values of K_S were very different to that expected from the LANDIS Horizon Hydraulics data (CARDT, ELMST, FINCH, HADLW, HYBRY, LODTN, RISEH, ROTH, SPENF, and WRTTL). Possible reasons for this include; local heterogeneity not represented in the soil map, localised soil compaction, tillage operations, and fissures and other drainage channels that have developed.

Where there is an appreciable organic layer overlying the mineral soil, the single layer model may not be ideal. HYDRUS-1D may be configured for two or more layers, but the optimisation of additional soil hydraulic parameters may not be practical.

The method developed here is dependent only on the soil hydraulic properties, of which it is assumed there is no seasonal variation. The model has been deliberately fitted to a whole year's length of observations to achieve a fitted set of parameters valid all year. It is acknowledged that soil hydraulic properties can be changed by anthropomorphic changes and this could introduce some uncertainty in the model.

The methods could be used with alternative soil moisture sensors where no CRNS is available, provided that measurements of rainfall and PE can be made. The soil hydraulic parameters could also be determined direct by soil sampling and laboratory analysis, but this an expensive and resource intensive process. It is more scalable to start with values derived from existing soil maps and adjust them empirically to match field observations.

3.7.2 Wet and dry references for converting SMIs to VWC

The results of this study, summarised in Table 3.6, confirm that FC and PWP are not the appropriate references to use when converting Copernicus SSM SMI values to VWC. For none of the 13 sites does PWP appear appropriate as a dry reference, and in only two cases does FC seem an acceptable choice as a wet reference. In most cases the Van Genuchten model parameters θ_S and θ_R are an appropriate choice for the wet and dry reference. Where optimised values are available from model fitting, these give even better results in most cases, as expected. In regions where values of θ_S and θ_R may not be readily available, the saturation value, P , which may be approximately estimated by the porosity of the soil, would be a better estimate of wet reference than FC. For the dry reference a value of 0 to 5 vol.% could be used, as the values of θ_{RX} are generally very low.

This finding may also be relevant to the calibration of other products presented as SMIs, where the sensing technology is only sensitive to a shallow surface layer of less than 5cm. This may include all products based solely on C- and X-band SAR or optical remote sensing.

3.7.3 Application of the method

The HYDRUS-1D model has been fitted to the COSMOS-UK CRNS sensor with a foot print of around 400 m diameter, using MODIS LAI data at 500 m resolution to partition evapotranspiration into evaporation and transpiration. There will be some uncertainty due to the difference in scale. The HYDRUS-1D predictions of soil moisture at 2 cm and 10 cm depth are derived from, and therefore at the same scale as COSMOS-UK. When using these predictions to validate the Copernicus SSM 1km product, a representativeness error (Gruber et al., 2020) may be introduced. For the purpose of this study, the magnitude of this error is assumed to be the same when validating at 2 cm and 10 cm soil depth.

The depth of penetration of C-band SAR depends on the dielectric constant of the soil, which is a function of soil moisture, and is in the range of 1-5 cm (Nolan and Fatland, 2003). This appears as a source of noise when comparing the SAR-derived soil moisture to any fixed depth measurement. A depth of 2 cm is close to the average penetration depth and will minimise the noise compared to 5 cm or 10 cm where validation is typically undertaken.

In validation of satellite soil moisture products, another potential uncertainty introduced by this method is caused by the satellite acquisition occurring at a fixed

time during the day. The HYDRUS-1D modelled soil moisture is a result of the rainfall and potential evapotranspiration during that day, potentially equivalent to the expected conditions at midnight. This uncertainty is likely to be random and relatively small.

The method of validation presented here should also be applicable to validation of SAR-based soil moisture products at, for example, X-band, which has an even shallower depth (Nolan and Fatland, 2003) of penetration than C-band.

3.7.4 Case study assessment of Copernicus SSM soil moisture

Figure 3.6a compares the time series of volumetric soil moisture derived from remote sensing and the HYDRUS-1D model output at 2 and 10 cm depth. As anticipated, the overall trends of the remote sensing output and the model simulation match reasonably well, especially at 2 cm depth, but the SSM-derived data appears to have a significant noise element. This varies so rapidly that it cannot be explained by variations in soil moisture, surface roughness or vegetation. The source is likely to be a combination of random noise (speckle), heavy rain, frozen soil or the occasional presence of scattering sources such as vehicles. Alternatively it may be systematic in nature, due to time of day or orbit geometry. This was the motivation for implementing the exponential filter in the course of this study. In implementing such a filter, some caution must be advised, as a similar approach may be used to estimate soil moisture at greater depths from surface soil measurements (Wagner et al., 1999). Soil moisture below the surface is dependent on the history of rainfall events and evaporation at the surface, with a time constant dependent on infiltration rates. When implementing an exponential filter for noise reduction, care must be taken to avoid damping the signal too much, and by doing so unwittingly predict soil moisture at a greater depth than the observations. Other types of filters will be the subject of further research.

Appendix 3.B shows that, for 10 out of the 13 selected COSMOS-UK sites, the assessment of the SSM derived soil moisture was more favourable overall when compared to HYDRUS-1D model output at 2 cm depth than they were compared to HYDRUS-1D simulations at 10 cm depth. This is based mainly on d_r values. At seven sites CHIMN, ELMST, FINCH, LODTN, RISEH, ROTH and SPENF the benefit of assessing at 2 cm is unambiguous, with improvements in almost all metrics. At CARDT, HADLW and WRTTL the results are a little mixed. The anomalous sites include CGARW and HYBRY. These are reported to have a

relatively shallow overall soil depth over rock and chalk, so the CRNS data may be more strongly correlated to surface soil moisture at these sites. The results at RISEH are generally poor, which appears to be due errors in setting the wet and/or dry references at this site (indicated by a large value of $|1 - b|$). At EUSTN, the performance metrics are similar at 2 cm and 10 cm. It is likely that the exceptionally high sand content >73 vol.%, has led to rapid drainage of water from the 2 cm to 10 cm layer.

The practical implication of the results just presented is that previous assessments of products such as Copernicus SSM may have overestimated the error in these products due to validation at an inconsistent depth and that future analyses should take account of this by adopting a similar method to that reported here.

The *RMSD* values associated with the Copernicus SSM-derived soil moisture compared to HYDRUS-1D 2 cm model output, is in the range 8.9 to 19.8 vol.% (unsmoothed data) or 7.6 to 18.3 vol.% (exponentially smoothed). The noise reduced by filtering will be partly random, but also seems to have a periodic component, which may be due to satellite orbit geometry, that should be further investigated.

3.8 Conclusions

This study has highlighted the importance of assessing the performance of surface soil moisture products against in-situ observations that are consistent with the penetration depth of the frequency of SAR being used. In the case of C-band SAR, this is at no greater depth than 2 cm, where instrumented soil moisture measurements appear to be rare. The new method proposed in this chapter offers a means to achieve this by simulating in situ soil measurements at 2 cm or any other depth, by fitting the HYDRUS-1D model to in situ observations at a much greater depth. The data required to achieve this is a time series of soil moisture measurements at (for example) 10 cm, leaf area index and potential evapotranspiration. A demonstrable improvement has been shown in the apparent performance of soil moisture derived from Copernicus-SSM between assessment at 2 cm and 10 cm in 10 out of 13 COSMOS-UK sites studied.

For many applications, the soil moisture indices (SMI) often used in remote sensing products, would be much more useful converted into absolute values of volumetric water content (VWC), or plant available water. This study has shown that, for the Copernicus-SSM product, to convert SMI to VWC, the wet and dry

references should ideally be the Van Genuchten model parameters θ_S and θ_R and not θ_{FC} and θ_{PWP} as commonly used. The potential error in using the latter is in the range 2 to 10 vol.% on average but increases up to as much as 20 vol.% at high or low soil moisture values for some sites. It has further been shown that use of Van Genuchten model parameters θ_S and θ_R derived from the HYDRUS-1D model optimisation can further improve accuracy over those obtained from soil maps, but this is site dependent and is generally less than a 10 vol.% improvement in average accuracy.

3.9 Acknowledgments

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This study brought together existing research data obtained from a number of different sources, some of which were upon request and subject to licence restrictions. Full details of how these data may be obtained may be found at doi: 10.17862/cranfield.rd.13028123.

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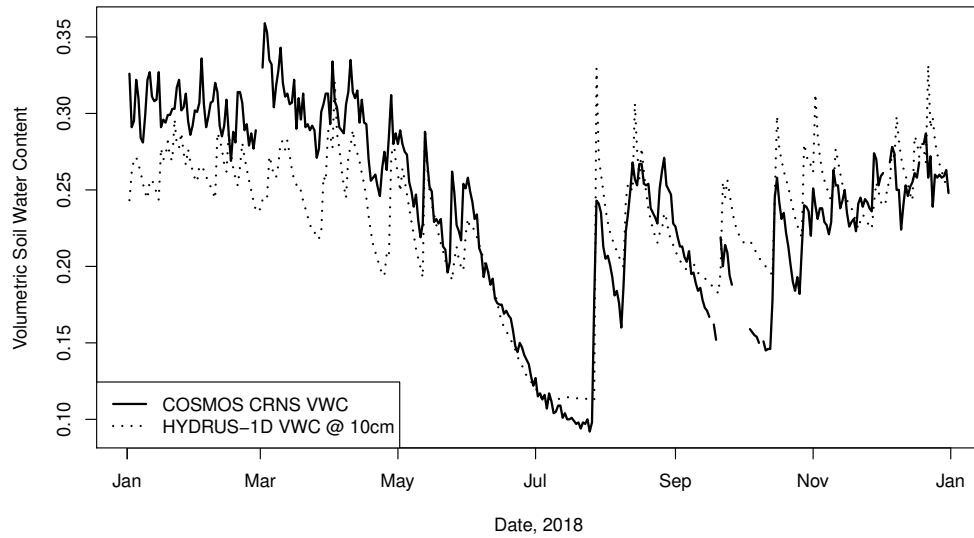
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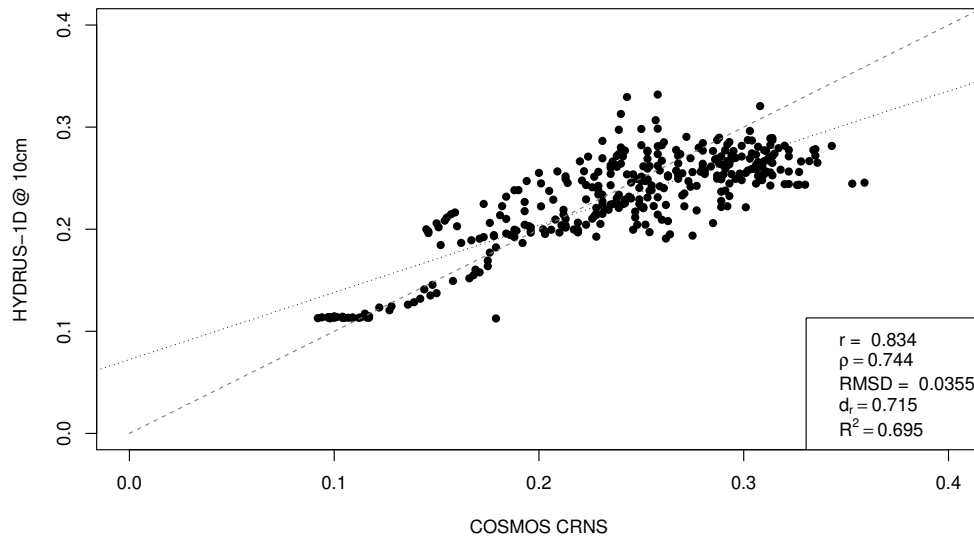
Appendices

3.A Model fitting results

An example of the time series fit at the Fincham (FINCH) site is given in Fig. 3.7 (before optimisation) and Fig. 3.8 (after optimisation). Before optimisation the model prediction is a little low in the winter and spring (January to May), a little high in the driest conditions during July, but the shape is very close to the COSMOS-UK data. This the optimisation process has been very effective in closing these gaps and matching the prediction to the observations. The remaining errors may be due, to some degree, to the effective measurement depth of the CRNS sensor, which varies with soil moisture.

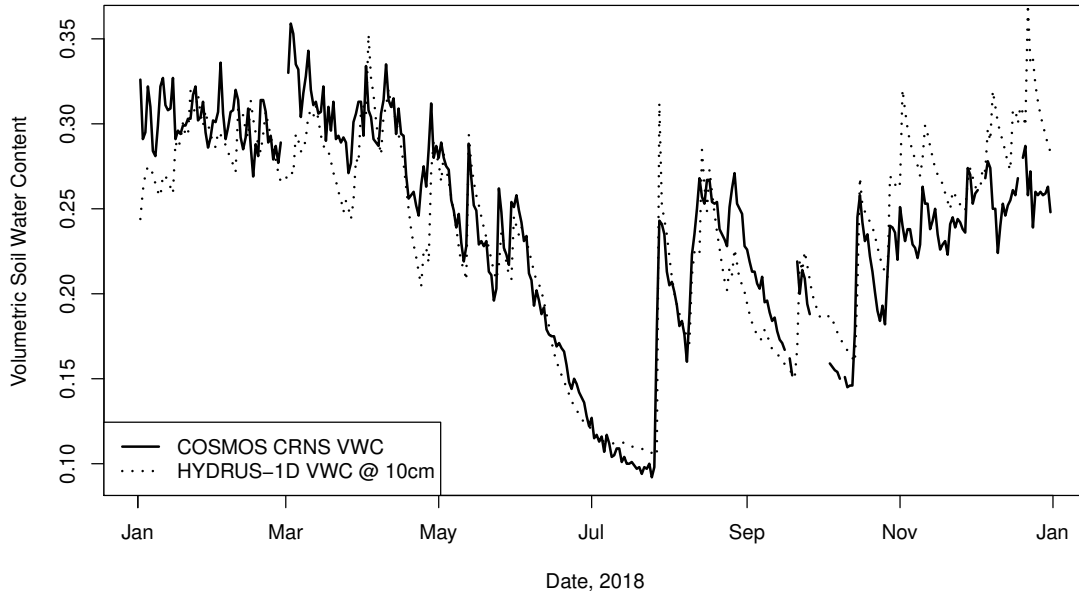


(a) Time series of predicted volumetric water content (VWC) at 10 cm and COSMOS-UK CRNS measurements

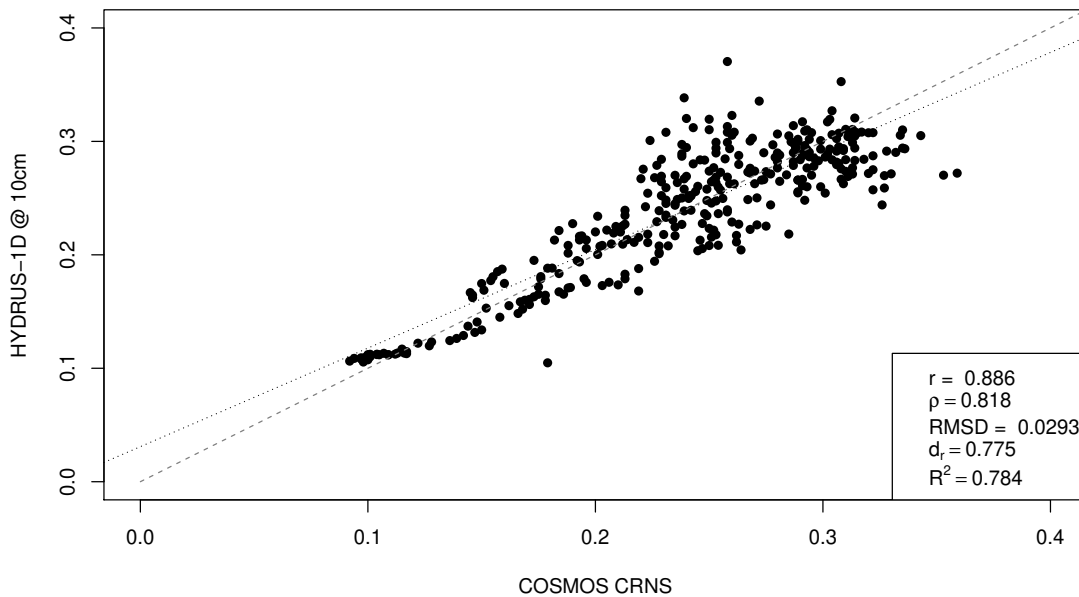


(b) Scatter plot of predicted versus observed values with model fit statistics including Pearson's r , Spearman's ρ , $RMSD$, Willmott Index d_r , and Coefficient of Determination R^2 . $RMSD$ is in units of volumetric water fraction ($0.0355 = 3.55\text{vol.}\%$), all other metrics are dimensionless.

Figure 3.7: HYDRUS 1-D model fit at the Fincham COSMOS-UK site, before optimisation, for 2018



(a) Time series of predicted volumetric water content (VWC) at 10cm and COSMOS CRNS measurements



(b) Scatter plot of predicted versus observed values with model fit statistics including Pearson's r , Spearman's ρ , $RMSD$, Willmott Index d_r , and Coefficient of Determination R^2 . $RMSD$ is in units of volumetric water fraction ($0.0293 = 2.93\text{vol.}\%$), all other metrics are dimensionless.

Figure 3.8: HYDRUS 1-D model fit at the Fincham COSMOS-UK site, after optimisation, for 2018

3.B Depth influence on assessment of Copernicus SSM soil moisture

Table 3.7 summarises the performance metrics for the SSM-derived volumetric soil moisture assessed against simulated soil moisture at 2 and 10 cm, at all 13 of the selected COSMOS-UK sites. The assessment was repeated for SSM data with and without the smoothing by exponential filter.

Table 3.7: SSM Performance Metrics assessed against HYDRUS-1D simulations of soil moisture at 2 and 10cm soil depths at 13 COSMOS-UK sites in 2018. Best values are shown in bold. *RMSD* and $|a|$ are in units of percentage volumetric water (vol.%), d_r and $|1 - b|$ are dimensionless.

Site identifier	Depth (cm)	SSM not smoothed				SSM Exponentially Smoothed			
		d_r	<i>RMSD</i>	$ a $	$ 1 - b $	d_r	<i>RMSD</i>	$ a $	$ 1 - b $
CARDT	2	0.525	9.807	3.809	0.002	0.593	7.670	4.819	0.020
	10	0.501	9.737	2.478	0.043	0.587	7.509	3.432	0.027
CGARW	2	0.024	18.843	18.746	0.414	0.355	12.876	4.204	0.103
	10	0.026	19.149	15.409	0.348	0.371	12.775	4.209	0.105
CHIMN	2	0.381	13.069	1.899	0.006	0.629	8.343	0.535	0.043
	10	0.304	13.359	4.863	0.067	0.594	8.354	4.769	0.069
ELMST	2	0.245	13.677	12.217	0.054	0.306	12.170	9.311	0.024
	10	0.112	14.377	16.642	0.159	0.181	12.659	15.143	0.121
EUSTN	2	0.246	14.574	10.915	0.119	0.359	11.530	11.981	0.147
	10	0.211	14.572	10.652	0.119	0.346	11.218	11.077	0.102
FINCH	2	0.406	9.369	5.325	0.118	0.478	7.827	3.523	0.052
	10	0.216	10.030	9.756	0.268	0.329	8.294	8.739	0.237
HADLW	2	0.510	13.586	3.639	0.123	0.618	11.041	2.721	0.093
	10	0.437	14.008	1.859	0.089	0.573	11.249	0.313	0.023
HYBRY	2	0.477	13.219	1.048	0.169	0.667	8.506	1.777	0.170
	10	0.455	13.323	0.037	0.141	0.665	8.447	0.220	0.127
LODTN	2	0.539	12.431	14.766	0.233	0.658	9.416	14.056	0.202
	10	0.458	13.272	19.505	0.321	0.591	10.160	19.953	0.318
RISEH	2	0.046	19.926	1.443	0.513	0.079	18.340	0.390	0.494
	10	-0.026	20.110	4.282	0.590	0.035	18.194	5.577	0.646
ROTHD	2	0.510	9.356	1.277	0.166	0.567	8.119	0.365	0.226
	10	0.346	10.127	6.520	0.011	0.407	8.720	5.287	0.053
SPENF	2	0.525	8.932	4.714	0.013	0.558	8.043	3.132	0.075
	10	0.492	9.117	6.395	0.037	0.534	8.109	5.158	0.012
WRTTL	2	0.580	13.820	10.794	0.240	0.653	11.170	11.120	0.247
	10	0.522	14.277	10.147	0.238	0.628	11.018	9.059	0.195

4 Field-scale implementation of the SAR change detection algorithm for surface soil moisture estimation, in Google Earth Engine

This chapter in paper format describes a novel implementation of a change detection algorithm for SAR soil moisture retrieval at field scale in Google Earth Engine. The results are compared to published map products and found to be equivalent at the 1 km pixel level. Spatial aggregation is then carried out at field scale using field boundary definitions. The performance is analysed across a range of crop types and as a function of crop stage and field tillage state.

Abstract

Synthetic Aperture Radar (SAR) is a remote sensing technique that may be used for mapping of soil moisture with high spatial resolution. Whilst C-band SAR can resolve features at field scale, or better, derived data sets such as Copernicus SSM are published at a lower resolution of about 1 km. This partly mitigates the problem that the assumptions of the underpinning change detection algorithm do not hold for arable fields. A new implementation of change detection at full sensor resolution in Google Earth Engine is presented and shown to create a field scale soil moisture estimate that is highly sensitive to the crop state. Almost no soil moisture monitoring capability exists when crops such as winter wheat, are in their key growth phase, with mean differences of around 20 vol.%. By contrast, the performance is good when the fields are mostly of bare soil or of short, grazed grass, with mean differences from 4 to 10 vol.%. This information can guide users on the validity of the data, and will inspire solutions to retrieve soil moisture estimates in the more challenging situations.

The contents of this chapter have not yet been included in a manuscript submitted for publication.

4.1 Introduction

Soil Moisture (SM) is essential information to assist farmers, agronomists and horticulturalists in decision making for irrigation (Adeyemi et al., 2017; Molden and James, 2000) trafficability and workability (Earl, 1997). SM varies at field scale due to land use, soil properties, irrigation, drainage, tillage, vegetation and other factors, but data at this resolution is not readily available. Synthetic aperture radar (SAR) is favoured as a remote sensing solution for its ability to image through clouds, partially penetrate vegetation (Doerry, 2004) and for its high spatial resolution. C-band, 5.4 GHz SAR (Torres et al., 2012) data from the European Space Agency's two Sentinel-1 (S1) satellites available through the Copernicus Open Access Hub (ESA, 2019) has an effective resolution on the ground of 20 metres¹, yet field-scale SM products based on this are not yet available due to the complexity of the SM retrieval problem.

The moisture of the soil is one of many factors contributing to the magnitude of the SAR backscatter coefficient, σ^0 . The incidence angle of the radar beam, its frequency, soil surface roughness, soil texture, soil organic matter content (Liu et al., 2013), vegetation (Romshoo et al., 2002) and temperature (Jackson, 1987; Zhang et al., 2003; Mironov and Lukin, 2009; Mironov et al., 2017) all have an effect. Machine learning approaches have been successful at handling this complex problem to retrieve SM (Hajj et al., 2017; Zappa et al., 2019), but require extensive training. Limited coverage of dense networks of soil moisture monitoring stations limits the scalability of such methods. By contrast, the change detection (CD) algorithm (Wagner et al., 1999b; Hornacek et al., 2012; Pathe et al., 2009) is a temporal processing solution that requires no training and no additional information other than topography. Though inherently scalable, it has not previously been used to create a field scale product that is usable for arable agriculture. This is a consequence of the underlying assumptions and approximations; that the vegetation component of SAR backscatter has a predictable seasonal variation whose timescale is relatively long compared to fluctuations in soil moisture, and that the effect of soil surface roughness is slowly changing compared to soil moisture.

These assumptions are reasonable for land that comprises mostly bare soil or sparse vegetation, where short timescale changes in backscatter coefficient will

¹Level-1, Ground Range Detected (GRD), Interferometric Wide (IW) swath mode product - <https://sentinel.esa.int/web/sentinel/user-guides/sentinel-1-sar/resolutions/level-1-ground-range-detected>

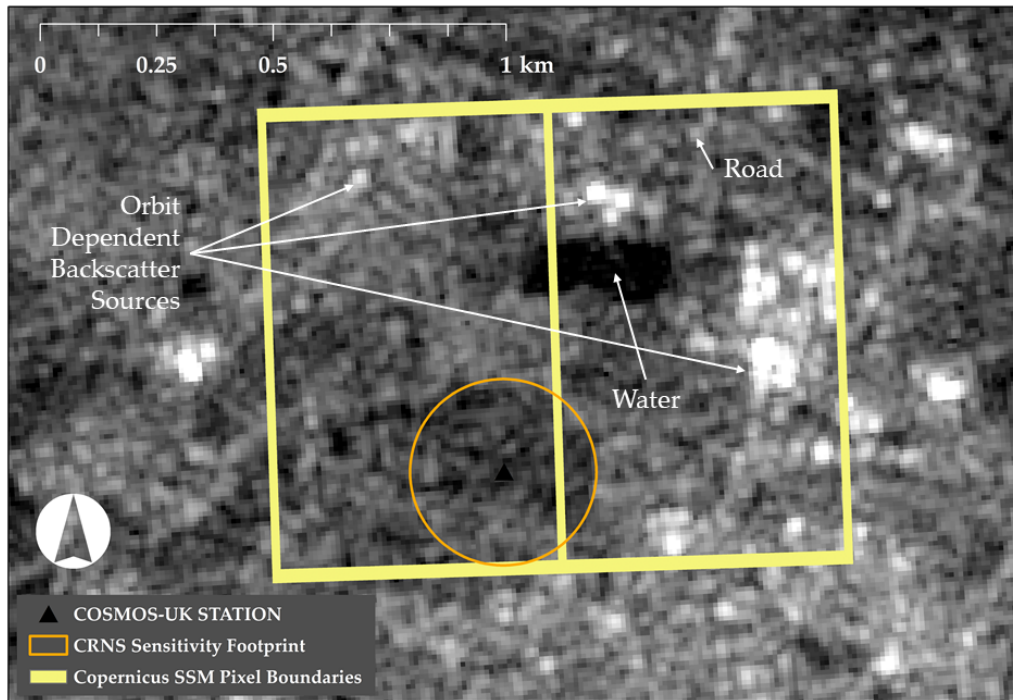
be correlated to changes in SM. However, land cultivated for arable crops sees anthropogenic change on much shorter timescales, down to hours and days, due to tillage and harvesting. Crops also grow very quickly in the main growing season and are not typical of the slow, seasonal variation assumed. Vegetation adds further backscatter and attenuates the soil response. Where it is dense and covers the soil completely the SAR may be insensitive to SM (Romshoo et al., 2002). Spatial averaging can mitigate these effects by mixing cultivated and non-cultivated areas and including multiple fields within a pixel. Any anthropogenic activity in one field has less overall impact on the result. Random noise due to image speckle, characteristic of SAR systems, is also reduced.

The Copernicus Surface Soil Moisture (SSM) (Bauer-Marschallinger and Paulik, 2019) product is derived from Sentinel-1 C-band SAR data, and is now available from the Copernicus Global Land Surface Portal (<https://land.copernicus.vgt.vito.be/>) as a daily netCDF format files. This is published at a nominal 1 km spatial resolution, which maps to a pixel size of around 0.6 km by 1 km in the UK as shown in Fig. 4.1a. The low spatial resolution relative to field size is clear in this example. It is also evident in Fig. 4.1b that each pixel includes man-made objects in the landscape that are often referred to as clutter sources because they can reflect the SAR strongly due to multiple reflections. Because these reflections are highly non-isotropic, they cause periodic noise in any backscatter time series compiled from multiple orbits. This will appear as periodic noise in the SM estimates. The pixels also include large areas of non-cultivated land. These include areas of trees, hedges, roads and small ponds where there will be no SM response causing a loss of sensitivity at pixel level.

An alternative approach is proposed by which spatial aggregation is performed within non-rectilinear field boundaries. By this means speckle noise is still reduced somewhat, but the majority of clutter sources, field boundaries, trees, roads and small ponds are excluded. The method leverages the capabilities of Geographical Information Systems (GIS) including cloud-based geoprocessing engines such as Google Earth Engine (GEE) (Gorelick et al., 2017), to calculate spatial statistics within arbitrary shapes. The output is an object or feature level SM associated with each field parcel. Field boundary information is now readily available for the UK, for example, that may be used for this purpose. By this approach, a decrease in periodic noise and an increase in SM sensitivity was expected. Increases in random noise due to averaging speckle due over a smaller area were also anticipated. The trade-off between sensitivity and noise is unknown and is key to determine the



(a) Overlap between Copernicus SSM 1 km pixels and fields at Writtle, showing locations of potential scatter sources. The sensitivity footprint of the COSMOS-UK soil moisture sensor (CRNS) of approximately 200 m radius, is also shown.



(b) The same Copernicus SSM pixels overlaid on a Sentinel-1 σ_{vv}^0 image taken on 29th June 2018, showing how the scatter sources appear and the general noise level due to speckle.

Figure 4.1: Relationship of Copernicus SSM 1 km width pixels to field sizes, COSMOS-UK sensor footprint, locations of clutter sources whose intensity varies with satellite orbit. The location is the Writtle COSMOS-UK site

feasibility of creating usable field-scale SM products from Sentinel-1 using the CD approach.

The initial objective addressed in this chapter was, therefore, to create a new implementation of the CD algorithm in Google Earth Engine (GEE), which would preserve sensor resolution through the processing chain. This new implementation would then be validated as equivalent to the published Copernicus SSM data by comparison of outputs at 1 km pixel resolution. The next objectives were to demonstrate the feasibility of creating object-level SM estimates for field parcels by aggregating to their boundaries and to compare the accuracy of this to deriving a field parcel estimate from a 1 km resolution raster output.

After establishing and verifying the capability to produce field-scale soil moisture estimates, the study developed two further objectives that explore the performance of the product. These were to assess the performance of the field-scale SM estimate as a function of time of year or crop stage, and to explore compensation measures for additional random noise levels due to averaging over reduced areas.

The study will lead to a better understanding of the capabilities of the CD algorithm for estimating surface soil moisture from Sentinel-1 C-band data in agricultural areas and lay foundations for future enhancements or mitigation measures to improve the usefulness of the data for end users.

4.2 Study sites and time period

In total, seven UK test sites were selected for this study, as shown in Fig. 4.2. Compared to the previous chapter, two of these sites are new, selected for specific purposes as described below. Only five of the previous thirteen COSMOS were included as this part of the study was focused on areas of cultivated land divided into field parcels, and where the crop types could be easily identified from metadata. The sites were used for three purposes:

1. To test the GEE implementation of terrain processing (slope and offset) and calculation of Local Incidence Angle (LIA), a 3 km area around Silbury Hill site in Wiltshire was chosen. Silbury Hill (Fig. 4.3) itself is a man-made conical shaped mound, providing a convenient visual verification for this calculation. This is not a COSMOS-UK site and was not used for soil moisture analysis.

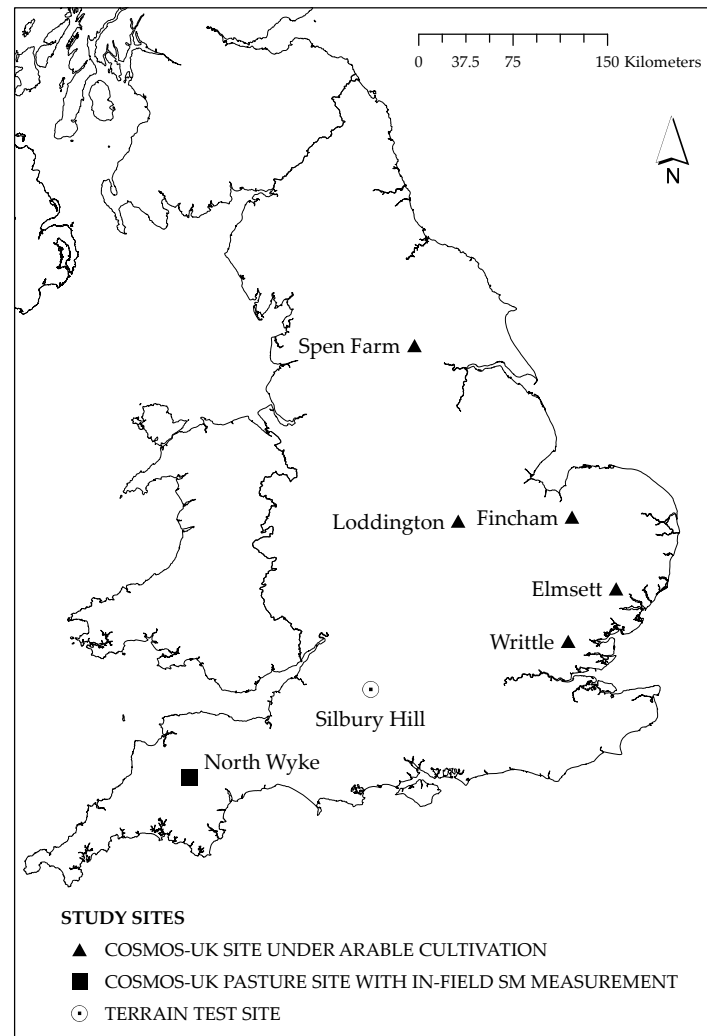


Figure 4.2: Locations of the sites selected for this study

2. To compare the performances of the field parcel and 1 km gridded SM estimates, a site at North Wyke in Devon, was selected. This is a 350 ha beef and sheep farm which hosts the North Wyke Farm Platform National Capability (NWFP) (Orr et al., 2011), a facility of Rothamsted Research. At this site, 15 individual fields are instrumented for 15 minute monitoring of soil moisture at 10, 20 and 30 cm depth and soil temperature at 15 cm depth using Adcon SM1 capacitance probes. Additionally, the soil moisture is monitored at the COSMOS-UK station (Evans et al., 2016) (see below) and three Eddy Co-variance towers. The field parcels, soil series (Harrod and Hogan, 2008) and locations of the soil moisture sensors at North Wyke are shown in the map of Fig 4.4. The soil series are defined according to the classification

scheme of the Soil Survey of England and Wales (Thomson et al., 1983). The dominant soil series for the majority of fields with SM monitoring is Halstow; only two (NW001 and NW011) are dominated by soil series Hallsworth, this demonstrates that soil texture variation across the site is not of great significance to this study.

3. To assess the performance of the field scale SM estimates in arable fields, five further sites were selected. In four of these a range of crops were being grown, including wheat, barley, sugar or feed beet and oil-seed rape. One site had a mixed use of grass and arable with the grass being cut in June, and grazed by sheep at other times. These sites are also part of the COSMOS-UK network (Evans et al., 2016) of a total of 50 soil moisture monitoring stations across the UK, operated by the UK Centre for Ecology and Hydrology (UKCEH). The prime sensor at each site is a Cosmic Ray Neutron Sensor (CRNS) (Andreasen et al., 2017) with has a measurement footprint of approximately 200 metres in diameter (Köhli et al., 2015). Four of the COSMOS-UK locations were arable sites.

The COSMOS-UK stations at all of the sites, excluding Silbury Hill, were also instrumented to measure, amongst several meteorological and environmental parameters, potential evapotranspiration and rainfall. This data was used to simulate soil moisture at a shallower depth for validation of the SAR-derived SM. The chosen sites also vary in soil texture, as shown by Table 4.1.

Table 4.1: Subset of COSMOS-UK sites selected for this study

Site identifier	Site name	Soil type	Land cover	Dominant soil series
ELMST	Elmsett	Loam and clay	Arable	Beccles
FINCH	Fincham	Freely draining lime-rich loamy soil	Arable	Swaffham Prior
LODTN	Loddington	Loam to clay	Arable	Denchworth
NWYKE	North Wyke	Loam to Silty Loam	Grass Pasture	Halstow
SPENF	Spen Farm	Clayey loam to silty loam	Arable	Aberford
WRTTL	Writtle	Loamy and clayey soil with impeded drainage	Arable	Hornbeam



Figure 4.3: Silbury Hill, Wiltshire - a monumental Neolithic mound of conical shape, the slope of the sides is approximately 30° . This was useful for testing of local incidence angle correction for SAR processing. *Image credit: LizzRoe, licence [CC BY-SA 4.0](#), via Wikimedia Commons*

During 2018 the UK experienced a very cold and wet spring followed by a prolonged heatwave and drought. Using this year in the study made it probable that the soil moisture would vary between the wettest and driest conditions.

The SM retrievals generated by the bespoke algorithm in GEE and the published Copernicus SSM product were both derived from Sentinel-1 data, so there was no time difference between these measurements, though the actual time of image acquisition dependent on whether the satellites were in an ascending or descending orbit and would either be around 6am or 6pm. By contrast the COSMOS-UK SM estimates and its associated meteorological data were averages or totals for the day. The difference in timing between the satellite and the ground measurement is acknowledged as a source of uncertainty.

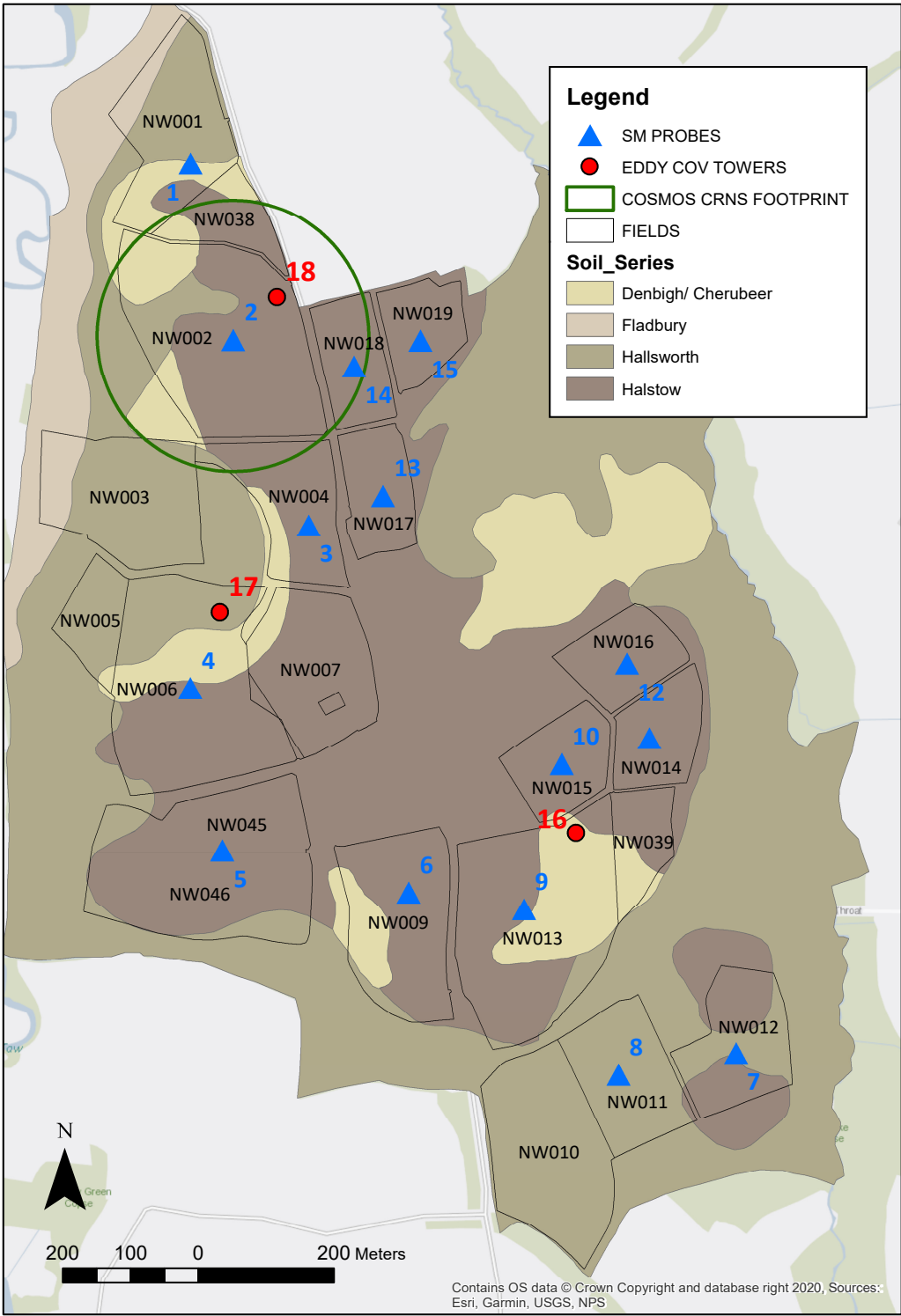


Figure 4.4: North Wyke Farm Platform showing field boundaries, soil series (Harrod and Hogan, 2008), the footprint of the COSMOS-UK station, and locations of the soil moisture sensors including those associated with the Eddy co-variance towers (Orr et al., 2011).

4.3 Materials and methods

To enable the creation of a SAR-derived surface soil moisture product at field scale, the CD algorithm was first implemented within GEE at the Sentinel-1 SAR spatial resolution. The rasterised output was spatially aggregated in two ways; to the same nominal 1 km pixel grid of the published Copernicus SSM product, and to field boundaries. Time series of the 1 km output and the Copernicus SSM product were then compared to independently derived predictions of soil moisture at the COSMOS-UK sensor locations using the method developed in Chapter 3. Having established broad equivalence between the products, the field-level output was compared to in-field soil moisture measurements for grass fields at the North Wyke site. To explore the performance within arable crops, a range of fields neighbouring the other five COSMOS-UK sites was selected offering a diversity of crop types.

4.3.1 Data

C-band SAR data

To generate high spatial resolution soil moisture estimates for this study, Ground Range Detected (GRD) Level 1 Interferometric Wide Swath (IW) C-band SAR data from the Sentinel-1 (S1) satellites (Torres et al., 2012) were obtained through the data catalogue of GEE. Each S1 platform has a 12-day orbit repeat cycle; there were two platforms (A and B) in service during 2018, so a 6-day repeat cycle was achievable. Overlapping orbit coverage resulted in images being available for the test sites every 1-3 days. The published data had been pre-processed (European Space Agency, 2021), including orbit file application, thermal noise removal, border noise removal, radiometric calibration, initial terrain correction and conversion of the backscatter coefficient to decibels via log scaling ($\sigma_{dB}^0 = 10 * \log_{10}(\sigma^0)$). The VV (co-polarised) image band (only) was selected, as it is more sensitive to soil moisture. Soil backscatter tends to be co-polarised whereas volume scattering from vegetation tends to change the plane of polarisation. The number of images processed, between December 2017 to January 2019 inclusive, ranged from 176 to 314 according to the site (as shown in Table 4.2), due to the effect of variable orbit coverage.

Table 4.2: Number of Sentinel-1 SAR images processed for this study, for the period 1st December 2017 to 31st January 2019.

Site identifier	ELMST	FINCH	LODTN	NWYKE	SPENF	WRTTL
Number of SAR Images	266	265	314	176	291	268

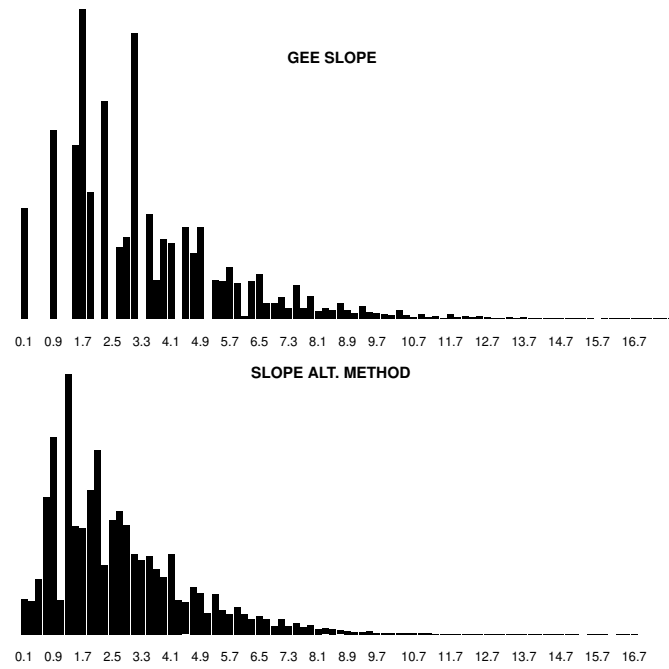
Copernicus SSM data

To benchmark the soil moisture estimates against an existing product, a time series of Copernicus Surface Soil Moisture (SSM) ([Bauer-Marschallinger and Paulik, 2019](#)) was obtained for the whole of 2018. This product is also derived from Sentinel-1 data using the CD algorithm, and is published as a Soil Moisture Index at a nominal resolution of 1 km (Fig. 4.1). Geographically clipped images were uploaded as private assets to GEE for processing alongside the S1 data.

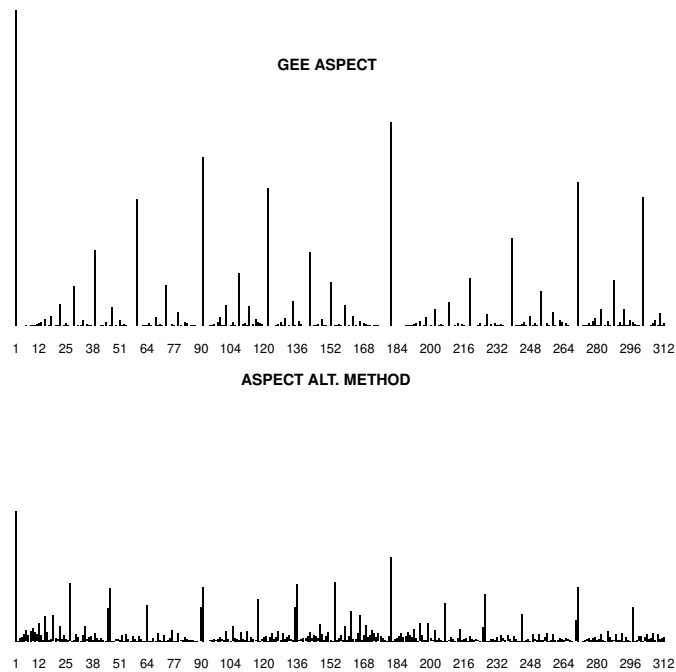
Ground slope and aspect

The local incidence angle (LIA) of the radar to the normal to the ground surface is one of the factors that determines the level of backscatter received. The angle supplied with the SAR data is relative to a locally flat ground surface, and does not take into account the slope and aspect at each pixel location, which had to be found independently. The NASA Shuttle Radar Topography Mission (SRTM) ([Farr et al., 2007](#)) (V3 – SRTM Plus) digital elevation map (DEM) was obtained via the GEE data catalogue. The spatial resolution of approximately 30 m was slightly less than the effective SAR resolution of 20 m, but in most areas of agriculture the topography is relatively flat and slowly varying with distance, so no scale error was anticipated. The intention was to create a raster image with slope and offset as individual bands, at the maximum spatial resolution the DEM would permit. However this proved to be more complex than anticipated.

Whilst native functions are provided in GEE for slope and aspect calculation, artefacts were observed in their output that would have propagated into the calculation of local incidence angle (LIA) and, potentially, as spatial noise in the soil moisture product. This was investigated by plotting histograms of the slope and aspect values within a 3 km zone around the Silbury Hill test site. With undulating terrain, a continuous frequency distribution was expected, but a level of quantisation in both slope and aspect were seen, as shown by the upper histograms of Figs. 4.5a and 4.5b. The quantisation is particularly noticeable at low slope values, which would typify the level ground suitable for arable crops. Some aspect values



(a) Slope



(b) Aspect

Figure 4.5: Silbury Hill test site, histogram comparison of slope (a) and aspect (b) calculated by the Google Earth Engine terrain functions (top) and by a bespoke method based on (Ritter, 1987), all within a 3 km zone around the centre of Silbury Hill itself.

are also favoured, especially at due North and South. To determine if these artefacts were a feature of the DEM data or the native functions, bespoke slope and aspect calculation functions were developed in GEE based on the vector method of Ritter (Ritter, 1987). By this method, elevation data at the pixels locations either side of the one of interest are used to calculate slopes in orthogonal x and y directions. The aspect was derived from these slopes and they were combined by Pythagoras's Law (root mean square) to find the overall slope. An efficient method of finding orthogonal slopes in GEE was implemented where the x and y directions aligned with the DEM raster axes. This comprised a convolution of the elevation data with the following Sobel filter kernels:

$$\mathbf{G}_x = \begin{bmatrix} 1 & 0 & -1 \end{bmatrix}, \quad \mathbf{G}_y = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \quad (4.1)$$

The bespoke function was found to reduce the quantisation of slope compared to the native function, indicating that the issue was more likely to be in the calculation rather than the DEM data. After further experimentation, the smoothness of the histogram distribution was further improved by alternative kernels that averaged the elevation across a trio of adjoining pixels from the column or row next to the pixel of interest:

$$\mathbf{G}_x = \begin{bmatrix} 1/3 & 0 & -1/3 \\ 1/3 & 0 & -1/3 \\ 1/3 & 0 & -1/3 \end{bmatrix}, \quad \mathbf{G}_y = \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 0 & 0 & 0 \\ 1/3 & 1/3 & 1/3 \end{bmatrix} \quad (4.2)$$

The results of this new method using the kernels of Eqn. 4.2 are shown in the lower histograms of Figs. 4.5a and 4.5b. These show that the bespoke function has reduced the quantisation of slope data significantly and has generated a greater range of possible values for aspect. This alternative function was subsequently used for slope and aspect generation.

Historical backscatter statistics

The CD algorithm calibrates each new observation of SAR backscatter relative to the range of values previously observed at the same location. Assuming the latter includes measurements over the full range of possible soil moisture values, a relative soil moisture index (SMI) is estimated without knowledge of soil properties. Backscatter statistics were collected from all available S1 VV backscatter coefficient (σ_{VV}^0) images from first launch in 2015 to the end of 2019. The images were clipped to circular regions of 5 km radius centred on each study site to provide a safe margin around the 3 km analysis zone. The statistics were calculated per SAR pixel and stored in multi-band images as assets in GEE for later use. An example of the mean VV backscatter $\bar{\sigma}_{VV}^0$ image is shown in Fig. 4.6.

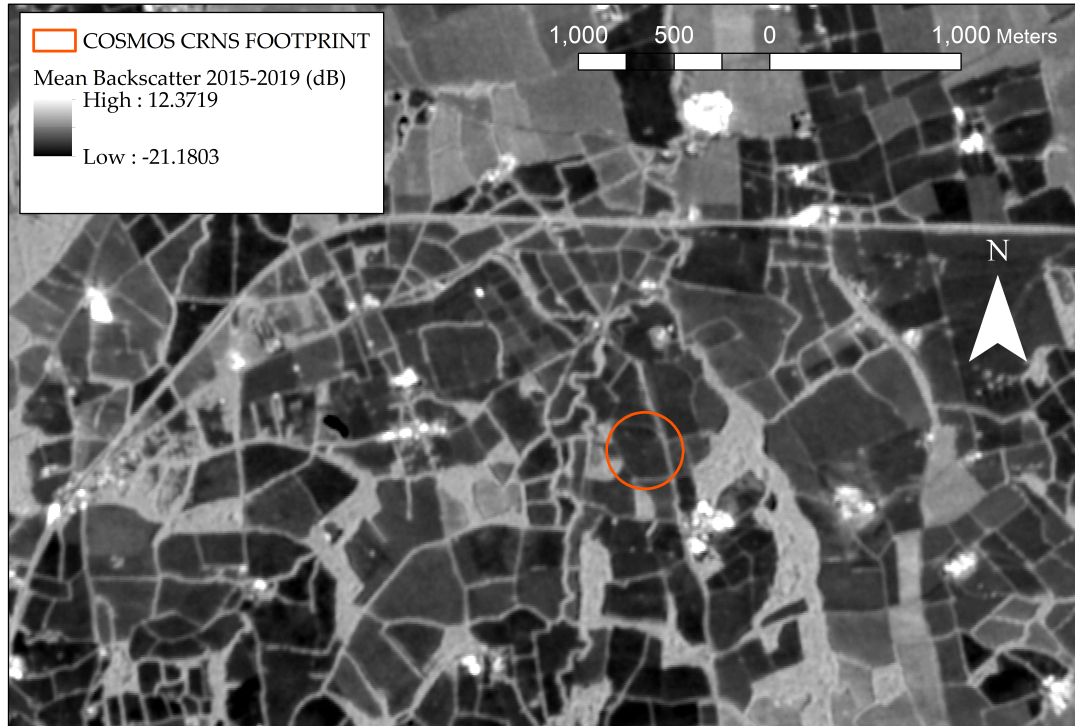


Figure 4.6: Grey-scale Image of mean $\bar{\sigma}_{VV}^0$ for an area around North Wyke COSMOS-UK site (footprint denoted by red circle) for S1 data from 2015-2019 inclusive. The black area in the middle, left is a small lake or pond, the white areas are consistently high backscatter values from buildings and hard surfaces. A railway line is seen (left to right) as well as roads, hedges and wooded areas. Relative to these, most fields have a relatively low average backscatter value.

The 5th and 95th percentile values of σ_{VV}^0 were used as the minimum and maximum values to prevent small numbers outlying data points biasing the statistics. In CD the difference between these values is taken as a measure of sensitivity to soil

moisture: $S = \sigma_{VV95}^0 - \sigma_{VV5}^0$. For normalisation of the backscatter to a single LIA of 40° , as discussed later in this section, a surrogate, β_r , for the linear regression slope of σ_{VV}^0 as a function LIA, θ_i , was calculated. The method of [Bauer-Marschallinger et al. \(2019\)](#) was used, as given by Eqn. 4.3:

$$\beta_r = aS + B\bar{\sigma}_{VV}^0 + c \quad (4.3)$$

Where $a = -0.01725$, $b = 0.00553$ and $c = 0.02546$ and $\bar{\sigma}_{VV}^0$ is the mean VV backscatter, and S is the sensitivity.

To further reduce the effect of outliers, the study followed the practice of [Bauer-Marschallinger et al. \(2019\)](#) to extrapolate reference backscatter values, representing the driest ($\sigma_{VV,dry}^0$) and wettest ($\sigma_{VV,wet}^0$) conditions at each pixel, from normalised values of the 10th and 90th percentiles of σ_{VV}^0 . The 10th and 90th percentile values were therefore collected and normalised to an LIA of 40° ($\sigma_{VV40-10,VV40-90}^0$) by Eqn. 4.16 and the wet and dry references were calculated by linear extrapolation:

$$\sigma_{VV,dry}^0 = \sigma_{VV10}^0 - 10u \quad (4.4)$$

$$\text{where } u = \frac{\sigma_{VV90}^0 - \sigma_{VV10}^0}{80} \quad (4.6)$$

$$\sigma_{VV,wet}^0 = \sigma_{VV90}^0 + 10u \quad (4.5)$$

Field boundaries, land use and crop information

The field boundaries at the study sites were extracted from the UKCEH Land Cover Plus:Crops 2018 (LCPC) data-set ([Morton et al., 2020](#)). This data also included crop information assessed retrospectively for 2018. The shapefile data was reduced in spatial extent to include only fields within approximately 3 km of the COSMOS-UK station. For the North Wyke site (NWYKE), alternative and more accurate geospatial data were obtained from the North Wyke Farm Platform (NWFP) ([Harris et al., 2016](#)) and combined with the LCPC data. At all sites the field boundaries were eroded by 20 metres to ensure that field margins, hedges and buildings would be excluded as far as possible. An example of the alignment between the eroded and non-eroded field boundaries at North Wyke is shown in Fig. 4.7.

The nature of edge effects at field boundaries was investigated by inspecting the raster image of sensitivity, S , at the North Wyke site (Fig. 4.8). Hedges, fences and roads appeared dark, indicating low sensitivity. The bright spots are parts of buildings, mainly, that caused intense reflections from some satellite orbits. Such

large swings in intensity result in a very high sensitivity value, which is erroneous. It was important to ensure that all of these dark and bright areas were excluded by the field boundaries. The 20 m eroded boundaries, shown in red, appeared effective at achieving this.

Also seen in Fig. 4.8 were some narrow, bright strips, 10 to 20 m wide, either side of some of the field boundaries that run North to South. This was assumed to be due to SAR layover of tall hedges. The viewing direction of Sentinel-1 is about $\pm 83^\circ$ from the meridian, depending on whether it is in an ascending or descending orbit. Tall objects will appear to be extended in the $\pm 83^\circ$ direction for a distance proportional to their height, as demonstrated in Fig. 4.9. Pixels within this distance of a tall hedge will see backscatter from either grass or hedge depending on whether the orbit is ascending or descending. This alternation also appears as a zone of abnormally high sensitivity that should be excluded from calculations. The dimension varies with the hedge height so a simple erosion of field boundaries would not be sufficient. The historical statistics, discussed above, were therefore calculated separately for ascending and descending orbit geometries. In the creation of the field-scale SM estimate, the erosion of field boundaries by 20 m appeared to be sufficient in the case of case to exclude these layover areas. Failure to achieve this would add further temporal noise to the SM estimate of affected fields. This could be mitigated by boundary erosion to a greater distance than 20 m, or by confining the time series to ascending or descending orbits only.

Soil properties

Soil hydraulic properties were required to provide a starting point for the optimisation of the HYDRUS-1D model (following the method of Chapter 3 prior to its use for simulating volumetric water content at 2 cm soil depth from meteorological measurements at the COSMOS-UK CRNS sites. The soil hydraulic properties required were the water retention parameters of the van Genuchten-Mualem model (van Genuchten, 1980; Mualem, 1976); water content at quasi-saturation (θ_s), residual water content (θ_R), saturated hydraulic conductivity (K_s) and model fitting parameters (n , α). Initial values were obtained from the National Soil Map of England and Wales (NATMAP) (Thomson et al., 1983). At each site, the dominant soil series was identified by overlaying the 200 m radius footprint of the CRNS sensor over the soil map. The main land use within the 200 m radius was categorised by inspection of COSMOS-UK phenocam images, site metadata, and

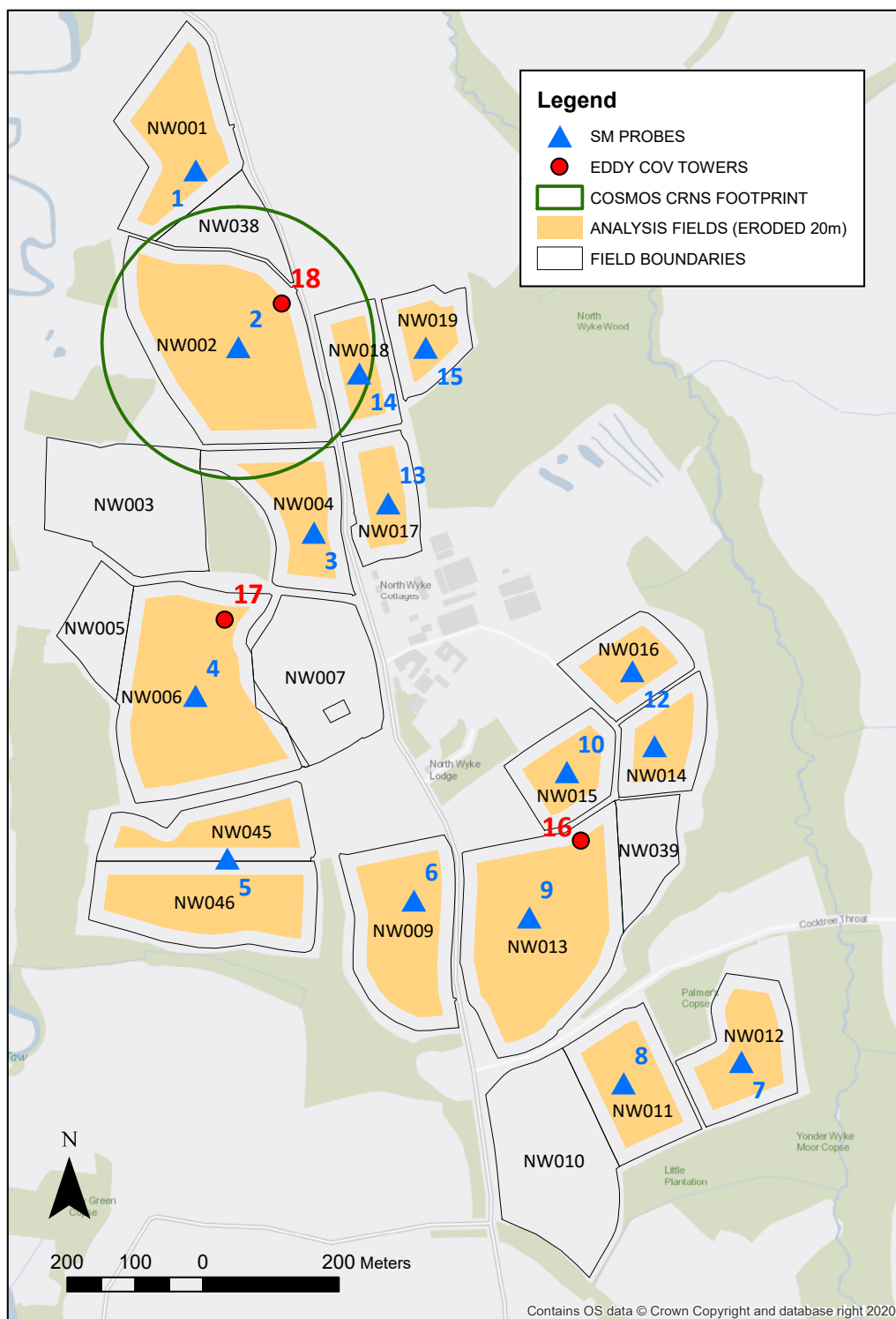


Figure 4.7: North Wyke Farm Platform showing the eroded boundaries of the fields with soil moisture sensors, selected for spatial averaging to field scale soil moisture



Figure 4.8: Grey-scale image of sensitivity, S calculated for both ascending and descending orbits from 2015-2019 for Sentinel-1 images over the area of North Wyke. The effect of the layover on sensitivity can be seen as bright fringes of abnormally high values of S close to high hedges and the edges of wooded areas. This is particularly noticeable where these boundaries run approximately North/South. Soil moisture estimation in these zones requires special measures to be taken. The eroded field boundaries (in red) appear to exclude most of these areas.

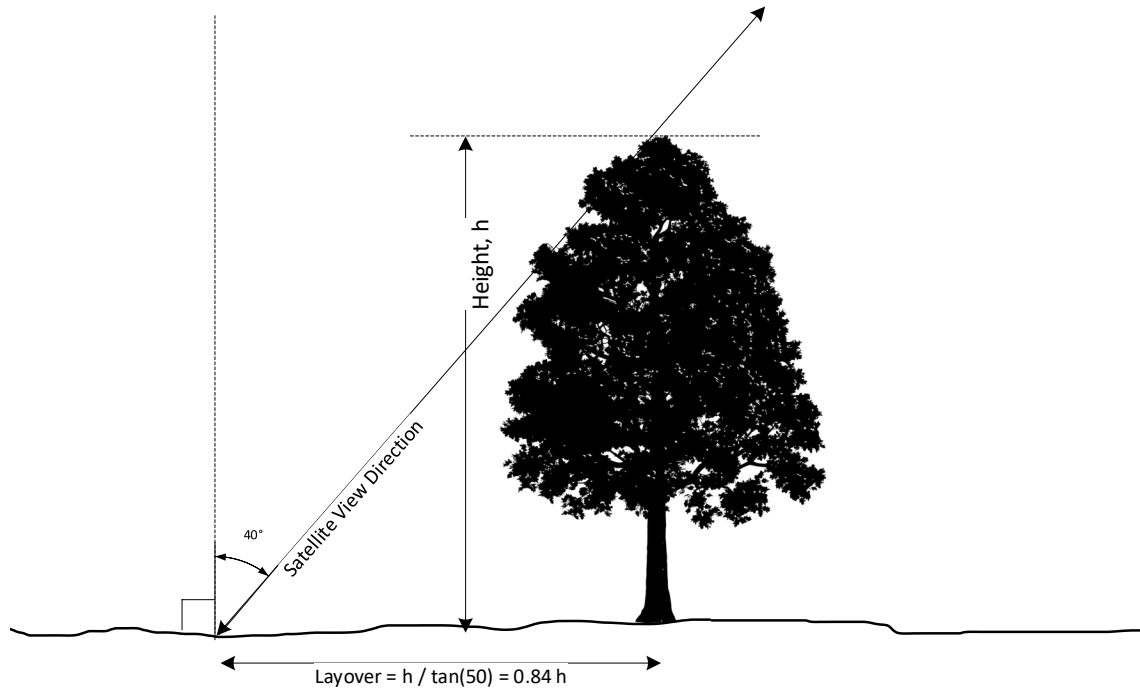


Figure 4.9: Principle of layover in SAR images. In this example, a tree line appears wider by 0.84 times its height in the direction away from the satellite, in addition to its proper width.

the LCPC data as either permanent grass (PG), grass that is cut for hay or silage (includes ley grass) (LE), arable (AR) or other (OT). The depth of the upper soil horizon, its texture and bulk density were obtained from the LANDIS Horizon Fundamentals (Cranfield University, 2021a; Hollis et al., 2015) table, by looking up the appropriate soil series and land use. In the same way, the soil hydraulic properties were obtained from the LANDIS Horizon Hydraulics table (Cranfield University, 2021b; Hollis et al., 2015).

Both the soil moisture estimate produced in GEE by the CD algorithm, and that published as the Copernicus SSM product, are in the form of a soil moisture index. To express them in units of volumetric water content for comparison with ground measurements, the recommendations of Chapter 3 were followed. This called for estimates of the values of two soil hydraulic parameters; water content at quasi-saturation (θ_s), and residual water content (θ_R). Though these parameters would have been obtainable from NATMAP, the values that resulted from fitting the HYDRUS-1D model to COSMOS-UK sites CRNS data were assumed to be more accurate and were used for this purpose.

In-situ soil moisture and meteorological data

S1 C-band SAR penetrates only 1 to 2 cm into soil surface. So reference SM data were provided by simulations of soil moisture at 2 cm depth by the method described in Chapter 3. For each site, the HYDRUS-1D model was fitted, at 10 cm depth, to CRNS soil moisture data from the COSMOS-UK stations (Evans et al., 2016). The revised set of soil hydraulic parameters were then used to generate the 2 cm soil moisture time series from inputs of rainfall and potential evapotranspiration, E_0 , which are routinely provided with COSMOS-UK site data. The COSMOS-UK rainfall gauge at North Wyke was not working for part of 2018, so equivalent data was obtained from an alternative rain gauge located in the same area, part of the North Wyke Farm Platform (NWFP).

To evaluate the performance of the field-scale SM retrieval required field-scale ground truth SM data. This was provided by the North Wyke Farm Platform (NWFP) in-field soil moisture probes at a depth of 10 cm. These probes did not record any soil moisture values over 40 vol.%, appearing to saturate at this value. This made it impossible to fit the HYDRUS-1D model to this data and obtain a 2 cm depth soil moisture simulation for each field. The probe data was, instead, used directly, accepting that the depth mismatch with the SAR and would add uncertainty analysis. Nevertheless, this provided useful insights into the relative performance of the two spatial resolutions of the same product from field to field. For other analyses at North Wyke, the average value of two 10 cm deep soil moisture probes installed as part of the COSMOS-UK station sensor suite, is used for qualitative comparisons in time series plots.

Vegetation properties

The HYDRUS-1D model being used to generate reference soil moisture time series required E_0 to be partitioned into evaporation (E_E) and transpiration (E_T). Leaf Area Index (LAI) was used for this, following the method described in Chapter 3: $E_E = E_0 e^{-\alpha LAI}$ (where the default extinction coefficient $\alpha = 0.463$). LAI data were obtained from the MODIS (MCD15A3H V6 level 4) (Myneni et al., 2015). The 4-day time series was smoothed according to the method outlined in Chapter 3, and aligned to the COSMOS-UK data time-series by linear interpolation.

HYDRUS 1-D uses rooting depth and the root density profile to calculate the transpiration profile with depth. For the purposes of this study, these parameters were set the same for each site, with the root density decreasing linearly with depth

over the upper 15 cm only. This assumption could introduce a small error in the model fitting.



Figure 4.10: Phenocam photographs from the Fincham site taken on 15th July 2018 at 10:49 am. This shows the wheat crop ripening in the surrounding fields. Image courtesy of the COSMOS-UK project.

To understand the impact of canopy closure, bare soil, harvesting and tillage, the performance of the CD algorithm at field-scale was analysed separately within periods defined by the tillage state of the field and the crop stage. These periods were determined by consulting daily phenocam images from each of the COSMOS-UK stations. A pair of cameras are installed, each with wide-angle lenses that, together, provide a complete panorama around the site location. An example image pair is shown in Fig. 4.10. From these images it was possible to assess the crop type, and estimate the dates of crop growth, ripening, harvesting and tillage. In some cases, NDVI data from MODIS was used to confirm periods of rapid vegetative growth where this was not clear from the photographs. The classification stages used comprised:

- Winter dormancy - the field had vegetation on it (whether crop or not) but it appeared to be static or very slow growing. This would also apply to autumn sown cereals after germination.
- Rapid growth - the crop appeared to be developing rapidly as indicated by the photograph sequence or rapid increase in NDVI
- Ripening - the crop appeared to cease growing and was turning yellow or brown but still standing
- Harvested - the crop has been harvested but there is residue remaining

- Tilled - the soil has been ploughed, including minimal tilling, exposing bare soil.
- Planted (potatoes only) - potatoes are planted in Spring into bare soil, forming ridges.
- Snow covered - dates when the ground was covered by ice and snow were noted, but there were too few contemporary satellite images to warrant a separate analysis.

4.3.2 Time series data processing

The processing of time series SAR data to estimate field-scale surface soil moisture followed the principles of the Change Detection (CD) algorithm developed by TU Wien ([Hornacek et al., 2012](#)) as implemented in the creation of the Copernicus SSM Product ([Bauer-Marschallinger and Paulik, 2019](#); [Bauer-Marschallinger et al., 2019](#)). This approach was modified for use in this study and implemented in GEE. The data processing steps are shown in Fig. 4.11:

The pre-processing steps that should need only to be repeated infrequently, and discussed earlier in this section, are shown on the left of Fig. 4.11 as brown and green boxes. The steps on the right of the figure were implemented in GEE to process a time series of SAR data to produce a time profile of soil moisture. These are the processes that would be updated in near real-time, and were carried out on each SAR image in the sequence. These will now be discussed in detail.

SAR image preparation

Time series of SAR data were acquired by filtering the S1 data catalogue by date range and location, the latter being achieved on the basis of an intersection between the image footprint and the 5 km region of interest (ROI) around each study site. The processing only required the VV waveband of the S1 SAR image, so the other backscatter bands were discarded. An image mask was then applied to each image that excluded any pixels that had very high (> -5.0 dB) or low (< -20 dB) backscatter value. High backscatter is the result of strong reflections, usually from corners of man-made objects (such as buildings and vehicles). Very low backscatter is caused by specular reflection of the radar beam by mirror-like flat surfaces, usually areas of water, such as rivers and lakes. Examples of both can be

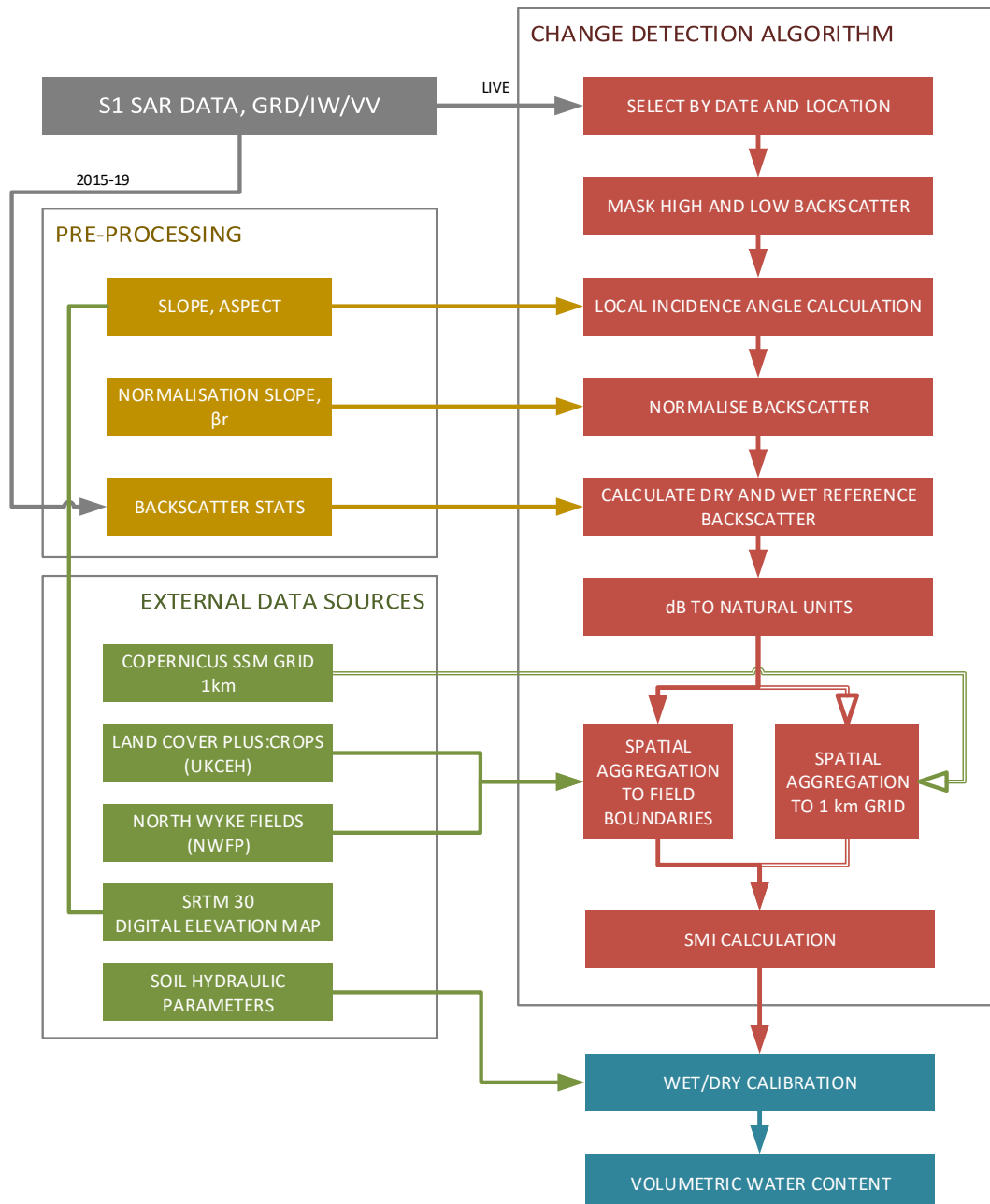


Figure 4.11: Implementation of a change detection algorithm to produce a Soil Moisture Index (SMI) and Volumetric Water Content (VWC) for surface soil moisture with averaging to field scale, and (for testing) to the 1 km pixel grid of the Copernicus SSM product. The box on the top, left contains the pre-processing steps comprising the slope and aspect calculation and compilation of historical backscatter statistics.

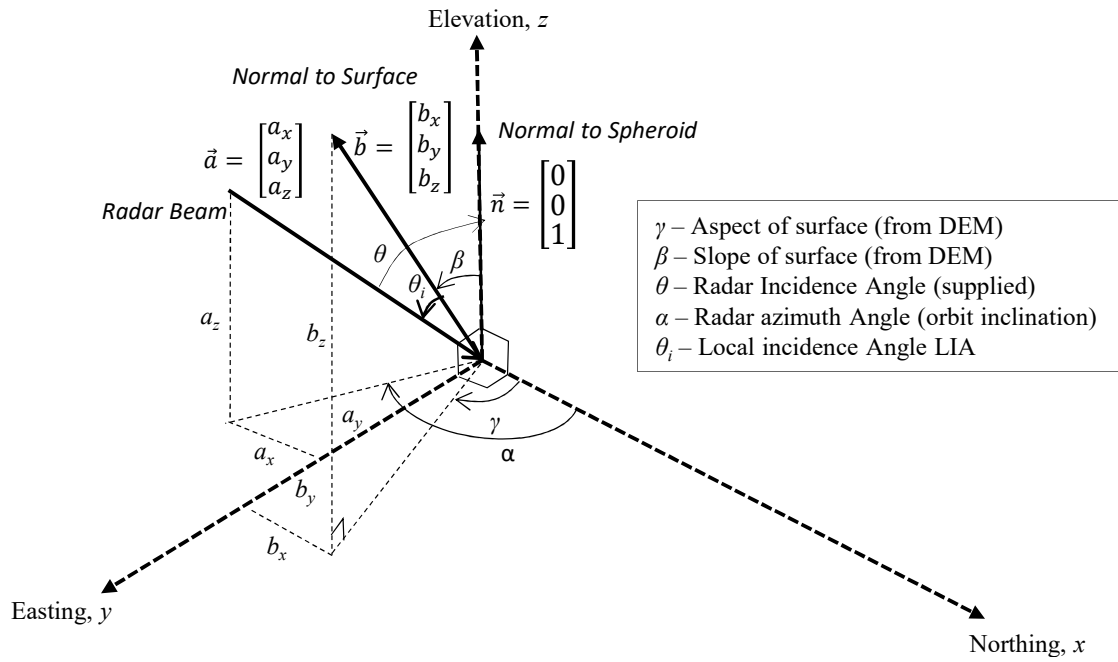


Figure 4.12: Geometry of Local Incidence Angle Calculation θ_i from Sentinel-1 supplied viewing angle θ and surface slope β and aspect γ derived from a Digital Elevation Map

seen in the composite SAR image of Fig. 4.6. Such pixels would severely affect the statistics of spatially aggregated data and reduce the sensitivity to soil moisture.

Local incidence angle (LIA) calculation

The S1 SAR images include a waveband labelled "angle", which provides, at each pixel location, the approximate viewing angle of the radar. This is the incidence angle between the radar beam and the normal to the flat Earth, $\vec{n}$. It is denoted as angle θ in Fig. 4.12. For soil moisture determination the local incidence angle (LIA), θ_i is required, which takes into account the slope and aspect of the ground as previously calculated in Section 4.3.1. Whilst the Sentinel-1 toolbox ([European Space Agency, 2021](#)) provides tools to perform the LIA calculation, similar functions had to be developed for use in GEE. The geometry of the calculation is shown in Fig 4.12, where the incoming radar beam is represented by vector $\vec{a}$, and the normal to the local surface by vector $\vec{b}$, such that the LIA, θ_i , is the angle between them.

The angle β is the slope of the ground, γ is the aspect and α is the heading of the incoming radar beam. α and γ are defined relative to North in a clockwise direction. $\alpha \approx 7^\circ$, is calculated as the aspect of the gradient of change of the angle band in the S1 image, minus 90° . Vectors $\vec{a}$ and $\vec{b}$ may then be written as functions

of α , β , γ and θ as follows:

$$\vec{a} = \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} = a \begin{bmatrix} \sin(\theta) \cos(\alpha) \\ \sin(\theta) \sin(\alpha) \\ \cos(\theta) \end{bmatrix} \quad (4.7)$$

$$\vec{b} = \begin{bmatrix} b_x \\ b_y \\ b_z \end{bmatrix} = b \begin{bmatrix} \sin(\beta) \cos(\gamma) \\ \sin(\beta) \sin(\gamma) \\ \cos(\beta) \end{bmatrix} \quad (4.8)$$

where a and b are arbitrary constants. The LIA, θ_i is related to vectors $\vec{a}$ and $\vec{b}$ by the cosine rule:

$$\cos(\theta_i) = \frac{\vec{a} \cdot \vec{b}}{|\vec{a}| |\vec{b}|} \quad (4.9)$$

Solving for θ_i gives:

$$\theta_i = \arccos(\sin(\theta) \sin(\beta) \cos(\alpha - \gamma) + \cos(\alpha) \cos(\beta)) \quad (4.10)$$

Whilst this method worked well it was found to be computationally slow. A more efficient method for calculating LIA in GEE was derived by the EURAC Research Institute for Earth Observation, Bolzano, Italy in their PYthon Sentinel-1 soil-Moisture Mapping Toolbox (PYSMM) ([Greifeneder, 2018](#)). This code was adapted and converted to Javascript for use in GEE, which computes LIA by the following equation:

$$\theta_i = \theta - \beta \cos\left(\frac{\pi(270 - \alpha - \gamma)}{180}\right) \quad (4.11)$$

In PYSMM ascending orbits only were considered. For descending orbits [4.9](#) has to be modified:

$$\theta_i = \theta - \beta \cos\left(\frac{\pi(90 + \alpha - \gamma)}{180}\right) \quad (4.12)$$

The mathematical equivalence of Eqn. [4.10](#) and Eqns. [4.11](#) or [4.12](#) could not be established analytically and the derivation has not been published at time of writing. It was assumed to be an approximation, the validity of which required testing by comparing it, alongside the calculation of Eqn. [4.10](#), to control data. The control data was an independent LIA calculation using the S1 Toolbox. for two

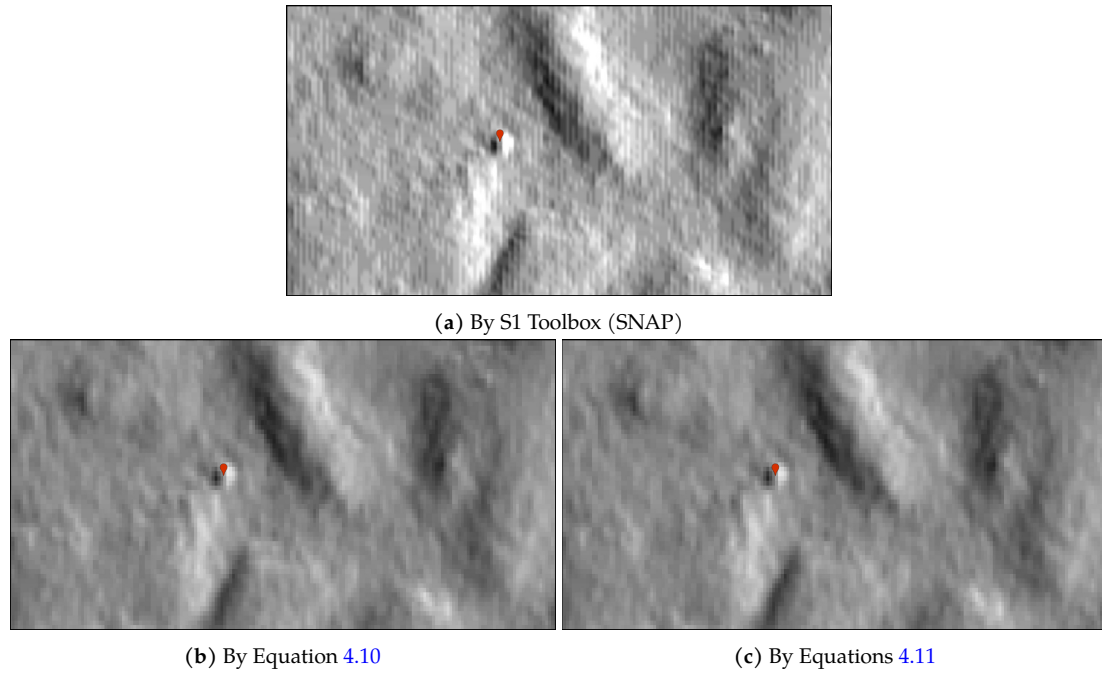


Figure 4.13: Visual comparison of LIA created by (a) the S1 Toolbox and (b), (c) in Google Earth Engine using the modified slope and aspect calculation after Ritter (Ritter, 1987). The grey-scale indicates the value of the LIA of radar beam relative to the normal to the land surface and varies between 30° and 50° . Data are contemporary with the S1 image taken in an ascending orbit at 17:57 on 24 July 2018 of the area around Silbury Hill, Wiltshire. Silbury Hill itself is marked by the red pin.

example S1 SAR images of the Silbury Hill study site. The image taken on 24 July 2018 is an ascending orbit at 17:57. Fig. 4.13 is a trio of grey-scale representations of LIA; Fig. 4.13a being calculated by the S1 Toolbox (SNAP), Fig. 4.13b by Eqn. 4.10 and Fig. 4.13c by Eqn. 4.11. Unexpectedly it was the control data from the S1 Toolbox that displays some structured noise in the form of vertical banding. This pattern noise that does not appear in the results of the two other methods.

A quantitative comparison was then made, represented by the scatter plots of Fig. 4.14 and Table 4.3. In this analysis the LIA was calculated at 500 points

Table 4.3: LIA calculated by two methods in GEE compared to the same in Sentinel-1 Toolkit at 500 random sample points around Silbury Hill. The metrics for comparison are the Coefficient of Determination, R^2 (dimensionless) and Root Mean Squared difference ($RMSE$) (in $^\circ$ LIA)

Method	Equation	Ascending Orbit		Descending Orbit	
		R^2	$RMSE$	R^2	$RMSE$
Rigorous calculation	4.10	0.90	0.69	0.90	0.68
EURAC	4.11	0.86	0.70	–	–
EURAC (modified)	4.12	–	–	0.86	0.71

randomly selected in area of Fig. 4.13, for both the ascending orbit image previously introduced and a descending orbit image at 06:22 on 21 July 2018. There is a very good fit between both GEE methods and the Sentinel-1 toolkit. The small amount of residual noise is less than 1° in LIA value and may be attributable to the pattern noise seen in the control LIA - Fig. 4.13a. There was also negligible little additional difference ($< 0.1^\circ$ in LIA) by using the EURAC Research LIA method of Eqn. 4.11 and (as modified for descending orbits) Eqn. 4.12. For the implementation of the CD algorithm in GEE, this method was selected for the LIA calculation.

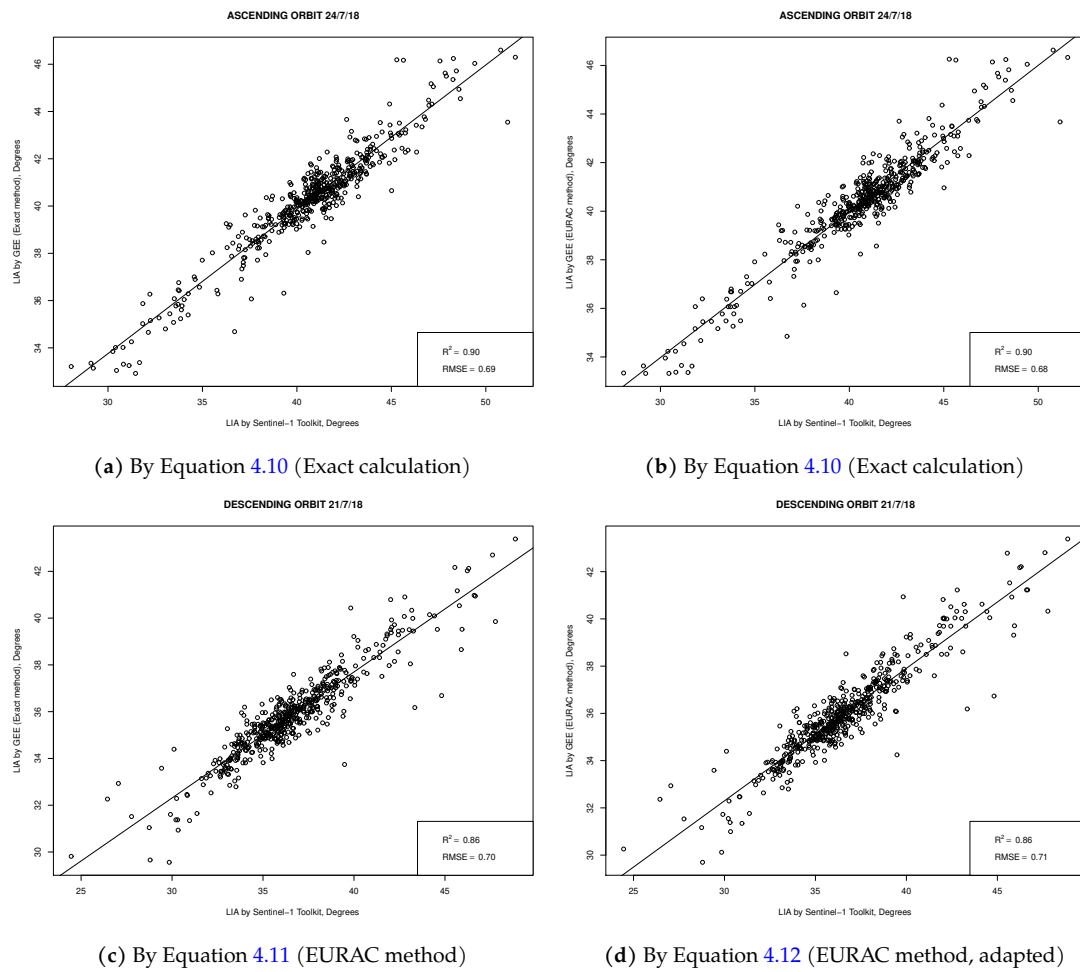


Figure 4.14: Scatter plot comparisons of LIA calculations in GEE (y-axis) and S1 Toolbox (x-axis). The GEE method of sub-figures (a) and (b) uses Eqn. 4.10 and the method of (c) and (d) uses Eqns. 4.11 and 4.12. Both methods process a slope and aspect calculated by a bespoke function after Ritter (Ritter, 1987) based on SRTM-30 DEM. Data are contemporary with the following S1 images taken of the area around Silbury Hill, Wiltshire; sub-figures (a) and (c) an ascending orbit at 17:57 on 24 July 2018 and sub-figures (b) and (d) a descending orbit at 06:22 on 21 July 2018. Approximately 500 points were randomly sampled from the area of Fig. 4.13

Normalisation of backscatter to a fixed LIA

The example of Fig. 4.14 shows that, even in a relatively small area, the LIA varies between 30° and 50° . This is due to variations in both the local slope and aspect of the ground surface, and the viewing angle of the satellites. The latter varies continuously in a lateral direction across the satellite image swath, and each point on the ground is will be seen at different relative locations in multiple swaths due to overlapping orbits. Ascending and descending orbits also have very different viewing directions. The angular dependence of backscatter on LIA may be demonstrated by considering a simple case in which the backscatter is re-radiated into a hemisphere according to a cosine law (Lambert's Law for optics). The intensity of the radar beam is also cosine dependent, so factoring these together we can show that the backscatter is a function of the cosine square of the LIA, θ_i :

$$\sigma_{\theta_i}^0 = \sigma_0^0 \cos^2(\theta_i) \quad (4.13)$$

where σ_0^0 is a scaling factor describing the backscatter independent of incidence angle. In practice the relationship is even more complex due to enhanced backscatter in certain directions due to surface roughness and vegetation.

A crucial part of the process, therefore, was to correct for this angular dependence by normalising the backscatter data to a single value of LIA. Assuming this were possible, according to the established linear regression method (Bauer-Marschallinger et al., 2019), $\sigma_{\theta_i}^0$ is measured for each pixel as a function of θ_i over a long time period. The assumption is that the variation in σ_0^0 caused by vegetation and changes in soil roughness will manifest as a noise signal about a mean value. The slope of the linear regression best-fit line through this data is therefore an estimate of $\delta\sigma_{\theta_i}^0/\delta\theta_i$. To normalise to a reference angle θ_{ref} for any daily measurement at time t :

$$\sigma_{\theta_{ref},t}^0 = \sigma_{\theta,t}^0 - (\theta_i - \theta_{ref}) \frac{\delta\sigma_{\theta_i}^0}{\delta\theta_i} \quad (4.14)$$

The reference angle was set as $\theta_{ref} = 40^\circ$ to minimise the seasonal impact of vegetation on the backscatter signal. According to (Wagner et al., 1999a), 40° angle minimises the seasonal variation in backscatter due to vegetation. It is noted, though, that this finding is based on a limited range of vegetation types (grassland, parkland, boreal and perialpine forest) in an area of Canada studied in 1992/3. The validity of this angle for arable crops if, for example, the UK, is a potential source of error.

The issue with this method of normalisation as it relates to S1 data, is that it relies on each pixel being imaged over a range of values of θ_i to calculate a satisfactory regression slope, $\delta\sigma_{\theta_i}^0/\delta\theta_i$. But with S1, θ_i has a limited range of possible values determined by the orbit geometry and the position of the ground location within the swath width. Within the UK, in the worst case, a given location might only be imaged by two orbits, one in an ascending direction, and one in the descending direction. Over time, there will be a spread of σ^0 values at each angle, but nevertheless the regression statistics will be of questionable quality. At other locations, there may be several more overlapping orbits and the statistics will be more reliable. In the example from North Wyke site in Fig. 4.15, the selected point on the ground is imaged from four values of LIA. The inconsistency of the normalisation from location to location could give rise to fixed pattern noise in the SM estimation. An alternative solution has been implemented according to the method of [Bauer-Marschallinger et al. \(2019\)](#):

$$\frac{\delta\sigma_{\theta_i}^0}{\delta\theta_i} \approx \beta_r = aS + B\bar{\sigma}_{VV}^0 + c \quad (4.15)$$

Where $a = -0.01725$, $b = 0.00553$ and $c = 0.02546$. Values of β_r having been calculated as part of the pre-processing activity, normalised backscatter was calculated:

$$\sigma_{\theta_{40},t}^0 = \sigma_{\theta,t}^0 - \beta_r(\theta_i - 40) \quad (4.16)$$

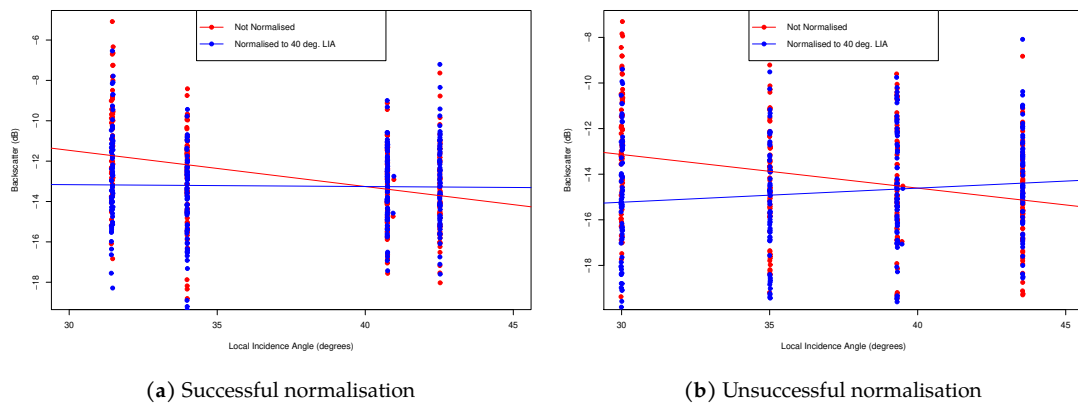


Figure 4.15: Results of normalisation Process for two image pixels in different fields near the North Wyke COSMOS-UK station. The blue dots are the values of backscatter plotted against LIA, the red dots are backscatter after normalisation to $\theta_{ref} = 40^\circ$ by Eqn. 4.16. The straight lines are best fit lines in each case, showing that the dependence on LIA has been minimised in one case (a) very effectively, but has been over compensated in the other case (b). The data is for the whole of 2018.

An example of the significance of the normalisation process is illustrated by the analysis of the backscatter from two single points on the ground (pixels) located in the vicinity of the COSMOS-UK station on the North Wyke site as shown in Fig. 4.15. Every value of backscatter is plotted for 2018 as red dots, prior to normalisation. The trend line (in red) provides an indication of the dependence of backscatter on LIA at these locations. The blue dots represent the backscatter values after normalisation to an LIA of 40° using Eqn. 4.16. The associated blue trend line shows that this dependency has been virtually eliminated in one case (Fig. 4.15a) but not the other (Fig. 4.15b). The trend lines cross at 40° as this is the invariant point of the transformation. The clusters of LIA seen in these two plots differ, despite the point being close to each other, because of the slope of the land varying between them. This example shows that the method of normalisation is not always successful and is a potential weakness in the change detection algorithm that should be further investigated in future work.

Spatial averaging

The calculations performed up until this point were carried out at the full resolution of the SAR data, on a 10 m pixel grid (though the effective resolution is 20 m). All of the parameters necessary for the SM estimation were collected and stored in GEE as a multi-band image, also known as an image stack, with one multi-band image or stack per measurement day, assembled into a GEE ImageCollection. The bands of, or derived from, SAR backscatter were expressed in logarithmic (dB) units as per convention. If this information is used at this resolution to obtain an estimate of soil moisture by the CD algorithm, the result is typified by the example of Figure 4.16, which is dominated by spatial noise, including speckle, which must be mitigated by spatial averaging. Before doing this, logarithmic data must be converted to linear units that relate directly to the physical quantity of reflected energy. Then all bands of each image were spatially averaged in different ways to provide two products.

To obtain a field scale output, the backscatter coefficients and reference values were spatially averaged within the eroded field boundaries provided by the UKCEH Land Cover Plus:Crops data-set. This is achieved by using the GEE function `ee.Image.reduceRegions()` with the weighted mean reducer, `ee.Reducer.mean()`, where pixels are included in the mean if more than 0.5% of the pixel area is inside the field, weighted by the fraction of the pixel area inside the field. The output of

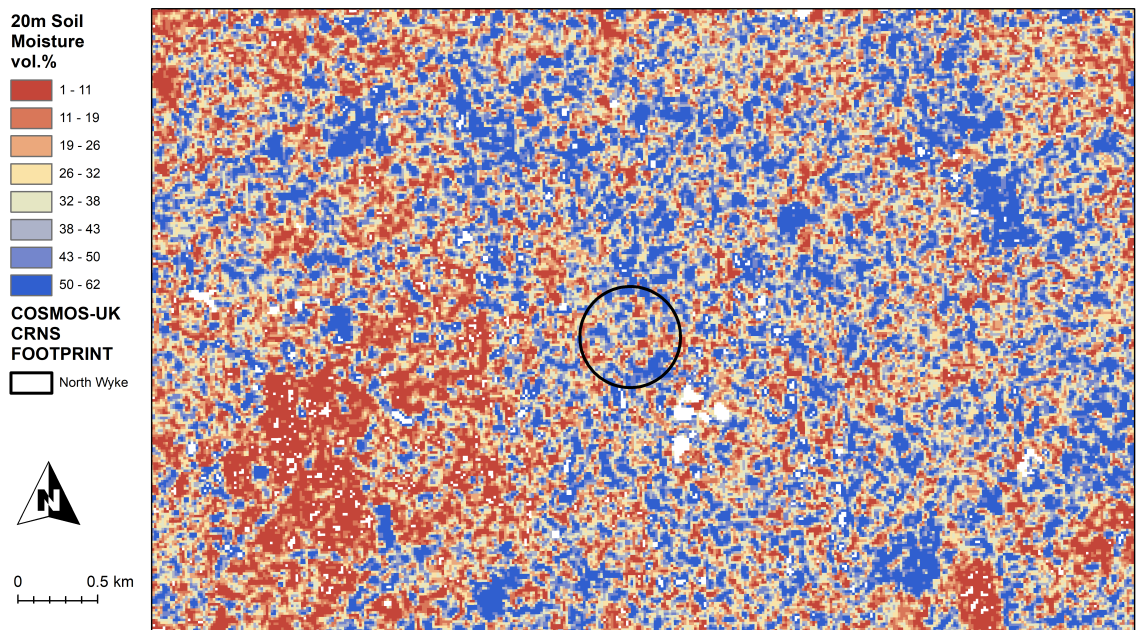


Figure 4.16: Sensor resolution SAR soil moisture example at North Wyke Farm for 28th May 2018. The colour scale represents volumetric soil moisture (vol.%). No spatial averaging has been applied at this stage.

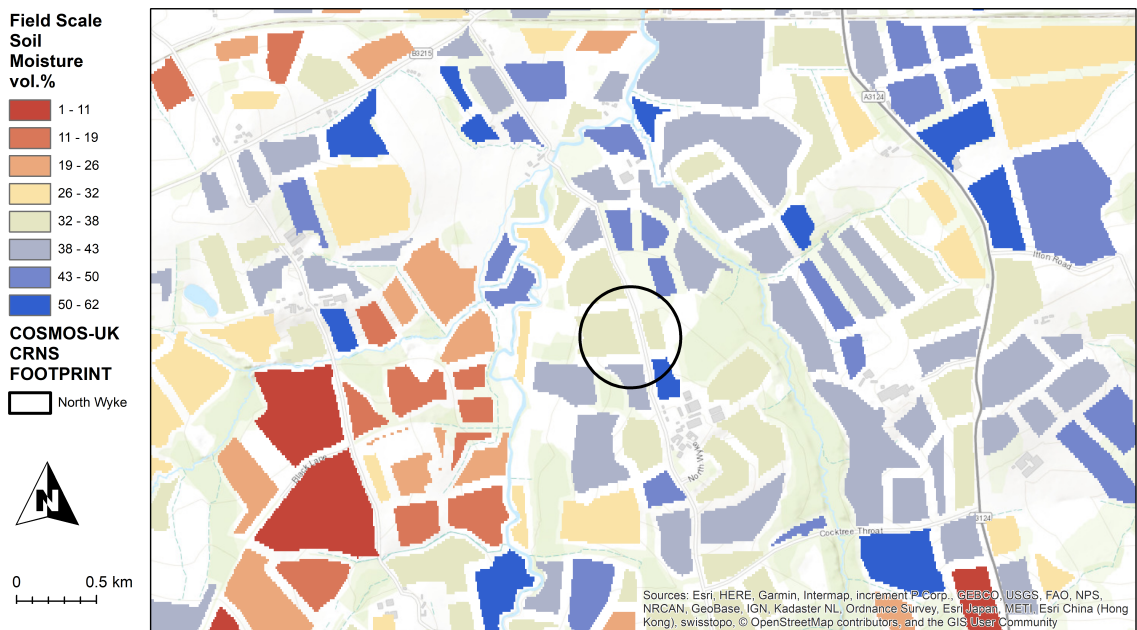


Figure 4.17: Field scale SAR soil moisture example at North Wyke Farm for 28th May 2018. The colour scale represents volumetric soil moisture (vol.%). Spatial averaging is to 20m eroded field parcel boundaries, avoiding most water bodies, roads, hedges, buildings and stands of trees.

this process is no longer an image, but geographical object level representations (features in GEE) of each field, replicated for each SAR image date. The averaged values of each waveband are stored as properties, referred to in some GIS systems as attributes. The properties that described backscatter and backscatter calibration references were converted back to logarithmic units (dB) to follow the convention for SAR data that is followed by the CD algorithm. The proprieties of each feature contained all of the parameters needed to calculate an SMI value for its geometry and date combination. An image representation of the result, after calibration to volumetric soil moisture units as described in the next section, is shown in Figure 4.17.

To simulate a nominal 1 km pixel product and for direct comparison to the published Copernicus SSM data, the multi-band images were reduced in resolution to match exactly the pixel footprints of the Copernicus SSM product. This was achieved by the GEE function `ee.Image.reduceResolution` with the weighted mean reducer, `ee.Reducer.mean()`, as above. The bands that described backscatter and related calibration references were converted back to logarithmic units (dB) to follow the convention for SAR data that is followed by the CD algorithm. The output of this process was a GEE `ImageCollection` with each image representing a single day of SAR image collection but covering all fields in the region of interest. The bands of each image contained all of the parameters needed to calculate an SMI value.

Calculation of soil moisture index (SMI) and surface soil moisture (SSM)

For the purposes of this study, the Soil Moisture Index (SMI) was defined a dimensionless quantity that varies between 0 and 1 to describe the soil moisture state relative to its range based on historical observations. A value of 0 signified that the observed backscatter was less than or equal to the dry reference, which was previously calculated as an estimate of the backscatter of the soil in its driest historically-observed state. A value of 1 meant that the observed backscatter was greater than or equal to the wet reference, which is the equivalent for soil in its wettest historically-observed state. This may be expressed as:

$$SMI = \frac{\sigma_{VV}^0 - \sigma_{VV,dry}^0}{\sigma_{VV,wet}^0 - \sigma_{VV,dry}^0} \quad (4.17)$$

According to the recommendations of Chapter 3, the soil hydraulic properties obtained for each test site were used to calibrate the SMI values to Surface Soil Moisture (SSM) in units of Volumetric Water Content (VWC). Specifically these properties were the Van Genuchten model parameters of water content at quasi-saturation (θ_S) and residual water content (θ_R). The values used for these parameters were the optimised values obtained from fitting the HYDRUS-1D model to CRNS data.

$$SSM = \theta_R + SMI(\theta_S - \theta_R) \quad (4.18)$$

The SMI and SSM calculations for the field-scale SM product were based on the parameter values stored as properties of the time series features in GEE, with the SMI and SSM values being and stored as additional properties. For the 1 km raster data, the calculations were performed using band arithmetic to derive new "SMI" and "SSM" wavebands for each image.

Filtering of the soil moisture estimates

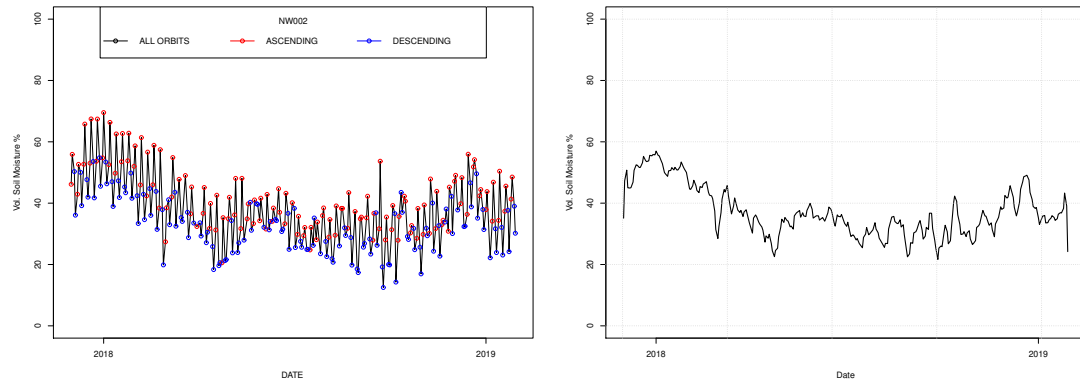
In Chapter 3 the issue of filtering of satellite derived SSM data was briefly discussed, resulting in the successful implementation of a simple exponential filter to reduce the noise that was seen in the data. It was assumed that the noise was a combination of random noise and some that might be systematic in nature, perhaps due to orbit geometry. This was investigated further for data at North Wyke, as shown in Fig. 4.18a. In this example, from field NW002, the soil moisture predicted from ascending orbits seems consistently higher than that predicted by descending orbit observations. There is a lower level of noise between measurements within either class, than between the different orbit geometries. The causes of inter-orbit SSM variation may be one or more of the following:

- The presence of scattering centres in a field that causes enhance backscatter preferentially at certain orbit geometries.
- Soil surface roughness that has a pattern that enhances backscatter preferentially into certain directions
- Normalisation of the backscatter data has being more effective in some orbit geometries compared to others
- The apparent soil moisture being genuinely different at the different times of day that the ascending and descending orbits capture data. At this test site,

the imaging times are close to 6am and 6pm.

- Layover affects that might be changing the average soil moisture statistics withing the boundary of the field by including different objects or vegetation in the scene, depending on geometry.

Pending further refinements in the method to eliminate these noise factors a Savitzky-Golay filter ([Savitzky and Golay, 1964](#)) was selected as an interim solution. It has the ability to average the results from all possible orbits, whilst preserving, as far as possible, the sensitivity to rapidly varying soil moisture conditions. The filter used a sliding window of adjustable time period, within which a n^{th} order model was fitted by least-squares regression. This model was then used to predict the value of the centre of that time window. A 3rd order polynomial was chosen to allow the filter to pass rapid changes in soil moisture. The window size was selected as 7, which was the smallest odd number that would ensure that all potential orbit geometries would be included at least once in the window. This was a trade-off, a large window would have produced a smoother output at the risk of loss of information. The results of applying this filter to the satellite derived surface soil moisture data is shown in Fig. 4.18b, showing complete elimination of the periodic noise which has a magnitude of around 20 vol.% in this example.



(a) Significant and structured noise in the results, with red and blue circles highlighting the ascending and descending satellite orbits. (b) The same data having been smoothed by a Savitzky-Golay filter with a window of 7 measurements and using a 3rd order polynomial fit

Figure 4.18: Time series of volumetric water content by the GEE implementation of the CD algorithm for field NW002 at North Wyke. The black line combines satellite observations from all orbits.

4.3.3 Performance assessment

The various satellite soil moisture estimates, E , were analysed with respect to reference soil moisture data, R , which were either probe/CRNS soil moisture data or the 2 cm soil moisture predictions derived from them by the HYDRUS-1D Model. The comparisons were made through scatter plots and a number of statistical measures commonly used for the assessment of retrieved soil moisture, similar to the approach of [van der Velde et al. \(2015\)](#), [Eweys et al. \(2017\)](#) and [El Hajj et al. \(2018\)](#). These comprised the coefficient of determination R^2 (Eqn. 4.19), Mean Absolute Difference MAD (Eqn. 4.20), Mean Percentage difference $MAPD$ (Eqn. 4.21), Root Mean Squared Difference $RMSD$ (Eqn. 4.22), bias, b (Eqn. 4.23) and unbiased $RMSD$ $ubRMSD$ (Eqn. 4.24). A good level of performance is characterised by a high value of R^2 and low values of MAD and $RMSD$. Bias (b) and $ubRMSD$ provide an indication of the magnitude of systematic and random errors, respectively. In some analyses the slope of the best-fit linear trend line through the scatter plot was used as measure of sensitivity of the algorithm to soil moisture. The ideal sensitivity value is represented by a slope of 1. To test for statistical significance the p -value at 95% confidence intervals was calculated using the two-tailed Student's t -distribution, with the value of t calculated by dividing the regression slope by its standard error.

$$R^2 = \frac{\sum_{i=1}^n (E_i - \bar{E})^2}{\sum_{i=1}^n (R_i - \bar{R})^2} \quad (4.19)$$

$$MAD = \frac{\sum_{i=1}^n |E_i - R_i|}{n} \quad (4.20)$$

$$MAPD = \frac{100}{n} * \sum_{i=1}^n \frac{|E_i - R_i|}{R_i} \quad (4.21)$$

$$RMSD = \sqrt{\frac{\sum_{i=1}^n (E_i - R_i)^2}{n}} \quad (4.22)$$

$$b = \frac{\sum_{i=1}^n (E_i - R_i)}{n} \quad (4.23)$$

$$ubRMSD = \sqrt{RMSD^2 - b^2} \quad (4.24)$$

For the assessment of the field-scale product the assumption was made that the soil hydraulic properties were sufficiently consistent within a field parcel to permit any 2 cm soil moisture predictions from the HYDRUS-1D Model to be taken as representative of the whole field. To obtain a comparable satellite estimate of soil moisture from 1 km resolution data, field-scale values were calculated as the mean of the pixels overlapping the eroded field boundaries, weighted proportionally to the area of intersection.

4.4 Results

The results of this study are presented in three subsections. The first presents results on the assessment of the validity of the GEE implementation by comparing to the published Copernicus results at 1 km resolution. The second part examines how the field-scale spatial aggregation performs by comparing it alongside the 1 km product to the reference SM. These results were all obtained at the North Wyke site, which consists only of grass fields. The final subsection looks at how well the field-scale algorithm performs in agricultural fields as a function of crop stage and tillage state, by looking at a diversity of field at the other five test sites.

4.4.1 Comparison of 1 km SM estimates from GEE with Copernicus SSM

The 1 km resolution output from the GEE implementation of the change detection algorithm was intentionally aligned on a pixel by pixel basis to the published 1 km Copernicus SSM product, so that a direct comparison could be made (see 4.19). For each product, the SM for each of the fields at North Wyke were obtained by the weighted mean of the pixels overlapping the eroded field boundaries, with the weighting factors proportional to the area of intersection. These estimates were quantitatively assessed against the in-field soil moisture measurements of the NWFP using the metrics of Equations 4.19 to 4.24, as shown in Table 4.4

Figure 4.19: Comparing the SMI images of 1 km gridded Sentinel-1 derived surface soil moisture estimates for the area around the North Wyke on 28th May 2018. Left is processed in Google Earth Engine, middle is the published Copernicus SSM result, right is the difference image. In each image black = SMI of 0, white is SMI of 0.75. The 200m nominal footprint of the COSMOS-UK CRNS sensor is shown as the hatched area.

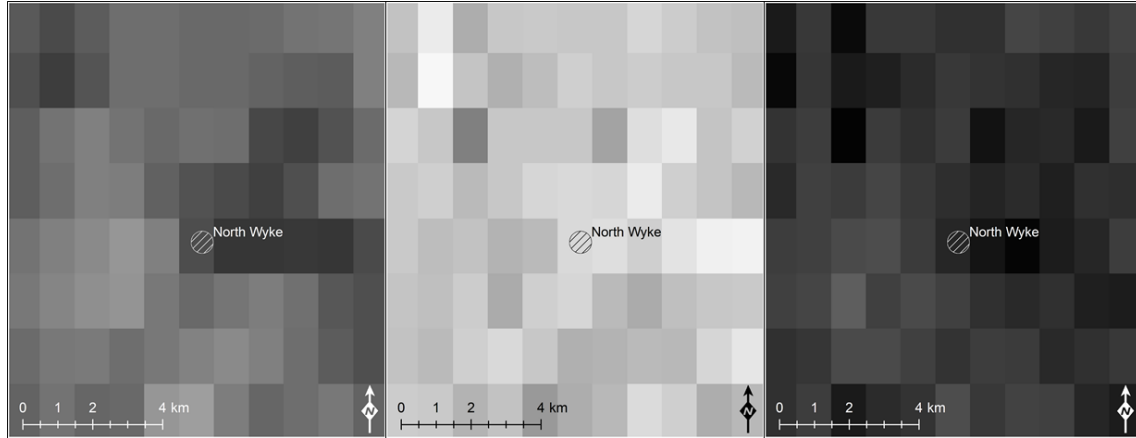
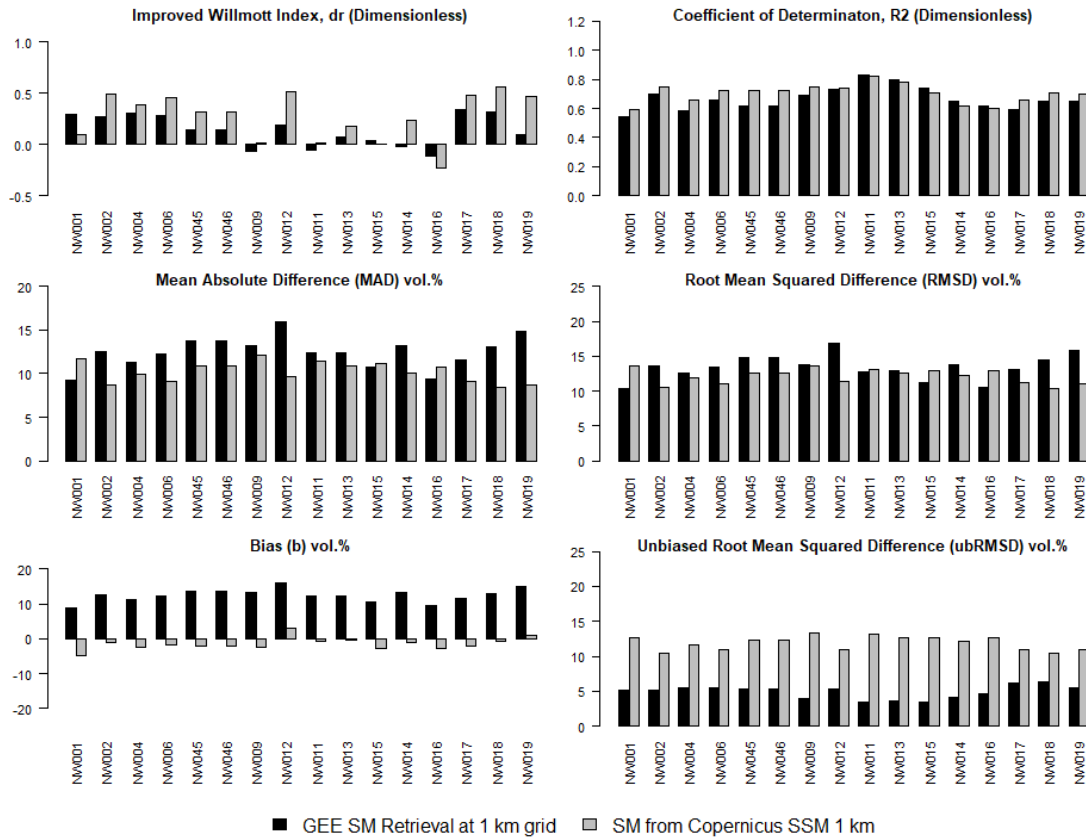


Figure 4.20: Performance of 1 km gridded Sentinel-1 derived surface soil moisture estimates processed in Google Earth Engine for fields at North Wyke for the whole of 2018. The ground reference values are the in-field soil moisture probe measurements at 10 cm depth. The bar plots contrast the relative performance of the 1 km resolution gridded GEE product, with the Copernicus SSM 1 km product published on the same pixel grid.



and a selection of these are shown as bar plots in Fig. 4.20. These results show that there is broad equivalence between the two products; some differences can be expected as there were significant variations in the method. Overall the GEE implementation has more bias than the Copernicus SSM product, but less random variation as measured by $ubRMSD$. In terms of the goodness of fit indicators, d_r and R^2 the bespoke calculation in GEE did not appear to be performing much better or worse than previously published results in these grassed fields.

4.4.2 Assessment of the field-scale soil moisture estimate

The performance of the field scale, satellite-derived, soil moisture estimate was assessed in two stages. Firstly the product was validated in North Wyke field NW002 site against 2 cm soil moisture simulations. Secondly the performance was compared to that of the 1 km resolution product at all other fields in the North Wyke test site.

Validation against 2 cm reference SM modelled by HYDRUS-1D

Field NW002 was chosen because it contained the majority of the footprint of the COSMOS-UK CRNS sensor. Figure 4.21 is a time series plot which compares, primarily, the field-scale soil moisture derived from the S1 SAR satellite through the CD algorithm implemented in GEE (in black) with HYDRUS-1D simulations of soil moisture at 2 cm soil depth (in red). Also shown are the average of soil moisture measurements by two in-field soil moisture probes at 10 cm depth, in green. Daily rainfall totals (in mm) are also shown, in blue. The first observation is that the HYDRUS-1D predictions at 2 cm are more variable and responsive to drying and rainfall events than the soil moisture probe data at 10cm, but this is exactly as expected. The changes in the 2 cm simulation are ahead of the probe response in both drying and wetting phases. This provides additional confidence in the simulated 2 cm data.

Looking at the field-scale satellite estimate of soil moisture, this is close to the 2 cm prediction in the summer period and in January and February, but this is not the case in the spring, autumn and early winter. The quantitative comparison for the whole year is shown in Fig. 4.22. The value of the metrics are shown in Table 4.5. The overall results are impacted by the periods of especially poor performance in the Spring, and Autumn. As this was a year with a dry summer, it was observed that these periods coincide with time when the grass would have been growing

Table 4.4: Comparison of performance of 1 km gridded volumetric soil moisture derived from S1 SAR for fields at North Wyke. The products compared were the results of processing developed in this study in Google Earth Engine (GEE) and the Copernicus SSM (C SSM) published data. In each case the performance was assessed relative to measurements of soil moisture from probes in each field. The metrics for comparison are the improved Willmott index of agreement (d_r), the coefficient of determination (R^2), the mean absolute difference (MAD), the mean absolute percentage difference ($MAPD$), bias (b) and unbiased RSMD ($ubRMSD$). The p-value for the regression between the retrieved SM and the probe values is also shown, in every case these values are very close to zero.

Field	Area m^2	SM 1km Source	d_r	R^2	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	b vol. %	$ubRMSD$ vol. %	p
NW001	8026	GEE	0.29	0.54	9.19	30.12	10.36	8.99	5.15	6.51E-30
		C SSM	0.1	0.59	11.65	35.94	13.56	-4.7	12.72	1.46E-34
NW002	31315	GEE	0.27	0.7	12.58	50.17	13.61	12.58	5.19	3.44E-46
		C SSM	0.49	0.75	8.73	30	10.58	-1.13	10.52	1.11E-53
NW004	3844	GEE	0.3	0.58	11.26	42.48	12.54	11.25	5.54	2.39E-34
		C SSM	0.38	0.66	9.88	32.21	11.87	-2.46	11.61	7.27E-42
NW006	28424	GEE	0.28	0.66	12.22	48.52	13.37	12.22	5.42	1.31E-41
		C SSM	0.46	0.72	9.05	30.53	11.01	-1.64	10.89	1.81E-49
NW009	11945	GEE	-0.07	0.69	13.26	42.71	13.86	13.26	4.03	8.98E-46
		C SSM	0.01	0.75	12.16	38.65	13.64	-2.46	13.42	5.8E-54
NW011	6545	GEE	-0.06	0.83	12.34	39.6	12.8	12.33	3.44	1.59E-67
		C SSM	0.01	0.82	11.5	37.79	13.14	-0.57	13.13	2.95E-66
NW012	5273	GEE	0.19	0.73	15.93	69.52	16.8	15.92	5.37	5.36E-51
		C SSM	0.51	0.74	9.64	36.14	11.39	3.02	10.98	1.41E-52
NW013	29552	GEE	0.07	0.8	12.42	41.56	12.91	12.41	3.56	2.11E-61
		C SSM	0.18	0.78	10.94	36.39	12.6	-0.49	12.59	3.58E-59
NW014	2358	GEE	-0.02	0.65	13.19	46.43	13.82	13.19	4.13	7.06E-41
		C SSM	0.23	0.62	10.03	32.44	12.16	-0.92	12.13	1.52E-37
NW015	2987	GEE	0.04	0.74	10.7	33.23	11.25	10.69	3.51	3.46E-52
		C SSM	0	0.71	11.19	34.87	12.93	-2.9	12.6	1.64E-48
NW016	2695	GEE	-0.11	0.62	9.4	28.25	10.47	9.39	4.63	5.59E-35
		C SSM	-0.23	0.6	10.74	31.98	12.92	-2.84	12.6	6.38E-33
NW017	1561	GEE	0.34	0.59	11.59	47.81	13.16	11.58	6.25	6.66E-35
		C SSM	0.48	0.66	9.07	30.06	11.17	-2.18	10.96	2.42E-41
NW018	1278	GEE	0.32	0.65	13.08	57.43	14.52	13.08	6.3	1.63E-40
		C SSM	0.56	0.71	8.4	29.18	10.41	-0.63	10.39	4.93E-48
NW019	1749	GEE	0.09	0.65	14.87	64.79	15.88	14.87	5.57	3.43E-41
		C SSM	0.47	0.7	8.68	30.38	10.97	1.13	10.91	5.24E-47
NW045	1644	GEE	0.14	0.62	13.76	48.59	14.74	13.75	5.31	1.13E-37
		C SSM	0.31	0.72	10.91	35.35	12.52	-2.15	12.33	9.36E-49
NW046	10021	GEE	0.14	0.62	13.76	48.59	14.74	13.75	5.31	1.13E-37
		C SSM	0.31	0.72	10.91	35.35	12.52	-2.15	12.33	9.36E-49

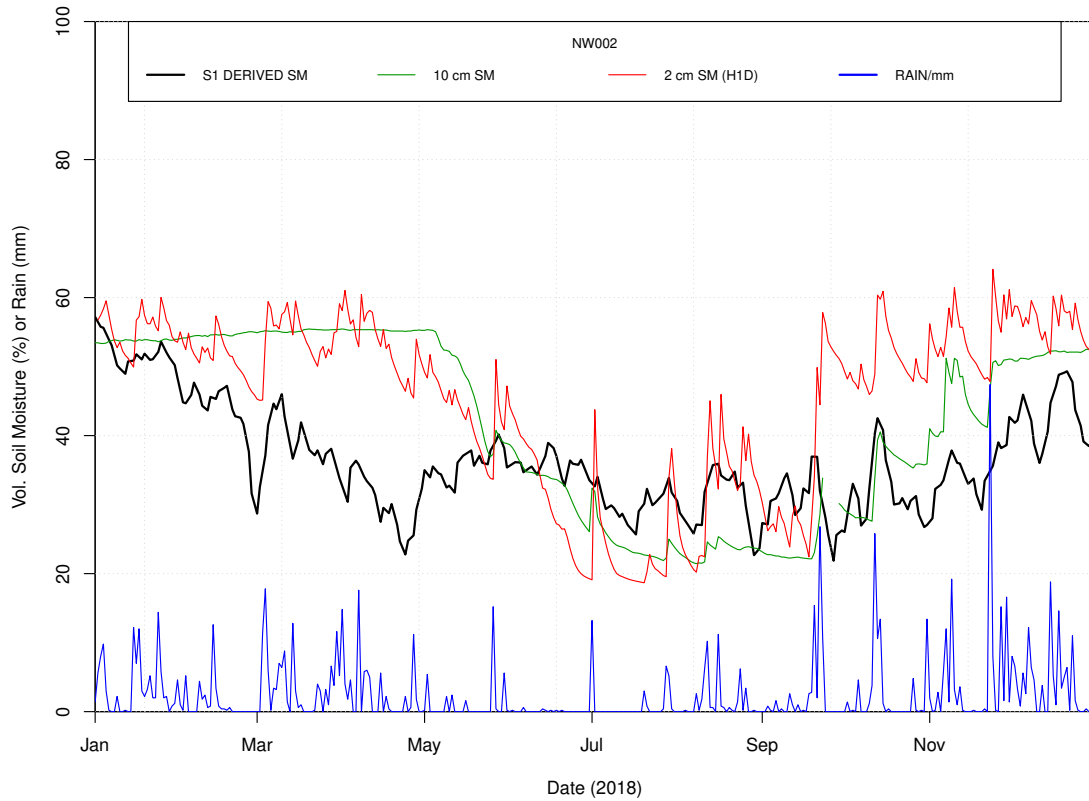


Figure 4.21: North Wyke field NW002, which contains the COSMOS-UK CRNS soil moisture sensor. 2018 Time series comparison of the volumetric soil moisture estimated by the field scale CD algorithm against the 2 cm modelled soil moisture from the fitted HYDRUS-1D model, driven by in-field measurements of potential evaporation (not shown) and rainfall (shown). Also plotted is the soil moisture at 10 cm as measured by the point probes installed alongside the CRNS sensor.

quickly.

Table 4.5: Performance metrics for field scale GEE CD SM at North Wyke field NW002

Field	d_r	R^2	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	Bias, b vol. %	$ubRMSD$ vol. %	p
NW002	0.43	0.25	11.93	27.0	14.01	-8.82	10.89	6.6E-16

Comparison of field-scale and 1 km resolution output

To compare the effect of spatial aggregation to field scale and to a 1 km pixel, the field scale SM estimate was compared to the 1 km SM estimate in all of the selected fields (Fig. 4.7) at North Wyke. Both sets of data were quantitatively assessed against the in-field soil moisture probes are presented in Table 4.6. The relative performance of the field scale estimate compared to the 1 km resolution product

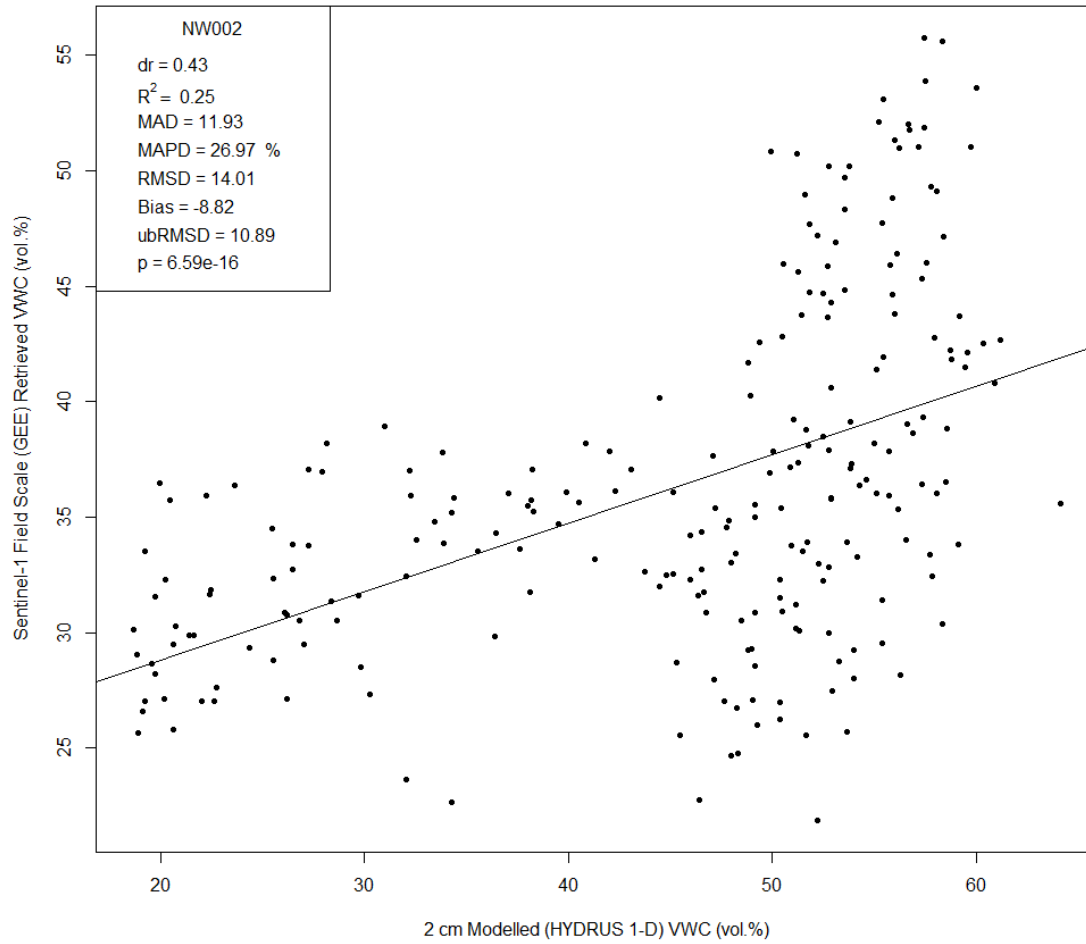


Figure 4.22: North Wyke field NW002, 2018 scatter plot analysis of the volumetric soil moisture estimated by the field scale CD algorithm against the 2 cm modelled soil moisture from the fitted HYDRUS-1D model, with performance metrics shown in the legend.

was of principle interest as there was a possibility that the reduces area of spatial aggregation for the field scale product would introduce additional random noise that might not be compensated for by reduced clutter. The second column of Table 4.6 shows the area within the eroded field boundaries for each field, which is of the order of $10^3 m^2$ to $10^4 m^2$. The area of a nominal 1 km pixel is of the order of $10^6 m^2$, which is two to three orders of magnitude larger. The MAD and RMSD were similar between these two resolutions, and in a few cases significantly lower. However, the coefficient of determination was slightly lower in all but three fields where the values are comparable. The field-scale product appears to have a higher bias but lower random noise ($ubRMSD$) than the 1 km product. MAD is a better indicator of the overall performance that a user would experience, so these results

suggest that there was not any significant penalty in aggregating to field scale for the North Wyke site.

Table 4.6: Comparison of performance results at field-scale and 1 km grid for S1 SAR derived surface soil moisture estimates in fields at North Wyke. The reference soil moisture for these calculations are the measurements of soil moisture from probes in each field. The metrics for comparison are the improved Willmott index of agreement (d_r), the coefficient of determination (R^2), the mean absolute difference (MAD), the mean absolute percentage difference ($MAPD$), bias (b) and unbiased RSMD ($ubRMSD$). The p-value for the regression between the retrieved SM and the probe values is also shown, in every case these values are very close to zero.

Field	Area m^2	Spatial Resolution	d_r	R^2	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	b vol. %	$ubRMSD$ vol. %	p
NW001	8026	Field parcel	0.49	0.7	6.61	19.65	8.37	4.91	6.78	1.69E-45
		1 km grid	0.29	0.54	9.19	30.12	10.36	8.99	5.15	6.51E-30
NW002	31315	Field parcel	0.51	0.45	8.36	33.1	9.56	6.53	6.98	5.86E-24
		1 km grid	0.27	0.7	12.58	50.17	13.61	12.58	5.19	3.44E-46
NW004	3844	Field parcel	0.44	0.49	9.05	30.87	10.36	6.18	8.31	1.41E-26
		1 km grid	0.3	0.58	11.26	42.48	12.54	11.25	5.54	2.39E-34
NW006	28424	Field parcel	0.31	0.12	11.7	48.09	13.9	10.04	9.61	3.15E-6
		1 km grid	0.28	0.66	12.22	48.52	13.37	12.22	5.42	1.31E-41
NW009	11945	Field parcel	0.07	0.33	11.44	36.43	13.69	10.78	8.44	1.11E-16
		1 km grid	-0.07	0.69	13.26	42.71	13.86	13.26	4.03	8.98E-46
NW011	6545	Field parcel	0.24	0.34	8.85	28.5	10.3	7.12	7.44	2.97E-17
		1 km grid	-0.06	0.83	12.34	39.6	12.8	12.33	3.44	1.59E-67
NW012	5273	Field parcel	0.36	0.43	12.7	55.18	14.59	11.85	8.51	8.01E-23
		1 km grid	0.19	0.73	15.93	69.52	16.8	15.92	5.37	5.36E-51
NW013	29552	Field parcel	0.16	0.27	11.27	36.81	13.05	7.22	10.87	3.68E-13
		1 km grid	0.07	0.8	12.42	41.56	12.91	12.41	3.56	2.11E-61
NW014	2358	Field parcel	0.41	0.31	7.65	26.65	10.69	6.47	8.51	2.11E-15
		1 km grid	-0.02	0.65	13.19	46.43	13.82	13.19	4.13	7.06E-41
NW015	2987	Field parcel	0.11	0.13	9.98	30.46	12.1	1.81	11.96	6.34E-7
		1 km grid	0.04	0.74	10.7	33.23	11.25	10.69	3.51	3.46E-52
NW016	2695	Field parcel	-0.3	0.28	11.88	34.43	14.89	7.65	12.77	4.37E-13
		1 km grid	-0.11	0.62	9.4	28.25	10.47	9.39	4.63	5.59E-35
NW017	1561	Field parcel	0.24	0.28	13.18	57.24	16.23	6.74	14.76	8.8E-14
		1 km grid	0.34	0.59	11.59	47.81	13.16	11.58	6.25	6.66E-35
NW018	1278	Field parcel	0.23	0.29	14.74	65.48	16.95	14.52	8.74	2.32E-14
		1 km grid	0.32	0.65	13.08	57.43	14.52	13.08	6.3	1.63E-40
NW019	1749	Field parcel	0.28	0.16	11.85	55.8	14.15	10.97	8.94	7.85E-08
		1 km grid	0.09	0.65	14.87	64.79	15.88	14.87	5.57	3.43E-41
NW045	1644	Field parcel	0.25	0.36	11.94	39.91	14.57	9.83	10.75	2.75E-18
		1 km grid	0.14	0.62	13.76	48.59	14.74	13.75	5.31	1.13E-37
NW046	10021	Field parcel	0.21	0.4	12.59	40.62	15.34	10.9	10.79	1.68E-20
		1 km grid	0.14	0.62	13.76	48.59	14.74	13.75	5.31	1.13E-37

4.4.3 Field scale product performance by crop stage and tillage state

The field scale satellite soil moisture estimate was assessed in more detail at the remaining five test sites: Fincham, Elmsett, Loddington, Spen Farm and Writtle. At each site, the fields that significantly intersect with the 200 m radius footprint of the COSMOS-UK CRNS were selected. It was anticipated that the performance of the change detection algorithm would depend on crop cover and soil roughness. To evaluate the magnitude of this effect, the study year 2018 was subdivided into shorter time periods defined by observed crop and tillage activity in each field, using the evidence from the phenocam images. The UKCEH Land Cover Plus:Crops data set was also used to confirm any ambiguities in the phenocam evidence. Four of the sites were observed growing crops that included winter wheat (or oats), oil-seed rape and potatoes. There were also two fields of grass. At the last site, Writtle, the grass fields were cut for silage or hay, but at other times were grazed by sheep. Maps of the field locations at each of the sites are presented in Appendix 4.A.

The performance metrics, also broken down by field activity, are set out in tables in Appendix 4.B and summarised here by crop type. Also presented here, for each field, are time series plots comparing the output of the field scale CD algorithm to the HYDRUS-1D simulation at 2 cm soil depth. The dates at which activities related to the crop and tillage state were observed are shown on these plots by vertical, dashed, green lines. Scatter plots are also shown where linear regression lines have been added to indicate the trend between the data sets. These have been sub-divided into sets according to crop stage or field tillage state, and these are differentiated by colour. For the regression lines the best case is a gradient of 1 and an offset of zero. A gradient less than this indicates a reduced sensitivity of the satellite product to soil moisture. Anomalous gradients with large positive or negative values are, most likely, the result of regression through an insufficient number of sample points being sampled.

Winter wheat

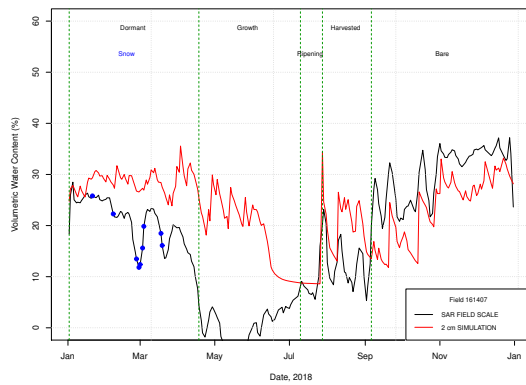
The time series plots of SM in Fig. 4.23 reveal that the satellite estimate deviated below the reference SM in the spring and early summer, dipping below 0 vol.% at times. Outside this period, especially after ploughing, there was better agreement. The scatter plots of Fig. 4.24 confirm that, during the wheat growing season, there

was a weak and often negative relationship between the SAR estimate and reference SM. During the winter dormancy phase, whilst the satellite estimates were clustered in the expected area, there was insufficient diversity in soil moisture to comment on the degree of correlation. The period after harvesting showed good sensitivity to SM, and was maximised when the soil was bare, after ploughing.

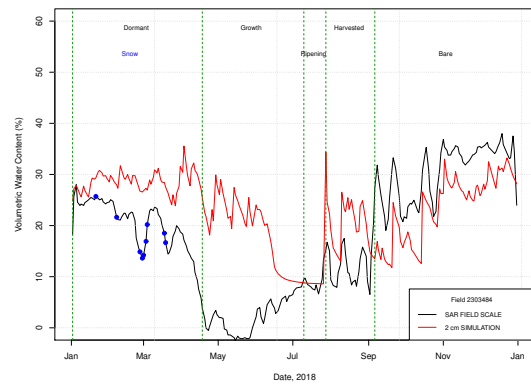
Turning to Table 4.7, the worst performance was detected in the growth phase, with an average mean difference about 19 vol.%. Overall the assessment is that the capability of the satellite estimate with winter wheat varies from nil in the growth phase to medium when the soil is bare, but in the latter case the differences is relatively small at around 6 vol.%. It appears that the bare soil performance is much better in fields 161407 and 2303484, so this could be the result of poor classification at the other field between bare soil and winter dormancy. The apparent period of high performance for the ripening of the crop cannot be relied upon due to the small number of observations in this class. The average performance all year is assessed as medium due to the low R^2 value.

Table 4.7: Performance metrics for S1 SAR derived surface soil moisture estimates for 4 winter wheat fields in 2018, relative to the HYDRUS-1D simulation of soil moisture at 2 cm depth at the appropriate COSMOS-UK site location.

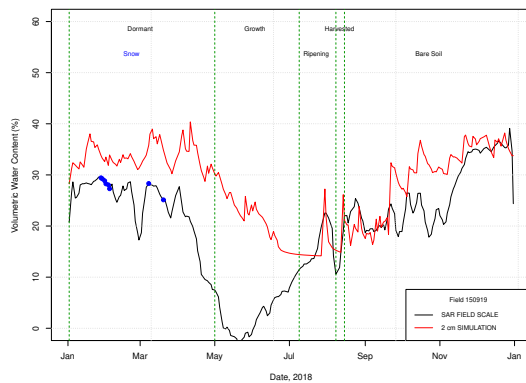
Crop state	d_r	R^2 vol.%	MAD vol.%	$MAPD$ %	$RMSD$ vol.%	b vol.%	$ubRMSD$ vol.%	p	S	Capability
All Year	0.26	0.26	9.39	38.86	11.92	-6.89	9.73	1.68E-61	0.74	MEDIUM
Dormant	-0.4	0.12	9.16	29.02	10.67	-9.15	5.49	1.52E-08	0.56	NONE
Growth	-0.52	0.18	18.82	86.58	20.43	-18.82	7.95	1.81E-09	-0.27	NONE
Ripening	0.69	0.69	2.08	16.42	2.64	-0.13	2.64	5.94E-15	0.9	HIGH
Harvested	0.1	0.19	7.84	37.22	9.04	-7.59	4.91	5.29E-04	0.34	POOR
Bare Soil	0.51	0.21	5.96	25.35	7.12	0.73	7.08	4.63E-18	0.4	MEDIUM



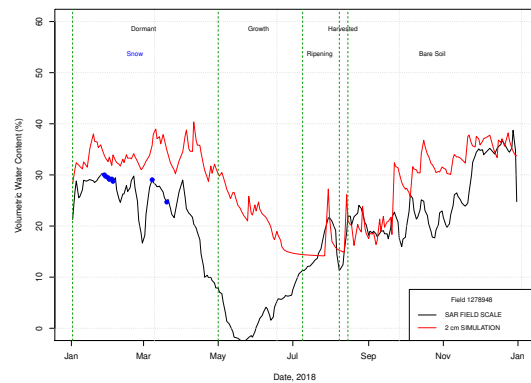
(a) Field 161407 at Fincham



(b) Field 2303484 at Fincham



(c) Field 150919 at Spen Farm



(d) Field 127948 at Spen Farm

Figure 4.23: Winter wheat fields: time series plots of estimated soil moisture by the CD field scale algorithm (black) compared to the HYDRUS-1D simulations at 2 cm depth (red). The dates of crop and tillage activities are shown as vertical, dotted, green lines. The blue dots represent days of snow or ice that make the SAR data potentially invalid.

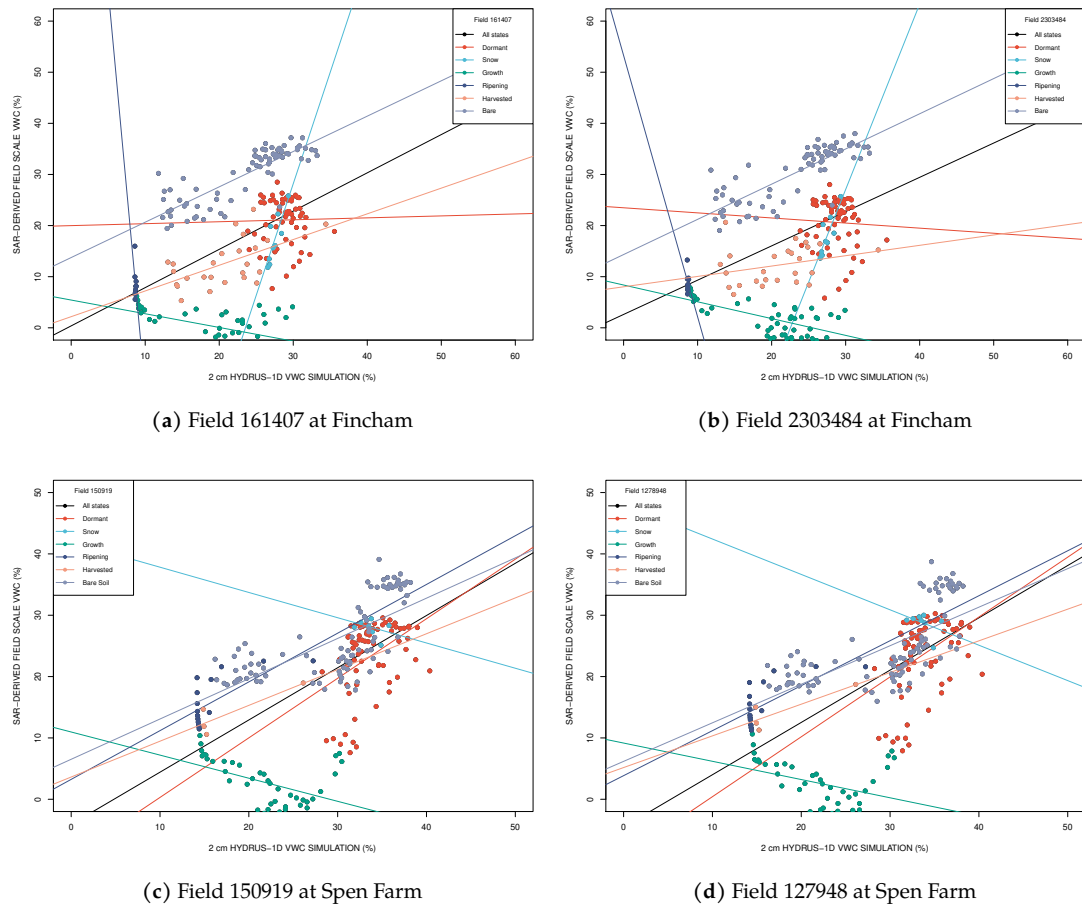
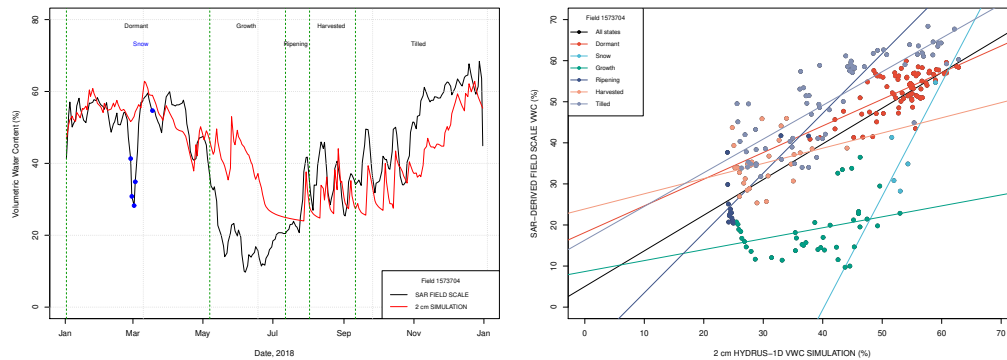


Figure 4.24: Winter wheat fields: scatter plots and trend lines of estimated soil moisture by the CD field scale algorithm compared to the HYDRUS-1D simulations at 2 cm depth. The time periods are restricted to periods between dates of crop and tillage activities shown in different colours as shown by the key.

Spring barley

There was only one spring barley field studied, at Loddington, which was under conservation tillage. The behaviour is very similar to that seen in winter wheat, with the SAR estimate of soil moisture falling below the expected value in the spring and early summer (Fig. 4.25a), but not by quite as much as winter wheat. This may be due to the later development of the crop, being spring sown. In this case the field was not ploughed but subject to conservation tillage, which probably involved some sub-surface de-compaction and direct drilling. This has had a similar effect to ploughing, but with the mean difference higher at over 9 vol.%. As shown in Fig. 4.25b and Table 4.8 the performance level is relatively good after tillage.



(a) Time series plot of estimated soil moisture by (b) scatter plot and linear regression lines of estimated the CD field scale algorithm (black) compared to the soil moisture by the CD field scale algorithm compared HYDRUS-1D simulations at 2 cm depth (red). The to the HYDRUS-1D simulations at 2 cm depth. The time dates of crop activities are shown as vertical, dotted, periods are restricted to periods between dates of crop green lines. The blue dots represent days of snow or activities shown in different colours as shown by the ice that make the SAR data invalid. key.

Figure 4.25: Spring barley field 1573704 at Loddington

Table 4.8: Performance metrics for S1 SAR derived surface soil moisture estimates for a spring barley field, relative to the HYDRUS-1D simulation of soil moisture at 2 cm depth for the COSMOS-UK site location.

Crop state	d_r	R^2 vol. %	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	b vol. %	$ubRMSD$ vol. %	p	S	Capability
All Year	0.58	0.44	8.66	22.52	11.62	-0.62	11.60	4.89E-31	0.87	MEDIUM
Dormant	0.56	0.44	3.43	6.57	4.14	-0.49	4.11	8.75E-11	0.65	MEDIUM
Growth	-0.27	0.11	19.10	48.98	20.89	-19.10	8.46	2.94E-02	0.27	POOR
Ripening	0.25	0.58	3.97	15.25	5.24	0.78	5.18	1.56E-03	1.46	MEDIUM
Harvested	0.19	0.09	6.13	21.40	7.83	4.79	6.19	1.28E-01	0.37	NONE
Conservation Tilled	0.49	0.68	9.45	25.23	10.94	8.80	6.50	6.96E-19	0.82	HIGH

Oil-seed rape

Time series plots for the two oil-seed rape fields that were both located at Elmsett are shown in Fig. 4.26. By contrast to wheat, this shows that the satellite estimate of SM is higher than reference SM in the early to mid summer. When the crop ripens, it drops suddenly to a very low value but recovers a little when the crop is harvested. After ploughing it is close to the reference SM. These trends are reflected in the scatter plots and trend lines of Fig. 4.27 and the performance metrics in Table 4.9. During the growing season, there is strong, slightly negative relationship between SAR estimated of SM and actual SM. In the winter dormant phase, the small range of variation in SM prevents the trend being analysed confidently. In this crop, the period after harvest gave the best sensitivity, but the bare soil period produced the lowest values of MAD and RMSD being between 4 and 5 vol.% Overall the performance of the CD algorithm for oil-seed rape is limited, with no capability in the main growth period of the crop.

Table 4.9: Performance metrics for S1 SAR derived surface soil moisture estimates for 2 oil-seed rape fields in 2018, relative to the HYDRUS-1D simulation of soil moisture at 2 cm depth at the appropriate COSMOS-UK site location.

Crop state	d_r	R^2 vol.%	MAD vol.%	$MAPD$ %	$RMSD$ vol.%	b vol.%	$ubRMSD$ vol.%	p	S	Capability
All	0.39	0.19	8.60	24.38	9.98	-5.69	8.20	8.21E-23	0.39	LOW
Dormant	-0.64	0.02	10.26	23.59	11.03	-10.23	4.12	1.04E-01	0.20	NONE
Growth	0.11	0.38	7.72	26.35	9.31	3.58	8.59	4.25E-11	-0.41	NONE
Ripening	-0.92	0.94	7.43	36.09	7.97	-1.76	7.77	4.56E-11	22.30	NONE
Harvested	0.19	0.63	11.56	38.47	12.42	-11.56	4.54	2.69E-09	0.61	LOW
Bare Soil	0.50	0.30	4.22	14.08	5.13	-2.75	4.33	5.88E-10	0.39	MEDIUM

Potatoes

There was only one potato field studied, at Spen Farm. The potato crop was planted late relative to the other crops, and the Winter dormant phase appeared to extend well into May. In this period, the time series (Fig. 4.28a shows there was good match between the satellite estimate and reference SM, but with negative bias of around 8.49 vol.% - the apparent soil moisture was consistently lower than expected. This may have been due to vegetation covering some of the soil, which may have been weeds or a cover crop. On planting of the potatoes, the proportion of bare soil was observed on camera to increase, and the apparent soil moisture rose to the expected level, briefly. Then, as the vegetation canopy grew, the apparent soil moisture continued to rise above the reference SM level. This may have been

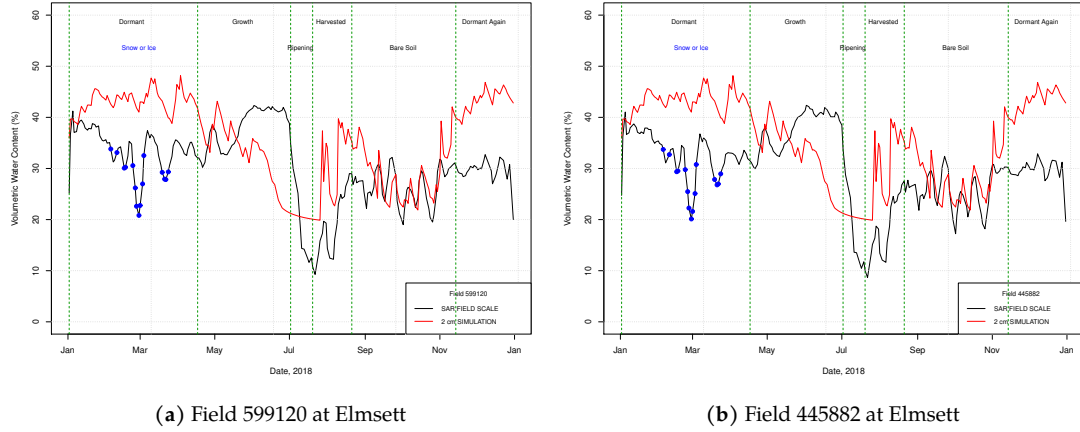


Figure 4.26: Oil-seed rape fields: time series plots of estimated soil moisture by the CD field scale algorithm (black) compared to the HYDRUS-1D simulations at 2 cm depth (red). The dates of crop and tillage activities are shown as vertical, dotted, green lines. The blue dots represent days of snow or ice that make the SAR data potentially invalid.

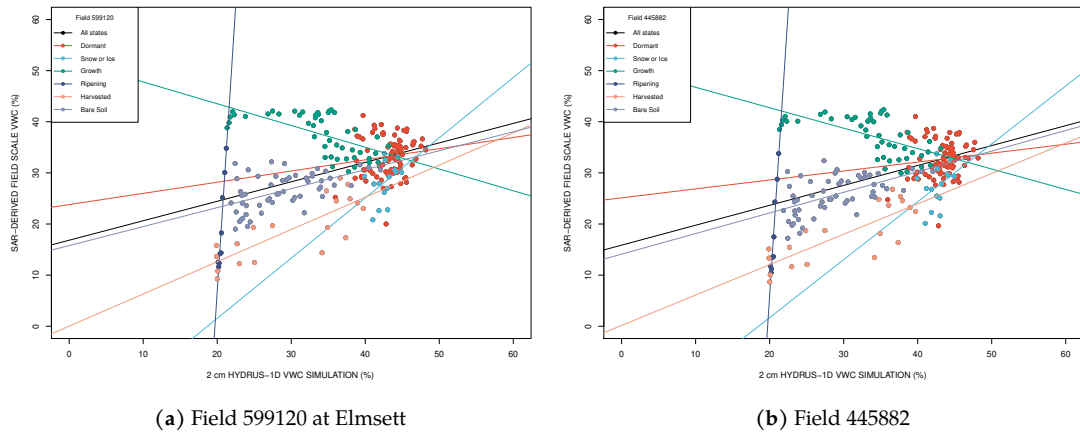
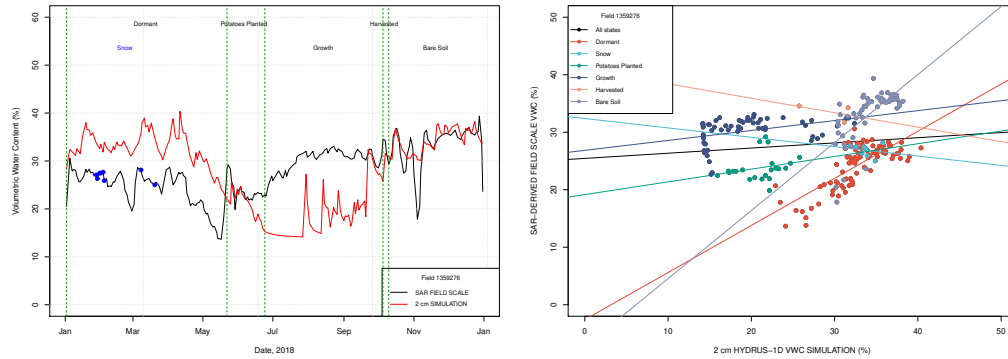


Figure 4.27: Oil-seed rape fields: scatter plots and trend regression lines of estimated soil moisture by the CD field scale algorithm compared to the HYDRUS-1D simulations at 2 cm depth. The time periods are restricted to periods between dates of crop and tillage activities in different colours as shown by the key.

caused by irrigation, commonly applied to potato crops in dry seasons, such as was experienced in 2018. After harvesting, with a significant fraction of the soil now bare, the apparent soil moisture matched very closely the expected level, except for one dip. As shown in Fig. 4.28b and Table 4.10 the performance level is good when there was significant bare soil present.



(a) Time series plot of estimated soil moisture by the CD field scale algorithm (black) compared to the soil moisture by the CD field scale algorithm compared HYDRUS-1D simulations at 2 cm depth (red). The time dates of crop activities are shown as vertical, dotted, periods are restricted to periods between dates of crop green lines. The blue dots represent days of snow or activities shown in different colours as shown by the key.

Figure 4.28: Potato field 1359276 at Spen Farm

Table 4.10: Performance metrics for S1 SAR derived surface soil moisture estimates for a potato field, relative to the HYDRUS-1D simulation of soil moisture at 2 cm depth for the COSMOS-UK site location.

Crop state	d_r	R^2 vol. %	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	b vol. %	$ubRMSD$ vol. %	p	S	Capability
All Year	0.46	0.02	7.05	30.77	8.51	-0.30	8.50	4.70E-02	0.09	NONE
Dormant	-0.37	0.58	8.49	26.16	8.87	-8.49	2.57	1.28E-16	0.82	MEDIUM
Potatoes Planted	0.27	0.06	3.04	15.76	4.02	2.75	2.93	2.59E-01	0.22	NONE
Growth	-0.23	0.15	10.93	65.35	11.92	10.90	4.82	2.24E-03	0.17	POOR
Harvested	0.20	0.28	4.02	14.85	5.34	4.02	3.51	6.46E-01	-0.25	NONE
Bare Soil	0.48	0.45	2.25	6.84	3.47	-1.05	3.31	4.63E-08	1.18	HIGH

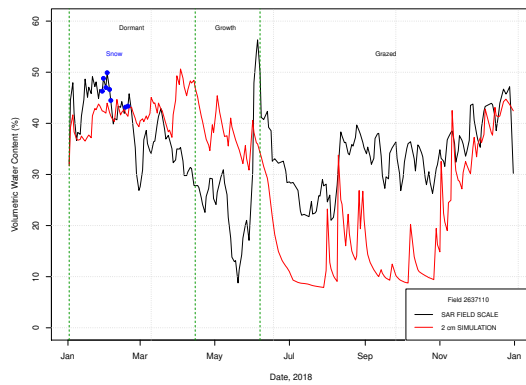
Grass

The time series plots of estimated soil moisture for the fields of grass are shown in Fig. 4.29. The observed behaviours split into two categories; fields 2578949 at Elmsett and 1462873 at Loddington showed no significant movement in soil moisture that were not reflected in the reference SM data. This suggests that the grass in these fields was likely to have been grazed all year. The mean difference for these fields was still significant, at around 8 vol.% in volumetric water content, due to a consistent offset where the satellite estimate was less than reference SM (bias of -3.6 vol.%).

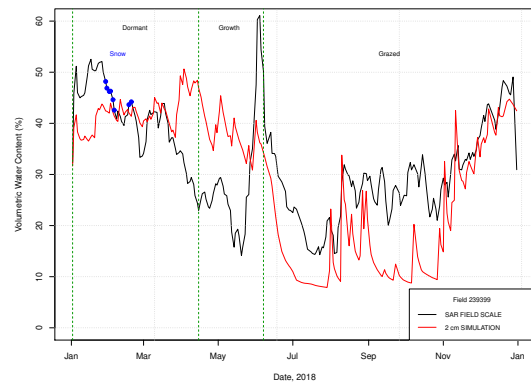
The other type of behaviour was seen in fields at Writtle, where there was seasonal variation in performance due to the grass being grown for cutting for silage and/or hay. During the winter, dormant phase, the satellite estimate was close to the expected level. It then started to deviate as the grass grew, akin to the trend observed in wheat. When the grass was cut, the apparent moisture rose very significantly and above the expected level. Whilst this positive offset was maintained through the Summer and into the Autumn, there was a good correlation between the apparent and simulated SM. By the early winter the satellite estimate was in good agreement with the simulated soil moisture at 2 cm. This was reflected in the regression plots of Fig. 4.30, and in Table 4.11. The grazed periods produced the best combination of high R^2 and sensitivity. The performance level is assessed as high in these periods. The R^2 value was close to zero and $p > 0.5$ during the rapid growth phase, so it is reasonable to conclude that the CD algorithm has no capability in this period.

Table 4.11: Performance metrics for S1 SAR derived surface soil moisture estimates for grass fields relative to the HYDRUS-1D simulation of soil moisture at 2 cm depth for the COSMOS-UK site location. 2 fields were grazed all year ("grazed") and 2 were grazed part of the year but the grass was also grown long and cut for hay or silage ("cut").

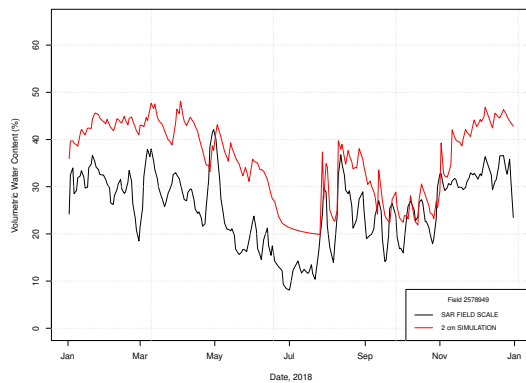
Crop state	d_r	R^2 vol.%	MAD vol.%	$MAPD$ %	$RMSD$ vol.%	b vol.%	$ubRMSD$ vol.%	p	S	Capability
All Year (cut)	0.57	0.24	10.71	63.50	12.87	4.02	12.23	2.38E-29	0.33	MEDIUM
Dormant (cut)	-0.15	0.15	6.86	15.95	9.12	-2.42	8.79	8.13E-06	-0.70	NONE
Growth (cut)	-0.60	0.00	15.31	39.97	16.28	-11.65	11.37	5.86E-01	0.20	NONE
Grazed (cut)	0.43	0.56	11.78	95.86	13.71	11.28	7.79	1.45E-47	0.50	HIGH
All Year (grazed)	0.54	0.52	8.12	22.59	9.67	-3.55	8.99	3.43E-76	0.87	HIGH



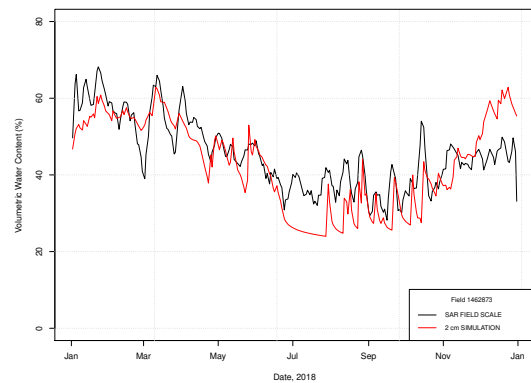
(a) Field 2637110 at Writtle



(b) Field 239399 at Writtle

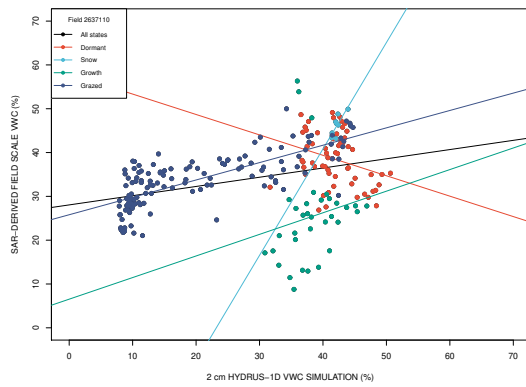


(c) Field 2578949 at Elmsett

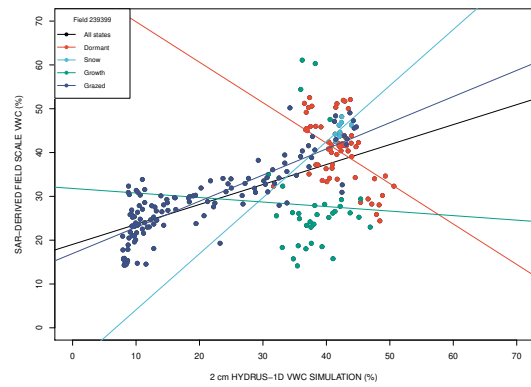


(d) Field 1462873 at Loddington

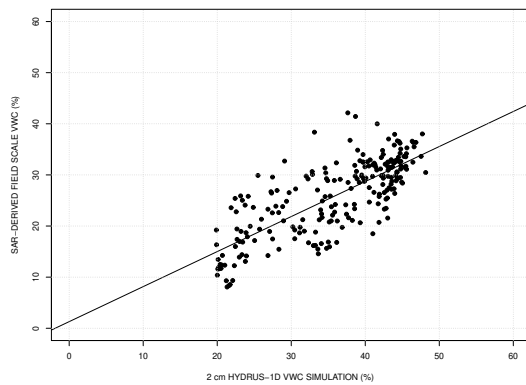
Figure 4.29: Fields of grass: time series plots of estimated soil moisture by the CD field scale algorithm (black) compared to the HYDRUS-1D simulations at 2 cm depth (red). The dates of crop activities are shown as vertical, dotted, green lines. The blue dots represent days of snow or ice that make the SAR data invalid.



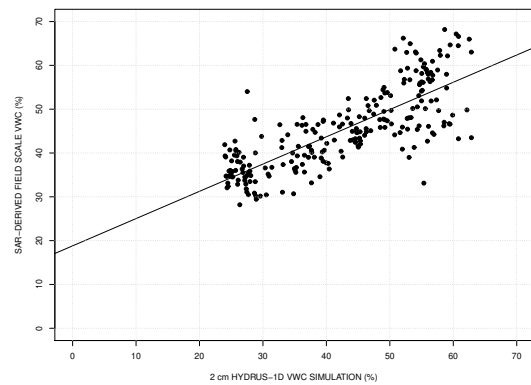
(a) Field 2637110 at Writtle



(b) Field 239399 at Writtle



(c) Field 2578949 at Elmsett



(d) Field 1462873 at Loddington

Figure 4.30: Fields of grass: scatter plots and linear regression lines of estimated soil moisture by the CD field scale algorithm compared to the HYDRUS-1D simulations at 2 cm depth. The time periods are restricted to periods between dates of crop activities shown in different colours as shown by the key.

4.5 Discussion

4.5.1 Implementation of the change detection algorithm in Google Earth Engine

The study chose to implement the same change detection algorithm that is behind the published data of the Copernicus SSM product. To reach a depth of understanding of the algorithm, and to make the process scalable, Google Earth Engine was chosen as a platform for development. This threw up some unexpected issues in the calculation of slope and offset, which demonstrated that the default calculations performed in GEE and in the Sentinel-1 toolkit, should not be blindly trusted to be accurate and warrant further investigation. Significant quantisation was observed in both slope and aspect that might have an impact on the normalisation process. The study created its own method for creating a smoother slope and offset calculation that created less quantisation for later use. This was not the only potential difference in the processing chain compared to the Copernicus product; the image statistics were calculated separately for ascending and descending orbits, as the statistics seemed significantly different. The processing was also carried out at full sensor resolution up until the point of spatial averaging to field scale. The normalisation of radar backscatter to a fixed angle of LIA using previously published methods was found to vary in its effectiveness, based on a very small sample of test points. This is a potential problems that warrants further investigation in any future work.

4.5.2 Equivalence of the Google Earth Engine output and Copernicus SSM

Having implemented the algorithm at sensor resolution the soil moisture estimates were then spatially aggregated to the same, nominal 1 km, pixel grid that the Copernicus SSM product used. The results of the quantitative comparison between the two products showed that there was broad equivalence between the two products in terms of overall noise. The GEE implementation has more bias but less random noise than the Copernicus product. The cause of this bias is unknown. Some differences can be expected as there were significant variations in the method. For example, the published data used the LIA calculation in the Sentinel-1 Toolbox, which was shown to have observable differences to the chosen

GEE implementation. The historic data pre-processing used by Copernicus SSM at time of download did not include the 2019 data. Finally, in the published data, the spatial averaging was accomplished in two stages, with an intermediate 500 m resolution being used. Overall the results showed that the GEE implementation has a similar performance to previously published results in these grass areas.

4.5.3 Progress towards field scale soil moisture estimation

The sensor resolution the soil moisture estimates were spatially aggregated to field boundaries derived from the UKCEH Land Cover Plus:Crops data-set. The boundaries were eroded by 20 m to minimise the impact of field boundaries themselves in the backscatter statistic, to eliminate as much as possible of the layover effects of the SAR image from tall hedges, and to mitigate against errors in the boundary definitions. This was found to work very well in Google Earth Engine, and it was possible to create time series of soil moisture at the field level.

4.5.4 Filtering as mitigation for higher noise levels at field scale

Both the soil moisture output of the GEE implementation and the published Copernicus SSM product was found to include some periodic noise that appeared to be orbit related. A review of smoothing filters led to the Savitzky-Golay filter being adopted, it having a good reputation in the smoothing of optical index data, which is affected by variable cloud cover. It was found that a third order filter using a window of 7 measurements could eliminate most of this periodic noise whilst having a minimal impact on the sensitivity of the technique to rainfall events. This filter was then used in all analysis, including (where used) to smooth the Copernicus SSM product. The use of this filter would also mitigate some of the additional random speckle noise that was expected to be a more significant source of noise at field Scale compared to 1 km resolution.

4.5.5 Field-scale and 1 km resolution SM compared

A number of fields at the North Wyke site, where in-field soil moisture measurements were available, were used to make the comparisons between the 1 km products and the field scale product. In this case the soil moisture measurement was at 10 cm which is much deeper than the SAR can penetrate, but the data is still reasonable for use for relative comparisons. It was shown that the 1 km product

produced in GEE was comparable to the 1 km Copernicus SSM product in these fields. The R^2 values were all between 0.5 and 0.8 depending on the field, and the absolute differences were similar, in the range 8 to 15 vol.%. The comparison between the 1 km product and field scale did revealed that, in some cases, the field scale product performed less well in some cases and as well in others. However, the differences not being so much worse is a good indication that the random noise increase in averaging over a smaller area is balanced, in many cases, by a stronger signal. This gave confidence to proceed to the next stage.

4.5.6 Performance of the field-scale SM estimate in arable fields

The study then looked at arable sites and investigated how well the CD algorithm performed for several arable crops, looking at different stages of the crop development and the tillage state of the fields. The results, summarised in Table 4.12, confirmed earlier hypotheses that the algorithm did not, overall, perform well for arable fields. The differences that were found were about 20 vol.%, and this difference occurred at the most critical time for farmers, the time when the crop is growing fastest in the spring and early summer months. This problem was particularly severe in winter wheat and oil-seed rape crops when there is no capability at this time of year. It is likely that the crop canopy is so dense that very little, if any, of the SAR backscatter signal is actually from the soil. What signal there is may be more likely to be from the crop itself. By contrast, it was found that a very good performance could be achieved when the soil was bare, for several months after ploughing. Mean differences in the range of 4 to 10 vol.% were then possible. It was interesting to discover that the minimum tillage fields gave a slightly higher performance in the more challenging periods than traditional tillage, but more data would be needed to confirm this. Oil-seed rape is also interesting to compare to wheat; in the high growth period, the wheat fields produced a SAR soil estimate that was much drier than it should be, whereas for the rape it was higher. This difference is probably due to the highly ordered structure of the wheat stalks, which might be causing enhanced scattering in certain directions only, whereas the more random orientation of the rape might be scattering more diffusely. Potato crops were found to give a quite good CD soil moisture performance for more months of the year. It is believed that the method of growing potatoes involved a significant amount of soil to remain bare, even during the rapid growth stage, compared to the other crops. The performance of the CD algorithm on grass fields

was found to be high when the grass was grazed but low if the grass was allowed to grow tall for cutting.

Table 4.12: Summary of performance levels for field Scale SM estimates from the CD algorithm as a function of crop type and stage

Crop Type	Year Round	Winter Dormancy	Growth Phase	Ripening	Post-harvest/Cut	Bare Soil
Winter Wheat (Trad. Till)	LOW	LOW	NONE	LOW	MEDIUM	HIGH
Winter Wheat (Min. Till)	MEDIUM	MEDIUM	LOW	MEDIUM	MEDIUM	HIGH
Oil-seed Rape	MEDIUM	LOW	NONE	NONE	MEDIUM	MEDIUM
Grass (Grazed)	HIGH					
Grass (Harvested)	LOW	HIGH	LOW		HIGH	
Potatoes	LOW	HIGH	LOW		LOW	HIGH

Overall, the results demonstrate that C-band Sentinel-1 SAR data, processed by the change detection algorithm, has no capability to estimate soil moisture in many crops when the vegetation canopy closes, at a crucial time of crop development when the information is most valuable to farmers. An alternative strategy must be found to provide a soil moisture capability during these periods.

4.5.7 Insights

This study set out to explore the potential for creating a field-scale soil moisture estimate using the change detection algorithm to process SAR backscatter from ESA's Sentinel-1 satellites. The change detection algorithm is one of several approaches to this problem, but one of the first to have regular data published as a service, due to its ability to operate with minimal *a priori* information and without training data. The algorithm is, however, based on several assumptions; the contribution of vegetation follows a slow, seasonal variation that can be minimised by normalisation to a fixed angle, and that soil surface roughness is approximately constant. All short-term variations in backscatter are attributed to changes in soil moisture. These assumptions are demonstrably untrue in the case of arable agriculture, where anthropogenic intervention causes rapid changes in vegetation biomass over a scale of days to weeks, and soil roughness can be altered in hours due to tillage operations. The mitigation of these issue is achieved, to some degree, by spatial averaging to lower resolution, for example a 1 km product that may include around ten fields in each pixel. The short-term changes that might occur in one small area are balanced by the relatively static situation elsewhere in the pixel. The larger pixels also include many areas that may not be under cultivation, such as field boundaries, gardens, road verges and similar. However, these areas also have the potential to add additional noise, especially where they cause enhanced

or depressed backscatter due to man-made objects or bodies of water. To achieve a field scale product from the change detection algorithm, it was necessary first to understand the nature of the problem, where the algorithm could perform well and where it cannot, and understand the trade-off between increased spatial resolution and noise levels, both due to random effects and the inclusion or not of scattering sources in the image.

The results of the study showed that it was feasible to create a field scale SM product from Sentinel-1 SAR data using the change detection algorithm with only a small penalty in terms of additional noise. However, the performance of the field scale product is more dependent on the diversity of the land cover, and this has a major impact in fields under arable cultivation. There are periods related to the crop phase when good performance can be achieved, but at other times the product has no use to the farmer. A solution to resolve this problem should be a focus for future study. In addition, a number of weaknesses in the change detection algorithm and into implementation have emerged, in particular the effects of layover and the potential problems with normalisation of backscatter. There may be other issues that contribute to a significant periodic noise in the output which should be investigated.

4.6 Conclusions and recommendations

The main conclusion of this study is that it is feasible to produce a soil moisture estimate at the field scale from Sentinel-1 C-band SAR by spatial aggregation to boundaries defined in to publicly available field boundary data sets. It has been shown to be possible to adapt a change detection algorithm to estimate soil moisture at the field scale, without incurring a significant noise penalty, provided that field boundaries are eroded to avoid edges and man-made scattering objects.

The field scale product was shown to suffer from a slightly higher noise level compared to the 1 km resolution product. However this was smaller than the periodic noise that was observed at both scales that appeared to be orbit related. This noise is also seen in published data, but it can be reduced effectively by the use of a Savitzky-Golay filter. It is suspected that the periodic noise could be the result of ineffective normalisation of the backscatter data, issues relating to layover in SAR imagery, geometry effects related to surface roughness or slope, or the presence of persistent scattering objects in the scene. Though there may be other issues, these factors require further investigation to mitigate this noise at source, if

possible.

The performance of the change detection algorithm in arable fields has been shown to be highly dependent on the stage of the crop and the tillage state of the field. In particular, the SAR soil moisture estimate is completely unusable when most crops are at their main growth stage. In operational terms this means that farmers, for example, cannot use this type of SAR-derived SM product at this crucial stage of their crops. An alternative approach is needed to provide a better estimate of SM in this period, one potential solution is investigated in the next chapter. Another significant finding is that the change detection algorithm does not always perform as well on grass fields as expected, unless the grass is grazed short by animals. Grass that is allowed to grow long and is then cut for silage or hay has some similarity to wheat for losing SM retrieval capability at key growth stages. It is recommended that means of in-filling periods of poor performance with more reliable data is key to user acceptance of such a product. For example, two dimensional interpolation of soil moisture between values of soil moisture reported for neighbouring fields where performance is much higher, may be of benefit. Such interpolation techniques could include kriging, or inverse distance weighting. To enable such an interpolation approach to be implemented, a method needs to be found to independently assess the crop stage of development, and, in particular, when a field has bare soil in it. As a minimum this would also allow a confidence level to be communicated alongside soil moisture estimates.

The output of this study provides a much more detailed understanding of the performance levels of the change detection algorithm for the estimation of soil moisture over arable field from Sentinel-1 C-band SAR data. At the very least this allows users to better understand the limitations of the product, but it also paves the way to developing new methods for mitigating poor performance and developing a product that is, eventually, much more usable.

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4.A.2 Fincham

The footprint of the COSMOS-UK CRNS sensor at Fincham overlaps two fields, 161407 and 2303484, that could be observed by the phenocams, as shown in Fig. 4.32. These were both planted with winter wheat or winter oats and were subjected to the same management timetable, with there being no more than 1-2 days between activities, such as ploughing, between them. These fields appeared to be subject to traditional tillage practices, with the land being ploughed some time after harvesting, when the soil would have been bare for some weeks or months.



Figure 4.32: Fields surrounding the Fincham site, showing the 200 m footprint (red circle) of the COSMOS-UK CRNS sensor (black triangle). The surrounding fields are labeled by GID, with coloured fill defining the eroded field boundaries used for spatial averaging and the crops that were grown in 2018.

4.A.3 Loddington

Two fields at Loddington, covered by the footprint of the COSMOS-UK CRNS sensor, as shown in Fig. 4.33, were visible in the phenocam images. Field 1462873 was a field of grass. Field 1573704 was planted with winter wheat or winter oats and was under conservation tillage. It was not ploughed in the traditional way after harvesting, but machinery did pass over the field to loosen the soil and later to sow seed. These operations which exposed some bare soil, the earlier date has been taken as a tillage date.

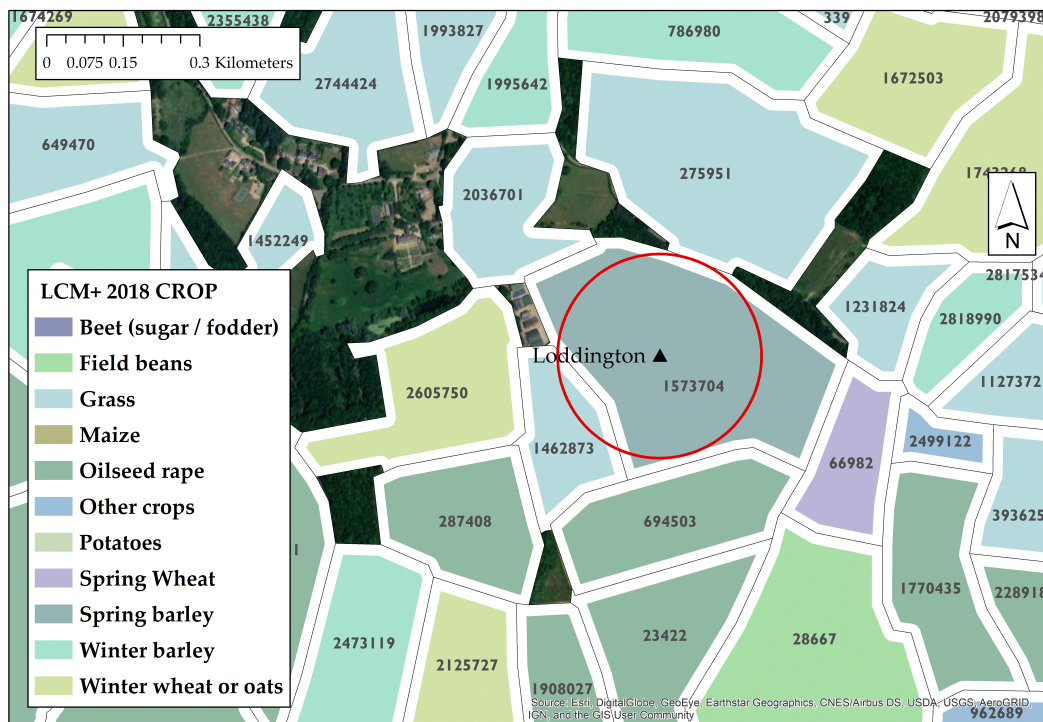


Figure 4.33: Fields surrounding the Loddington site, showing the 200 m footprint (red circle) of the COSMOS-UK CRNS sensor (black triangle). The surrounding fields are labeled by GID, with coloured fill defining the eroded field boundaries used for spatial averaging and the crops that were grown in 2018.

4.A.4 Spen Farm

Three fields at Spen Farm are covered by the footprint of the COSMOS-UK CRNS sensor, and could be monitored by phenocam, as shown in Fig. 4.34. Fields 150919 and 1278948 were being used to grow winter wheat or winter oats, whilst field 1359276 was growing potatoes. The latter were planted quite late in the season so there were more times during the year when this field was of mostly bare soil.

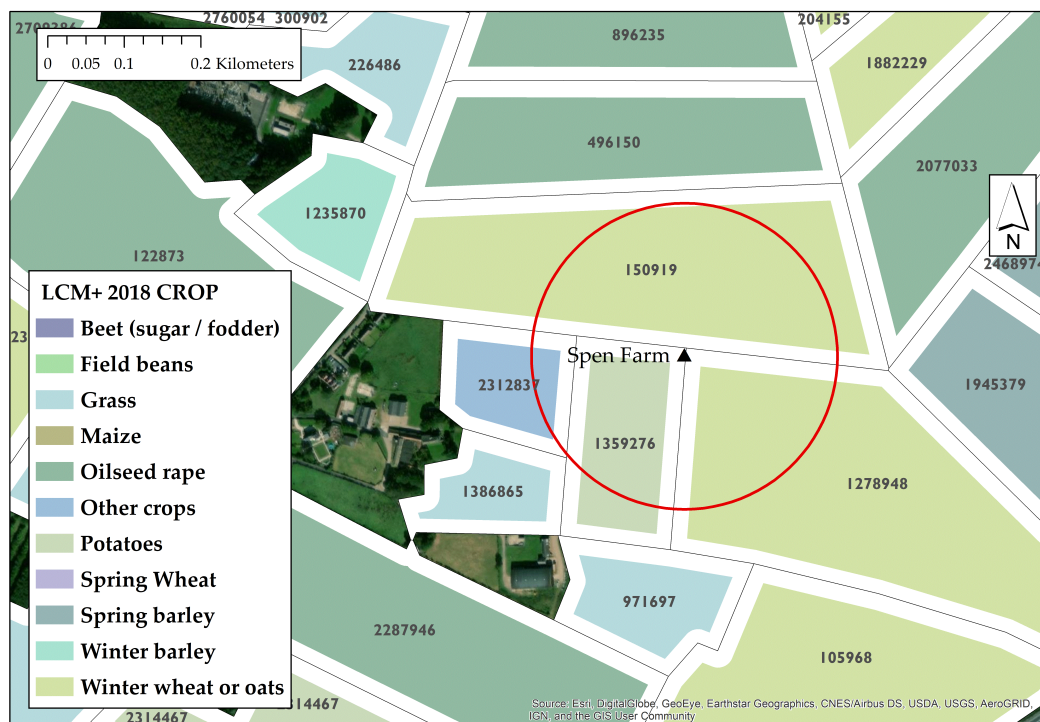


Figure 4.34: Fields surrounding the Spen Farm site, showing the 200 m footprint (red circle) of the COSMOS-UK CRNS sensor (black triangle). The surrounding fields are labeled by GID, with coloured fill defining the eroded field boundaries used for spatial averaging and the crops that were grown in 2018.

4.A.5 Writtle

Two fields at Writtle, 2637110 and 239399, intersect the footprint of the COSMOS-UK CRNS sensor, as shown in Fig. 4.35, and were visible in the phenocam images. Though normally an arable farm, in 2018 both fields were used for grazing by sheep and a crop of grass was grown and cut in early summer. There were no periods of bare soil, but extensive periods of short grass where the CD algorithm should also work well.

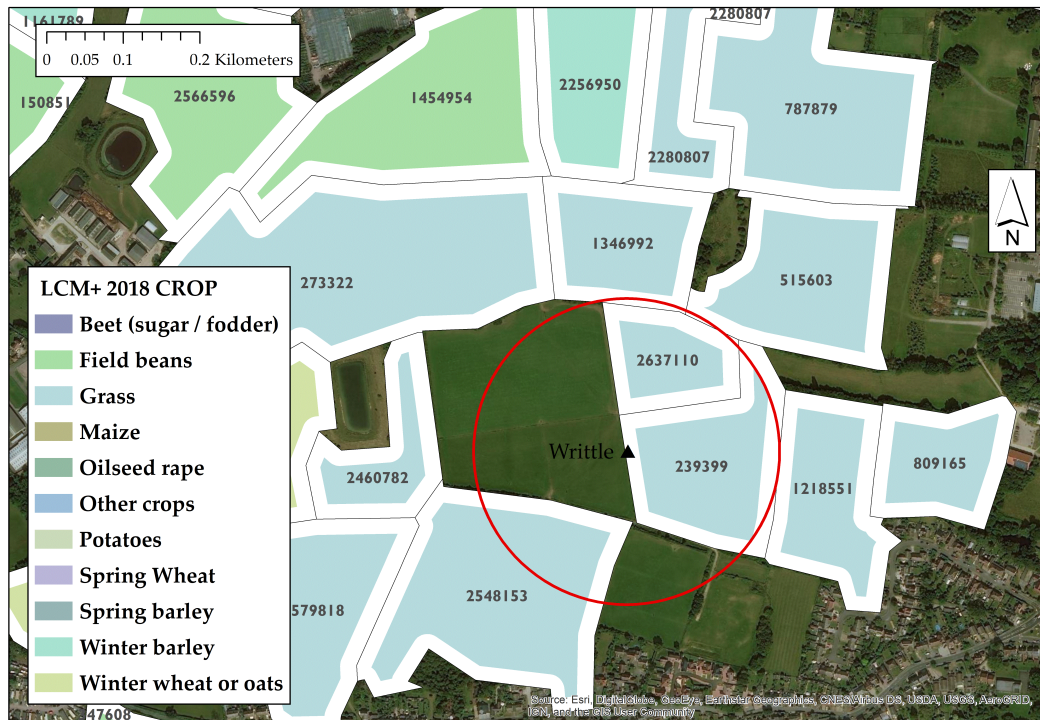


Figure 4.35: Fields surrounding the Writtle site, showing the 200 m footprint (red circle) of the COSMOS-UK CRNS sensor (black triangle). The surrounding fields are labeled by GID, with coloured fill defining the eroded field boundaries used for spatial averaging and the crops that were grown in 2018.

4.B SM performance for individual fields

This appendix presents, by crop type and crop stage, tables of performance metrics for S1 SAR derived surface soil moisture estimates for individual fields in 2018. They are calculated relative to the HYDRUS-1D simulation of soil moisture at 2 cm depth at the appropriate COSMOS-UK site location. The metrics are the Willmott index of agreement (d_r), the coefficient of determination (R^2), mean absolute difference (MAD), mean absolute percentage difference ($MAPD$), root mean squared difference ($RMSD$), bias (b), unbiased RMSD ($ubRMSD$), the p -value ($p < 5.0E - 2$ indicates statistical significance) and regression slope (S). The final column of each table is a subjective assessment of how capable the field-scale satellite SM product is in the retrieval of soil moisture at each crop stage. In these tables, the individual fields will be referred to by their "GID" number in the UKCEH Land Cover Plus:Crops data set.

Table 4.13: Performance metrics for winter wheat fields in 2018

Crop state	d_r	R^2 vol.%	MAD vol.%	$MAPD$ %	$RMSD$ vol.%	b vol.%	$ubRMSD$ vol.%	p	S	Capability
Field 161407 at Fincham										
All	0.14	0.18	9.76	44.90	12.28	-5.48	10.99	1.40E-11	0.75	MEDIUM
Dormant	-0.57	0.00	7.71	26.46	9.16	-7.68	4.99	8.92E-01	0.04	NONE
Growth	-0.47	0.25	19.42	93.74	21.19	-19.42	8.48	2.81E-04	-0.27	POOR
Ripening	-0.95	0.11	2.05	23.77	2.82	-0.25	2.81	3.43E-01	-15.63	NONE
Harvested	0.04	0.33	8.06	38.25	9.19	-8.06	4.42	2.62E-03	0.50	MEDIUM
Bare	0.40	0.70	6.62	33.88	7.35	6.49	3.45	2.64E-20	0.69	HIGH
Field 2303484 at Fincham										
ALL	0.15	0.16	9.70	43.58	11.99	-5.05	10.87	4.63E-10	0.67	MEDIUM
Dormant	-0.59	0.00	8.15	27.91	9.76	-8.14	5.38	7.36E-01	-0.10	NONE
Growth	-0.41	0.44	17.66	82.59	19.67	-17.66	8.66	1.74E-07	-0.33	POOR
Ripening	-0.92	0.03	1.28	14.81	1.77	0.16	1.76	6.29E-01	-5.11	NONE
Harvested	-0.06	0.08	8.95	42.02	9.94	-8.40	5.31	1.66E-01	0.20	NONE
Bare	0.35	0.68	7.12	36.27	7.88	7.01	3.60	4.79E-19	0.69	HIGH
Field 150919 at Spen Farm										
All	0.32	0.39	8.93	33.13	11.62	-8.31	8.12	8.26E-26	0.85	LOW
Dormant	-0.59	0.18	10.39	31.02	11.71	-10.39	5.40	3.15E-04	0.97	LOW
Growth	-0.60	0.22	19.12	84.38	20.44	-19.12	7.23	1.60E-03	-0.38	POOR
Ripening	0.47	0.50	2.32	14.73	2.80	0.00	2.80	1.62E-03	0.79	HIGH
Harvested	0.55	0.77	3.78	19.99	4.55	-3.78	2.53	1.25E-01	0.58	NONE
Bare Soil	0.58	0.49	4.79	16.18	6.20	-3.62	5.03	2.69E-14	0.66	HIGH
Field 127948 at Spen Farm										
ALL	0.30	0.40	9.17	33.86	11.77	-8.70	7.93	7.22E-27	0.85	MEDIUM
Dormant	-0.58	0.17	10.14	30.30	11.58	-10.14	5.59	4.45E-04	0.98	LOW
Growth	-0.60	0.14	19.19	85.09	20.41	-19.19	6.95	1.30E-02	-0.30	POOR
Ripening	0.47	0.47	2.32	14.73	2.78	-0.36	2.76	2.22E-03	0.73	HIGH
Harvested	0.58	0.75	3.51	18.07	4.39	-3.44	2.73	1.32E-01	0.52	NONE
Bare Soil	0.51	0.45	5.63	18.56	7.12	-4.79	5.27	7.70E-13	0.63	HIGH

Table 4.14: Performance metrics for oil-seed rape fields in 2018

Crop state	d_r	R^2 vol. %	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	b vol. %	$ubRMSD$ vol. %	p	S	Capability
Field 599120 at Elmsett										
All	0.40	0.19	8.41	23.90	9.80	-5.37	8.20	5.61E-12	0.38	LOW
Dormant	-0.63	0.02	9.98	22.93	10.78	-9.94	4.17	2.17E-01	0.22	NONE
Growth	0.10	0.39	7.82	26.77	9.47	3.79	8.68	2.67E-06	-0.43	NONE
Ripening	-0.92	0.94	7.31	35.48	7.90	-1.29	7.79	1.55E-05	22.38	NONE
Harvested	0.22	0.63	11.10	36.95	11.99	-11.10	4.53	4.57E-05	0.63	LOW
Bare Soil	0.52	0.30	4.06	13.62	4.96	-2.37	4.36	2.17E-05	0.37	MEDIUM
Field 445882 at Elmsett										
All	0.38	0.19	8.80	24.87	10.16	-6.02	8.18	2.70E-12	0.39	LOW
Dormant	-0.65	0.01	10.55	24.25	11.27	-10.52	4.04	2.94E-01	0.18	NONE
Growth	0.12	0.37	7.61	25.93	9.16	3.37	8.52	6.10E-06	-0.40	NONE
Ripening	-0.92	0.94	7.55	36.70	8.04	-2.23	7.72	1.44E-05	22.22	NONE
Harvested	0.15	0.64	12.03	39.99	12.85	-12.03	4.52	4.22E-05	0.60	LOW
Bare Soil	0.49	0.32	4.37	14.55	5.30	-3.12	4.28	7.98E-06	0.40	MEDIUM

Table 4.15: Performance metrics for potato fields in 2018.

Crop state	d_r	R^2 vol. %	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	b vol. %	$ubRMSD$ vol. %	p	S	Capability
Field 1359276 at Spen Farm										
All	0.46	0.02	7.05	30.77	8.51	-0.30	8.50	4.70E-02	0.09	NONE
Dormant	-0.37	0.58	8.49	26.16	8.87	-8.49	2.57	1.28E-16	0.82	MEDIUM
Potatoes Planted	0.27	0.06	3.04	15.76	4.02	2.75	2.93	2.59E-01	0.22	NONE
Growth	-0.23	0.15	10.93	65.35	11.92	10.90	4.82	2.24E-03	0.17	POOR
Harvested	0.20	0.28	4.02	14.85	5.34	4.02	3.51	6.46E-01	-0.25	NONE
Bare Soil	0.48	0.45	2.25	6.84	3.47	-1.05	3.31	4.63E-08	1.18	HIGH

Table 4.16: Performance metrics for grass fields in 2018.

Crop state	d_r	R^2 vol. %	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	b vol. %	$ubRMSD$ vol. %	p	S	Capability
Field 2578949 at Elmsett										
All	0.27	0.58	10.29	28.75	11.37	-9.99	5.43	2.05E-44	0.69	MEDIUM
Field 1462873 at Loddington										
All	0.71	0.62	6.02	16.64	7.68	2.66	7.20	5.31E-51	0.62	HIGH
Field 2637110 at Writtle										
All	0.52	0.12	11.99	74.28	14.21	4.94	13.32	5.21E-08	0.21	LOW
Dormant	-0.11	0.09	6.55	15.14	8.57	-3.39	7.87	2.12E-02	-0.47	NONE
Growth	-0.61	0.03	15.68	41.22	16.59	-12.87	10.47	3.12E-01	0.49	NONE
Grazed	0.31	0.55	14.10	115.30	15.97	13.70	8.21	1.70E-23	0.40	MEDIUM
Field 239399 at Writtle										
All	0.62	0.38	9.44	52.72	11.38	3.10	10.95	1.94E-25	0.46	MEDIUM
Dormant	-0.19	0.23	7.17	16.76	9.64	-1.45	9.53	8.03E-05	-0.92	NONE
Growth	-0.59	0.00	14.93	38.71	15.97	-10.43	12.09	8.46E-01	-0.10	NONE
Grazed	0.54	0.71	9.46	76.41	11.00	8.87	6.51	2.37E-35	0.60	HIGH

Table 4.17: Performance metrics for spring barley fields in 2018.

Crop state	d_r	R^2 vol. %	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	b vol. %	$ubRMSD$ vol. %	p	S	Capability
Field 1573704 at Loddington (conservation tillage)										
ALL	0.58	0.44	8.66	22.52	11.62	-0.62	11.60	4.89E-31	0.87	MEDIUM
Dormant	0.56	0.44	3.43	6.57	4.14	-0.49	4.11	8.75E-11	0.65	MEDIUM
Growth	-0.27	0.11	19.10	48.98	20.89	-19.10	8.46	2.94E-02	0.27	POOR
Ripening	0.25	0.58	3.97	15.25	5.24	0.78	5.18	1.56E-03	1.46	MEDIUM
Harvested	0.19	0.09	6.13	21.40	7.83	4.79	6.19	1.28E-01	0.37	NONE
Tilled	0.49	0.68	9.45	25.23	10.94	8.80	6.50	6.96E-19	0.82	HIGH

5 Field-scale soil moisture estimation with Sentinel-1 SAR for cropped arable land

This chapter, in paper format, describes an approach to retrieve a useful field-scale soil moisture estimate from Sentinel-1 C-band SAR at times when the vegetation in the field is growing so rapidly that the radar does not directly measure soil moisture as it cannot penetrate the canopy. The approach is a two-dimensional interpolation solution, which gives good results. This plugs a significant gap in the capability for remote sensing of soil moisture in the main growing season, for the benefit of farmers and agronomists.

Abstract

The change detection method of multi-temporal analysis is often used to estimate surface soil moisture from Sentinel-1 SAR data. The underlying assumptions - that vegetation cover and soil surface roughness vary significantly more slowly with time than soil moisture - are problematic in areas under crop cultivation. These are characterised by seasonal cycles of rapid crop growth, senescence, harvesting and tillage. The issue becomes more acute when data is processed at the field scale as there is no spatial averaging to mitigate these effects. Areas where the vegetation cover is persistently high, are known to exhibit poor sensitivity of SAR backscatter to soil moisture. More generally, the performance is related to the relative cover fractions of vegetation and bare soil. We propose a new method based on optical indices derived from Sentinel-2 combined with spectral unmixing to estimate these fractions as time series at field scale. Combined with knowledge of land use, confidence levels may be assigned to each field. The soil moisture may then be estimated by two dimensional interpolation using inverse distance squared weighting across a range of neighbouring fields within a local zone. During the peak growing season, the mean absolute error in the soil moisture estimate for wheat fields is significantly reduced, in one example from around 20% volumetric water content to less than 5%. This will benefit users of such products in agriculture, for example, in determining soil moisture deficit in the growing season, for crop modeling, decision support or trafficability assessment.

This paper is intended for publication in a peer-reviewed journal. It is due to be presented at the EGU General Assembly 19-30 April 2021 as "Improved soil moisture estimation with Sentinel-1 for arable land at the field scale", by John Beale, Toby Waine, Ronald Corstanje, Jonathan Evans

5.1 Introduction

SAR data from satellites, such as ESA's Sentinel-1, are being exploited to estimate surface soil moisture at scale, which has potential benefit to farmers, agronomists and horticulturalists who need to understand the level of soil moisture (SM) in their fields (Adeyemi et al., 2017; Molden and James, 2000; Earl, 1997). It has potential for areas such as the UK which suffer from regular cloud cover, making optical remote sensing impractical for regular SM monitoring. High spatial resolution, C-band, 5.4 GHz SAR (Torres et al., 2012) data is now freely available through the Copernicus Open Access Hub (ESA, 2019). The challenge is that SM is one of many factors contributing to SAR backscatter, including soil surface roughness and vegetation.

Change detection (CD) algorithms, exemplified by SMOSAR (Mattia et al., 2018) and the Copernicus SSM Product (Hornacek et al., 2012; Bauer-Marschallinger and Paulik, 2019; Bauer-Marschallinger et al., 2019), use temporal processing without need for extensive *a priori* information or model training. In assuming that soil moisture is the main cause of short term changes in SAR backscatter, CD performs less well over areas of arable cultivation, especially at field-scale (Benbrahim et al., 2020; Mattia et al., 2020; El Hajj et al., 2018a). These areas are characterised by short timescale variations in crop biomass and soil surface roughness caused by crop cycles and tillage operations. In Chapter 4, the errors in CD SM estimation were found to be up to 20 vol.% in volumetric water content (VWC) during the main growth period of the crops, but only between 4 and 10 vol.% when the soil was bare. Such unreliable performance is of limited benefit to agriculture, where a 5 vol.% accuracy is required (Chapter 1). To address this issue, the periods of low accuracy must first be identified at field-scale, by an automated, unsupervised and scalable method.

The crop canopy has its own backscatter signal, σ_{veg}^0 , and acts as an attenuating medium for both the microwave beam and backscatter from the soil (Bindlish and Barros, 2001), such that the received backscatter is approximately given by

$$\sigma^0 = \sigma_{veg}^0 + \tau^2 \sigma_{soil}^0 \quad (5.1)$$

where τ^2 is the vegetation transmission in two directions. Both τ^2 and σ_{veg}^0 are functions of the moisture in the canopy, its density and the amount of soil covered by the vegetation. The periods of low CD accuracy for SM estimation will correspond

to high values of σ_{veg}^0 and/or low values of τ^2 . Periods of high σ_{veg}^0 may be identified by the Normalised Difference Vegetation Index (NDVI) (Mattia et al., 2020; El Hajj et al., 2018a), but in Chapter 4 it was found a usable, if degraded, sensitivity to SM occurring after harvesting, when NDVI would also be low. In these situations both σ_{veg}^0 and τ^2 may be low due to a thick layer of crop residue being present. A three level performance classification is proposed based the relative fractional land cover of bare soil (BS), photosynthetically active vegetation (PV) and non-photosynthetically active vegetation (NPV).

To mitigate periods of low accuracy, crop rotation, typical of most arable systems of farming, offers an opportunity. Patchwork distributions of fields of different crops are commonly observed within relatively small areas. Levels of CD SM uncertainty will vary across an area on any given date, opening up the potential to interpolate values spatially, weighting higher confidence estimates more heavily.

The aim of this study was to demonstrate an improvement in the accuracy of SM estimation from Sentinel-1 SAR by correcting for the influence of crop cover and anthropogenic change and identify a route to scale this to UK national coverage. We propose a new method of applying the change detection algorithm at field-scale that is effective for arable crops at all times of year, and lay foundations for future enhancements or mitigation measures to improve the usefulness of soil moisture data for end users.

5.2 Materials and methods

The key feature of the proposed new method is to use spatial interpolation to improve the accuracy of field-scale satellite soil moisture retrieval when the performance of the change detection algorithm is poor, as dictated by the growth stage of the crops. Ordinary kriging has a reputation for giving good results in spatial interpolation and is based on weightings derived by prior observations of co-variances, usually by computing semi-variograms - in this case of soil moisture with distance. This would typically be base on the statistical analysis of high resolution rasterised data. However, the field-scale implementation of the CD algorithm produced one SM value per field parcel, distributed in an irregular pattern. This would generate insufficient data-points within the expected scale of the factors that effect soil moisture (soil texture, aspect and rainfall) to construct a usable semi-variogram, leading to large potential uncertainty. For this reason, the simpler method of inverse distance weighting was selected, as it could be applied

simply and effectively to sparse data that is not on a regular grid.

The method is summarised in the flow chart of Fig. 5.1. The boxes edged in black were pre-processing steps that were carried out once, to calculate eroded field boundaries, field centroid locations and the distances between all fields in the area of interest. This task would need to be repeated after an update in the field boundary information. The red-edged boxes identify the following steps that were carried out for each Sentinel-1 SAR image date. Starting on the left, with the Sentinel-1 backscatter data, the CD algorithm was used to estimate the relative soil moisture index (SMI) at field-scale within a 3 km processing region around each test site. This was scaled to volumetric SM by application the van Genuchten model parameters θ_S and θ_R as wet and dry references, following the recommendation of Chapter 3. These reference values had been calculated for each COSMOS-UK site as part of the HYDRUS1-D model fitting in Chapter 3, but, in general, could have been obtained from a soil hydraulics properties database, such as LANDIS Horizon (Cranfield University, 2021). On the right of the flow chart, Sentinel-2 data was used to classify every field into one of three categories by the expected level of accuracy of the CD SM estimate. This a method will be described, in detail, below. The confidence level and the field centroid separation distances were then used to calculate, for each field, an improved SM estimate by Inverse Distance and Confidence Weighting (IDCW).

For analysis, a subset of fields were selected to represent a diversity of crops for which to compare the relative performance of CD SM estimate with and without the IDCW spatial interpolation. The remainder of this section explores the proposed method in more detail, including all data sources used and the test sites used to assess the effectiveness of the proposed solution.

5.2.1 Study sites and time period

Five test sites were selected, as shown in the map of Fig. 5.2, where the soil hydraulic parameters and 2 cm soil moisture profiles for 2018 were already available from earlier work (Chapter 4, (Beale et al., 2021)). The sites are all subject to arable farming, and are part the COSMOS-UK network (Evans et al., 2016) of SM monitoring stations operated by the UK Centre for Ecology and Hydrology (UKCEH).

The choice of 3 km as the spatial extent of the IDCW interpolation was to limit the interpolation to a distance within which soil moisture is likely to be correlated.

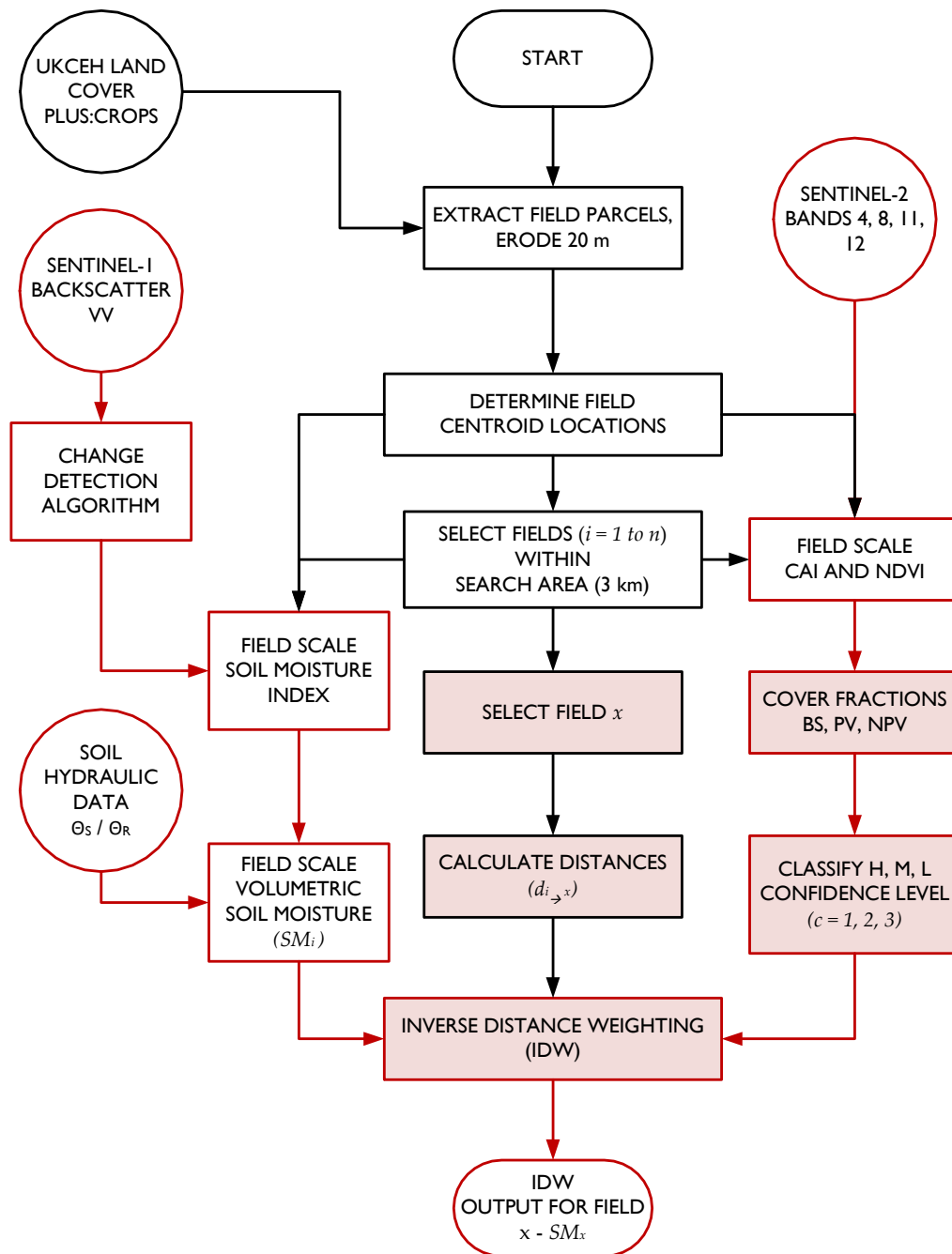


Figure 5.1: Flowchart of the implementation of Inverse Distance and Confidence Weighting (IDCW) spatial interpolation function to derive an more reliable estimate of soil moisture SM_x for field x through the change detection algorithm from Sentinel-1 data. The data sources are shown in the circles. The boxes edged in black are steps that need to performed just once per season, the red edged boxes are time series steps that must be performed at each S1 measurement date. The pink-shaded boxes are tasks performed in , all others used Google Earth Engine. n is the total number of fields i that contribute to the IDCW interpolation. Cover fraction abbreviations are: BS - Bare Soil, PV - photosynthetically active vegetation, NPV - non-photosynthetically active vegetation.

The limiting factors are soil texture, rainfall, and potential evapotranspiration. Topography would also be a factor in some areas, but the study sites all had low relief, which is typical of arable farming in England. Published semi-variograms characterising the spatial auto-correlation of soil texture indicated ranges that varied widely from approximately 100 m for a hilly area in Austria (Delbari et al., 2011) to over 13 km in the plains of Oklahoma (Dong and Ochsner, 2018). Other studies in various parts of the World (Paterson et al., 2018; Mondejar and Tongco, 2019; Delbari et al., 2019) report ranges between 600 m and 10 km. The pattern within these results is not unexpected; soil texture is correlated over longer distances in low relief areas typical of arable agriculture. Studies of the spatial auto-correlation of rainfall (Jewell and Gaussiat, 2015; Schuurmans et al., 2007; Ly et al., 2011) reported a large diversity of ranges from under 10 km to several hundreds of kilometers. Potential evapotranspiration is likely to have a similar or greater range as rainfall, as it is also a function of weather patterns, though no specific data could be found. For the sites in this study it was assumed that soil texture, rainfall and potential evapotranspiration would be correlated within 3 km.

The circular zone of 3 km radius from the COSMOS-UK station included the centroids of over 100 fields at each test site, as shown in Table 5.1). All the main arable crop types grown in the UK were represented. For purposes of selection and interpolation, the field locations were described by their centroid co-ordinates. Fields whose centroids were close to 3 km from the COSMOS-UK site extended beyond this range, so an outer limit of 5 km radius was set for the processing of

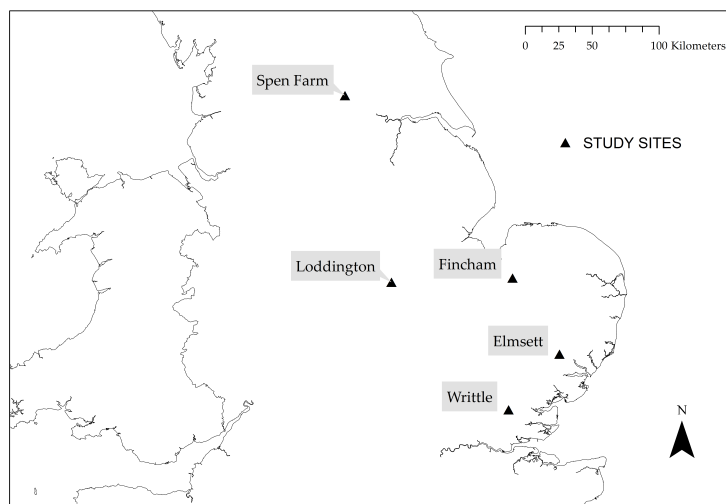


Figure 5.2: Locations of the sites selected for this study

Sentinel-1 and Sentinel-2 data.

Between 8 and 10 fields were identified at each test site to test the benefit of IDCW for a diversity of crops. They were chosen for proximity to the COSMOS-UK location so that the soil hydraulic parameters and 2 cm soil moisture profiles from earlier work (Chapter 4, (Beale et al., 2021)) would be valid. Details of the crops grown in these fields are listed in Table 5.1. Maps showing their locations and some of the fields included in the IDCW are provided in Appendix 5.A.

The calendar year of 2018 was selected as the period of the study because, in that year, the UK experienced a very cold and wet spring followed by a prolonged heatwave and drought. This meant that the soil moisture would vary more widely between the historically-observed wettest and driest conditions. For example, the range of SM at Writtle was from 9 vol.% to 48 vol.%, a large change of 39 vol.% over the year.

Table 5.1: Crop details within the 3 km interpolation zone at each of the sites selected for this study. n is the total number of fields used for IDCW, x is the number of test case fields. Data is derived from the UKCEH land Cover Plus:crops data-set, which does not separately identify grass that is permanently grazed from that that is allowed to grow to be cut as a crop. The latter fields at Writtle were identified visually from phenocam images, at Fincham and Spen Farm they were identified by the time profile of the cover fraction of photosynthetically active vegetation (PV).

Site name	Elmsett		Fincham		Loddington		Spen Farm		Writtle		Total	
Crop	n	x	n	x	n	x	n	x	n	x	n	x
Oil-seed rape	11	2	9	1	3	1	13	1	3	0	39	5
Winter wheat	34	2	27	2	10	2	25	2	41	2	137	10
Spring wheat	13	0	2	1	2	1	8	0	2	1	27	3
Winter barley	8	0	6	0	14	1	7	1	9	1	44	3
Spring barley	4	1	13	1	3	1	12	1	2	0	34	4
Field Beans	4	0	3	0	65	1	5	0	11	2	88	3
Potatoes	0	0	1	1	0	0	5	1	0	0	6	2
Maize	0	0	8	2	21	0	1	0	0	0	30	2
Beet, Sugar/Feed	8	1	12	1	8	0	2	0	0	0	30	2
Cut/Ley grass	-	0	-	1	-	0	-	2	-	3	-	6
Permanently grazed grass	23	2	24	0	6	2	31	1	50	0	134	5
Other	7	0	6	0	0	0	11	0	1	0	25	0
Total	112	8	111	10	132	9	120	9	119	9	594	45

5.2.2 Data

Field scale SAR-derived soil moisture

For the 5 km processing zone at each test site, all available C-band Sentinel-1 (S1) (Torres et al., 2012) Ground Range Detected (GRD Level 1 Interferometric Wide Swath (IW)) were obtained for 2018. The VV backscatter images were processed at sensor resolution using a Change Detection (CD) algorithm (Bauer-Marschallinger

and Paulik, 2019; Bauer-Marschallinger et al., 2019) implemented on the Google Earth Engine (GEE) platform (Gorelick et al., 2017). The resulting relative SM (soil moisture index) was then scaled to volumetric SM by application the van Genuchten model parameters θ_s and θ_R as wet and dry references, following the recommendation of Chapter 3. These reference values had been calculated for each COSMOS-UK site as part of the HYDRUS1-D model fitting in Chapter 3, but, in general, could have been obtained from a soil hydraulics properties database, such as LANDIS Horizon (Cranfield University, 2021). The rasterised data of estimated surface soil moisture was aggregated to eroded field parcel boundaries to obtain a time series of estimated soil moisture for each field in the 3 km region of interest at each site. Smoothing was applied using a Savitzky-Golay filter of the third order with a window of 7 observations, to reduce the orbit-related and random noise on the data. This method was described in detail in Chapter 4.

Field boundaries and crop information

The UKCEH Land Cover Plus:Crops 2018 (Morton et al., 2020) (LCPC) data-set was used to define field boundaries surrounding the study sites. This data included crop information assessed retrospectively for 2018. The shape-file data was clipped in spatial extent to include only fields within 5 km of the COSMOS-UK station. The field boundaries were eroded by 20 metres to ensure that field margins, hedges and buildings would be excluded, as far as possible, from the SM estimates. The centroid of each field was calculated and those fields whose centroids were within the 3 km region of interest were retained for analysis.

Modelled soil moisture at 2 cm depth

The prime SM sensor at each site is a Cosmic Ray Neutron Sensor (CRNS) (Andreasen et al., 2017) with a measurement footprint of approximately 200 metres in diameter (Köhli et al., 2015). The average sensitivity depth of 10 cm (Beale et al., 2021) does not match the SAR penetration depth of around 2 cm. By the method developed in Chapter 3 (Beale et al., 2021) the HYDRUS-1D model was fitted to CRNS data at each of the test sites and used to generate a 2 cm soil moisture time series for the purpose of validation of the interpolated soil moisture. On-site measurements of potential evapotranspiration and rainfall, and estimates of Leaf Area Index from MODIS (MCD15A3H V6 level 4) (Myneni et al., 2015) were also used as inputs to the HYDRUS-1D model.

5.2.3 Field-scale confidence level classification

The level of confidence in the performance of the CD algorithm (based on expected uncertainty) is important to understand whether the SM estimate is of value to the end user. It was also to be used as a weighting factor in the IDCW spatial interpolation. The automated process of classifying each field by confidence on each measurement date is represented by the three boxes on the right of Fig. 5.1. These will be described below.

Collecting field-scale vegetation indices

Vegetation spectral indices, derived from Sentinel-2 data, were used to estimate the cover fractions of PV, NPV and BS. Following the recommendation of Daughtry et al. (Daughtry et al., 2005), a combination of Normalised Difference Vegetation Index (NDVI) and Cellulose Absorption Index (CAI) (Nagler et al., 2003) was used. NDVI was calculated from Sentinel-2 bands B4 (red) and band B8 (near-infrared, NIR) in Google Earth Engine (GEE) using built-in functions according to Eqn. 5.2;

$$NDVI = \frac{(NIR - red)}{(NIR + red)} = \frac{(B8 - B4)}{(B8 + B4)} \quad (5.2)$$

CAI could not be obtained from Sentinel-2 data, it being a narrow band, hyperspectral index originally calculated from three SWIR bands of the AVIRIS instrument (Nagler et al., 2003). This is shown in Eqn. 5.3 where $R_{2.0}$, $R_{2.1}$, and $R_{2.2}$ are the AVIRIS reflectance bands at $2.00 - 2.05 \mu m$, $2.08 - 2.13 \mu m$, and $2.19 - 2.24 \mu m$, respectively:

$$CAI = 0.5(R_{2.0} + R_{2.2}) - R_{2.1} \quad (5.3)$$

A surrogate of CAI (Guerschman et al., 2009) proposed for calculation with MODIS spectral bands was recently extended to Sentinel-2 spectral bands (Solano-Correa et al., 2019) as defined by Eqn. 5.4.

$$CAI^* = \frac{B12}{B11} \quad (5.4)$$

Sentinel-2 Level 2 MSI instrument data was obtained for every acquisition date in 2018. The images were filtered to select only those that, according to the accompanying metadata, contained fewer than 25% cloudy pixels to reduce

the potential impact of cloud on the calculation of the indices. At each pixel, the value of *NDVI* and *CAI** were calculated, then averaged within each of the field boundaries, to produce a field-scale *NDVI* and *CAI* time series. The time series data was noisy due to some cloud-affected pixels remaining after the initial filtering. The data was smoothed using a Savitzky-Golay filter (Savitzky and Golay, 1964) of 3rd order with a window size of 7. The *NDVI* and *CAI* time series were then aligned to Sentinel-1 image acquisition dates by linear interpolation.

Estimating the fractions of BS, NPV and PV

When *CAI* is plotted against *NDVI* for a large number of observations, the points are distributed within triangular envelope (Fig. 5.3). The vertices of the triangle represent 100% cover of BS, NPV and PV. By analogy to multispectral spectral analysis, the values of *NDVI* and *CAI* can be considered as the intensity of spectral lines, and the triangle vertices as class end-members. For any measured combination of *NDVI* and *CAI*, the values of PV, NPV and BS may be estimated by a spectral unmixing technique. The principle of the triangular space method (Yue and Tian, 2020), is illustrated in Fig. 5.3.

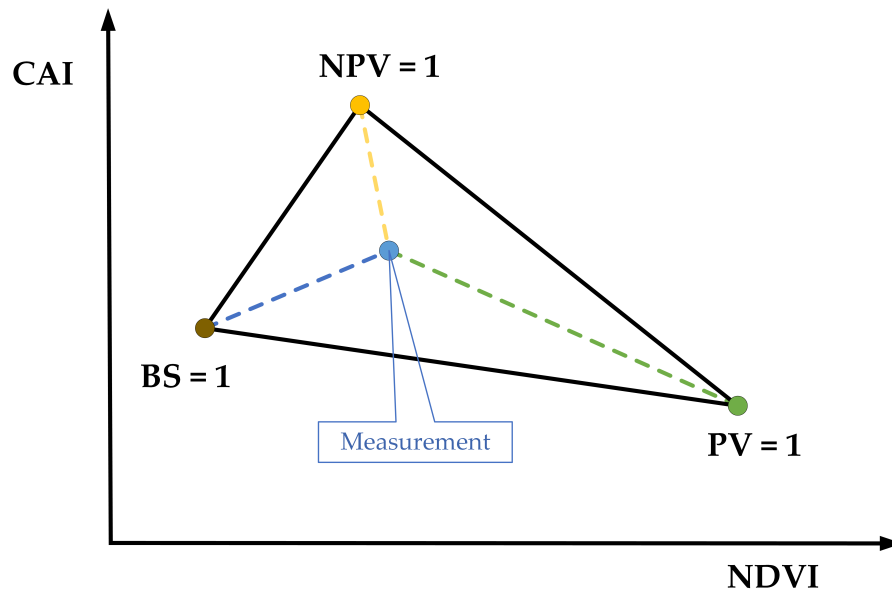


Figure 5.3: Triangle Space Method for estimating BS, PV and NPV from measurements of *NDVI* and *CAI*, adapted from Yue and Tian (2020).

End-member values of *NDVI* and *CAI* were derived empirically for the whole of 2018 at each of the five test sites. The process involved producing scatter-plots of *CAI* versus *NDVI* including measurements from every field in the 3 km search

area. For each site, a triangle was drawn on the plot, manually, to enclose the vast majority of points. A few outliers were tolerated due to noise in the data. The intersections of the lines defined the spectral end-members for 100% BS, 100% PV and 100% NPV. Little variability was found in their values between adjacent fields within a local area, but there were differences between sites, which may be due to differences in soil spectral properties. The triangle plots for the five sites are shown in Fig. 5.4 and the spectral end-members are listed in Table 5.2.

Table 5.2: End-members in terms of NDVI and CAI for cover fractions of Bare Soil (BS), non-photosynthetically active vegetation (NPV) and photosynthetically active vegetation (PV).

Site	BS		NPV		PV	
	NDVI	CAI	NDVI	CAI	NDVI	CAI
Fincham	0.03	0.60	0.11	0.92	0.93	0.35
Elmsett	0.16	0.57	0.02	0.92	0.97	0.36
Loddington	0.05	0.62	0.10	0.81	1.00	0.32
Spen Farm	0.00	0.58	0.00	1.00	0.90	0.37
Writtle	0.00	0.59	0.12	0.91	1.00	0.35

The processing up to the point of collecting vegetation indices had been accomplished in Google Earth Engine. However, this part of the process, and all later stages of analysis were carried out in  (R Core Team, 2019) to take advantage of existing packages. These included `readxl` (Wickham and Bryan, 2019), `dplyr` (Wickham et al., 2020) and `raster` (Hijmans, 2020) for data manipulation and the `mesma` function of the `RSToolbox` package (Leutner et al., 2019) for spectral unmixing. The latter outputted relative values of cover fractions, which were normalised to ensure that $BS + NPV + PV = 1$.

Classification scheme

The final stage was to classify each field on each Sentinel-2 measurement date into one of three levels confidence, c , in the CD SM retrieval according to the scheme shown in Table 5.3.

5.2.4 Spatial interpolation algorithm

The proposed inverse distance and confidence (IDCW) method of spatial interpolation algorithm is a natural extension of inverse distance weighting (Shepard, 1968).

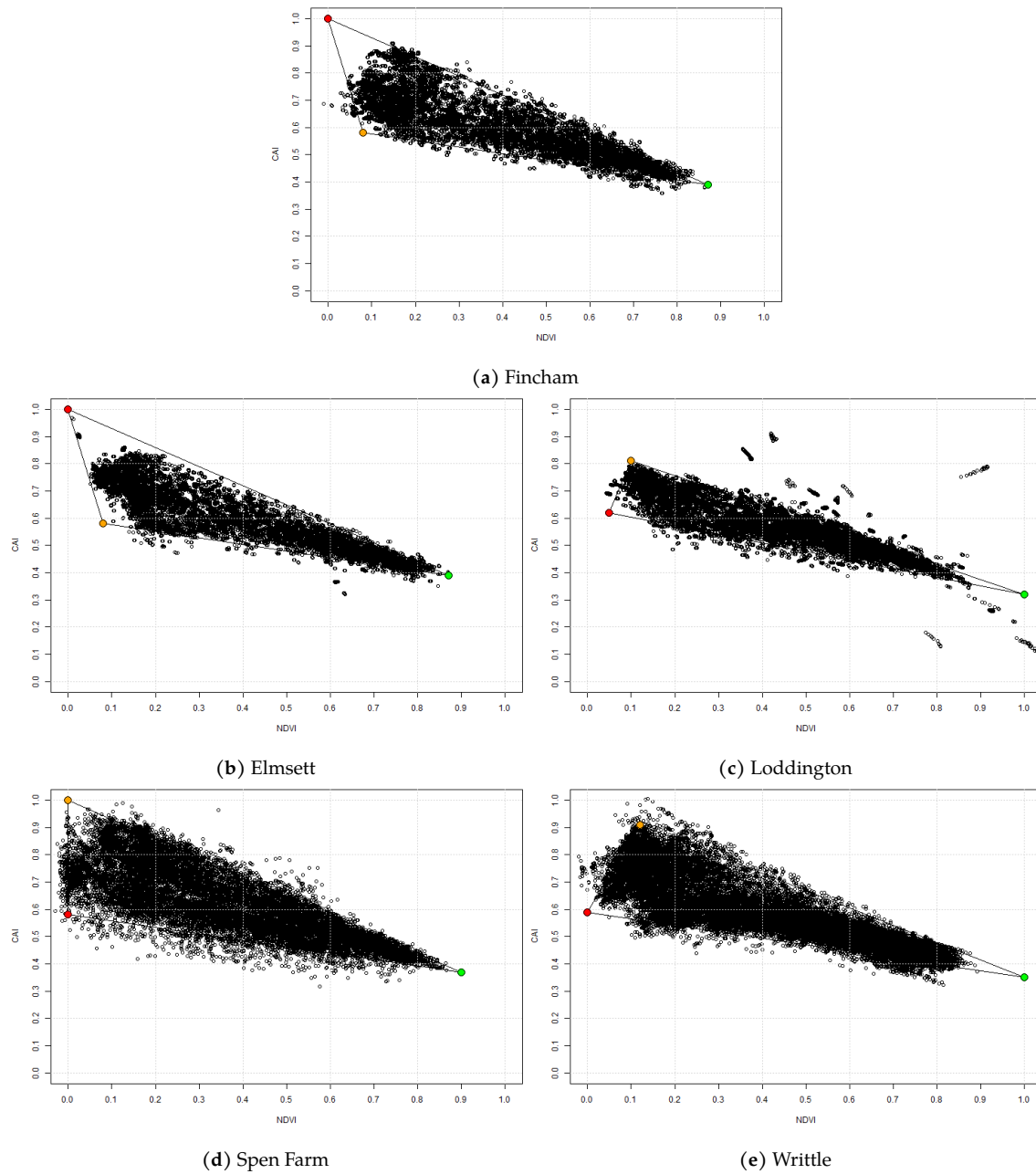


Figure 5.4: Scatter plots of CAI* vs. NDVI for every field in 3 km search area for every valid Sentinel-2 measurement date. Showing the land cover fraction triangles and spectral end-members estimated for 100% BS, PV and NPV.

Table 5.3: Three level classification scheme for expected confidence in the CD SAR soil moisture estimate, expressed as cover fractions of Bare Soil (BS), non-photosynthetically active vegetation (NPV) and photosynthetically active vegetation (PV). The final column shows how the conditions are combined.

Class, c	Confidence Level	BS	NPV	PV	Logic
1	HIGH	> 0.6	< 0.2	< 0.3	AND
2	MEDIUM	> 0.4	< 0.2	< 0.5	AND
3	LOW	≤ 0.4	≥ 0.2	≥ 0.5	OR

This was selected for ease of implementation and for ease of inclusion of additional weighting terms related to the degree of confidence in the satellite-derived soil moisture estimate. The proposed calculation for IDCW is given by Eqn. 5.5:

$$SM_x = \frac{\sum_{i=1}^n \frac{SM_i}{|d_{i \rightarrow x}|^p * c_i^q}}{\sum_{i=1}^n \frac{1}{|d_{i \rightarrow x}|^p * c_i^q}} \quad (5.5)$$

where SM_x is the IDCW estimate of soil moisture for the field x being analysed, SM_i is the satellite estimate of soil moisture at a neighbouring field i (see section 5.2.2), $d_{i \rightarrow x}$ is the great circle distance separating their centroids (in metres) and c_i is the confidence level for the field, i (see section 5.2.3). $p = 2$ is a factor that ensures that fields close to x are weighted significantly higher, to compensate for the number of fields available for IDCW increasing with range. For two-dimensional interpolation the minimum value of p is 2, as used in this study. In areas where SM correlation over a distance might be low, such as in a high relief area, the value of p could be increased. Parameter q may be used to increase the relative impact of the confidence level on the weighting. This was also set to 2, but finding an optimum value could be explored in future work.

Figure 5.5 illustrates the process on 1st July 2018 for the Fincham study site. The fields used to test the IDCW process are edged in black, with one example labelled x . Another is labelled i , being one of the fields being used for IDCW interpolation. The distance between the field centroids is shown by the black double-ended arrow, $d_{i \rightarrow x}$, as used in Eqn. 5.5. The figure also shows the confidence levels on that date, c , by the colour of the round symbols at the field centroid locations.

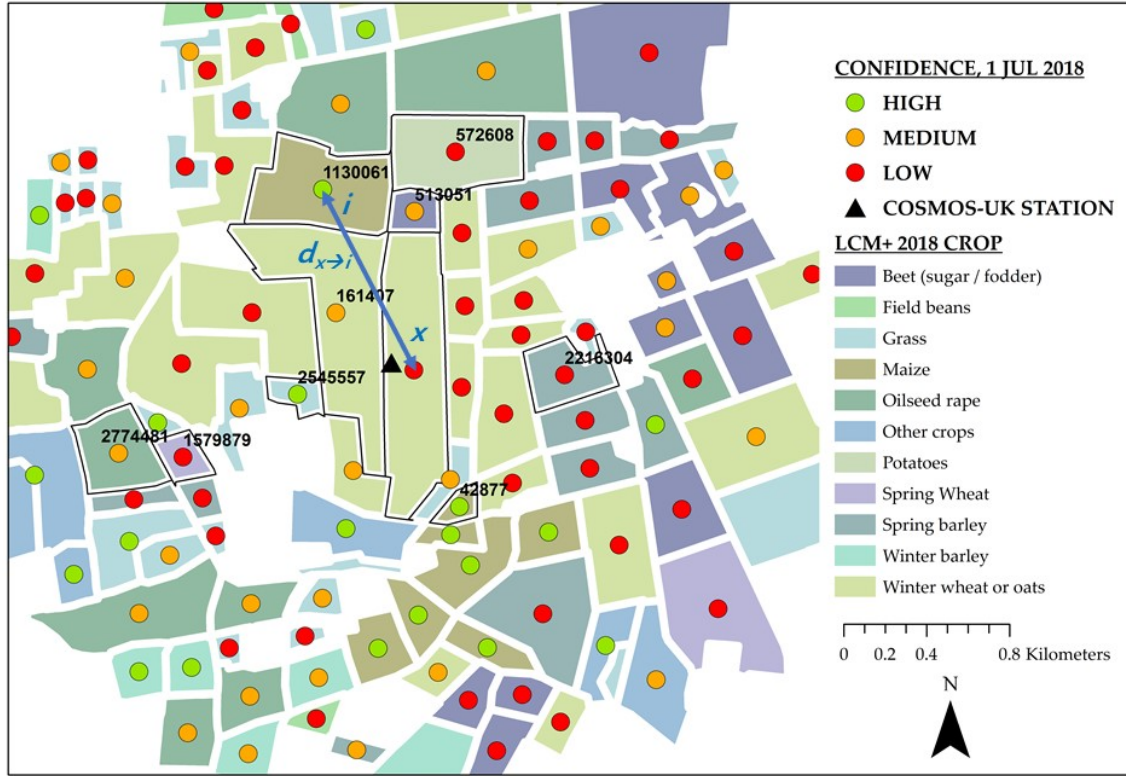


Figure 5.5: Illustration of the eroded field boundaries with the associated crops and CD soil moisture retrieval confidence levels. Also showing the locations of the field centroids used for distance calculations in the spatial interpolation of soil moisture by IDCW. The confidence levels shown are as assessed by land cover fractions on 1st July 2018.

5.2.5 Method of performance assessment

The performance was compared of the field-scale SM estimates before and after IDCW at each of the five test sites. These soil moisture estimates, E , were analysed with respect to reference soil moisture data, R , which were the 2 cm soil moisture predictions derived from them by the HYDRUS-1D Model. Quantitative comparisons were made through scatter plots and a number of statistical measures commonly used for the assessment of retrieved soil moisture, similar to the approach of [van der Velde et al. \(2015\)](#), [Eweys et al. \(2017\)](#) and [El Hajj et al. \(2018b\)](#). These comprised the coefficient of determination, R^2 (Eqn. 5.6), and Mean Absolute Difference (MAD) (Eqn. 5.7), Mean Percentage Difference $MAPD$ (Eqn. 5.8), Root Mean Squared Difference $RMSD$ (Eqn. 5.9), bias, b (Eqn. 5.10) and unbiased $RMSD$, $ubRMSD$ (Eqn. 5.11). An improvement in performance as a result of IDCW would result in an increase in the coefficient of determination, R^2 (Eqn. 5.6), and/or a decrease in mean absolute error, MAD (Eqn. 5.7). Qualitative comparisons of SM estimates before and after IDCW were made by plotting time

series of the SM estimates against the 2 cm soil moisture simulation, at each site. In some analyses the slope of the best-fit linear trend line through the scatter plot was used as measure of sensitivity of the algorithm to soil moisture. The ideal sensitivity value is represented by a slope of 1. To test for statistical significance the p -value at 95% confidence intervals was calculated using the two-tailed Student's t -distribution, with the value of t calculated by dividing the regression slope by its standard error.

$$R^2 = \frac{\sum_{i=1}^n (E_i - \bar{E}_i)^2}{\sum_{i=1}^n (R_i - \bar{R}_i)^2} \quad (5.6)$$

$$MAD = \frac{\sum_{i=1}^n |E_i - R_i|}{n} \quad (5.7)$$

$$MAPD = \frac{100}{n} * \sum_{i=1}^n \frac{|E_i - R_i|}{R_i} \quad (5.8)$$

$$RMSD = \sqrt{\frac{\sum_{i=1}^n (E_i - R_i)^2}{n}} \quad (5.9)$$

$$b = \frac{\sum_{i=1}^n (E_i - R_i)}{n} \quad (5.10)$$

$$ubRMSD = \sqrt{RMSD^2 - b^2} \quad (5.11)$$

5.3 Results

5.3.1 Unsupervised classification of fields by confidence in the SAR SM estimate

Using the example of one of the winter wheat fields at Fincham, Figure. 5.6 presents time series plots of the results of the classification process described in Section 5.2.3 (dotted line) and its intermediate estimations of cover fractions of bare soil (BS),

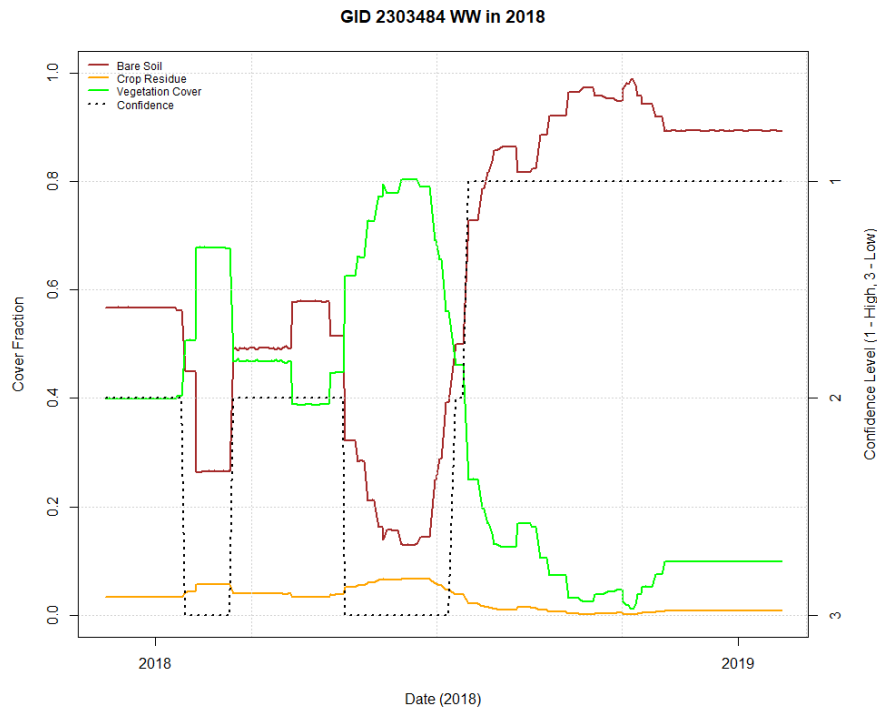


Figure 5.6: Cover fraction and confidence level time series for winter wheat field (GID: 2303484) at Fincham in 2018.

non-photosynthetically active vegetation (NPV) and photosynthetically active vegetation (PV). To test the validity of the classification, the dates on which the confidence level changed were compared to the dates of crop and field activities that had been determined (as reported in Chapter 4 by visual examination of daily COSMOS-UK site camera (phenocam) images).

Table 5.4 shows that the classification process has correctly identified the dates of several events to within a few days accuracy, even including the onset of cold weather accompanied by snow and ice in March 2018. The harvesting of the crop is anticipated perhaps too early, accompanied by a rapid change from low to high confidence. The early date may be a result of extremely dry conditions immediately before harvest, and the move to high confidence suggests that the harvesting process revealed more bare soil than would normally be expected. Similar agreement was found at the other locations. It was concluded that the classification process was working well enough within the limitations of the temporal resolution of cloud-free imagery from the Sentinel-2 satellite.

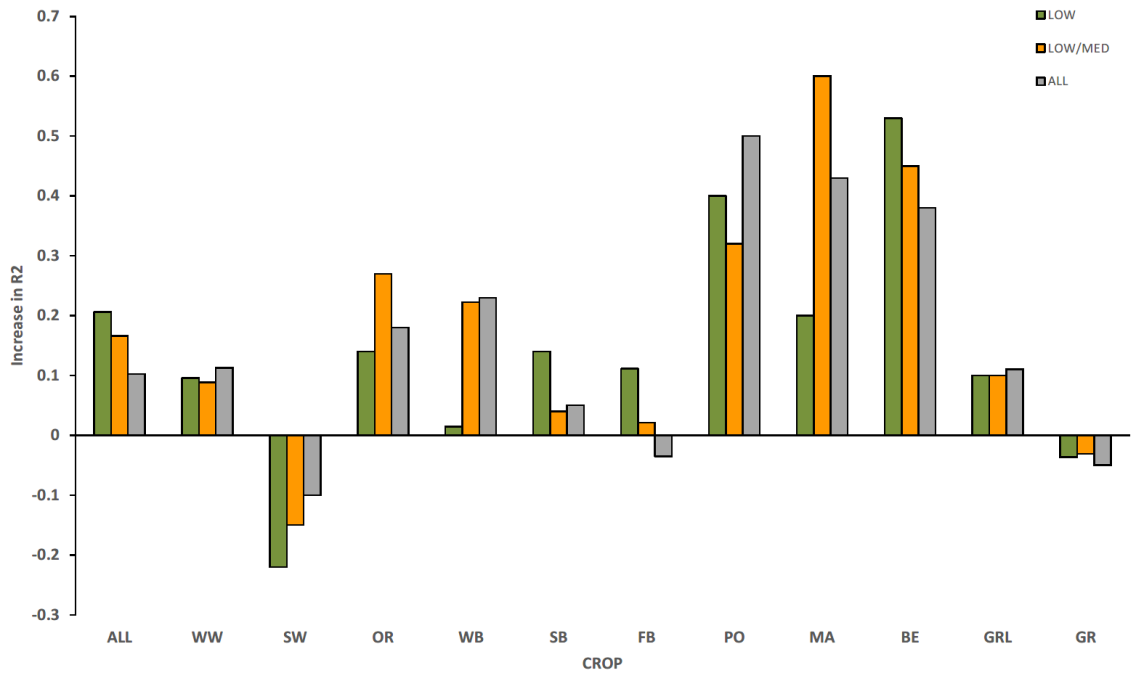
5.3.2 Benefits of IDCW in periods of low confidence

The analysis initially combined the results for all 45 fields in this study, then combined fields of the same crop type. The grass fields were split into two groups after different behaviours were observed, confirmed by ground observations of field activity. In some fields the grass was allowed to grow long in the spring and then cut for hay or silage, which was designated "cut grass" which includes ley grass. In other grass fields there was regular grazing which kept the grass relatively short all year. The analysis was further sub-divided into time periods defined by the confidence level of the test fields. These are fully listed in Appendix 5.B, but are presented here grouped into three periods; low confidence only, low and medium confidence and low, medium and high confidence (the whole year). To better highlight the differences between crops, changes in R^2 , MAD , bias (b) and $ubRMSD$ after use of IDCW are shown as bar charts in Fig. 5.7. The study aimed to demonstrate beneficial impacts for IDCW at least in the low confidence period. It can be seen that the R^2 value increases for all crops and periods except for spring wheat and permanently grazed grass. The measurements of error, MAD and $ubRMSD$ show similar improvements with the same exceptions. Bias shows a mixed picture, with an overall improvement, but a number of crops where additional bias is introduced (spring wheat, oil-seed rape, beet and grass). Success against these criteria is summarised in Table 5.5.

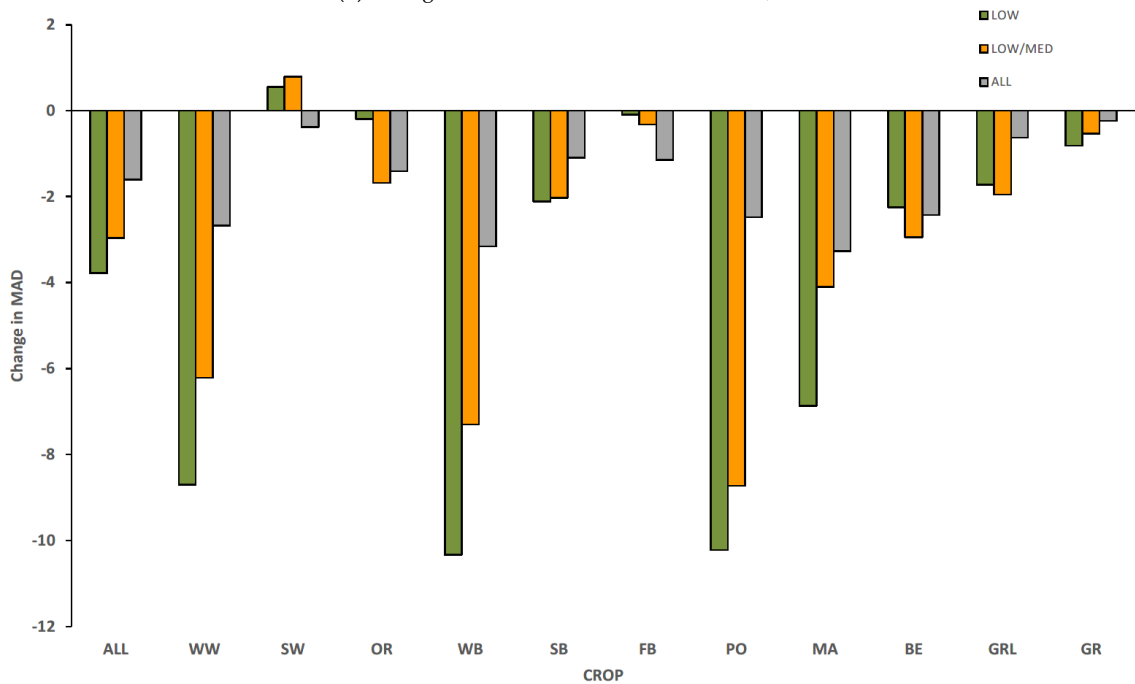
Where the IDCW process was of most benefit was during the peak of the crop

Table 5.4: Comparing dates of crop and tillage events as observed in the COSMOS-UK phenocams with dates of transition between confidence levels calculated by the unsupervised classification process

Phenocam Observations		Classification Algorithm	
Date	Activity	Date	Confidence Level Change
1-Jan-18	Dormant winter conditions	1-Jan-18	MEDIUM
21-Jan-18	Snow Events start	23-Jan-18	MEDIUM → LOW
		17-Feb-18	LOW → MEDIUM
18-Apr-18	Rapid growth starts	30-Apr-18	MEDIUM → LOW
10-Jul-18	Ripening	8-Jul-18	LOW → MEDIUM
		16-Jul-18	MEDIUM → HIGH
27-Jul-18	Harvesting		
6-Sep-18	Ploughing		



(a) Change in the coefficient of determination, R^2



(b) Change in the mean absolute difference, MAD , in volumetric water content (vol.%)

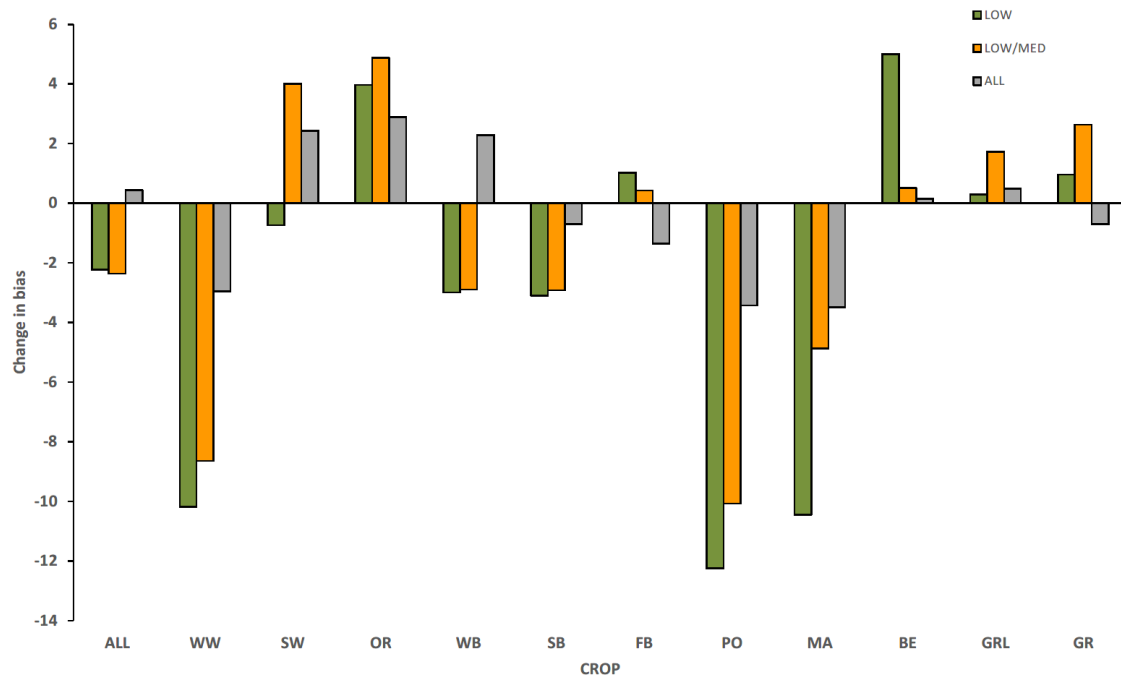
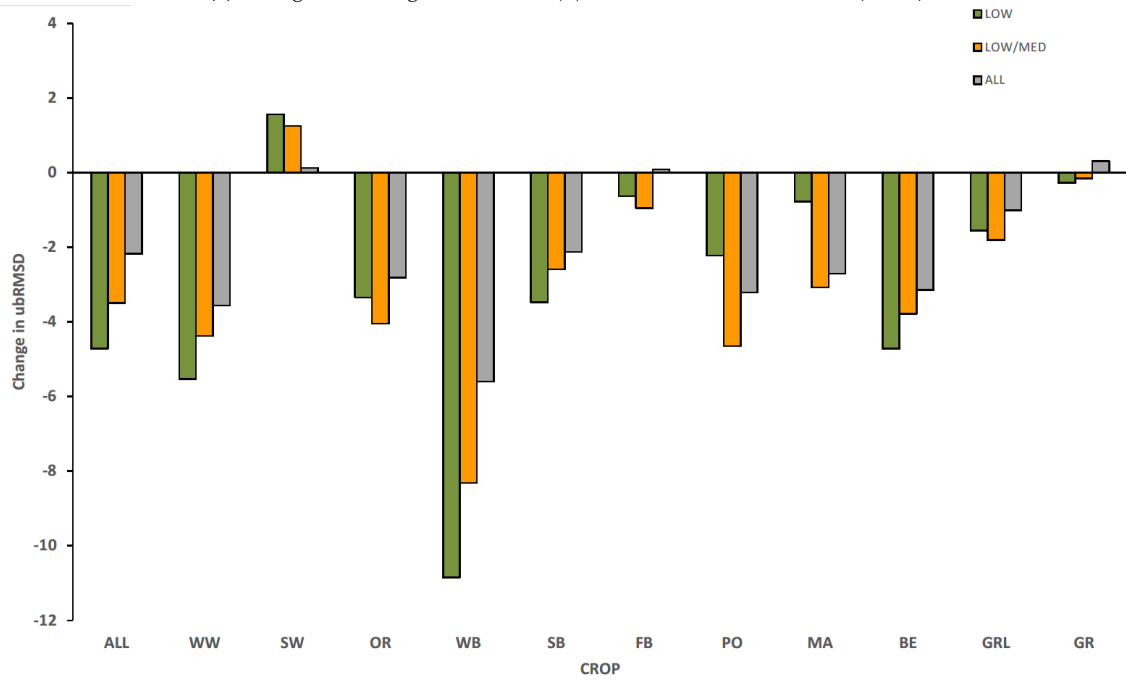
(c) Change in the magnitude of bias, $|b|$, in volumetric water content (vol.%)(d) Change in the unbiased RMSD, $ubRMSD$, in volumetric water content (vol.%)

Figure 5.7: Impact of IDCW on performance of SAR-derived SM in 2018 broken down by crop type. The crop codes are: ALL - all crops, WW - winter wheat, SW - Spring wheat, OR - oil-seed rape, WB - winter barley, SB -spring barley, FB - field beans, PO - potatoes, BE - beet, GRL - cut/ley grass and GR - grass (permanently grazed). R^2 and MAE were calculated over the low confidence period (green bars), over the low plus medium confidence periods (yellow bars), and over the whole year (grey bars).

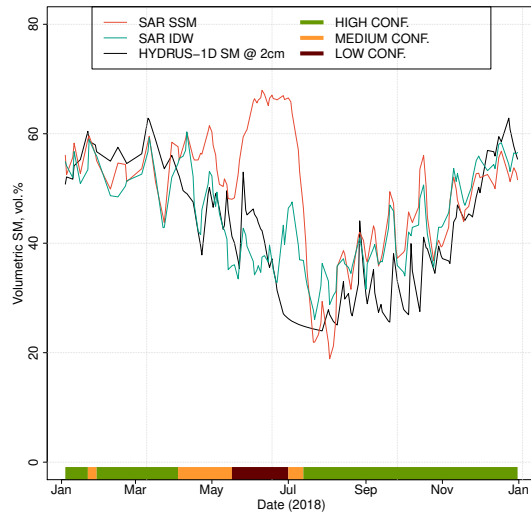
Table 5.5: Summary of findings, by crop type, of the benefits of Inverse Distance and Confidence Weighting (IDCW) to the accuracy of SAR-derived surface soil moisture estimates by the change detection algorithm at field scale.

Crop	Period of confidence level:			Headline
	All Year	Low	Low/Medium	
All	▲	▲	▲	
Oil-Seed Rape	▲	□	▲	MAE down from 7.42 vol.% to 6.01 vol.% over the whole year
Winter Wheat	▲	▲▲	▲▲	For LOW confidence MAE down from 16.1 vol.% to 7.39 vol.%
Spring Wheat	□	▽	▽	Reduction in R^2
Winter Barley	▲	▲▲	▲▲	MAE down from 20.5 vol.% to 10 vol.% in low conf.
Spring Barley	▲	▲	▲	R^2 up from 0.39 to 0.53 in low conf.
Field Beans	□	□	□	No benefit
Potatoes	▲▲	▲▲	▲▲	MAE down from 15 vol.% to 4.7 vol.% in low conf.
Maize	▲▲	▲▲	▲▲	MAE down from 11.5 vol.% to 4.5 vol.% in low conf.
Beet	▲	▲	▲▲	R^2 up from 0.09 to 0.62 in low conf.
Cut/Ley Grass	□	▲	▲	MAE down from 10 vol.% to 8 vol.% in low conf.
Permanently Grazed Grass	□	□	□	No benefit

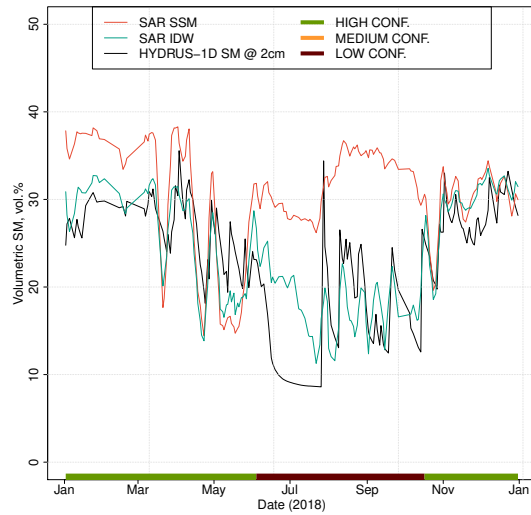
▲▲ = Large benefit, ▲ = Small benefit, □ = No benefit, ▽ = Small disbenefit.

growing season (see Fig. 5.8). The non-IDCW SM estimate had deviated from the reference SM in the period, the onset and duration of which varied by crop. The direction of the deviation also differed, with three types of behaviour seen. The SAR SM estimate rose in absolute terms (despite falling soil moisture) for oil-seed rape (Fig. 5.8a), potatoes (Fig. 5.8b), maize and beet. For cereals, such as winter wheat (Fig. 5.8c), winter and spring barley, the opposite was seen; the SAR estimate dropped to very low, or negative values, well below realistic SM values. This was also seen in cut/ley grass and in one field of spring wheat. Finally, for field beans (Fig. 5.8d), grass that was grazed and the remaining fields of spring wheat, the SAR SM followed the trend in reference SM but appeared to dry much more slowly.

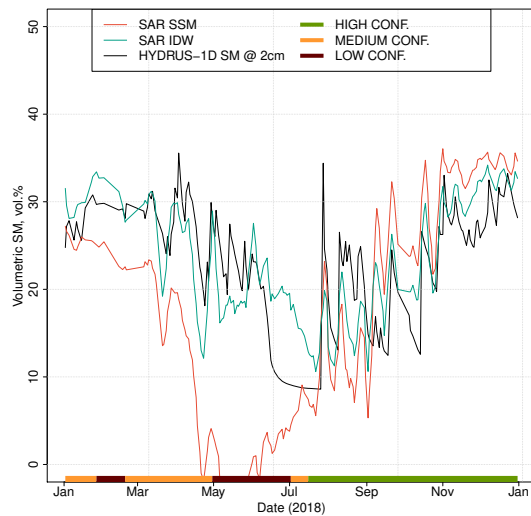
Further detailed analysis results are contained in the appendices. Appendix 5.B presents more detailed results by crop type, including the performance impacts in the high and medium confidence periods. Further example time series are included, one for each crop. This appendix also includes, for each crop, an array of scatter plots of Sentinel-1 SAR derived soil moisture (with and without IDCW) versus the modelled soil moisture at 2 cm depth using HYDRUS-1D. These are repeated by periods of HIGH, MEDIUM, LOW and ALL confidence levels. Appendix 5.C breaks down the results even further to individual field parcels, in Tables 5.20 to 5.28.



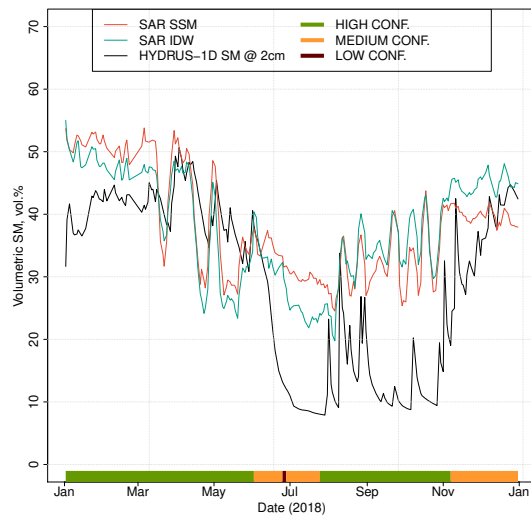
(a) Oil-seed rape field 694503 at Loddington



(b) Potato field 572608 at Fincham



(c) Winter wheat field 161407 at Fincham



(d) Field beans crop in field 347608 at Writtle

Figure 5.8: Example time series of field-scale SAR-derived surface soil moisture (red lines) for four fields in 2018, contrasting the nature of the deviations seen in the growing season compared to the ground SM simulation (black lines). The green lines show the result of IDCW interpolation.

5.4 Discussion

The overall aim of this study was to develop a better understanding of the capabilities of the CD algorithm for estimating surface soil moisture from Sentinel-1 C-band data in agricultural areas and to lay foundations for future enhancements or mitigation measures to improve the usefulness of the data for end users. Progress against the specific objectives will now be considered.

5.4.1 Unsupervised classification of fields according to confidence in the SAR SM estimate

To this aim the classification scheme described in Section 5.2.3 was implemented, fulfilling the need to assign, without supervision, a level of confidence in the SAR-derived SM estimate for each field on every date of Sentinel-1 image acquisition. This novel, remote sensing method utilised multispectral data from the Sentinel-2 satellite to derive two spectral vegetation indices that could be used with the triangular space method to determine the relative cover fractions of bare soil and of photosynthetically active and inactive vegetation, by spectral unmixing. A three-level classification scheme was developed, to assign a confidence level to each field on each SAR image date, which would describe the expected reliability of the SAR soil moisture estimate by the change detection algorithm. It was found that the change in confidence level was consistent, within a few days, with the observations of crop stage and tillage events on the ground. Demonstrating a proposed method to define periods of low confidence in the CD SM estimate, in a scalable and unsupervised way, is a key contribution of this study towards improving the overall usefulness of SAR-derived SM products. The dates that bound phases of poor performance will be critical to the deployment of any mitigation measures.

There are a number of potential improvements that should be investigated in future studies. For example, in the spectral unmixing process the end-members of each cover type were determined empirically on the assumption that these values would be a function only of soil texture and, therefore, only site-specific. The factors determining the end-member values should be further investigated so that they can be automatically and accurately determined. The threshold levels for cover fractions in the classification scheme were also preliminary choices, and fine tuning of these may produce better results.

It is recognised that a major disadvantage of using any optical satellite for

time series processing is that large gaps in the record will occur due to images affected by cloud cover in areas such as the United Kingdom. This means that there may be a delay between, for example, a tillage event and this being picked up by the classification process. Smoothing or interpolation can reduce the temporal inaccuracy, as was used in this study, but future work should examine classifying the fields by using the SAR data itself. The ratio of cross-polarised backscatter to co-polarised backscatter (Vreugdenhil et al., 2020; Vavlas et al., 2020) is known to be sensitive to vegetation biomass, and there are various vegetation indices (Szigarski et al., 2018) proposed for SAR systems that could also be investigated.

5.4.2 Inverse distance and confidence weighting to improve the accuracy of SAR SM estimation

An IDCW solution was successfully implemented as a mitigation measure to provide a more accurate soil moisture estimate in low confidence periods. Given the extent of crop rotation and heterogeneity in arable farming areas in the United Kingdom, there was a good prospect of finding neighbouring fields that would, on any particular date, have a higher confidence of providing a good soil moisture estimate. IDCW is an extension of two dimensional spatial interpolation that was attractive because of its simplicity, and its ability to easily incorporate an additional weighting factor related to the level of confidence in each of the field in the search area. Other approaches, such as this based on kriging (Zhang et al., 2017) or linear mixed effects modelling (Cafarelli et al., 2015) could have been used and should be investigated in future. In using IDCW an assumption was made that the rainfall, soil texture and potential evapotranspiration would be correlated over an area of approximately 3 km. This assumption probably is reasonable in many agricultural areas, but there may be areas such as fertile valleys, where significant heterogeneity exists in all of these factors, plus slope may also have an impact. Spatial interpolation may still be a solution in these areas, but may require a more sophisticated treatment.

Alternative methods of spatial interpolation might be used, including ordinary kriging, but the performance level of this is notoriously hard to predict. If it were possible to generate a semi-variogram at each location (which would be challenging) then the kriging approach might give better results in areas of greater spatial heterogeneity in soil moisture due to soil texture, relief and local weather variations. A different approach would be to substitute lower spatial resolution

data in low confidence periods, for example, by substituting the SM estimate from the 1 km aggregated rasterised CD product (Mattia et al., 2020). By doing this, however, the field-scale factors that affect the accuracy of the SAR estimate will be diluted by contributions from other field and non-cultivated areas. This would also be the case if even coarser resolution SM products were down-scaled (Zappa et al., 2019; Eweys et al., 2017; Rudiger et al., 2016; Peng et al., 2017). The IDCW approach is not simply a more complex way of averaging over a larger area. Its major benefit of the proposed approach is that extraneous sources of backscatter, such as field boundaries, buildings, roads and structures are excluded, whereas a spatial aggregation to a larger pixel size would include them as contaminating features. Spatial interpolation also takes account of spatial trends. A quantitative comparison of IDCW with some of these other proposals should be undertaken in future work.

A major limitation of the proposed IDCW method is that the output cannot respond to any field-specific natural or anthropogenic change in SM due to irrigation or flooding. The alternative approaches would also be largely unresponsive due to spatial resolution. For this reason, future work could investigate how to combine the IDCW and non-IDCW estimates in a hybrid solution that would retain some sensitivity to such events.

5.4.3 Crop influences on SAR SM estimation and related benefits of IDCW

The results summarised in Table 5.5 showed that the impact of IDCW was highly dependent on crop type. The crops in which it provided the greatest benefit were potatoes and maize, where this applied throughout the whole year in addition to the low confidence periods. IDCW also benefited winter cereal crops, such as barley and wheat, and beet crops. In these crops the benefit was seen mainly in the low to medium confidence periods. By contrast, spring barley only showed a marginal gain with IDCW and there was a small disbenefit in spring wheat. Oil-seed rape and cut/ley grass were other crops where there were small performance gains in the low and medium confidence periods. IDCW produced no performance improvement for non-ley grass fields, which is to be expected as these fields represent best match to the standard assumptions behind the CD algorithm (no short term changes in vegetation and soil surface roughness).

In summary, with the exception of spring wheat and grazed grass fields only,

IDCW has been shown to generally produce an improvement in performance compared to the SAR-derived field-scale SM without IDCW. IDCW could also be applied all year in most crops, without performance penalty, or with slight overall improvement. The study did not investigate combining the IDCW and non-IDCW outputs which might provide an improved performance still further, and this could be the topic of further investigation. The IDCW algorithm itself may be able to be improved further by determining optimum values of the parameters p and q that affect the severity of the weightings for distance and confidence level.

The time series plots of the SAR-derived SM that were presented in Fig. 5.8 and Appendix 5.B reveals interesting and contrasting behaviours during the periods of low confidence. In wheat, barley and cut/ley grass fields the satellite estimate of soil moisture is always lower than the ground truth as the canopy develops. Often the apparent soil moisture falls to around zero. [Mattia et al. \(2015\)](#) reported that wheat crops displayed soil attenuated scattering, which means that the vegetation is acting purely as a attenuation medium and not a scattering medium. The results of this study are consistent with this, but the levels of attenuation must have been too high for any soil moisture to be measurable, as found by [El Hajj et al. \(2018a\)](#). The canopy may be more dense or there was enhanced anisotropic scattering of the microwaves by canopy structure, due to the tall, slender stalks oriented vertically. This is supported by [Brown et al. \(2003\)](#) who noted such phenomena, especially at VV band and incidence angles over 40° . In the case of autumn sown cereal crops the period of poor CD SM estimation extended from mid-winter through to harvest. For spring sown crops this period was shorter between spring and early summer.

By contrast, the CD estimate behaved very differently in the growing period of broad-leaved crops such as oil-seed rape, beet, potatoes, field beans and maize. In these examples, the apparent soil moisture was higher than expected. The SAR was receiving an enhanced level of backscatter from the vegetation canopy, greater than that from the soil. The canopy was likely to be scattering isotropically, like a cloud of water vapour. The structure of the canopy is less ordered than the cereal crops with more random orientation of leaves and stalks, which explains this difference to cereal crops. This contrasting behaviour as also noted by [El Hajj et al. \(2018a\)](#). Despite these contrasting behaviours it was, nevertheless, observed that the IDCW approach is of benefit in both cases.

5.5 Conclusions and recommendations

The results obtained from the proposed new method are the first that are encouraging for estimating field-scale SM from Sentinel-1 SAR. The demonstrate a capability that is effective for arable crops at all times of year, meeting the accuracy requirements of 5 vol.% for agricultural use. Prior to the application of this method, during the peak growth period errors of 20 vol.% were commonly seen. This achievement lays the foundations for future enhancements or mitigation measures to further improve the usefulness of the data for end users.

The field-scale arable crop performance of CD for SM estimation from Sentinel-1 SAR data is a function of crop canopy development and the tillage state of the field. By classifying fields by an automated process based on spectral vegetation indices, mitigation of the periods of poor performance is achieved by the implementation of the proposed inverse distance and confidence weighting (IDCW) algorithm. This spatial interpolation approach can even be applied all year to all crops, with exception of grazed grass. The benefit is greatest in the case of autumn-sown cereal crops, where the mean error in the growing season can be as much as 20 vol.%. With IDCW the mean error can be reduced to around 5 vol.%. This level of performance will allow farmers to make informed decision to manage their crops at the most crucial time of the year (Moran, 2000).

The proposed method is capable of further refinement and enhancements, such as adaptation to cope with landscape heterogeneity, where more sophisticated spatial interpolation could be developed. The SAR data itself might be used to classify the performance level of each field to remove the dependency on multispectral data, which is subject to cloud cover limitations, Other information, such as soil maps and rainfall radar, could be incorporated to improve the sophistication of the spatial interpolation. Efficient means should be developed to identify grazed grass fields separately from cut or ley grass, as the method is not effective against them. The residual noise level in the satellite retrievals, and the effect of the IDCW method on this, could be further explored using time-series analysis. This might indicate the likely sources of uncertainty due to orbit geometry, time of day or other factors that could inform future algorithm refinement.

Based on the change detection algorithm, this approach has benefits over other field-scale products in that it requires no model training or *a-priori* knowledge of land use and crop type. The processing can be carried out on near real-time data as it does not rely on retrospective processing to arrive at crop types. It is,

therefore, easily transferable to other locations and sites. Its performance may, however, be limited where the landscape, soil texture, evapotranspiration or rainfall intensity is subject to high spatial heterogeneity, such as on steep slopes and in narrow valleys or terraces. Other problematic would be irrigated fields where neighbouring field are subject to differing water inputs. In these locations the assumptions in the inverse distance weighting would break down and a bespoke form of weighting may be required. Nevertheless, the output from this study is a step towards providing a useful and reliable field-scale soil moisture product that works as well on arable fields as it does for other land uses.

5.6 Acknowledgments

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Appendices

5.A Site field maps

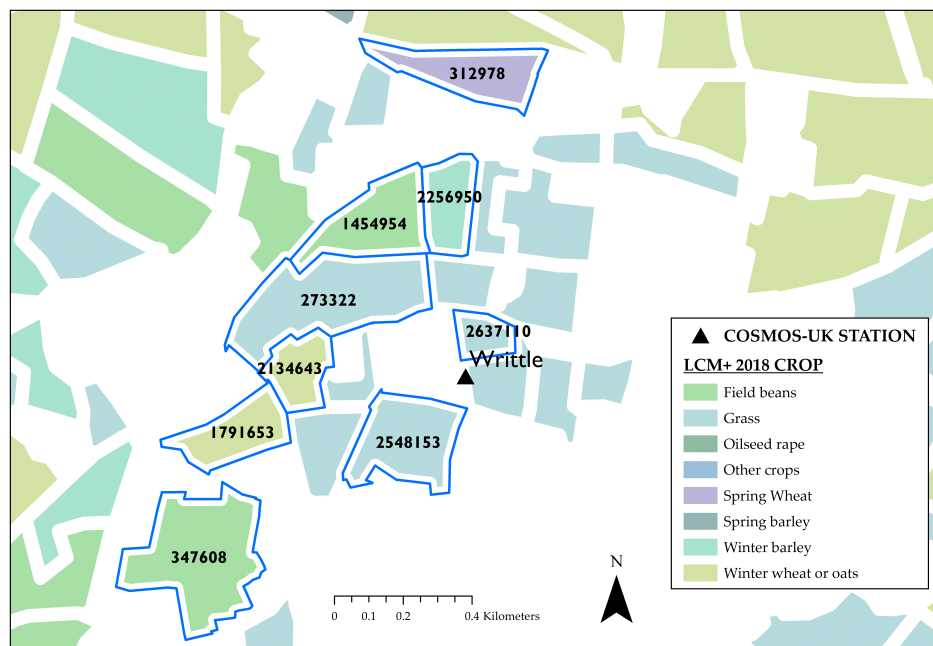
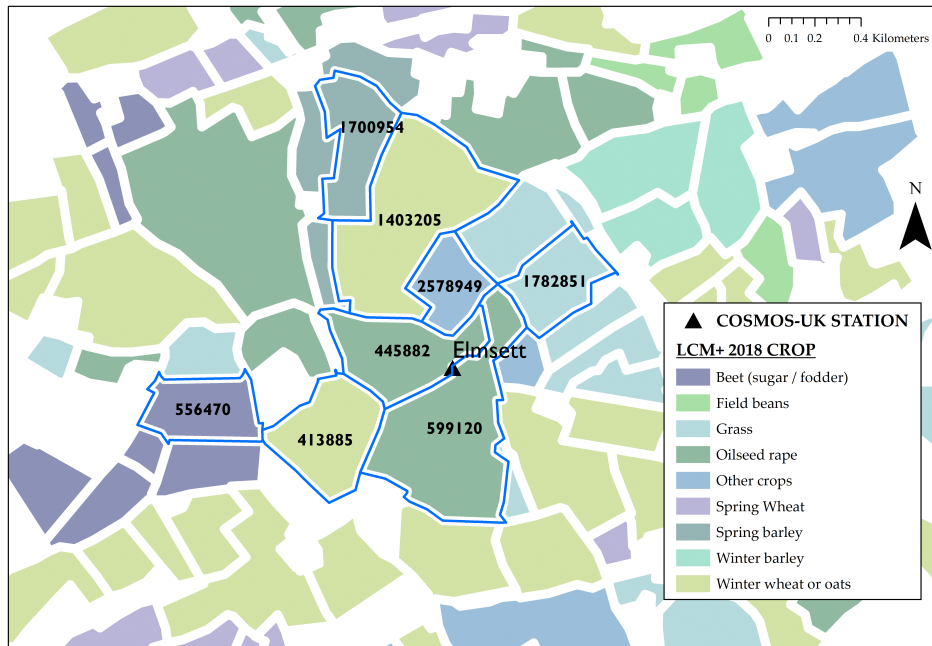
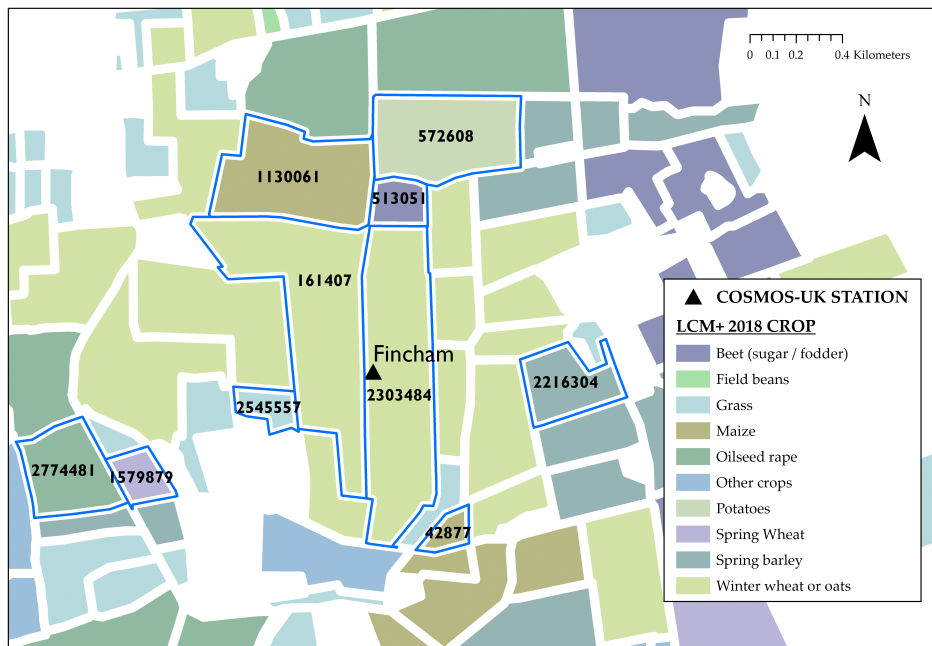


Figure 5.9: Fields surrounding the COSMOS-UK sites at Writtle. The fields with coloured fills are within the 3 km zone and used in the interpolation. The field boundaries are show eroded by 20 m as used in the field-scale SM calculation. The colours show the crops that were grown in 2018. Case study fields selected for spatial interpolation are edged in blue and labeled by GID.

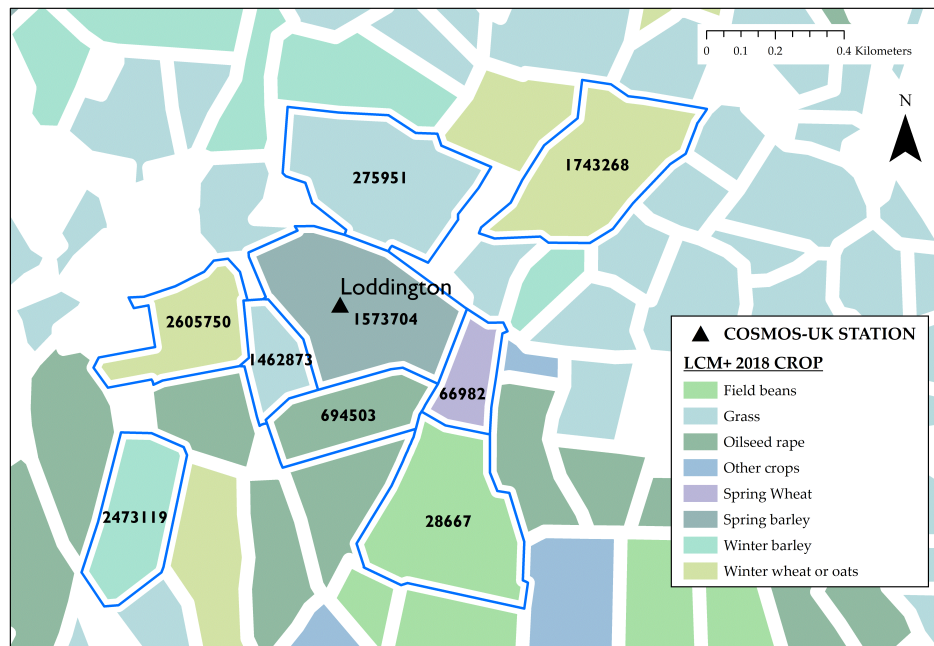


(a) Elmsett Site

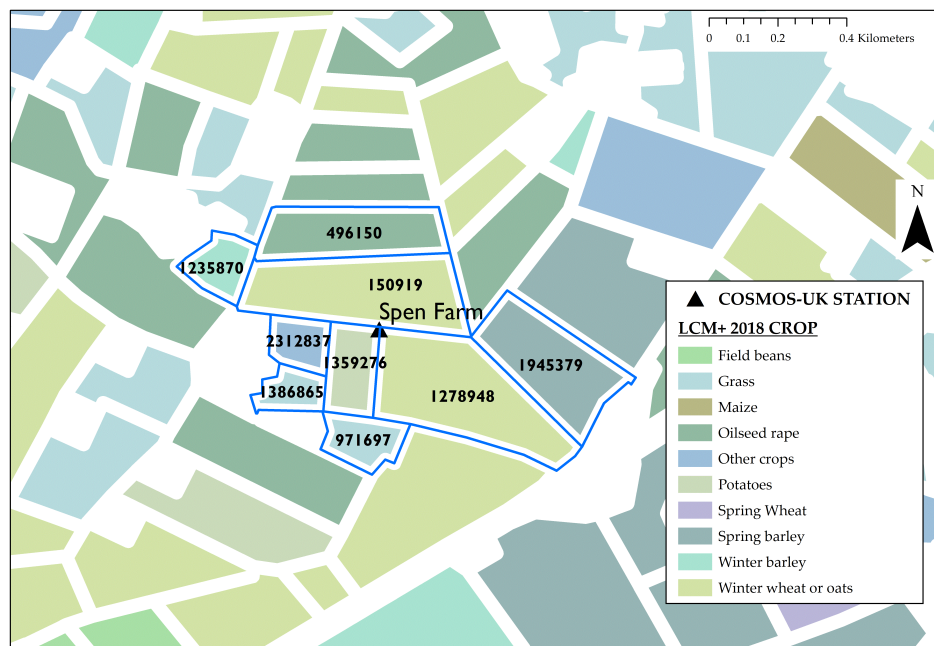


(b) Fincham Site

Figure 5.10: Fields surrounding the COSMOS-UK sites at Elmsett and Fincham. The fields with coloured fills are within the 3 km zone and used in the interpolation. The field boundaries are shown eroded by 20 m as used in the field-scale SM calculation. The colours show the crops that were grown in 2018. Case study fields selected for spatial interpolation are edged in blue and labeled by GID.



(a) Loddington Site



(b) Spen Farm Site

Figure 5.11: Fields surrounding the COSMOS-UK sites at Loddington and Spen Farm. The fields with coloured fills are within the 3 km zone and used in the interpolation. The field boundaries are show eroded by 20 m as used in the field-scale SM calculation. The colours show the crops that were grown in 2018. Case study fields selected for spatial interpolation are edged in blue and labeled by GID.

5.B IDCW performance by crop type.

This appendix presents detailed results broken down by crop type, and includes three parts:

Section 5.B.1 contains summary performance tables by crop type, listing the key metrics, R^2 and MAE , calculated for each period defined by confidence levels, plus the whole year.

Example time series for a field of each crop type are presented in section 5.B.2. These contrast the behaviour of the SAR-derived estimate of soil moisture and IDCW outputs compared to the HYDRUS-1D simulations of soil moisture at 2 cm depth.

The final section 5.B.3 comprises a series of 2 by 4 arrays of scatter plots. These compare Sentinel-1 SAR derived soil moisture (y -axis), with or without IDCW, to (on the x -axis) the simulation of soil moisture at 2 cm depth using HYDRUS-1D. Each row, from top to bottom, represents periods of HIGH, MEDIUM, LOW and ANY confidence in the performance of the change detection algorithm used. The solid lines are the best fit trend lines, the gradient of which indicates sensitivity, and the degree of fit is measured by R^2 . The dashed lines represent the expected 1:1 relationship against which the Mean Absolute Error was calculated.

5.B.1 Summary performance tables

The following tables present performance metrics for satellite-derived soil moisture, with and without Inverse Distance and Confidence Weighting (IDCW), with each table aggregating the results for one crop, across all 5 analysis sites, for the year 2018. The results are broken down by periods of different confidence levels. The performance metrics displayed in each table are listed below in Table 5.6.

Table 5.6: Performance metrics for comparison of field-scale satellite soil moisture retrieval with and without IDCW

Symbol	Metric	Units	Ideal Value
R^2	Coefficient of Determination	Dimensionless	1
MAD	Mean Absolute Difference	vol.%	0
$MAPD$	Mean Absolute Percentage Difference	%	0
$RMSD$	Root Mean Square Difference	vol.%	0
b	Bias	vol.%	0
$ubRMSD$	Unbiased RMSD & vol.%	0	
p	p -value	Dimensionless	< 0.05
S	Slope (sensitivity) of regression	Dimensionless	1

Table 5.7: ALL CROPS (45 FIELDS)

Confidence Period	R^2	MAD vol.%	$MAPD$ %	$RMSD$ vol.%	b vol.%	$ubRMSD$ vol.%	p	Slope
No IDCW								
ALL	0.32	8.28	36.87	11.24	-0.25	11.23	0.00E+00	0.61
HIGH	0.53	7.58	36.35	9.54	2.23	9.28	0.00E+00	0.75
MEDIUM	0.33	8.95	39.72	11.21	-1.23	11.14	2.09E-161	0.53
LOW	0.14	11.19	46.05	14.65	-3.28	14.28	1.31E-83	0.46
LOW/MED	0.20	10.24	43.37	13.31	-2.41	13.09	5.69E-220	0.50
With IDCW								
ALL	0.43	6.67	32.34	9.08	0.69	9.05	0.00E+00	0.59
HIGH	0.49	6.44	34.45	9.02	1.94	8.81	0.00E+00	0.64
MEDIUM	0.41	7.11	35.48	9.56	1.56	9.43	1.09E-203	0.54
LOW	0.34	7.41	31.49	9.62	-1.05	9.56	1.94E-226	0.53
LOW/MED	0.37	7.28	33.18	9.60	0.05	9.60	0.00E+00	0.54

Table 5.8: OIL-SEED RAPE (5 FIELDS)

Confidence Period	R^2	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	b vol. %	$ubRMSD$ vol. %	p	Slope
No IDCW								
ALL	0.37	7.42	26.55	9.97	-0.19	9.97	3.15E-93	0.68
HIGH	0.66	6.94	26.69	8.36	-0.55	8.35	7.59E-81	0.84
MEDIUM	0.17	9.80	33.48	12.12	-2.70	11.81	2.52E-12	0.46
LOW	0.17	7.83	27.34	10.82	2.39	10.55	4.53E-14	0.58
LOW/MED	0.15	8.76	30.23	11.45	0.00	11.45	2.13E-22	0.47
With IDCW								
ALL	0.55	6.01	20.05	7.79	-3.08	7.15	2.72E-158	0.68
HIGH	0.74	4.63	18.01	6.18	-0.36	6.17	5.20E-86	0.80
MEDIUM	0.46	6.46	19.03	7.93	-3.21	7.25	1.57E-36	0.56
LOW	0.31	7.63	24.06	9.61	-6.36	7.20	6.55E-26	0.54
LOW/MED	0.42	7.08	21.70	8.86	-4.87	7.40	2.87E-67	0.61

Table 5.9: WINTER WHEAT (10 FIELDS)

Confidence Period	R^2	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	b vol. %	$ubRMSD$ vol. %	p	Slope
No IDCW								
ALL	0.32	9.44	37.97	12.99	-3.34	12.55	4.00E-153	0.72
HIGH	0.59	7.84	39.32	9.71	3.19	9.18	3.32E-181	0.75
MEDIUM	0.53	8.31	28.13	10.75	-6.46	8.59	1.12E-57	0.84
LOW	0.21	16.10	53.91	19.87	-14.43	13.66	3.05E-28	0.74
LOW/MED	0.31	12.97	43.56	16.81	-11.23	12.51	5.75E-71	0.84
With IDCW								
ALL	0.43	6.76	31.84	8.99	0.38	8.98	4.25E-230	0.60
HIGH	0.53	7.20	41.27	9.84	3.45	9.21	3.53E-141	0.64
MEDIUM	0.53	5.80	22.73	7.49	-0.10	7.49	6.63E-56	0.72
LOW	0.31	7.39	25.31	9.16	-4.24	8.12	4.46E-42	0.46
LOW/MED	0.40	6.75	24.27	8.53	-2.58	8.13	1.93E-94	0.60

Table 5.10: SPRING WHEAT (3 FIELDS)

Confidence Period	R^2	MAD vol.%	$MAPD$ %	$RMSD$ vol.%	b vol.%	$ubRMSD$ vol.%	p	Slope
No IDCW								
ALL	0.64	7.20	32.05	8.84	2.05	8.60	1.74E-141	0.79
HIGH	0.63	6.90	28.47	8.51	3.68	7.67	2.98E-97	0.81
MEDIUM	0.81	7.87	45.61	9.47	0.94	9.42	8.74E-40	0.65
LOW	0.49	7.95	33.95	9.77	-5.81	7.85	1.03E-12	0.75
LOW/MED	0.71	7.91	40.73	9.60	-1.89	9.41	3.54E-51	0.76
With IDCW								
ALL	0.54	6.82	40.48	9.81	4.48	8.72	5.21E-97	0.60
HIGH	0.54	6.04	31.19	8.63	3.89	7.71	6.03E-70	0.64
MEDIUM	0.66	8.85	70.83	13.16	6.50	11.44	7.70E-22	0.52
LOW	0.27	8.50	52.14	10.69	5.07	9.41	2.83E-06	0.52
LOW/MED	0.56	8.70	63.01	12.19	5.90	10.66	9.59E-30	0.57

Table 5.11: WINTER BARLEY (3 FIELDS)

Confidence Period	R^2	MAD vol.%	$MAPD$ %	$RMSD$ vol.%	b vol.%	$ubRMSD$ vol.%	p	Slope
No IDCW								
ALL	0.15	10.65	46.22	15.55	-1.47	15.48	1.20E-19	0.46
HIGH	0.67	7.90	42.95	10.40	5.08	9.07	2.35E-51	0.74
MEDIUM	0.22	9.44	35.62	13.03	-4.51	12.22	5.62E-09	0.50
LOW	0.04	20.48	82.36	24.35	-7.97	23.01	1.62E-02	-0.32
LOW/MED	0.03	15.41	60.91	19.97	-6.38	18.92	5.49E-03	0.23
With IDCW								
ALL	0.38	7.49	41.60	10.56	3.75	9.87	2.75E-54	0.49
HIGH	0.62	7.74	52.53	11.10	6.24	9.19	3.76E-35	0.52
MEDIUM	0.50	5.72	26.00	8.24	1.73	8.05	3.81E-20	0.66
LOW	0.05	10.15	52.49	13.14	4.98	12.16	5.28E-03	0.18
LOW/MED	0.25	8.12	40.33	11.16	3.49	10.60	8.04E-19	0.42

Table 5.12: SPRING BARLEY (4 FIELDS)

Confidence Period	R^2	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	b vol. %	$ubRMSD$ vol. %	p	Slope
No IDCW								
ALL	0.55	6.72	22.61	9.81	-3.28	9.25	2.28E-120	0.96
HIGH	0.73	6.02	20.62	7.87	-0.37	7.87	9.17E-105	1.06
MEDIUM	0.57	9.67	29.92	11.96	-9.08	7.78	5.02E-17	1.02
LOW	0.39	9.14	31.21	13.07	-7.10	10.97	8.19E-26	0.79
LOW/MED	0.42	9.29	30.84	12.76	-7.67	10.20	2.06E-38	0.83
With IDCW								
ALL	0.60	5.63	19.30	7.57	-2.58	7.12	3.42E-141	0.78
HIGH	0.74	4.60	16.25	6.67	-0.91	6.61	7.54E-98	1.00
MEDIUM	0.46	7.82	23.57	10.04	-6.60	7.56	2.02E-12	0.82
LOW	0.53	7.03	23.97	8.50	-4.00	7.50	3.26E-37	0.48
LOW/MED	0.46	7.26	23.85	8.97	-4.75	7.61	1.23E-41	0.54

Table 5.13: FIELD BEANS (3 FIELDS)

Confidence Period	R^2	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	b vol. %	$ubRMSD$ vol. %	p	Slope
No IDCW								
ALL	0.53	10.24	62.61	12.87	8.15	9.96	5.18E-104	0.44
HIGH	0.55	10.41	63.92	13.11	8.22	10.21	9.64E-79	0.47
MEDIUM	0.61	10.13	68.77	12.83	8.46	9.65	1.47E-21	0.34
LOW	0.31	9.29	45.69	11.28	7.29	8.60	4.40E-07	0.19
LOW/MED	0.53	9.78	59.03	12.20	7.97	9.24	4.94E-29	0.30
With IDCW								
ALL	0.50	9.09	57.05	12.12	6.79	10.04	7.88E-88	0.42
HIGH	0.49	8.96	58.74	12.24	6.21	10.55	2.10E-61	0.41
MEDIUM	0.60	9.64	58.19	11.99	8.44	8.51	5.68E-20	0.52
LOW	0.42	9.19	44.59	11.52	8.32	7.97	2.06E-09	0.33
LOW/MED	0.55	9.45	52.45	11.79	8.39	8.29	1.84E-29	0.47

Table 5.14: POTATOES (2 FIELDS)

Confidence Period	R^2	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	b vol. %	$ubRMSD$ vol. %	p	Slope
No IDCW								
ALL	0.01	6.63	39.74	9.40	4.25	8.39	1.19E-01	0.08
HIGH	0.31	4.75	19.06	6.05	2.18	5.64	8.52E-15	0.81
MEDIUM	0.01	9.64	39.82	10.21	-4.77	9.02	7.19E-01	-0.07
LOW	0.01	14.96	110.83	15.91	13.80	7.92	4.09E-01	0.04
LOW/MED	0.09	13.92	96.99	14.97	10.18	10.98	1.12E-03	-0.19
With IDCW								
ALL	0.51	4.15	20.36	5.24	-0.82	5.18	2.21E-55	0.57
HIGH	0.44	3.45	13.03	4.31	-0.90	4.22	2.63E-22	0.79
MEDIUM	0.39	7.03	25.93	7.84	-5.90	5.16	1.38E-03	0.49
LOW	0.41	4.74	35.93	5.91	1.55	5.70	3.91E-12	0.42
LOW/MED	0.41	5.19	33.98	6.33	0.10	6.33	8.79E-15	0.39

Table 5.15: MAIZE (2 FIELDS)

Confidence Period	R^2	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	b vol. %	$ubRMSD$ vol. %	p	Slope
No IDCW								
ALL	0.13	7.30	44.85	8.80	4.46	7.59	3.50E-14	0.34
HIGH	0.24	6.90	39.22	8.17	3.58	7.34	3.54E-16	0.56
MEDIUM	0.11	4.16	25.61	5.95	0.75	5.90	4.26E-03	0.17
LOW	0.12	11.38	79.45	12.19	10.53	6.14	1.59E-03	0.20
LOW/MED	0.02	7.91	53.55	9.70	5.82	7.76	1.01E-01	0.07
With IDCW								
ALL	0.56	4.03	23.24	4.97	0.96	4.88	7.69E-74	0.73
HIGH	0.51	4.18	23.34	5.10	0.96	5.00	9.45E-40	0.70
MEDIUM	0.66	3.04	15.93	4.05	1.89	3.58	5.63E-19	0.71
LOW	0.32	4.51	29.70	5.36	0.08	5.36	2.47E-08	0.44
LOW/MED	0.62	3.81	23.08	4.78	0.95	4.68	7.28E-35	0.76

Table 5.16: BEET (2 FIELDS)

Confidence Period	R^2	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	b vol. %	$ubRMSD$ vol. %	p	Slope
No IDCW								
ALL	0.13	8.55	39.69	10.56	2.95	10.14	5.47E-14	0.27
HIGH	0.30	5.11	22.12	6.01	2.30	5.56	3.30E-09	0.66
MEDIUM	0.36	9.96	55.54	11.70	9.83	6.34	1.55E-09	0.51
LOW	0.09	9.52	41.40	11.61	0.69	11.59	4.27E-06	0.21
LOW/MED	0.09	9.64	45.23	11.63	3.16	11.20	3.02E-08	0.21
With IDCW								
ALL	0.51	6.12	23.00	7.65	-3.10	6.99	2.04E-65	0.51
HIGH	0.35	4.31	18.59	5.21	-1.30	5.04	1.07E-10	0.66
MEDIUM	0.39	5.11	29.05	6.22	1.76	5.97	1.40E-10	0.48
LOW	0.62	7.27	22.66	8.91	-5.69	6.87	3.64E-50	0.57
LOW/MED	0.54	6.69	24.39	8.27	-3.67	7.41	3.20E-54	0.50

Table 5.17: CUT/LEY GRASS (4 FIELDS)

Confidence Period	R^2	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	b vol. %	$ubRMSD$ vol. %	p	Slope
No IDCW								
ALL	0.20	7.19	37.36	10.03	-1.42	9.93	1.31E-29	0.47
HIGH	0.20	6.48	32.31	8.21	-3.37	7.48	1.62E-05	0.27
MEDIUM	0.20	9.32	49.65	10.87	-0.45	10.86	1.09E-09	0.54
LOW	0.18	9.87	50.97	12.28	-2.08	12.10	1.24E-15	0.44
LOW/MED	0.19	9.68	50.53	11.82	-1.53	11.72	5.71E-24	0.46
With IDCW								
ALL	0.31	6.56	37.61	9.11	1.91	8.91	6.29E-59	0.52
HIGH	0.43	4.74	31.16	6.46	1.63	6.25	4.00E-12	0.50
MEDIUM	0.33	6.92	45.08	9.64	4.96	8.26	5.77E-16	0.52
LOW	0.28	8.14	46.56	10.81	2.37	10.55	4.38E-25	0.51
LOW/MED	0.29	7.73	46.06	10.43	3.25	9.91	2.21E-38	0.51

Table 5.18: GRASS (7 FIELDS)

Confidence Period	R^2	MAD vol. %	$MAPD$ %	$RMSD$ vol. %	b vol. %	$ubRMSD$ vol. %	p	Slope
No IDCW								
ALL	0.37	7.93	33.07	9.92	-1.33	9.84	9.13E-132	0.52
HIGH	0.33	8.71	35.50	10.14	-4.93	8.86	1.28E-35	0.53
MEDIUM	0.34	9.08	43.38	10.99	1.02	10.95	3.61E-43	0.40
LOW	0.37	7.47	26.27	9.44	-0.91	9.40	3.03E-46	0.48
LOW/MED	0.35	8.28	34.86	10.25	0.06	10.25	5.08E-88	0.43
With IDCW								
ALL	0.32	7.69	35.84	10.16	0.63	10.14	8.65E-109	0.49
HIGH	0.20	8.28	35.66	10.22	-3.80	9.48	2.36E-20	0.35
MEDIUM	0.30	8.83	47.79	11.45	3.50	10.90	2.25E-35	0.38
LOW	0.33	6.65	27.32	9.31	1.87	9.12	4.70E-37	0.43
LOW/MED	0.32	7.75	37.59	10.44	2.69	10.09	7.43E-72	0.40

5.B.2 Example time series

The following plots present 2018 time series for satellite-derived soil moisture, with and without Inverse Distance and Confidence Weighting (IDCW), and the HYDRUS-1D simulation of soil moisture at 2 cm soil depth for comparison. The periods of different confidence levels are shown by the coloured bar at the bottom of each plot.

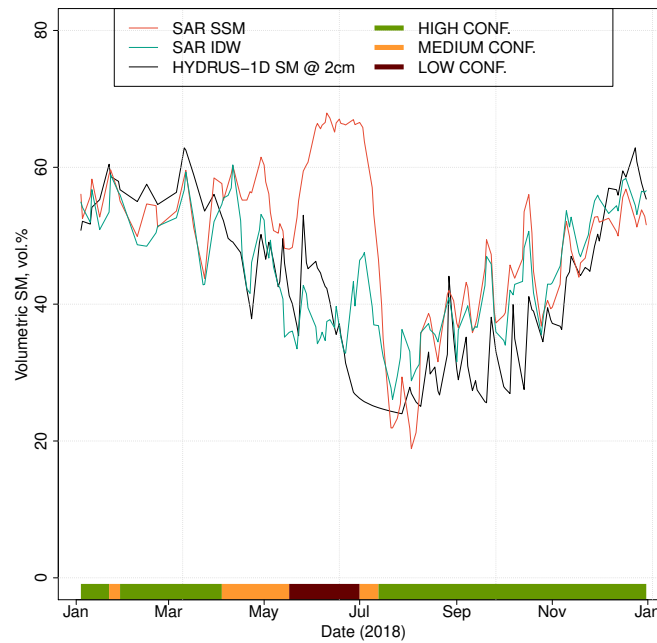


Figure 5.12: IDCW 2018 time series: oil-seed rape field 694503 at Loddington

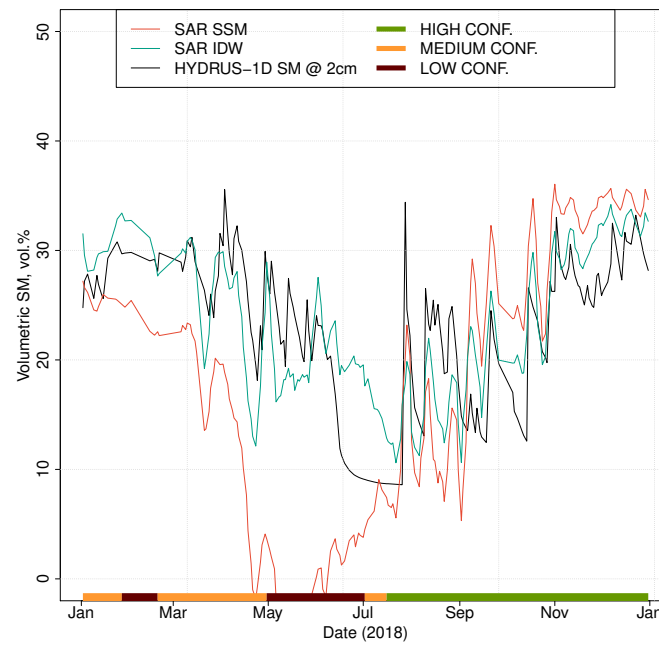


Figure 5.13: IDCW 2018 time series: winter wheat field 161407 at Fincham

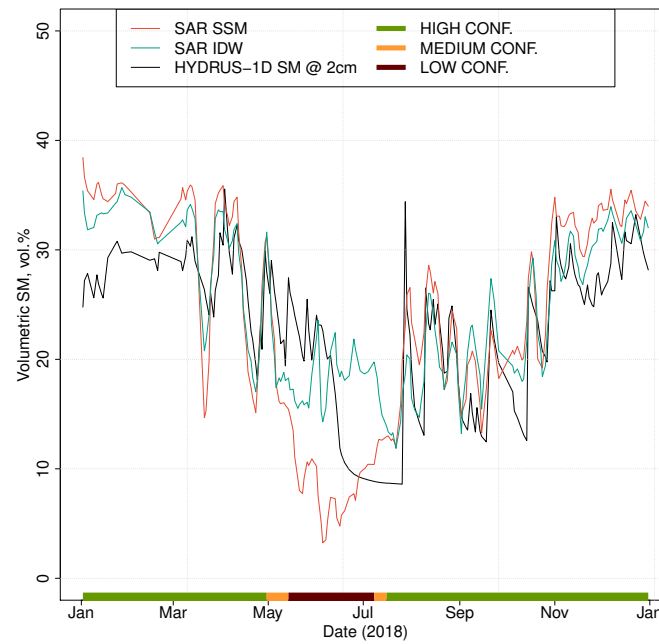


Figure 5.14: IDCW 2018 time series: spring wheat field 1579879 at Fincham

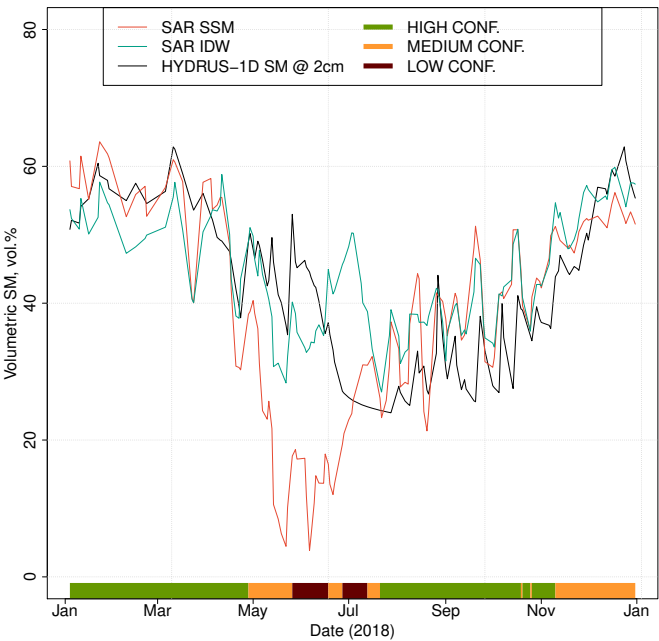


Figure 5.15: IDCW 2018 time series: winter barley field 2473119 at Loddington

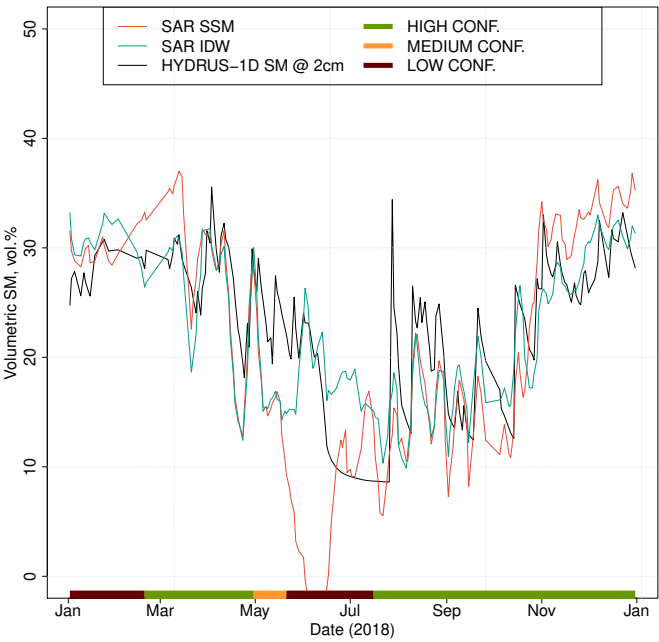


Figure 5.16: IDCW 2018 time series: spring barley field 2216304 at Fincham

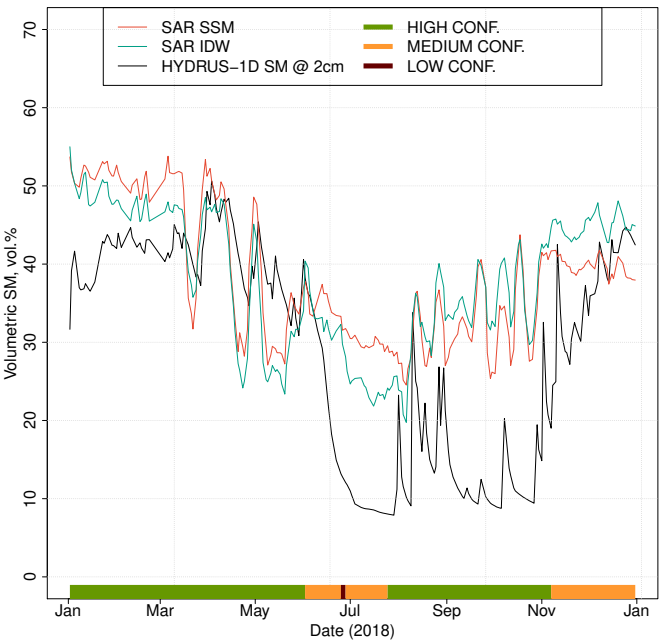


Figure 5.17: IDCW 2018 time series: field beans field 347608 at Writtle

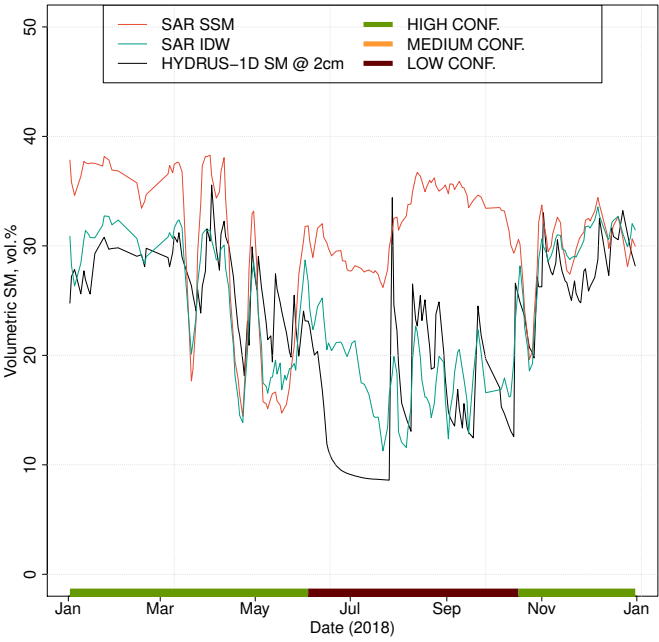


Figure 5.18: IDCW 2018 time series: potatoes field 572608 at Fincham

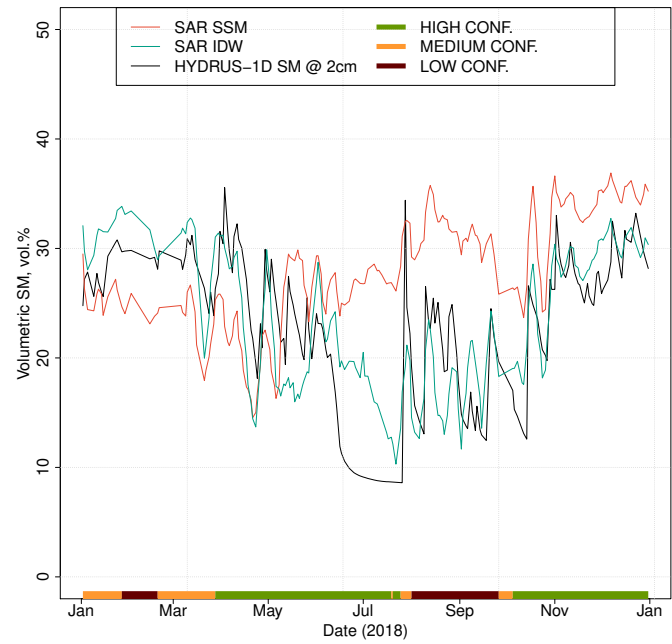


Figure 5.19: IDCW 2018 time series: maize field 1130061 at Fincham

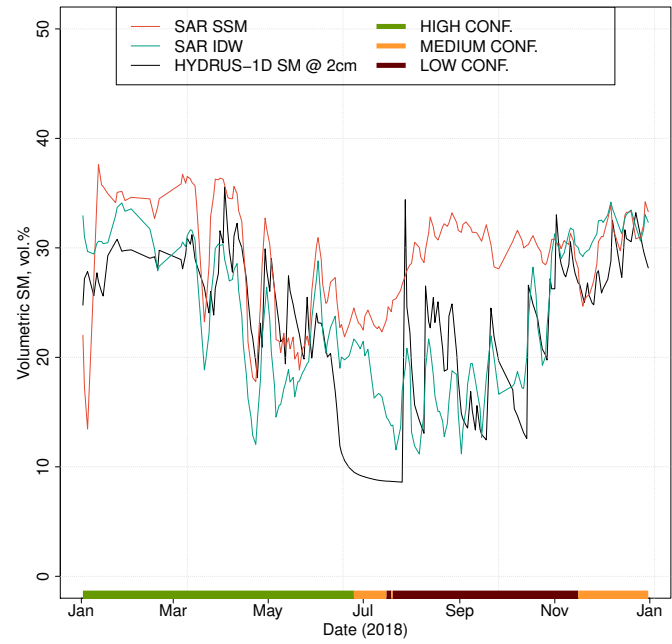


Figure 5.20: IDCW 2018 time series: beet field 513051 at Fincham

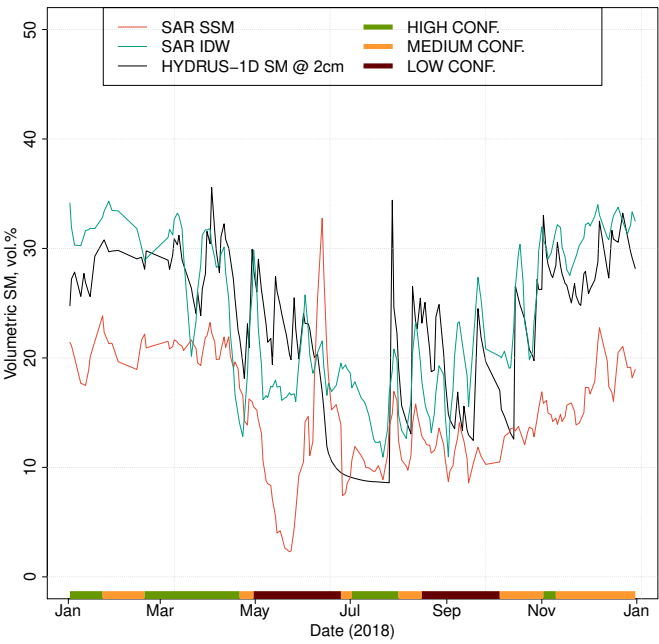


Figure 5.21: IDCW 2018 time series: cut/ley grass field 2544447 at Fincham

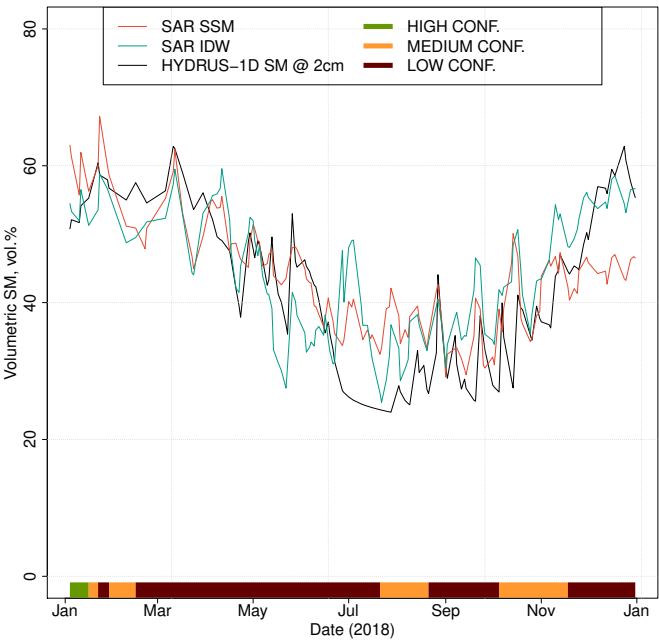


Figure 5.22: IDCW 2018 time series: grass field 1462873 at Loddington

5.B.3 Scatter plots

This section presents a number of 2 by 4 arrays of scatter plots of Sentinel-1 SAR derived soil moisture (y-axis) in volumetric water content vol.% (left column) with the same after IDCW (right column). On the x -axis, in each case, is the modelled soil moisture at 2 cm depth using HYDRUS-1D. Each row, from top to bottom, represents periods of HIGH, MEDIUM, LOW and ANY confidence in the performance of the change detection algorithm used. The solid lines are the best fit trend lines, the gradient of which indicates sensitivity, and the degree of fit is measured by R^2 . The dashed lines represent the expected 1:1 relationship against which the Mean Absolute Error was calculated.

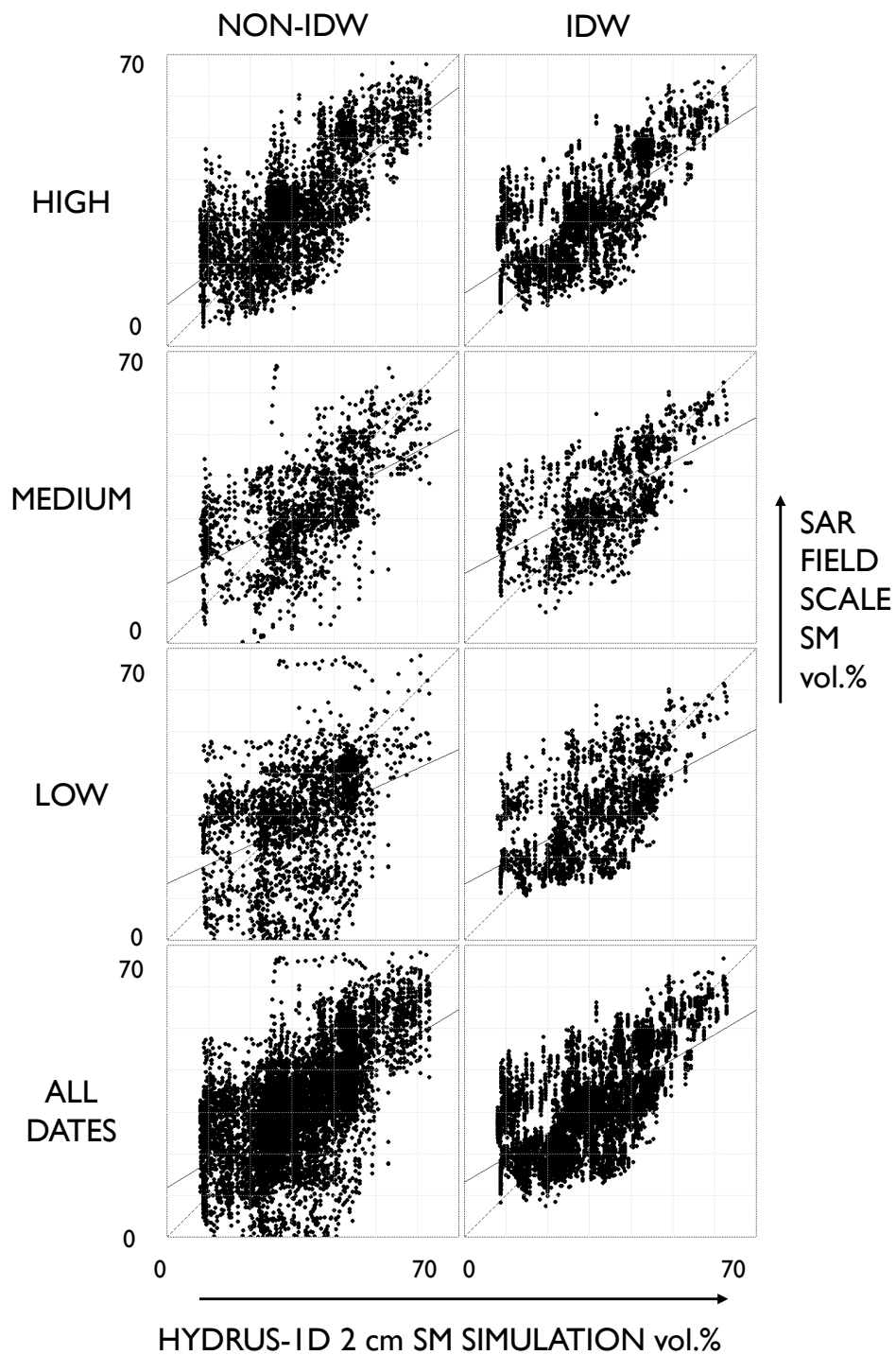


Figure 5.23: IDCW 2018 scatter plots: all crops

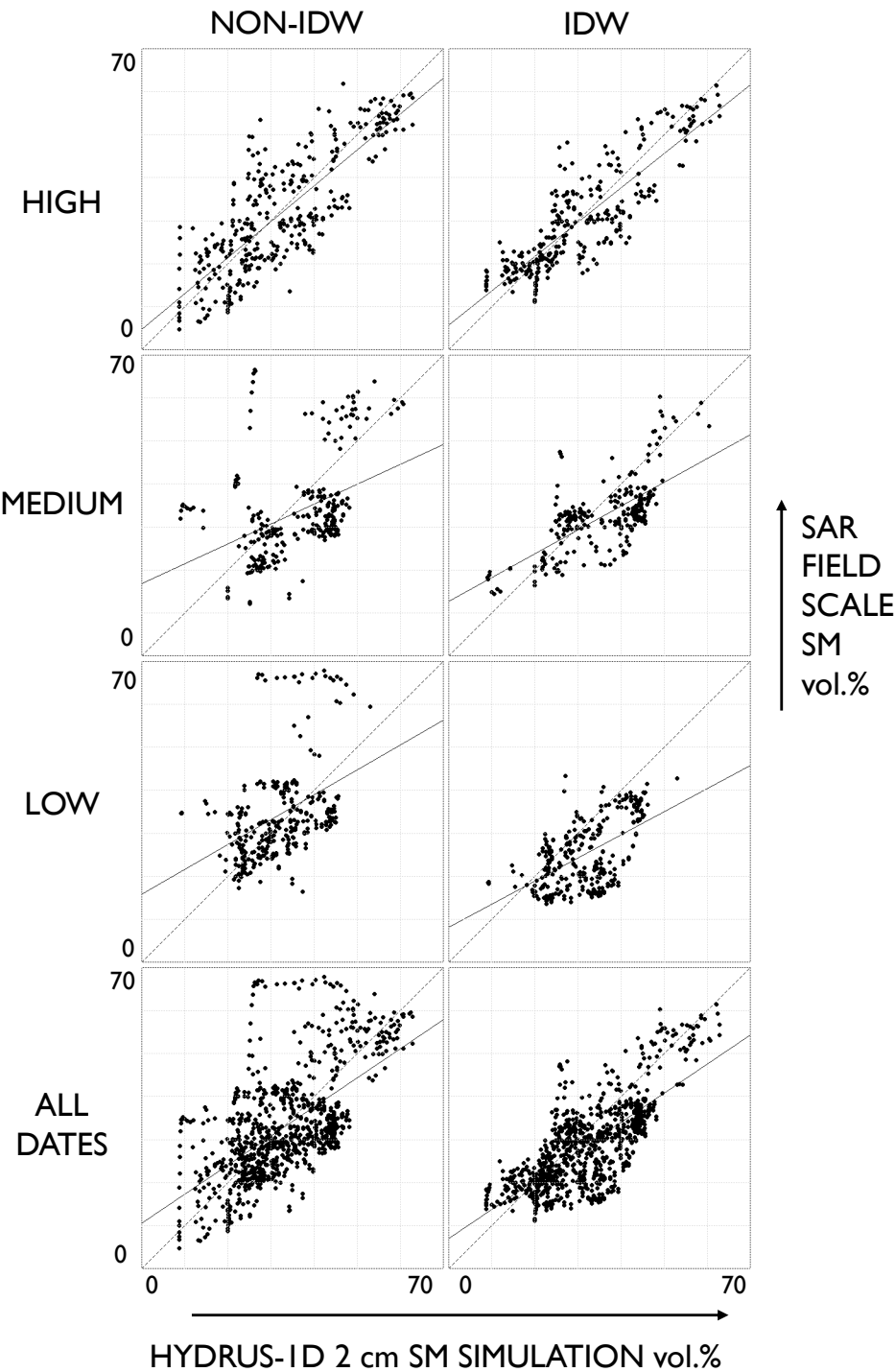


Figure 5.24: IDCW 2018 scatter plots: oil-seed rape

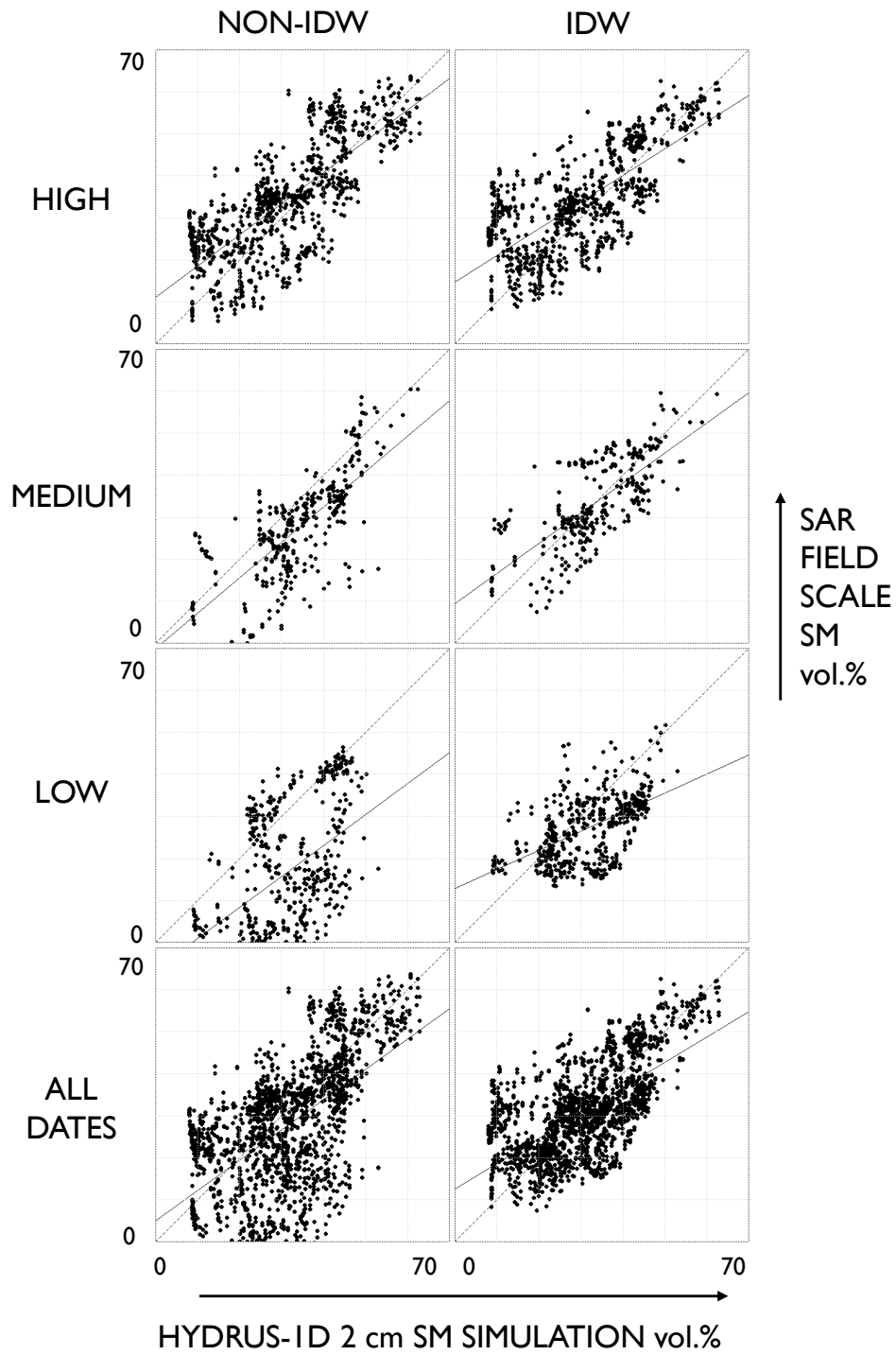


Figure 5.25: IDCW 2018 scatter plots: winter wheat

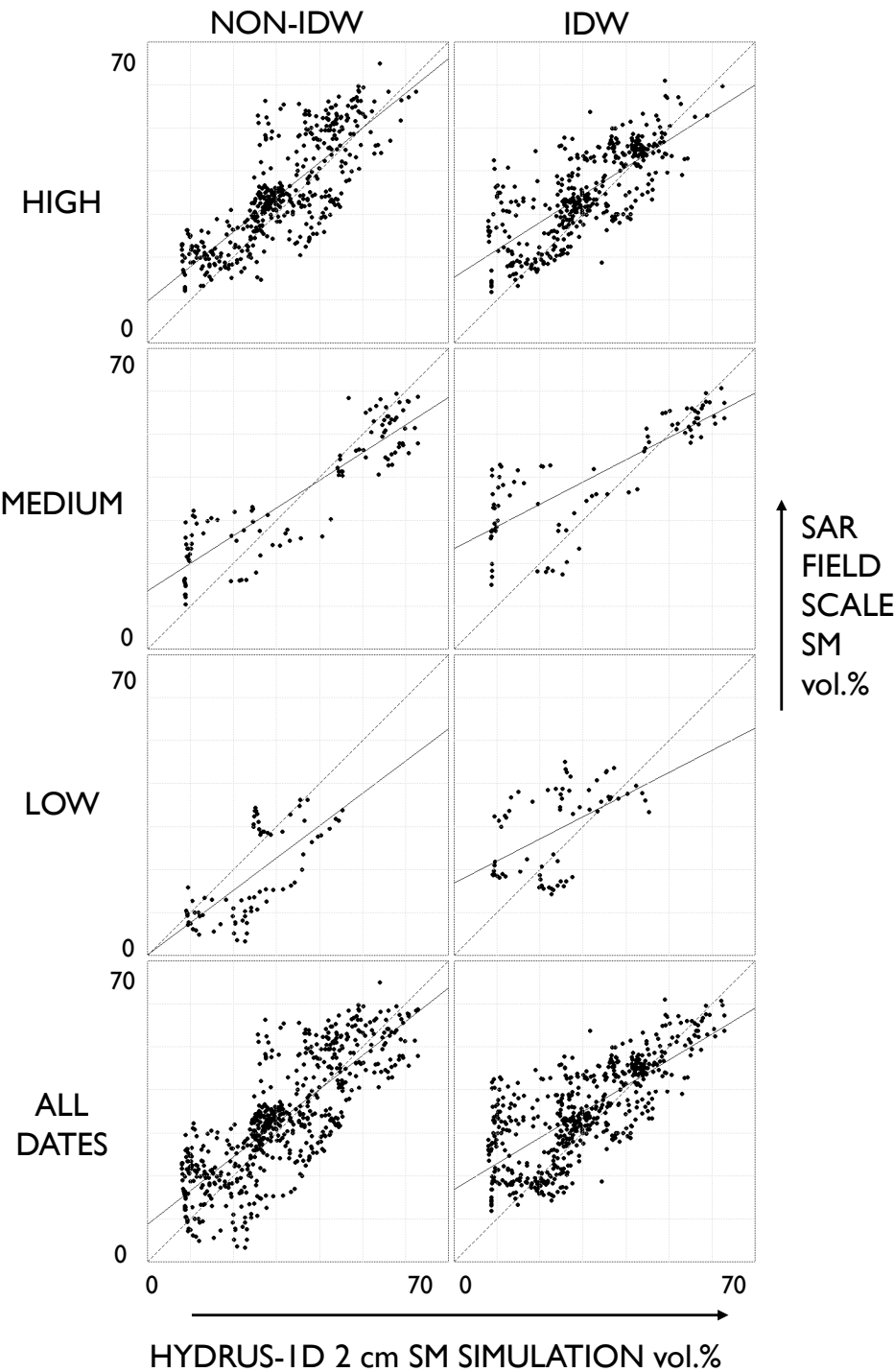


Figure 5.26: IDCW 2018 scatter plots: spring wheat

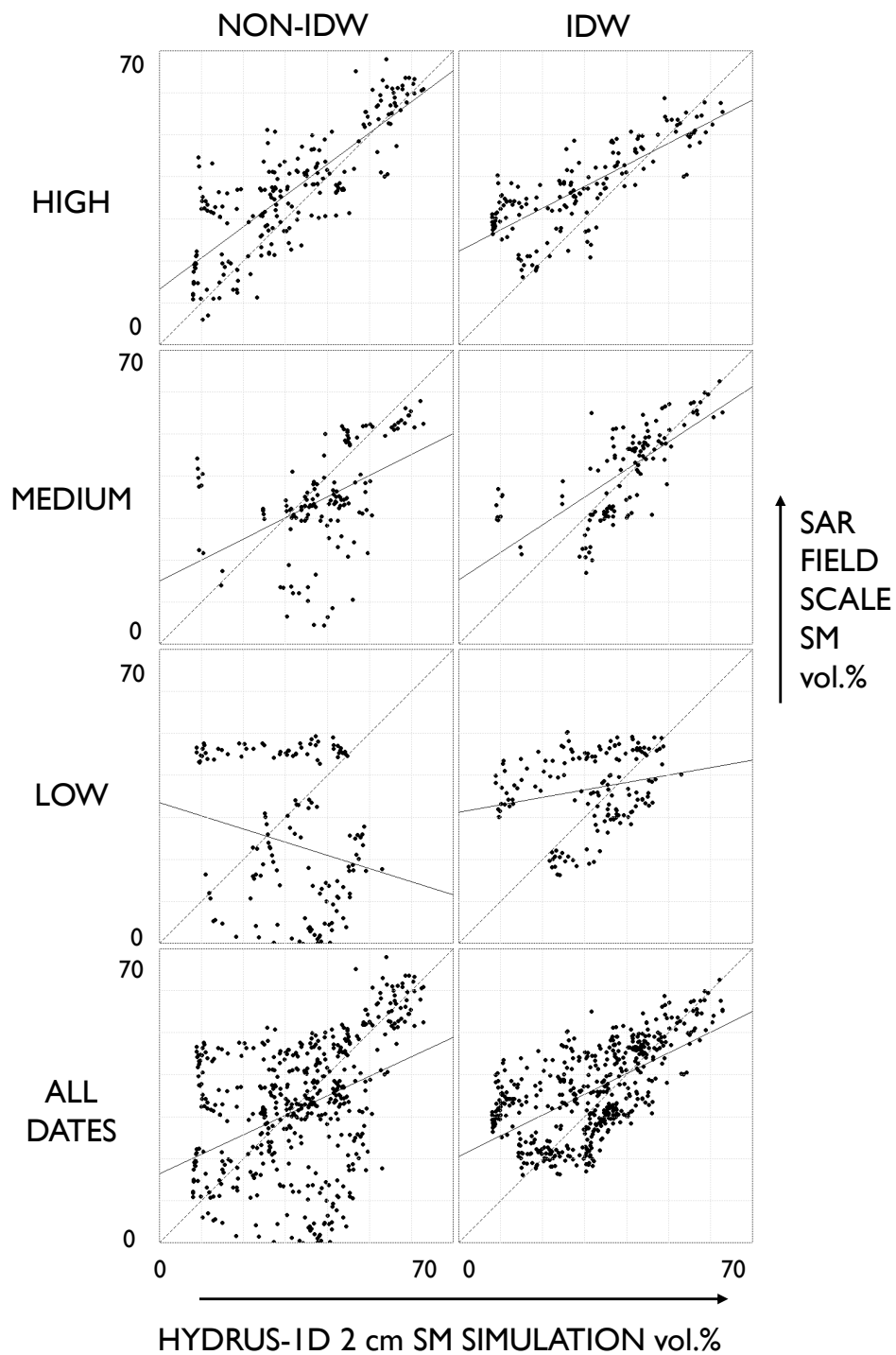


Figure 5.27: IDCW 2018 scatter plots: winter barley

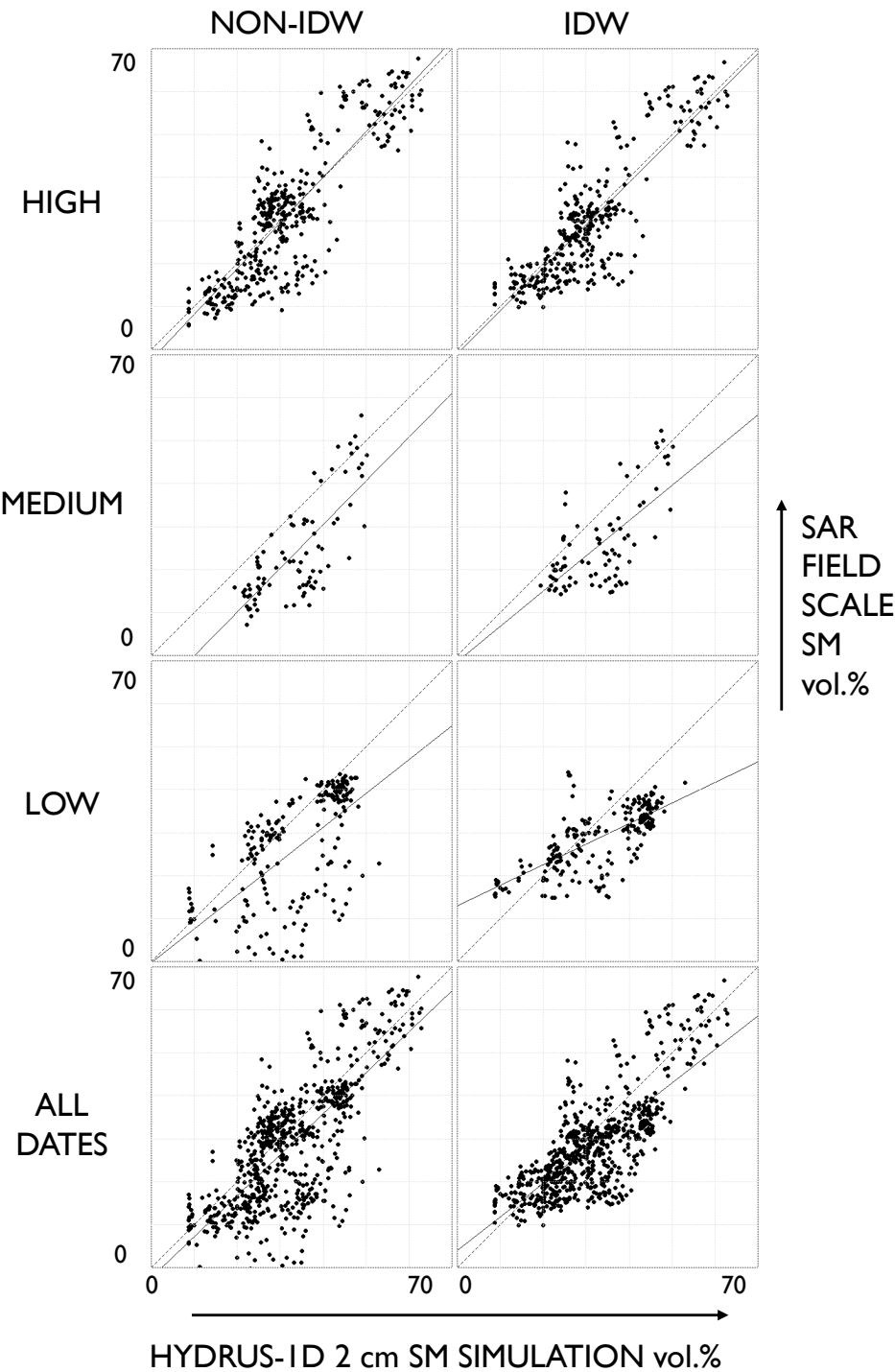


Figure 5.28: IDCW 2018 scatter plots: spring barley

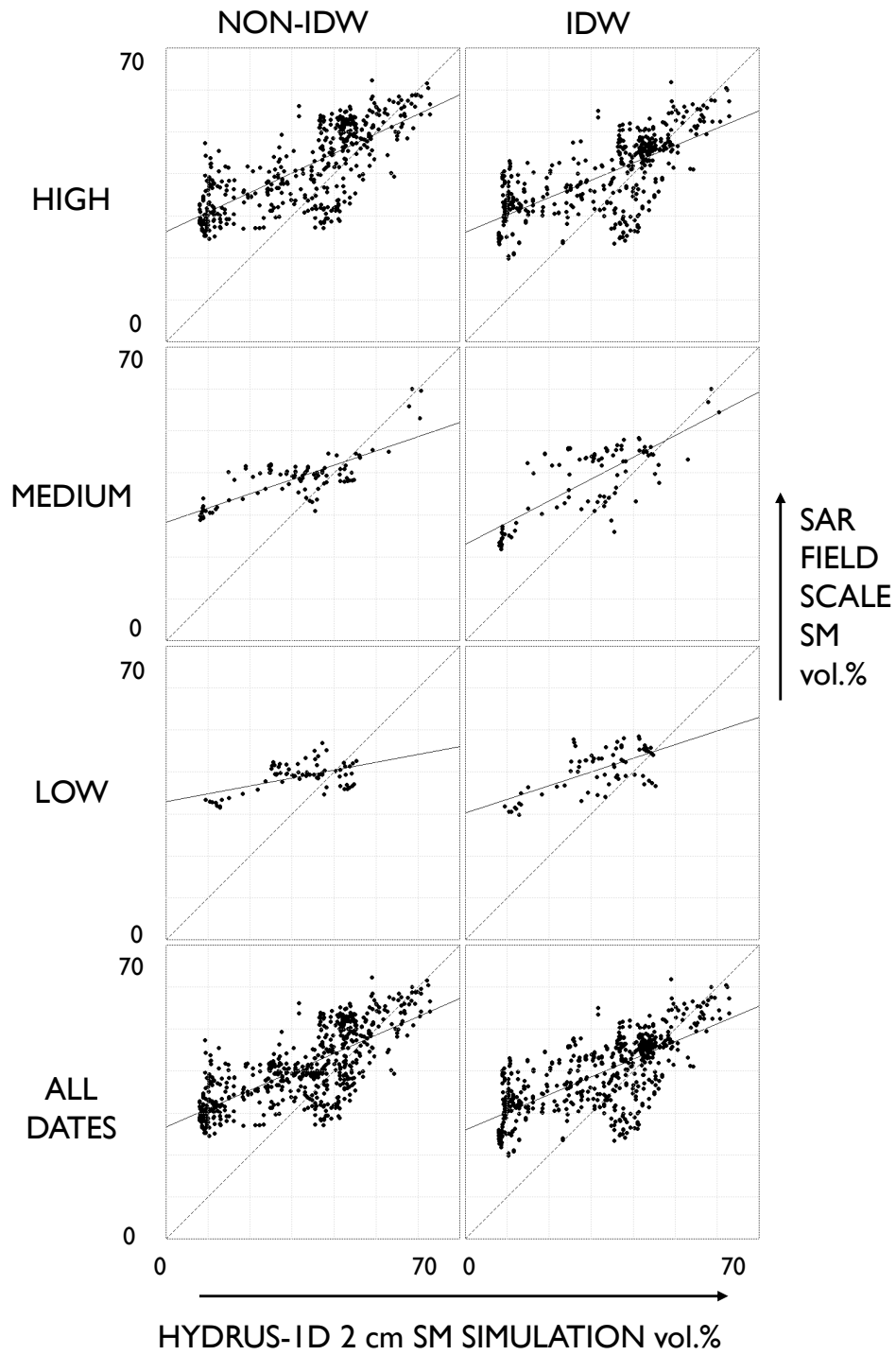


Figure 5.29: IDCW 2018 scatter plots: field beans

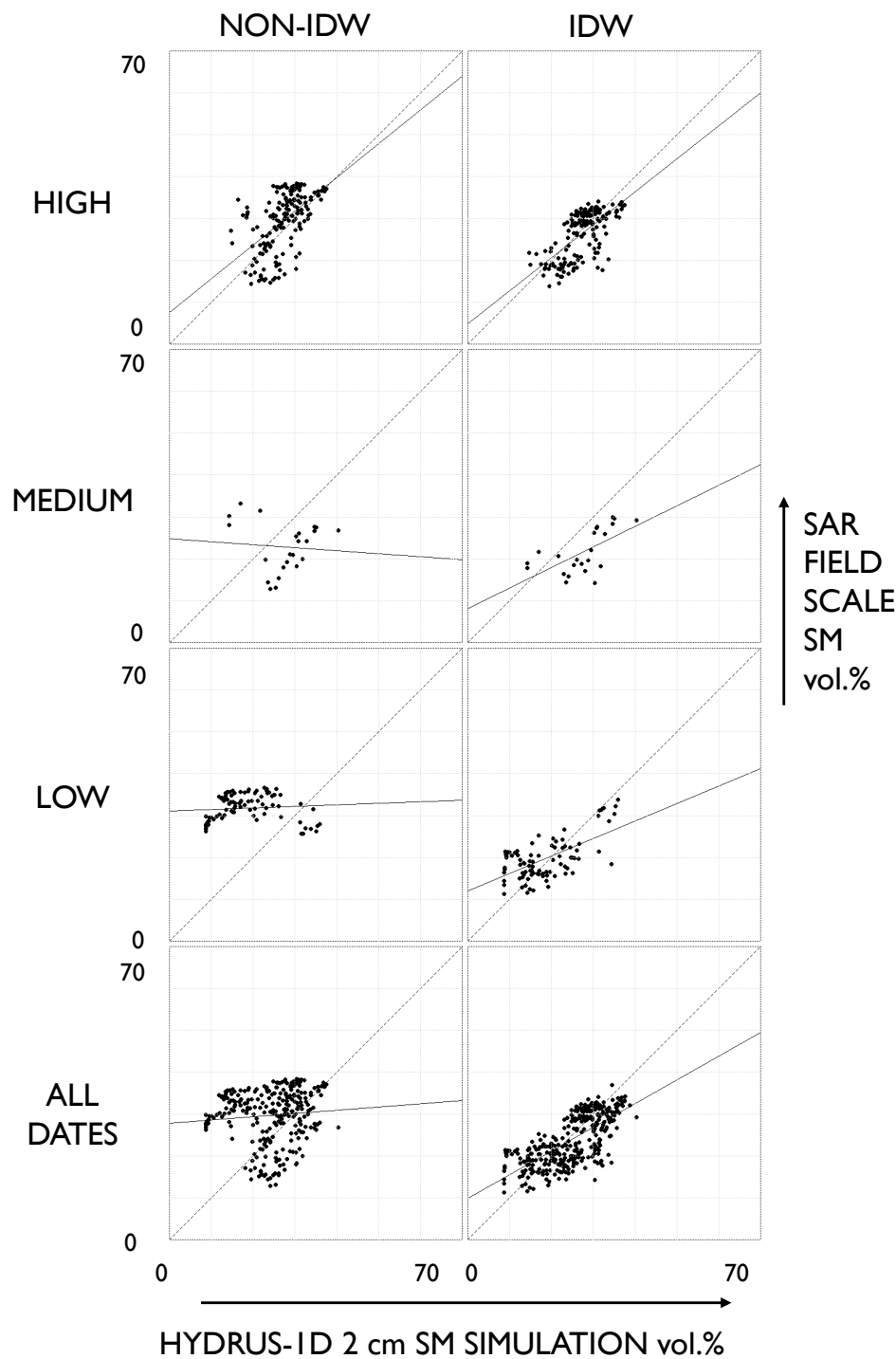


Figure 5.30: IDCW 2018 scatter plots: potatoes

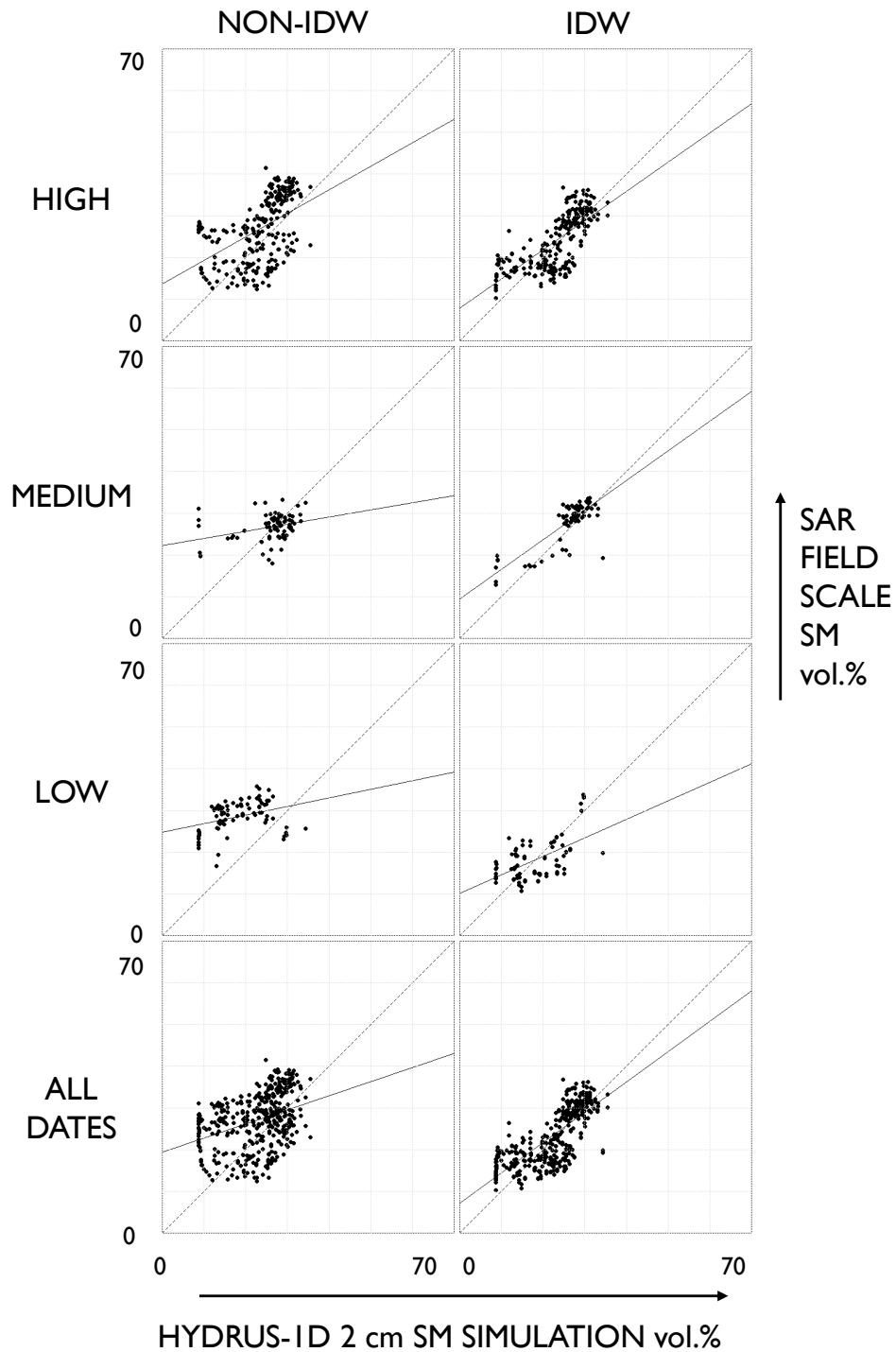


Figure 5.31: IDCW 2018 scatter plots: maize

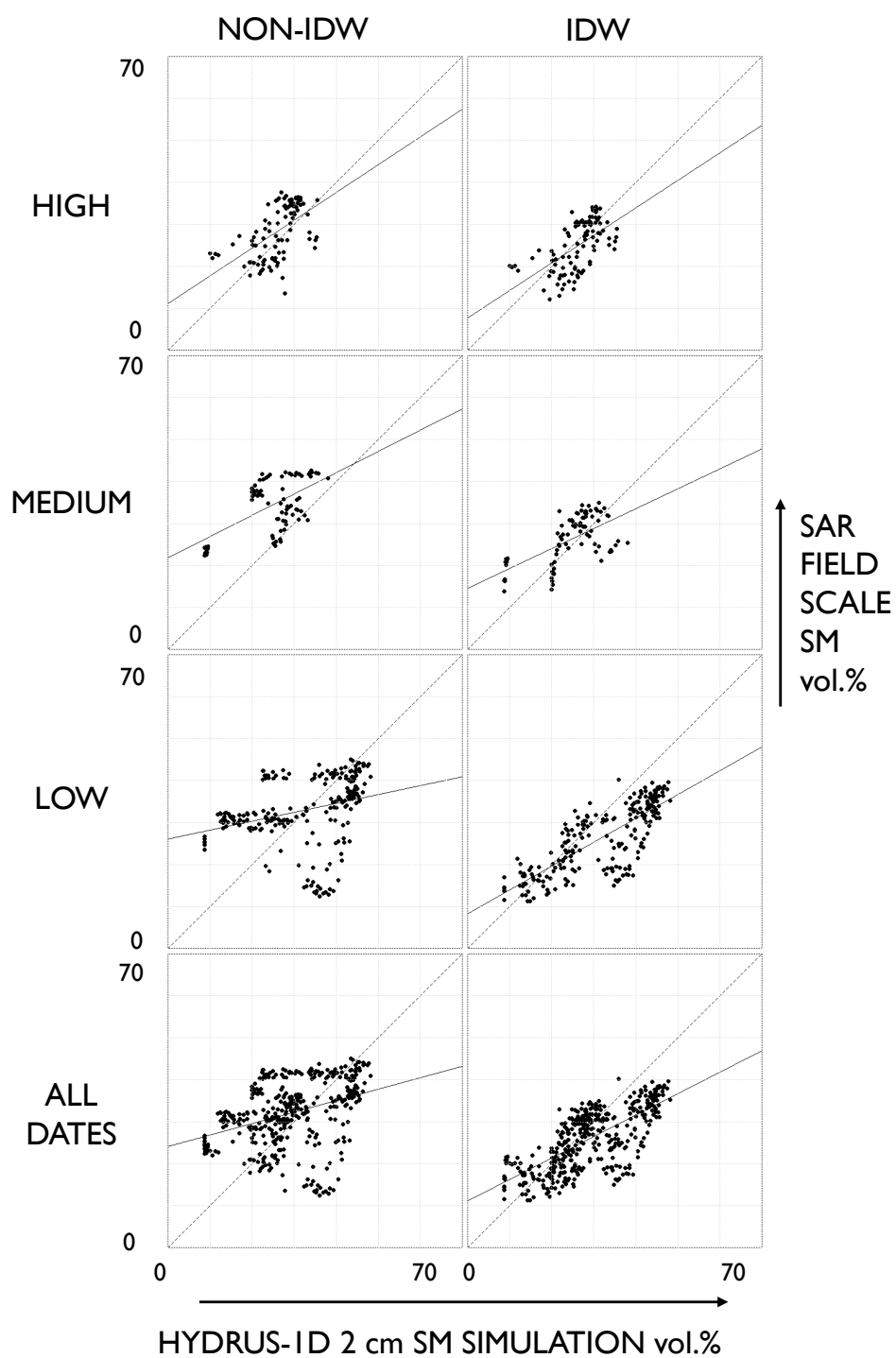


Figure 5.32: IDCW 2018 scatter plots: beet

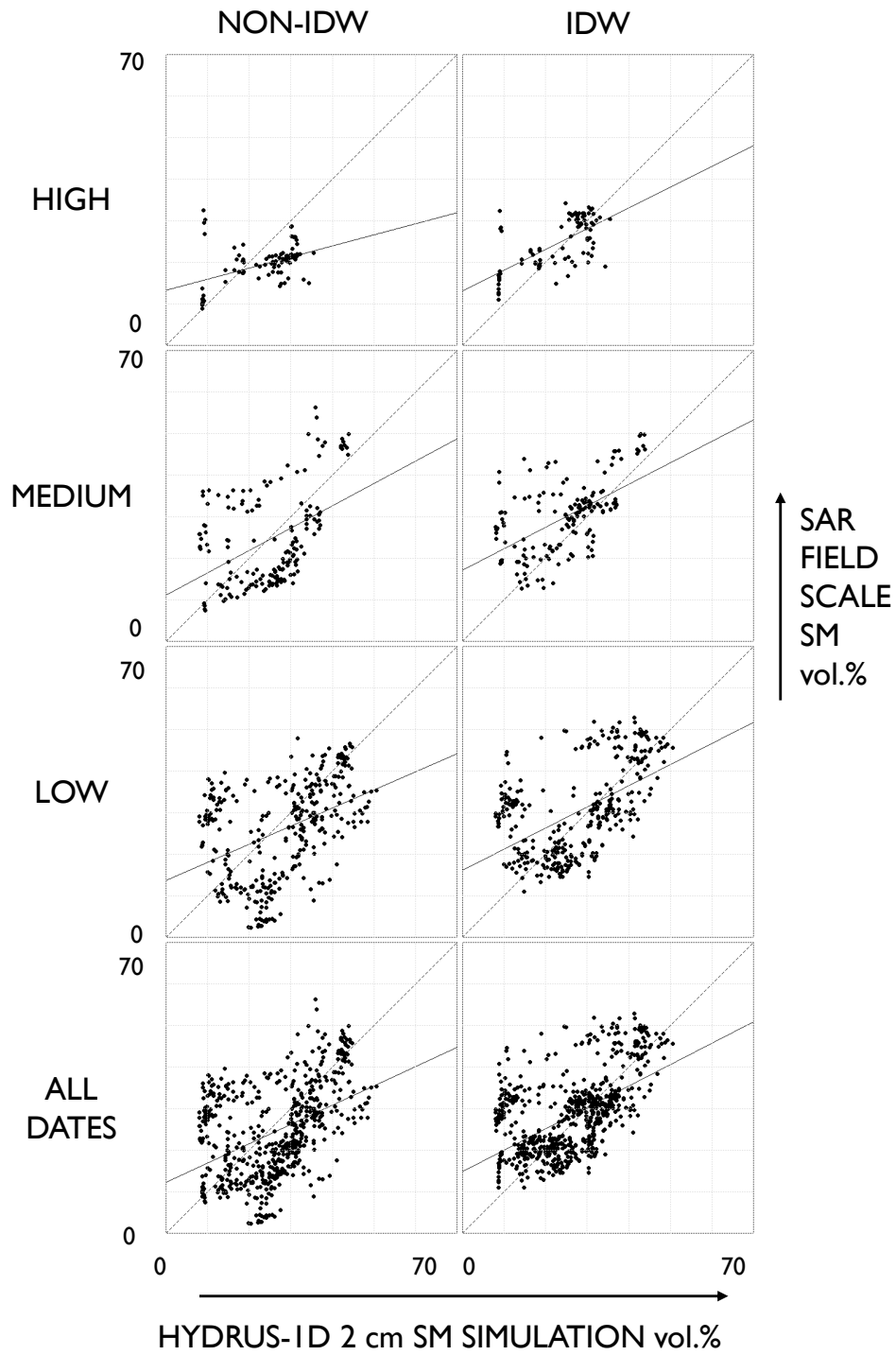


Figure 5.33: IDCW 2018 scatter plots: cut/ley grass

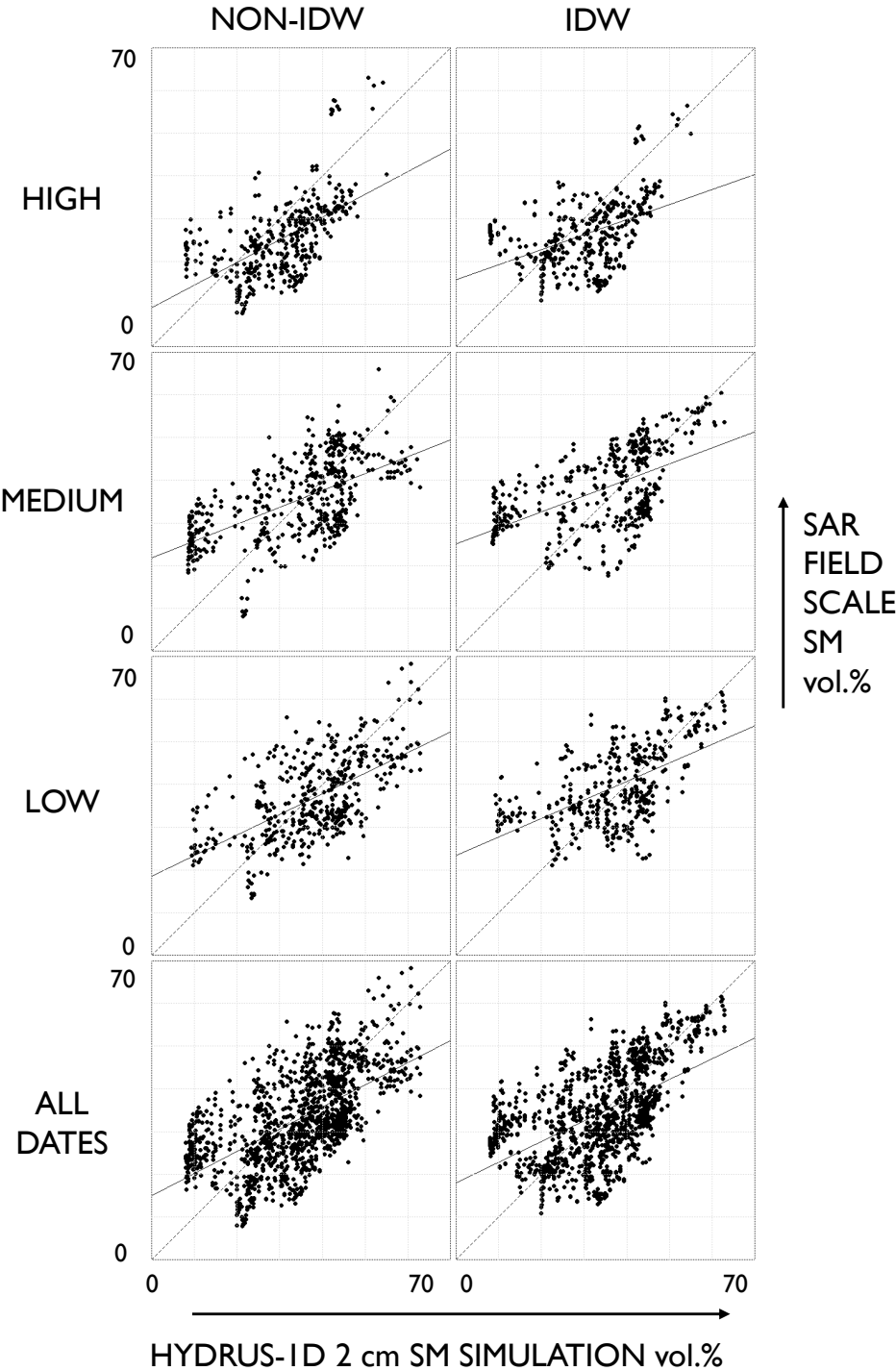


Figure 5.34: IDCW 2018 scatter plots: grass

5.C IDCW performance by site and individual field parcel.

This appendix comprises a series of tables that present the qualitative metrics of the coefficient of determination, R^2 , and Mean Absolute Error, MAE for the SAR-derived soil moisture, and the IDCW output. These metrics were calculated for each individual field for the whole year and, separately, for periods of high, medium and low confidence in the Change Detection algorithm, based on the classification scheme used by this study. The key to the sites in each table are E - Elmsett, F - Fincham, L - Loddington, S - Spen Farm and W - Writtle.

Table 5.19: IDCW Impact on individual fields of Oil-seed rape

Field GID	Site Confidence	No IDCW				Pure IDCW				Hybrid			
		ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW
Coefficient of determination, R^2 :													
445882	E	0.22	0.53	0.08	0.14	0.48	0.75	0.55	0.12	0.46	0.66	0.55	0.12
599120	E	0.21	0.31	0.06	0.26	0.49	0.67	0.69	0.25	0.47	0.50	0.69	0.25
2774481	F	0.07	0.15	0.21	0.08	0.58	0.57	0.64	0.35	0.55	0.39	0.64	0.35
694503	L	0.26	0.63	0.07	0.03	0.62	0.78	0.36	0.01	0.59	0.73	0.36	0.01
496150	S	0.00	0.07	0.45	0.15	0.48	0.51	0.70	0.51	0.42	0.30	0.70	0.51
Mean absolute error, MAE vol. %:													
445882	E	8.41	9.29	9.99	6.56	8.52	7.27	8.22	9.55	8.78	8.28	8.22	9.55
599120	E	8.05	7.76	11.81	5.66	8.34	5.25	8.90	9.03	8.55	6.48	8.90	9.03
2774481	F	6.43	5.82	6.53	7.32	4.19	3.88	3.97	5.10	4.20	3.90	3.97	5.10
694503	L	10.00	6.48	12.76	23.33	5.96	5.96	6.25	5.59	5.97	5.97	6.25	5.59
496150	S	6.93	7.43	8.98	5.93	5.27	5.42	5.78	5.24	5.48	6.37	5.78	5.24

Table 5.20: IDCW Impact on individual fields of Winter Wheat

Field GID	Site Confidence	No IDCW				Pure IDCW				Hybrid			
		ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW
Coefficient of determination, R^2 :													
413885	E	0.13	0.48	0.72	0.04	0.44	0.73	0.53	0.22	0.42	0.64	0.53	0.22
1403205	E	0.22	0.66	-	0.10	0.48	0.74	-	0.28	0.48	0.72	-	0.28
161407	F	0.17	0.47	0.32	0.07	0.53	0.62	0.53	0.23	0.47	0.54	0.53	0.23
2303484	F	0.15	0.42	0.20	0.09	0.42	0.55	0.44	0.34	0.38	0.48	0.44	0.34
2605750	L	0.36	0.72	0.61	0.00	0.56	0.80	0.71	0.00	0.57	0.80	0.71	0.00
1743268	L	0.38	0.74	0.08	0.79	0.61	0.78	0.38	0.05	0.61	0.78	0.38	0.05
150919	S	0.34	0.75	0.48	0.50	0.48	0.71	0.33	0.25	0.49	0.74	0.33	0.25
1278948	S	0.34	0.66	0.51	0.53	0.51	0.79	0.42	0.25	0.51	0.73	0.42	0.25
2134643	W	0.35	0.85	0.48	0.02	0.52	0.77	0.26	0.00	0.60	0.86	0.26	0.00
1791653	W	0.26	0.83	0.52	0.13	0.47	0.72	0.41	0.05	0.58	0.84	0.41	0.05
Mean absolute error, MAE vol.%:													
413885	E	12.85	10.12	8.39	15.31	8.04	7.84	5.95	8.66	8.30	8.79	5.95	8.66
1403205	E	11.63	8.32	-	13.94	8.58	7.81	-	9.12	8.61	7.87	-	9.12
161407	F	10.09	6.76	9.75	18.55	4.13	3.92	3.84	5.00	4.78	5.18	3.84	5.00
2303484	F	10.03	7.26	10.49	15.67	5.18	5.30	5.07	5.03	5.66	6.23	5.07	5.03
2605750	L	8.19	5.29	6.87	17.81	6.47	5.78	5.81	8.61	6.12	5.20	5.81	8.61
1743268	L	8.29	5.30	16.52	17.54	6.16	5.43	7.01	9.00	5.93	5.11	7.01	9.00
150919	S	9.85	3.24	7.12	20.74	5.15	4.34	5.37	6.41	4.94	3.45	5.37	6.41
1278948	S	10.05	3.84	6.42	20.55	5.00	3.99	4.51	6.93	4.95	3.73	4.51	6.93
2134643	W	11.50	12.8	6.20	16.43	11.36	13.85	8.26	7.24	11.00	13.24	8.26	7.24
1791653	W	12.50	12.91	6.85	19.38	11.53	14.25	8.12	6.05	11.06	13.48	8.12	6.05

Table 5.21: IDCW Impact on individual fields of Spring Wheat

Field GID	Site Confidence	No IDCW				Pure IDCW				Hybrid			
		ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW
Coefficient of determination, R^2 :													
1579879	F	0.56	0.69	0.68	0.09	0.58	0.7	0.35	0.15	0.59	0.72	0.35	0.15
66982	L	0.45	0.38	0.54	0.02	0.57	0.37	0.76	0.03	0.60	0.47	0.76	0.03
312978	W	0.52	0.53	0.10	0.61	0.37	0.38	0.12	0.18	0.42	0.53	0.12	0.18
Mean absolute error, MAE vol. %:													
1579879	F	5.22	4.46	4.27	9.47	4.1	3.44	5.52	6.85	4.4	3.82	5.52	6.85
66982	L	7.03	7.74	6.05	5.70	6.60	7.18	3.63	9.70	6.37	6.79	3.63	9.70
312978	W	9.20	8.63	11.94	8.68	11.70	9.72	19.92	12.55	10.88	8.61	19.92	12.55

Table 5.22: IDCW Impact on individual fields of Winter Barley

Field GID	Site	No IDCW				Pure IDCW				Hybrid			
	Confidence	ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW
Coefficient of determination, R^2 :													
2473119	L	0.33	0.67	0.38	0.40	0.48	0.68	0.58	0.62	0.51	0.70	0.58	0.62
1235870	S	0.40	0.67	0.31	0.50	0.45	0.59	0.38	0.62	0.48	0.72	0.38	0.62
2256950	W	0.00	0.26	0.04	0.05	0.39	0.76	0.52	0.07	0.39	0.49	0.52	0.07
Mean absolute error, MAE vol. %:													
2473119	L	9.36	6.57	10.42	19.64	6.93	6.61	5.17	12.56	6.63	6.04	5.17	12.56
1235870	S	6.24	3.51	5.31	9.71	5.23	3.84	5.53	5.65	5.14	3.23	5.53	5.65
2256950	W	17.86	12.26	11.51	23.60	12.52	16.60	8.65	11.72	11.64	13.58	8.65	11.72

Table 5.23: IDCW Impact on individual fields of Spring Barley

Field GID	Site Confidence	No IDCW				Pure IDCW				Hybrid			
		ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW
Coefficient of determination, R^2 :													
1700954	E	0.32	0.00	0.24	0.35	0.41	0.11	0.02	0.50	0.40	0.05	0.02	0.50
2216304	F	0.53	0.7	0.37	0.28	0.56	0.66	0.33	0.63	0.59	0.7	0.33	0.63
1573704	L	0.43	0.69	0.49	0.00	0.50	0.71	0.34	0.29	0.50	0.69	0.34	0.29
1945379	S	0.61	0.68	0.90	0.95	0.51	0.62	0.67	0.71	0.51	0.67	0.67	0.71
Mean absolute error, MAE vol. %:													
1700954	E	9.35	12.02	15.05	7.87	8.77	10.33	12.93	7.80	8.90	11.01	12.93	7.80
2216304	F	5.69	4.5	7.54	8.76	3.89	3.31	6.91	4.74	4.06	3.55	6.91	4.74
1573704	L	9.08	6.94	9.77	20.59	7.54	6.68	8.73	10.28	7.65	6.84	8.73	10.28
1945379	S	6.66	6.13	8.10	7.85	5.09	5.07	5.42	6.42	5.24	5.43	5.42	6.42

Table 5.24: IDCW Impact on individual fields of Field Beans

Field GID	Site Confidence	No IDCW				Pure IDCW				Hybrid			
		ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW
Coefficient of determination, R^2 :													
28667	L	0.67	0.69	0.72	0.08	0.61	0.70	0.66	0.51	0.61	0.70	0.66	0.51
1454954	W	0.37	0.43	0.23	0.38	0.43	0.45	0.07	0.69	0.44	0.45	0.07	0.69
347608	W	0.45	0.45	0.65	1.00	0.37	0.26	0.78	1.00	0.46	0.36	0.78	1.00
Mean absolute error, MAE vol. %:													
28667	L	6.83	6.44	6.94	9.38	6.31	5.63	7.19	9.86	6.51	5.87	7.19	9.86
1454954	W	12.99	14.21	12.89	9.21	11.23	11.54	12.76	9.52	12.11	12.83	12.76	9.52
347608	W	11.70	12.22	10.15	19.44	11.74	12.42	9.82	18.03	11.63	12.26	9.82	18.03

Table 5.25: IDCW Impact on individual fields of Potatoes

Field GID	Site Confidence	No IDCW				Pure IDCW				Hybrid			
		ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW
Coefficient of determination, R^2 :													
572608	F	0.03	0.47	-	0.35	0.57	0.55	-	0.08	0.56	0.52	-	0.08
1359276	S	0.03	0.25	0.01	0.47	0.51	0.59	0.39	0.81	0.47	0.47	0.39	0.81
Mean absolute error, MAE vol.%:													
572608	F	9.49	5.1	-	16.26	3.85	3.02	-	5.13	4.39	3.91	-	5.13
1359276	S	6.74	4.31	9.64	9.08	5.08	5.11	7.03	3.02	4.81	4.15	7.03	3.02

Table 5.26: IDCW Impact on individual fields of Maize

Field GID	Site Confidence	No IDCW				Pure IDCW				Hybrid			
		ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW
Coefficient of determination, R^2 :													
1130061	F	0.01	0.07	0.02	0.08	0.58	0.58	0.64	0.43	0.42	0.34	0.64	0.43
42877	F	0.34	0.53	0.72	0.4	0.55	0.48	0.83	0.2	0.56	0.52	0.83	0.2
Mean absolute error, MAE vol.%:													
1130061	F	8.52	8.14	5.83	12.28	3.8	3.9	3.25	4	4.79	5.5	3.25	4
42877	F	6.08	5.6	2.58	10.57	4.26	4.47	2.84	4.98	4.57	4.99	2.84	4.98

Table 5.27: IDCW Impact on individual fields of Beet

Field GID	Site Confidence	No IDCW				Pure IDCW				Hybrid			
		ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW
Coefficient of determination, R^2 :													
556470	E	0.00	0.16	0.34	0.04	0.38	0.07	0.14	0.32	0.37	0.12	0.14	0.32
513051	F	0.18	0.4	0.72	0.07	0.52	0.36	0.92	0.54	0.58	0.43	0.92	0.54
Mean absolute error, MAE vol. %:													
556470	E	9.60	5.46	13.19	8.88	7.91	5.06	4.68	9.12	7.92	5.26	4.68	9.12
513051	F	7.44	5.05	6.14	10.8	4.23	4.2	5.61	3.57	4.18	4.07	5.61	3.57

Table 5.28: IDCW Impact on individual fields of grass and other - fields with an * were believed to be cut or ley grass, as the evolution of soil moisture follows a similar trend to wheat, in contrast to the other grass fields. Fields with a † were classified by UKCEH Land Cover Plus:Crops as crop type "other", but look similar to grass pasture fields.

Field GID	Site Confidence	No IDCW				Pure IDCW				Hybrid			
		ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW	ALL	HIGH	MED	LOW
Coefficient of determination, R^2 :													
1782851	E	0.63	0.42	0.47	0.79	0.43	0.09	0.52	0.68	0.53	0.27	0.52	0.68
2578949†	E	0.61	0.63	0.49	0.73	0.49	0.58	0.33	0.78	0.52	0.62	0.33	0.78
2545557*	F	0.28	0.74	0.62	0.07	0.56	0.67	0.69	0.03	0.51	0.78	0.69	0.03
1462873	L	0.60	0.01	0.57	0.63	0.57	0.42	0.67	0.51	0.57	0.11	0.67	0.51
275951	L	0.70	0.66	0.77	0.60	0.53	0.71	0.80	0.43	0.55	0.72	0.80	0.43
971697*	S	0.39	0.86	0.66	0.76	0.52	0.36	0.86	0.55	0.55	0.78	0.86	0.55
1386865*	S	0.37	0.25	0.75	0.36	0.52	0.19	0.51	0.49	0.51	0.23	0.51	0.49
2312837†	S	0.48	0.48	-	-	0.51	0.52	-	-	0.50	0.53	-	-
2637110*	W	0.12	0.27	0.76	0.05	0.37	0.60	0.70	0.27	0.37	0.49	0.70	0.27
2548153	W	0.52	0.92	0.81	0.31	0.47	0.90	0.76	0.22	0.47	0.91	0.76	0.22
273322	W	0.62	0.55	0.72	0.23	0.53	0.48	0.56	0.12	0.53	0.52	0.56	0.12
Mean absolute error, MAE vol.%:													
1782851	E	9.70	9.12	11.10	7.80	8.35	7.85	10.01	5.34	8.62	8.39	10.01	5.34
2578949†	E	9.81	10.08	10.67	8.40	8.58	10.11	8.00	4.64	8.55	10.06	8.00	4.64
2545557*	F	8.55	7.07	8.58	9.94	4.15	4.05	3.73	4.76	4.22	4.29	3.73	4.76
1462873	L	6.23	8.29	7.37	5.71	6.17	1.87	6.63	6.18	6.26	5.08	6.63	6.18
275951	L	7.60	3.72	7.16	9.04	6.47	5.93	5.79	7.25	6.17	3.15	5.79	7.25
971697*	S	6.84	2.81	6.00	8.59	4.83	4.90	3.54	5.42	4.70	3.76	3.54	5.42
1386865*	S	5.95	3.66	5.96	6.19	4.92	2.81	5.00	5.30	4.93	3.24	5.00	5.30
2312837†	S	5.95	5.95	-	-	4.86	4.81	-	-	5.06	5.19	-	-
2637110*	W	12.36	20.57	13.16	11.89	12.26	19.90	13.62	11.60	12.26	20.23	13.62	11.60
2548153	W	11.14	12.21	12.72	10.22	11.79	12.26	12.80	11.26	11.79	12.24	12.80	11.26
273322	W	8.87	12.02	9.05	6.00	11.50	14.57	11.83	8.00	11.37	13.27	11.83	8.00

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6 Synthesis and Discussion

6.1 Introduction

This chapter provides a synthesis of the preceding paper format chapters contained within this thesis and discusses the key findings, contribution to knowledge insights gained, and impact of the work in terms of improved soil moisture estimation at field scale for agricultural use. In Section 6.2 the outputs of Chapters 2 to 5 are assessed against the four thesis objectives related to the initial hypotheses followed by the overall progress towards the aims of the thesis and its potential impact of this work are reviewed in Section 6.3.

6.2 Synthesis of objectives

The aim of this thesis was to establish that C-band synthetic aperture radar data from satellites can be used to map soil moisture (SM) at the field scale. To address this aim, four objectives were set, which will be discussed in terms of the key findings.

6.2.1 Objective 1 - Evaluate and select from *state of the art* SAR satellite SM retrieval algorithms for their potential to create field-scale resolution products.

The attraction of SAR, compared to other techniques, is its ability to operate through cloud cover, which is a major issue in northern latitudes. Of the available SAR satellite platforms, C band SAR systems provide a compromise between soil moisture sensitivity, penetration of vegetation and sufficient spatial resolution (~20m) from which to develop field-scale soil moisture products. The European Space Agency's Sentinel-1 satellite was first launched in 2015 and has since been joined by a second

in constellation. There is now a freely available resource of high-quality, C-band SAR data, with global coverage, offering a 1 to 6 day repeat cycle over the UK.

Chapter 2 includes a detailed review of the algorithms for retrieving soil moisture from C-band SAR data. The factors that contribute uncertainty include soil surface roughness, the overlying vegetation, the structure of the surface, soil texture, organic matter content, temperature and radar incidence angle. The factors of major concern being the contributions from vegetation and soil surface roughness, which are particularly relevant in agricultural areas. A key finding was that soil texture, often neglected in the published literature, makes a significant contribution to uncertainty, at about 10-20 vol.% in retrieved soil moisture. Whilst machine learning solutions could be effective, they required many datasets and extensive training data, presenting a challenge when scaling up to national or global contexts.

Temporal processing techniques such as the Change Detection (CD) algorithm ([Bauer-Marschallinger and Paulik, 2019](#); [Mattia et al., 2018](#)), were attractive in requiring no model training and only needed a set of SAR backscatter statistics based on the historical record of previous observations. In late 2018 the Copernicus SSM (Surface Soil Moisture) product ([Bauer-Marschallinger and Paulik, 2019](#)) was released and became the first freely available soil moisture product on a global scale based on Sentinel-1 data. It is based on the CD algorithm, and as the new "state of the art", its performance was evaluated for agricultural use at field scale. Two issues were immediately obvious, the resolution for the published product was 1 km, which may contain around 11 average-sized arable fields in the UK. The spatial resolution is an order of magnitude lower than UK field scale requirements, with each pixel also including non-cultivated areas such as hedges, trees, buildings and roads. Key assumptions, that soil surface roughness and vegetation vary slowly relative to soil moisture, contradict farming practice. Tillage and crop harvesting break these assumptions where arable crops are grown.

6.2.2 Objective 2 - Assess the performance of existing Copernicus SSM product for agricultural fields

Objective 2a - Develop a validation method for C-band SAR derived surface soil moisture products at COSMOS-UK ground stations

Key to developing any SM data product is the ability to assess its performance against independent observations of SM on the ground. The COSMOS-UK net-

work of 50 soil monitoring stations within the UK operated by the UK Centre for Ecology and Hydrology (UKCEH), was established, in part, to satisfy this need. By using the Cosmic Ray Neutron Sensing (CRNS) method to measure soil moisture averaged over a large area of 200 m radius, the scale is almost ideal to validate the performance of a field-scale satellite product. However, the mismatch in measurement depth represented a significant research gap that had not been investigated before, as discussed in Chapter 3. Existing best practice, as described by Gruber et al. (2020), was to compare C-band SAR-derived SM estimates against probes installed at 5-10 cm depth. With the penetration depth of the SAR only 2 cm, Chapter 3 demonstrated that validations carried out in this way would have significantly underestimated the performance of the satellite products.

To address this problem a novel method was proposed to generate soil moisture simulations at 2 cm soil depth, based on measurements of rainfall and potential evapotranspiration that were available at the COSMOS-UK sites. The simulations were carried out using an established hydrological model, HYDRUS-1D, fitting the soil hydraulic parameters to COSMOS-UK CRNS measurements. To achieve this, the equivalent, or mean measurement depth of the CRNS sensor had first to be determined. It is standard practice to accompany each CRNS SM measurement with its effective measurement depth, D86 (Köhli et al., 2015). This is defined as the soil depth above which 86% of the cumulative sensitivity is predicted. But Tian and Song (2019) found that CRNS SM is strongly correlated with 10 cm soil moisture, even though D86 is usually much deeper, due to an exponential decrease in sensitivity with soil depth. Chapter 3 describes a new method to calculate a mean sensitivity depth, D50. Its average value over the 13 study sites was almost exactly 10 cm in 2018 confirming the findings of Tian and Song (2019). The model fitting used the point measurements of rainfall and potential evapotranspiration at the centre of the COSMOS-UK sites, which were assumed to be constant over the radius of sensitivity of the CRNS sensor. This radius, though assumed to be 200 m, is also slightly dependent on soil moisture. The uncertainties introduced in the model fit due to these assumptions are likely to be small as the spatial variation of rainfall and evapotranspiration are on a much larger scale. A greater source of uncertainty would arise from the assumption that the same model parameters are valid across one or more overlapping fields, this is a function of soil heterogeneity and is almost impossible to predict.

The selection of HYDRUS-1D as the model to fit was based on its reputation in the published literature for accuracy in predicting soil moisture at shallow depths.

Many soil moisture models were designed with the sole objective of predicting root zone soil moisture for drought prediction and irrigation scheduling. For example, the WASIM model (Hess, 2019) was considered but found to be unsuitable for 2 cm depth simulation without significant modification which would have required further validation. The HYDRUS-1D model was found to be able to reproduce the soil moisture observed at 10 cm whilst also predicting a surface soil moisture profile that was consistent with the temporal characteristics of the satellite backscatter signal. The potential use of alternative models could be considered in future studies.

The simulated soil moisture at 2 cm is based on daily totals of measurements of rainfall and evapotranspiration and therefore represents the expected soil moisture at midnight on the day in question. The Sentinel-1 acquisition times are, in the case of the UK, typically 6 or 18 hours either side of this, and this will be the source of further uncertainty, especially whether there are extreme changes in rainfall, temperature or wind. In further work, the possibility of generating simulated soil moisture at 6 or 12 hourly intervals could be considered. It should also be recognised that the proposed technique uses a modelled output as its reference as a best estimate of the actual conditions in the soil. This modelled output itself may be in error, which will propagate into the final assessment and gives a slightly pessimistic view of the accuracy of SM retrieved from remote sensing. However, similar considerations should be made for comparisons against in-situ soil moisture probes or CRNS sensors. In these cases, the measurements are also the output of models that convert measurements of electrical parameters or neutron counts into soil moisture. As discussed in Chapter 1, these errors can be as high as 3-5%.

A major advantage of the proposed assessment technique is that it is not limited to sites in any geographical location, in principle. All that is required is a set of in-situ soil moisture measurements with contemporary and co-located measurements of rainfall and potential evapotranspiration. The soil hydraulic parameters can be set at initial values by soil textural class that does not require an extensive database, that latter only serving to reduce the time it should take to reach an acceptable model fit. The limitations are more likely to come from soil types that are hard to model in HYDRUS-1D, which might be due to shallow soil depth, very high organic matter content, or extreme relief. Otherwise, the technique should be applicable worldwide.

Having fitted the HYDRUS-1D model at 10cm, it was used to generate soil moisture time series at 2 cm and 10 cm from site meteorological data and MODIS

measurements of LAI. The performance of the Copernicus SSM soil moisture was assessed against these two sets of reference data. In 10 out of the 13 COSMOS-UK sites (chosen to represent a range of lowland sites with an equal mix of arable and pastureland), the Copernicus SSM estimate appeared more accurate when compared to 2 cm soil moisture than when compared to 10 cm soil moisture. This new method for SAR SM validation at 2 cm soil depth was adopted for all subsequent assessments in this thesis, rather than use the 10 cm depth SM probes installed at the COSMOS-UK sites. The other reason for not using the probes was that the simulated 2 cm reference soil moisture is modelled at the spatial scale of the CRNS sensor footprint (around 200 m radius). This is a much closer match to the spatial scale of the field-scale SM retrieval than that represented by a point measurement, which would have added extra uncertainty.

Chapter 3 also investigated the error in the conversion of relative SM, or soil moisture index (SMI) values, to volumetric soil moisture. The output of the Copernicus SSM product is an SMI, leaving the end user to make the conversion. The choice of wet and dry reference values should be based on the most accurate soil hydraulic parameters available and take account of the wider range of potential SM within the top 2cm of soil. Chapter 3 concluded that the best calibration references to use were the van Genuchten model parameters θ_s and θ_R . The potential error in using θ_{FC} and θ_{PPP} , as commonly recommended, was shown to be as high as 20 vol.% under some conditions. These references were used in all future analysis.

Objective 2b - Use this method to quantify the performance of Copernicus SSM in the context of agricultural land uses

This objective was addressed partially in Chapter 3, when the Copernicus SSM product was assessed at the 13 COSMOS-UK sites using the validation method that was developed previously. At least half of these sites were under arable cultivation, where the performance seemed particularly poor with errors of around 10% to 20% in volumetric soil moisture (vol.%). However, with a 1 km product it was not possible to gain further insights until a field-scale equivalent had been developed. This is reported in Chapter 4, where further analysis is presented for individual fields, where the crops and dates of key farming activities (such as harvesting or tillage) were identified by daily observations of the COSMOS-UK phenocams. A key finding from this analysis was that the performance of the CD algorithm was highly dependent on the crop type and stage. Good performance was observed

when the soil was bare, usually after tillage, with errors of around 4 vol.% to 7 vol.%, whereas in the peak growing season of most crops, there was no apparent SM measurement capability with errors around 20 vol.% being typical.

This is consistent with the lack of a published, reliable field-scale soil moisture product below 1 km resolution, which has only been explicitly addressed relatively recently (El Hajj et al., 2018; Mattia et al., 2020). The correlation between radar backscatter and NDVI is well established and incorporated in some algorithms (Bazzi et al., 2019; Mattia et al., 2018), but the mitigation of the complete loss of capability appears to have been a major barrier to the creation of field-scale products on a large scale.

Another key finding was that the SM derived by the CD algorithm was very noisy, with much of that noise having a periodic element. An exponential filter was found to be useful in reducing this noise but with some loss of temporal response to rainfall events. However, there remains a question of how to resolve this issue at source. The results of this thesis suggest that the problem may be a mixture of clutter effects (Tadono et al., 2000), SAR layover issues, and interactions between the SAR and the structure of the crop canopy (Joseph et al., 2010).

6.2.3 Objective 3 - Increase the spatial resolution of the algorithm to achieve field scale output by using field parcel boundaries and compare the performance levels to the 1km gridded product

The completion of this objective was reported in Chapter 4. The implementation of a change detection algorithm in Google Earth Engine (GEE) (Gorelick et al., 2017) was a necessary first step towards field-scale soil moisture estimation that became one of the major challenges of the thesis. It was necessary in order to gain control of the spatial resolution of the output and preserve the processing of data at the sensor resolution so that the later aggregation to the arbitrary shape of agricultural fields would contain as many pixels as possible. On the way, issues were discovered with the detail of the implementation such as the calculation of local incidence angle (LIA) (both in GEE and the Sentinel-1 toolbox (European Space Agency, 2021)) and the normalisation of SAR backscatter to a fixed angle of 40° to minimise vegetation effects (according to the method of Bauer-Marschallinger et al. (2019)). The LIA issues were improved by devising a bespoke slope and aspect calculation,

treating the ascending and descending orbits separately, eroding field boundaries and temporally smoothing the soil moisture estimates with a Savitzky-Golay filter.

A 20 m resolution soil moisture output was created that could then be spatially aggregated to field scale and to the same 1 km pixel grid allowing direct comparison with the published Copernicus SSM product. In a small majority of grass fields, the 1 km gridded product produced slightly lower errors than the field-scale, but the opposite was true in some other fields. Where observed, the small amount of additional noise in the field-scale estimate was believed to be a result of averaging speckle noise over a smaller area. This had been anticipated, but the magnitude was less than expected, suggesting that noise from other sources had been reduced in compensation. Clutter from objects such as buildings, hedges and roads would have contributed to noise in the SAR backscatter for the 1 km pixel product. The conclusion of the work in Chapter 4 was that it was feasible to create a field scale SM product from Sentinel-1 SAR data using the change detection algorithm.

As the implementation of the Change Detection algorithm on GEE is based on the published methods of [Bauer-Marschallinger et al. \(2019\)](#), it is subject to the same geographical limitations of the Copernicus SSM product, which is Europe. To extend the capability beyond this will require the development of a suitable backscatter normalisation process for the region in question. There would be potential to develop the GEE code further and offer it as a resource to other developers or even develop from it a soil moisture application for public access.

6.2.4 Objective 4 - Demonstrate an improvement in performance of the field scale algorithm by correcting for the influence of crop cover and anthropogenic change and identify a route to scale this to UK national coverage.

Chapter 5 addressed the poor performance of the change detection SM estimates at field-scale for arable fields that was concluded in earlier chapters. Such a product would be of limited benefit to agriculture if the loss of performance during the key growing season of these crops is not resolved. The solution was proposed in two stages. Firstly, a scalable, automated method was developed and demonstrated to classify fields with a confidence level to predict the expected performance level of the field-scale SM estimate on a particular date. This method used a spectral unmixing approach ([Yue and Tian, 2020](#)) with vegetation indices (NDVI and

CAI) derived from Sentinel-2 data to estimate relative land cover fractions of bare soil and photosynthetically active and inactive vegetation. The second stage was the successful implementation of an inverse distance and confidence weighting (IDCW) algorithm to provide a more accurate estimate of SM at field scale, based on neighbouring fields.

The automated confidence classification and IDCW mitigation was found to be suitable for use, not only within the low confidence periods, but over the whole year. The only exception was grass pasture, where it was of no benefit. The benefits were greatest for autumn-sown cereal crops, where the mean error in the growing season was reduced from almost 20 vol.% to around 5 vol.%. The level of performance now achieved matches the requirements of farmers for a 5 vol.% accuracy with an update of once to twice per week. This is a very significant improvement during the growing season when farmers need this information for key decision making related to the management of their crops. The output is also very close to the performance requirements of 4 vol.% of the research community and is likely to achieve that with modest future improvements.

This achievement in performance compares favourably to assessments of other field-scale algorithms using Sentinel-1 C-band SAR data, reported in recent studies. For example, [Benbrahim et al. \(2020\)](#) reported an RMSD over agricultural fields of no less than 9.3 vol.%, whilst [Mattia et al. \(2018\)](#) and [Mattia et al. \(2020\)](#) have reported a RMSD of 6 vol.% for their short term change detection (STCD) technique - though this probably excludes masked out fields that have recently been harvested, for example. The earlier SMOSAR approach ([Mattia et al., 2017](#)) reported an RMSD of 6.6 vol.%. Neural network approaches, such as that behind the S²MP product have achieved RMSD values between 4.0 and 5.1 vol.% ([Hajj et al., 2017](#); ?). However, the latter technique has the disadvantage of requiring training datasets, which the approach developed here does not, being based entirely on change detection and contemporary remote sensing data. A downscaling approach ([Zappa et al., 2019](#)) to retrieve field-scale SM output from coarser resolution SAR-derived SM products was also reported as having an RMSD of 5.6 vol.%.

6.3 Summary

The improved prototype field-scale soil moisture product, based on C-band Sentinel-1 data, meets the performance requirements of farmers and agriculturalists who need a 5 vol.% accuracy estimate of in-field surface soil moisture, every 1-6 days

Moran (2000); Moran et al. (1997). It will be possible, in the near future, to publish a regularly updated product for farmers and agriculturalists that would give them an estimate of in-field surface soil moisture, every 1-6 days (in the UK). The latency should be no more than 1-2 days and could be delivered by value-added web or mobile apps. Such data would be of immediate benefit for decision making in managing crops, especially in avoiding pollution when spraying or spreading fertilizer and for workability assessment and livestock welfare. Whilst farmers also require estimation of root zone soil moisture in the management of crops this should be achievable as a next step.

The prototype SM estimation capability is very close to meeting the needs of the research community for data to support land surface models and numerical weather prediction. The required accuracy of 4 vol.% as specified for the SMOS satellite sensor (European Space Agency, 2017) is almost met. The field-scale product offers the considerable benefit of the exclusion of low SM sensitivity areas and most clutter sources. The data could be used to inform scientists, engineers, infrastructure engineers and environmentalists on potential issues such as the potential for flooding, soil erosion, ground movement and landslip. The field-scale soil moisture could be assimilated into products being developed by the Hydro-JULES project (UK Centre for Ecology and Hydrology, 2018), made available as a dataset in Google Earth Engine, or through the Copernicus programme as an enhancement to their SSM product.

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7 Conclusions and Recommendations

7.1 Conclusions

Objective 1: Evaluate and select from *state of the art* SAR satellite SM retrieval algorithms and their suitability for potential field-scale resolution products.

This study concludes that change detection algorithms have the greatest potential for scalability in remote sensing of soil moisture. They have low demands, compared to other methods, for model training and other sources of data. The main disadvantages of poor performance in agricultural areas and at field-scale have been demonstrated but have potential solutions, including those developed in thesis.

Through its implementation of a change detection (CD) algorithm in Google Earth Engine this thesis exposed a number of issues and weaknesses in the algorithm. These include artefacts in the calculation of local incidence angle (LIA), and unreliable normalisation of backscatter to a fixed LIA. These issues contribute to orbit-related dependencies that manifest as periodic noise (up to 20 vol.% in magnitude) in the time series of soil moisture. The study identified other causes, such as clutter sources, SAR layover and interactions between the SAR beam and the structure of the crop canopy and soil roughness. Pending an algorithmic solution to this problem, the study has demonstrated that use of exponential or Savitzky-Golay filters may be effective in the reduction of this noise and improving the performance of the algorithm output and the published Copernicus SSM product.

Objective 2: Assess the performance of existing Copernicus SSM product for agricultural fields

(a) Develop a validation method for C-band SAR derived surface soil moisture products at COSMOS-UK ground stations

The soil texture and depth of SAR penetration are important to the conversion of relative surface SM to volumetric units. The estimation of wet and dry references is a source of uncertainty in this process. This study has shown that the van Genuchten soil hydraulic parameters θ_S and θ_R are a better choice than field capacity and permanent wilting point to define the range of SM at the surface. Here rainfall and evaporation are more significant drying and wetting mechanisms than at lower levels. By following this recommendation, the errors are reduced by up to 20 vol.%.

When validating SAR-derived surface SM estimates the C-band depth of penetration also must be taken into account, but it is near impossible to measure soil moisture at 1-2 cm depth reliably. This study has developed an alternative new method which simulates soil moisture at 2 cm depth of soil using a model fitted to *in situ* SM observations of the COSMOS-UK ground stations, and using the proposed calibration references. Current validation methods (Gruber et al., 2020), using soil moisture probes, were shown to underestimate the performance of C-band soil moisture products in 10 out of 13 test sites evaluated. The limitation here is likely to be the additional uncertainty introduced by the model sitting error, which varied between sites.

(b) Use this method to quantify the performance of Copernicus SSM in the context of agricultural land uses

The estimation of SM by the change detection method from C-band SAR data suffers a loss of capability in most crops at the peak of the growing season (RMSE of up to 20 vol.%), but good performance where the soil is bare (RMSE 4 to 7 vol.%). In cereal crops and ley grass CD underestimated SM, but overestimated SM in other crops (such as oil-seed rape and potatoes). The field scale output reveals the true performance of the CD processing of SAR imagery in fields of arable crops.

Objective 3: Increase the spatial resolution of the algorithm to achieve field scale output by using field parcel boundaries and compare the performance levels to the 1 km gridded SM estimates

The study has demonstrated that by use of eroded field parcel boundaries for spatial aggregation of the results of the CD algorithm produces field-scale SM estimates with little or no additional uncertainty compared to a 1 km gridded output (both with 8-16 vol.% RMSD). The increase in random error introduced by averaging radar speckle over a smaller area is balanced by the elimination of areas of low sensitivity and sources of clutter outside the cultivated areas. The erosion of field boundaries by 20 m is sufficient to achieve this in the examples studied.

Objective 4: Demonstrate an improvement in performance of the field scale algorithm by correcting for the influence of crop cover and anthropogenic change and identify a route to scale this to UK national coverage.

A novel method of applying the CD algorithm at field-scale is proposed, using spatial interpolation. The first stage is the date-wise classification of arable fields into categories of low, medium and high confidence in the accuracy of the CD algorithm. The SM estimate for each field is then determined by inverse distance and confidence weighting (IDCW). This is shown to be effective for arable crops at all times of year, but is most beneficial for autumn-sown cereal crops. For example, implementation of the proposed method demonstrated an accuracy improvement from mean absolute errors of >16 vol.% to 7.4 vol.% ($p < 10^{-41}$) when used in the main growing season of winter wheat crops. Against all crops studied and in all seasons the mean absolute error improved from 8.3 vol.% to 6.7 vol.% ($p = 0$). This is much closer to the 4 vol.% target accuracy of respected low resolution passive microwave satellite sensors such as SMOS. Further improvements should be possible following the recommendations of this study.

Thesis Aim: To establish that C-band synthetic aperture radar data from satellites can be used to map soil moisture (SM) at the field scale.

Overall the thesis has established that C-band synthetic aperture radar data from satellites can be used to map soil moisture at the field scale using the CD

For crop management and irrigation, root zone soil moisture is of much greater importance to the farmer. A significant research gap still exists in converting surface soil moisture estimates to the root zone, and how the sparse time series of the satellite observations can be managed. The methods of [Wagner et al. \(1999\)](#) using the surface soil moisture estimate as a surrogate for rainfall and propagating this water to deeper soil levels may be a solution, but the gaps in measurement by the satellite risk missing rainfall events altogether. This remains an area of concern until the frequency of satellite measurements is increased to daily. It should be possible to make further use of the HYDRUS-1D model, fitting it to satellite surface SM estimates to deduce rainfall amounts. From this the model may then be used to simulate the soil moisture at any depth required.

In the proposed method, Sentinel-2 data is used for field classification. This optical data is prone to missing observations due to cloud cover. The use of the radar backscatter itself to estimate the vegetation status would be a significant step forward if it can be done effectively.

The weaknesses discovered during the implementation of the change detection algorithm in Google Earth Engine, should be investigated in further. The main issue was that the TU Wien normalisation process for Sentinel-1 data was not reliable for the sites studied. The reasons for this require further investigation, or alternative approaches should be developed. This may be a major contributor to the temporal noise that appeared to be related to orbit geometry, but other causes such as layover and crop structure could also be examined. A statistical analysis of temporal trends and frequency components should be undertaken as a first stage to inform this investigation.

The soil moisture retrieval process includes comparison to historical records of backscatter observations at each scene location. In the case of arable fields, these statistics include periods when it is now known that the soil moisture sensitivity is very low. It would be beneficial to discover if excluding the periods of rapid crop growth in this historical record would increase the accuracy of the estimation still further.

Despite the use of field boundaries to eliminate non-cultivated areas from the field scale product, some clutter sources remain in the calculation. These include electricity pylons, wind turbines, small structures and small areas of compacted soil and hard-standing. An automated method of masking these areas may have a beneficial impact on the accuracy of the product. Similarly, automated feature extraction could be used to define the field boundaries and eliminate dependence

on third party data which may be out of date or inaccurate.

Refinements that could be made to the IDCW method, starting with the optimisation of the relative weighting powers for distance and confidence. Other two-dimensional spatial interpolation methods could also be explored, including kriging and linear effects modelling. The IDCW technique does not currently take account of the direct soil moisture estimate from the satellite without interpolation, an obvious step is to explore how to combine these two results statistically to get the best overall accuracy and sensitivity to in-field changes in soil moisture due to irrigation or flooding, for example.

Finally, the results of this thesis could be used to create a mapping product for use by farmers and agronomists using Google Earth or other GIS tool. An illustration of what is already achieved is shown in Fig.7.1, which is based on actual results of the IDCW SM estimate for the 1st July 2018 in a number of field surrounding the Fincham study site.

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