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**Sensing Charcoal Making and
Understanding Links to Deforestation in
Tanzania**

School of Water, Energy and Environment
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PhD

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Impacts of COVID 19

The outbreak of COVID 19 had an impact on my research activities regarding changing objectives, methodology and plan. The original methodology proposed required a set of interviews to the community to be conducted in the research area as part of the source apportionment studies. The interviews aimed to firmly understand the views of local community regarding impact of charcoal making in the area. This methodology was abandoned based on the COVID-19 outbreak as it was strictly prohibited to conduct face to face interviews during the research. Also, the initial research plan aimed to conduct physical inventories on the charcoal kilns in the area. Instead, GIS based approach using proxy variables and image classification was used to identify possible kilns in the field. The use of the GIS based approach without ground truthing could have resulted on possible errors. Ground truthing was planned to be conducted through surveying around the Usambara mountain. However, the planned was changed due to COVID 19 restrictions. Further, during the outbreak, I was admitted into the hospital after contracting COVID-19. This resulted in requesting multiple study extensions due to both physical and mental strain. Sometime was spent thinking of quitting due to stress as the result of the COVID 19 impacts. I thank Our Almighty God for keeping me safe and completing this study.

Abstract

Charcoal making produces atmospheric pollutants that have an impact on human health. In Tanzania, charcoal making activity is widely spread and not properly regulated. The spatial distribution of charcoal kilns is unknown, and this makes management and control of such activity extremely difficult, especially in nature reserves. The aim of this study was to advance current knowledge on environmental impacts (i.e., deforestation and air quality) of charcoal making in Tanzania. The specific objectives were, to develop a methodology to quantify charcoal production emissions in ambient conditions; to identify areas of high-density kilns and changes in charcoal production around the East Usambara Mountains using GIS approaches; and to link charcoal production with catchment impact and degradation. The data analysis involved the isolation of charcoal emission plumes from other regionally important sources, the identification of areas of high-density kilns and changes in charcoal production around east Usambara mountains using GIS-based approaches and the link of charcoal production with catchment environmental impacts. The statistical testing for significant difference in the distribution of concentrations in the pre, during and post periods was identified to comprehend the variation in the observed mean across phases of the testing procedure. The results suggest that there were no statistically significant differences between pre, during and post periods. However, the sensor used in the study was effective in identifying pollutants in tropical regions, despite calibration challenges. The study also identified the sources of pollutants and their trajectories, with southern-eastern winds being a significant factor. Human-induced activities and local emissions were found to contribute to the pollution. The study analysed the emission ratios of pollutants, but found insignificant links between CO and CO₂, as well as PM₁ and CO₂. Furthermore, this study establishes a connection between charcoal production and negative effects on the East Usambara Mountain catchment area. The research findings show that humid forest regions had a significant concentration of proxy variables associated with charcoal production. The study also identifies differences in charcoal-making activities among different forest regions. The prevalence of dark patches indicates a high frequency of charcoal production in

the area. The study also reveals a decrease in the quantity of charcoal-making activities between 2013 and 2015, followed by an increase from 2016 to 2019. The study estimates that a significant amount of charcoal was produced, resulting in the harvesting of many trees and the emission of CO and CO₂. Overall, the findings highlight the need for sustainable charcoal production practices to mitigate the negative impacts on the surrounding environment. The findings presented in this study demonstrate a mechanism that enables the characterisation of and differentiation between charcoal burning and production signatures. It is recommended that a citizen scale technique developed for detection of emissions and consequence of charcoal making into the community. To investigate strategies to move toward non-fossil fuel sources in Tanzania to reduce pressure on the use of forest. To set up sound regulation around charcoal making activities in Tanzania and development of approaches for sustainable charcoal production in Tanzania.

Keywords: Deforestation, Charcoal, Electrochemical sensors, Geographical Information System, Catchment management, environmental impact, and degradation.

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List of Abbreviations

ARL	- NOAA's Air Resources Laboratory
CH ₄	- Methane
C ₂ H ₆	- Acetic acid
CO	- Carbon monoxide
CO ₂	- Carbon dioxide
DBH	- Diameter at Breast Height
DESA	- Department of Economic and Social Affairs of the United Nations
FAO	- The Food and Agricultural Organisation of United Nations
GDAS	- Global Data Assimilation System
GIS	- Geographical Information System
GFS	- Global Forecasting System
GPS	- Geographical Positioning System
HQ	- Headquarter
HYSPLIT	- HYbrid Single-Particle Lagrangian Integrated Trajectory
KML	- Keyhole Markup Language
LULUCF	- Land use and cover change
LCS	- Low-cost sensors
NCEP	- NOAA National Centers for Environmental Prediction
NDIR	- Non-dispersive Infrared
NMHC	- Non-Methane Hydrocarbons
NO	- Nitrogen oxide
NO ₂	- Nitrogen dioxide
NOAA	- US-National Oceanic and Atmospheric Administration
O ₃	- Ozone
OLI/TIRS	- Operational Land Imager/ Thermal Infrared Scanner
OPC	- Optical Particle Counter
PM	- Particulate matter
PM ₁	- Particulate matter have a diameter of 1 micron or smaller
PM _{2.5}	- Particulate matter have a diameter of 2.5 micron or smaller
PM ₁₀	- Particulate matter have a diameter of 10 micron or smaller
POM	- Polycyclic organic matter

ppb	- Part per billion levels
QGIS	- Quantum Geographical Information Software
READY	- Real-time Environmental Applications and Display sYstem
TFCG	- Tanzania Forest Conservation Group
URT	- United Republic of Tanzania
USD	- United States Dollar
USGS	- United States Geological Survey explorer
UTC	- Universal Time Coordinated

CHAPTER 1. Introduction

1.1. Background

Natural tropical forests provide a wide range of ecosystem services including provisioning services (e.g., food, fuel wood), regulating services (e.g., climate regulation and pollination), cultural services (e.g., spiritual, recreational), and supporting services (e.g., soil formation, hydrological cycle). People in underdeveloped nations rely on forest ecosystem services for a living (Folke et al., 2005). In emerging economies such as Tanzania (Fig.1.1), people significantly use wood and charcoal as a source of energy for household consumption (Dallas et al., 2010; Lusambo, 2016; Mangi, 2011; Monela et al., 1999; Mwampamba, 2007). Tanzania is one of the top ten nations in the world for overall charcoal production (FAO, 2010a; Moses, 2017). Uncontrolled demand and use of some of these ecosystem services can have a harmful impact on the environment (Moses, 2017; Sedano et al., 2016; Sosovele, 2010). Recreation, for example, may place additional demands on resources (e.g., pollution or soil erosion) (Jouanjean et al., 2014; Sedano et al., 2016).

The environmental effect of charcoal manufacturing, as a provisioning ecosystem service, is also of significance. Charcoal production emits pollutants into the atmosphere that have been linked to human health problems (Msuya et al., 2011). Acute respiratory infection, chronic bronchitis, and reduced lung function are among the health impacts of charcoal manufacturing on human beings (Sola et al., 2017).

In the United Republic of Tanzania (URT), the usage of charcoal is widespread and mostly uncontrolled (Moses, 2017). It is reported that more than one million tonnes of charcoal are used for cooking in the country's metropolitan regions each year (Msuya et al., 2011). Emissions of charcoal are spread throughout communities and metropolitan centres (Charkovska et al., 2019; Girard, 2002; Pfothenhauer et al., 2019; Shen et al., 2012). Emissions from charcoal production on the other hand are limited due to fewer kilns and the lengthy charcoal production cycle (Chomba, 2018; FAO, 2008; Fitwangile, 2017; Kimaryo & Ngereza, 1989; van Beukering et al., 2007). It was reported that processing one

tonne of charcoal takes around 5-12 tonnes of raw wood, and kiln locations are governed by access to raw materials and transit links (FAO, 1987a; Mead et al., 2008). Charcoal making is an important socio-economic enterprise that provides a substantial source of income for low-income and uneducated families (Eniola, 2018a; Kiruki et al., 2020; Zulu & Richardson, 2013). It has a greater calorific value per kilogramme and does not decay during transit or storage (unlike wood fuel). It is abundantly accessible and may be transported or stored without specialised equipment.

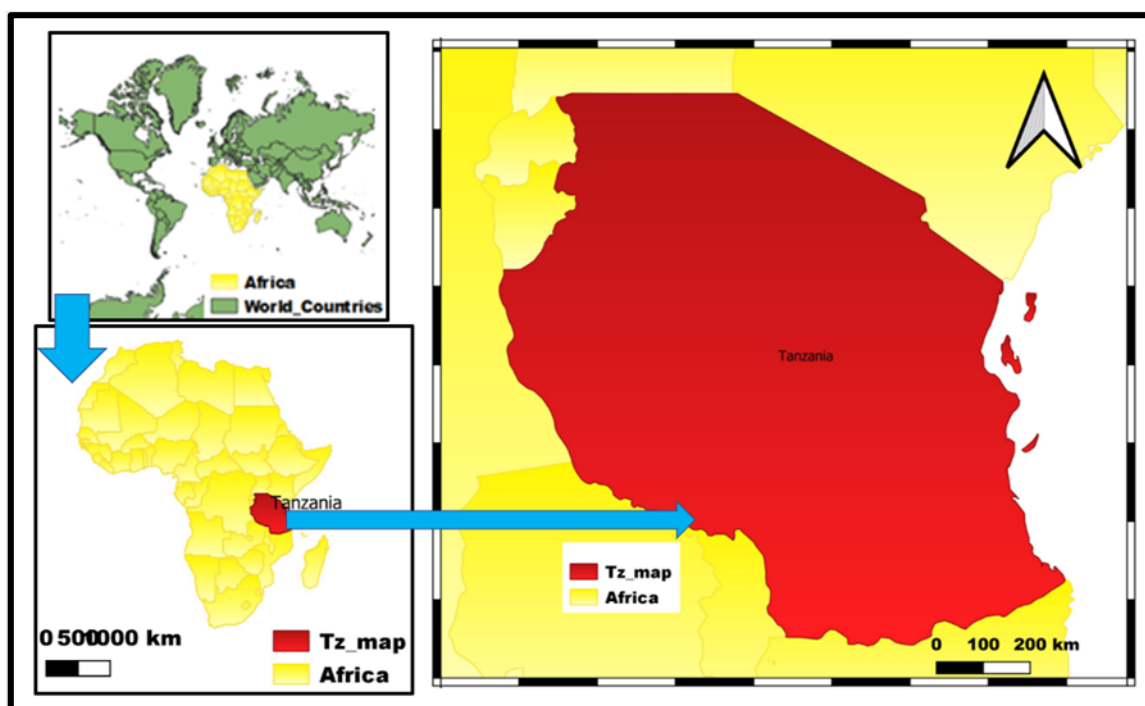


Figure 1 - 1:Global map showing the location of United Republic of Tanzania

Charcoal is the primary source of energy in many developing-country families for food preparation, lighting, and heating due to the features described above, as well as its inexpensive cost and the absence of alternatives in many circumstances. It is mostly generated in rural, wooded regions and delivered to urban markets. Long-distance buses and trucks on the region's few major transport arteries connect metropolitan areas and serve the region's rising urban population. These buses and trucks pick up and deliver artisanal charcoal manufactured in wooded regions to metropolitan areas on a regular basis. There is regulation in place controlling charcoal production (Malimbwi & Zahabu, 2009),

but it is ineffective as a monitoring tool since a considerable amount of the charcoal produced is effectively unreported and hence uncontrolled. Importantly, this legislation is directed at consuming regions rather than producing areas (for example, checkpoints near metropolitan centres and sales terminals). As a result, the levels and distribution of charcoal kilns are unknown, but they may be a better route for effective regulation. Because of their size and distribution, these charcoal kilns could potentially be better controlled and constrained using ambient air monitoring programmes in conjunction with source apportionment studies, demographic information, and GIS analysis of charcoal kiln distribution.

The population division within the United Nations Department of Economic and Social Affairs (DESA) stated in 2019 that the world's population continues to grow, but the rates of growth vary greatly across the globe's regions. Tanzania is one of nine countries that will account for more than half of the projected population growth between 2019 and 2050, according to the report. (URT, 2013) reported that the population growth rate in the country in 2012 was 2.7%. The regions surrounding the East Usambara Mountain range have some of Tanzania's fastest population growth. It is also relatively close to Dar es Salaam, Tanzania's de facto economic capital, where reported population growth is fuelling an increase in anthropogenic activity (Kilahama, 2008). Dar es Salaam could consume up to 75% of all charcoal produced in Tanzania, including charcoal from the East Usambara mountain range (Kilahama, 2008).

In Northern Tanzania, the East Usambara Mountain range and associated forests are a biodiversity hotspot that is largely unexplored and sparsely populated. The East Usambara mountain range was divided into nine wards with a total population of 58,023. The East Usambara mountain range is under intense pressure, which could impact river catchments due to an increase in water demand, particularly in its steeper mountainous areas. There is a risk of loss of cover, decreased water storage capacity, increased seasonal flash flooding, and changes in the underlying fluvial geometry (both because of changing catchment

and acute flooding events) (Kayombo et al., 2020; United Republic of Tanzania, 2016).

This research study focuses on the growing charcoal industry and how it affects forest density and coverage in Tanzania's East Usambara mountain range. Using the emerging low-cost network-based monitoring methodology, the study will help to define a potential new tool for the generation of evidence on emissions associated with charcoal making activities in the region. Furthermore, when combined with spatial information on deforestation within a GIS environment, the fine scale data derived from this study could assist in understanding the links between charcoal production, deforestation, and inform improvements in the design and manufacturing of the sensors for regions with similar environmental and climatic conditions as Tanzania through the collection of analysis of on-site atmospheric data. Finally, it will assist scientists and policymakers in developing economies in establishing a proper method of conducting air monitoring using low-cost sensors.

1.2. Aim and objectives.

The aim of this study is to advance current knowledge on environmental impacts (i.e., deforestation and air quality) of charcoal making in Tanzania. The specific objectives are:

Objective 1. To develop a methodology to quantify charcoal production emissions in ambient conditions;

Objective 2. To identify areas of high-density kilns and changes in charcoal production around the East Usambara Mountains using GIS approaches;

Objective 3. To link charcoal production with forest impact and degradation.

1.3. Research questions

The objectives were translated into research questions as follows:

- a) How to conduct controlled observational studies around charcoal making sites using traditional earth kiln techniques to generate a characteristic

emissions factor for these activities. This research question will explore the use of emission factors to quantify emissions derived from a charcoal kiln and to differentiate them from other important sources such as transport and small-scale household burning around the experimental study and field site of East Usambara mountain.

- b) How to use GIS based approaches and any existing data (such as broad swath satellite data) to identify areas of high charcoal kiln density and changes in charcoal production around East Usambara Mountain.
- c) How to identify areas of high charcoal kiln density around East Usambara Mountain using GIS based tools, link charcoal production with increased deforestation in the region and quantify impacts to forest around East Usambara Mountain.

CHAPTER 2. Literature Review

The variables which influence the effects of charcoal production on the forest and its ecosystem are summarised in this chapter. The current configuration and use of forest resources in Tanzania, the causes and impacts of deforestation as well as the process of charcoal production, are discussed in Section 2.1. This covers a review of the primary reasons for charcoal production, notably in Tanzania, as well as the current understanding of the environmental implications of charcoal production. It identifies the environmental impacts of charcoal making and the pressures leading to land use and cover change, with deforestation recognised as one of the most important reasons. In section 2.2, the challenges concerning the development of approaches for monitoring air quality in low-income countries are discussed, including the use of miniaturised sensors in least developed countries (LDCs).

2.1 Forest resources

Forests cover 31% of the Earth's land surface (4.06 billion ha) but the area is shrinking, with 420 million ha of forest lost through deforestation between 1990 and 2020 (FAO, 2022). It is estimated that the globe has lost 178 million ha of forest during the 1990s, which is approximately an extent equivalent to Libya (FAO, 2020b). Africa had the highest yearly rate of net forest loss between 2010 and 2020 at 3.9 million ha, followed by South America at 2.6 million ha (FAO, 2020b). Since 1990, the pace of net forest loss in Africa has grown on a decade-by-decade basis. However, it dropped significantly in South America, to almost half the rate between 2010 and 2020 when compared to the 2000-2010 period (FAO, 2020b).

The rate of deforestation in the world is declining but was still 10 million ha per year from 2015 to 2020. Approximately seven per cent of the world's total forest area is made up of planted forests, which occupy 294 million ha. From 2015 to 2020, the area of planted forests was expected to grow at a somewhat slower pace of 1% than it did from 2010 to 2015 (1.4%). While the area of other land with tree cover (including trees in urban settings, tree orchards, palms, and

agroforestry landscapes) rose by more than one-third between 1990 and 2020. At least 45 million ha of land are currently used for agroforestry, and this amount is growing on a yearly basis (FAO, 2020a).

2.1.1 Forest resources in Tanzania

The United Republic of Tanzania is a low-income country in the tropics (World Bank Group, 2017). The forests cover approximately 48.1 million ha on Tanzania's mainland, with an estimated wood volume of 3.3 billion m³ (URT, 2015b). Tanzania's vegetation types include humid montane, lowland forest, mangrove forest, plantation, as well as closed and open miombo woods (URT, 2015b). Approximately 55% of the land area is covered by forests, with woodland making up most of these areas, accounting for roughly 93% of the total land area. Plantations, mangrove forests, humid montane forests, and lowland forests make up the remaining 7% (URT, 2015a). Miombo forests, a vernacular term used by ecologists to designate forest habitats dominated by trees from the genera *Brachystegia*, *Julbernardia*, and *Isoberlinia* (Leguminosae, sub-family *Caesalpinioideae*) (Abdallah & Monela, 2007b). In Tanzania, around 37% of wooded land is classified as a reserve controlled by the central government (Hurst, 2003). Wooded land is managed by locals, whereas land in village areas is improperly managed as general land (Mgaya, 2016). For home and certain agro-industry purposes, millions of Tanzanians living in rural and urban areas rely heavily on Miombo woods. The use of Miombo woods is not sustainable and deforestation is alarming and it is essential to market and enhance Miombo product processing methods (Abdallah & Monela, 2007a).

Woodlands and forests are vital as a source of a wide range of wood and non-wood goods, as well as a source of employment and money via the sale of wood and non-wood products and derived services (Agustino et al., 2011; Nunes, Meireles, & Gomes, 2019). They maintain soil, help to reduce climate change by sequestering carbon, and provide water for residential and industrial usage, irrigated crops, and power generation (Nunes, Meireles, & Gomes, 2019). They are also useful for aesthetic, recreational, cultural, spiritual, medical, and

scientific purposes (Agustino et al., 2011; Nunes, Meireles, Gomes, et al., 2019). Their great biodiversity value helps to reduce poverty as well as agricultural stability, including soil conservation (Blomley & Iddi, 2009). Human actions at many temporal and geographical dimensions have a significant impact on tropical forest biodiversity (Gardner et al., 2009). Land-use intensification, over-harvesting of wood (including charcoal manufacture and poles for houses), and non-timber resources (including game) are the principal causes of biodiversity changes (Gardner et al., 2009).

Most wood products produced in Tanzania are used for fuel. Charcoal and firewood produced from Miombo woodland and closed forests account for roughly 90% of household energy sources (Ishengoma, 2015; Lusambo, 2016; URT, 1998). Due to the high cost of alternative energy sources, most Tanzanian communities rely on biomass fuel as a source of energy. Income influences energy source choices in developing economies (Choumert et al., 2017; Lusambo, 2016). Although forests are essential to humans and other organisms, they are facing deforestation because of increased use of their products for fuel energy production (Acheampong & Opoku, 2023).

2.1.2 Causes of deforestation.

Deforestation can refer to loss of forest through land conversion as well as to the degradation of forest quality (e.g., tree density and structure, ecological services provided, biomass of plants and animals, species richness, and genetic diversity) (FAO, 2007). The worldwide drivers of deforestation differ by nation (FAO, 2020a; Hosonuma et al., 2012; Kissinger et al., 2012a), with the drivers of deforestation in African and Asian nations being the most comparable (Hosonuma et al., 2012). Population growth (51%) is the most prevalent cause of deforestation, followed by poverty (48%) (Kissinger et al., 2012a). Tanzanian rural families rely on these woods for a variety of purposes, including employment, energy, food, building materials, revenue production, and other necessities of life (Ntiyakunze & Stage, 2022). In Tanzania, most of the poor as well as those living in extreme poverty reside in rural areas (The World Bank, 2019). Population increase, density,

distribution, migration, and urbanisation are significant causes of deforestation; demographic characteristics are thus strongly associated to deforestation in the region (Fig. 2.1) (UN DESA, 2019).

Tanzania's forest acreage has declined from 3 ha/capita in the early 1980s to 1.1 ha/capita in 2012 based on 2012 population census data (URT, 2015), indicating that deforestation rates have grown since the 1980s owing to population growth. Figure 2-1 depicts a worldwide map showing the impact of population expansion on forest loss (UN DESA, 2019).

Tanzania is losing almost 38% of its forest cover at an annual rate of 400,000 hectares per year; if this trend keeps up, the nation will run out of forest cover in the next 50 to 80 years (Interactive Country Fiches, 2024).

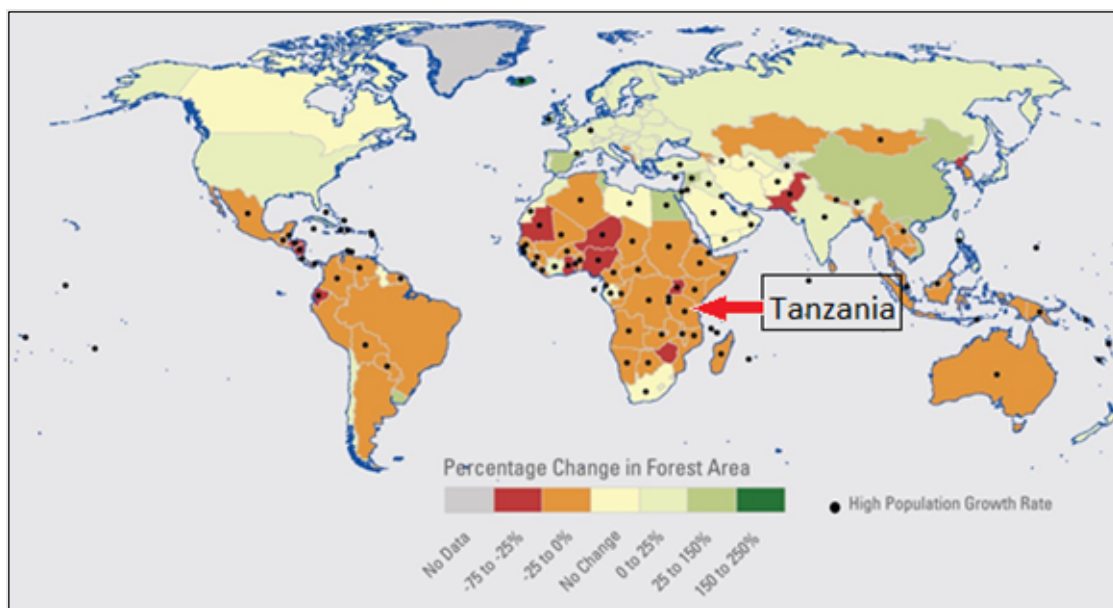


Figure 2 - 1: Global map showing the influence of population growth on forest loss (UN DESA, 2019). It shows Tanzania has recorded a high population growth rate from 1990 to 2022 that influenced change in forest areas (URT, 2022).

2.1.3 Impacts of charcoal making driven deforestation and kiln activity on the environment.

The environment is the sum of all conditions that surround man at any given time on the earth's surface (Larsson, 2009; Sanlaville, 2003). The three basic

elements of the environment are air, land, and water. Land and catchments on the planet's surface include trees that can and are used to make charcoal. The effect of deforestation on rivers and catchments (water component) is detailed in section 2.1.4. This section expands on the explanation of the environmental impact of charcoal production on the land and air components.

Several studies, including (Misana, 1999; URT, 2015b; Vatn et al., 2017; WB, 2009), report that the rate and reasons of deforestation vary among emerging economies. It was reported that a range of factors caused deforestation in various regions of Tanzania. These were caused by local economic activity, the kind and form of vegetation, and the need for charcoal as a fuel in the region (Misana, 1999). Further, it was found that the contribution of diverse variables such as agricultural settlement and expansion, tree cutting for timber, mining, and charcoal manufacturing to the deforestation problem in different places is vital for quantifying deforestation (Misana, 1999).

Household charcoal consumption is likely to rise further over the next few years as the urban population grows (Lusambo, 2016; Nyamoga *et al.*, 2022). A significant amount of wood is cut to meet household charcoal consumption in Tanzanian mainland urban areas (Kilahama, 2008). This is because most households rely heavily on charcoal and firewood to meet their domestic energy needs (Kilahama, 2008). According to data collected in Dar es Salaam, Tanga, and Morogoro, the per capita charcoal consumption day is approximately 0.2 kg. This means that a family of six will use 1.2 kgs of charcoal per day, but the exact amount will depend on the type of food, the number of meals cooked per day, and the efficiency of the cooking stove (Kilahama, 2008). Widespread tree loss has serious social and economic consequences (Cuaresma & Heger, 2019; Kideghesho, 2015). This is because extensive deforestation processes, such as increased soil erosion, poor infiltration and retention of rainwater, and eventually worsening microclimate conditions, lead to socio-economic hardship (GLOWS-FLU, 2014; United Republic of Tanzania, 2016). Charcoal production contributes to the emissions of many pollutants, including 46% of CH₄, 42% of CO 44% of

non-methane hydrocarbons (NMHC), and 32% of CO₂ (Msuya et al., 2011; Norconsult, 2002). Pollutants released into the atmosphere may create stress in the environment (Relić & Đukić-Stojčić, 2023). The ecological modelling programme STELLA® used to anticipate the impact of ongoing charcoal production and determined that it might result in the release of 49.7 million tonnes of CO₂ into the Tanzanian atmosphere until 2030 (Msuya et al., 2011).

Charcoal usage also produces particulate matter such as PM₁₀ and PM_{2.5} (Msuya et al., 2011). It was revealed that charcoal manufacture and use lead to several community health impacts, including pneumonia and chronic respiratory illness (von Schirnding et al., 2000). For Africa and other developing countries, it is imperative to evaluate and create long-term strategies regarding charcoal (Kammen & Lew, 2005). A limited use of low-cost, efficient, and trustworthy technologies makes estimating harmful emissions from charcoal manufacturing difficult in underdeveloped nations.

In addition to the above-mentioned air emissions, it is generally recognised that charcoal production has an influence in other areas as well. For example the environmental effect of charcoal production divided into three areas: the environmental, economic, and health consequences (Fig. 2.2) (Alfaro & Jones, 2018; Chidumayo & Gumbo, 2013; Serenje et al., 1994). The activity causes disruption to catchments and riverine systems. In catchments it causes deforestation and soil compaction due to the heavy weight and high temperatures during by kiln installation (Alfaro & Jones, 2018; Chidumayo & Gumbo, 2013). In rivers, it causes increased sediment load and poor water quality as a result of soil erosion occurring in deforested areas. The employment of minors as main labourers in charcoal production has socio-economic consequences. Common injuries (moderate to severe lacerations and burns to the lower limbs) and employees feeling dizzy, lightheaded, and nauseous while engaged in tasks are among the health impacts (Alfaro & Jones, 2018).

During combustion activities such as charcoal manufacture, a mixture of air pollutants is released, including, CO, NO_x and particles. If humans are exposed to the hazardous gases generated by charcoal production operations for a lengthy period, they may cause brain damage and death (Idowu et al., 2023; Jiang et al., 2016; Msuya et al., 2011). There is a high rate of accidents, both small (burns) and serious (deaths), as well as a high rate of child labour associated to charcoal making activities (Alfaro & Jones, 2018). Studies on perceived health impacts of charcoal manufacturing on Nigerian communities discovered that it could cause skin irritation, respiratory tract irritation/infection, cuts, laceration, and laceration of hands, back discomfort, muscular pain, and bodily wounds. High cumulative dust exposure was linked to common cough, common phlegm, phlegm and cough episodes, and shortness of breath (Alfaro & Jones, 2018; Eniola, 2018b; Jiang et al., 2016).

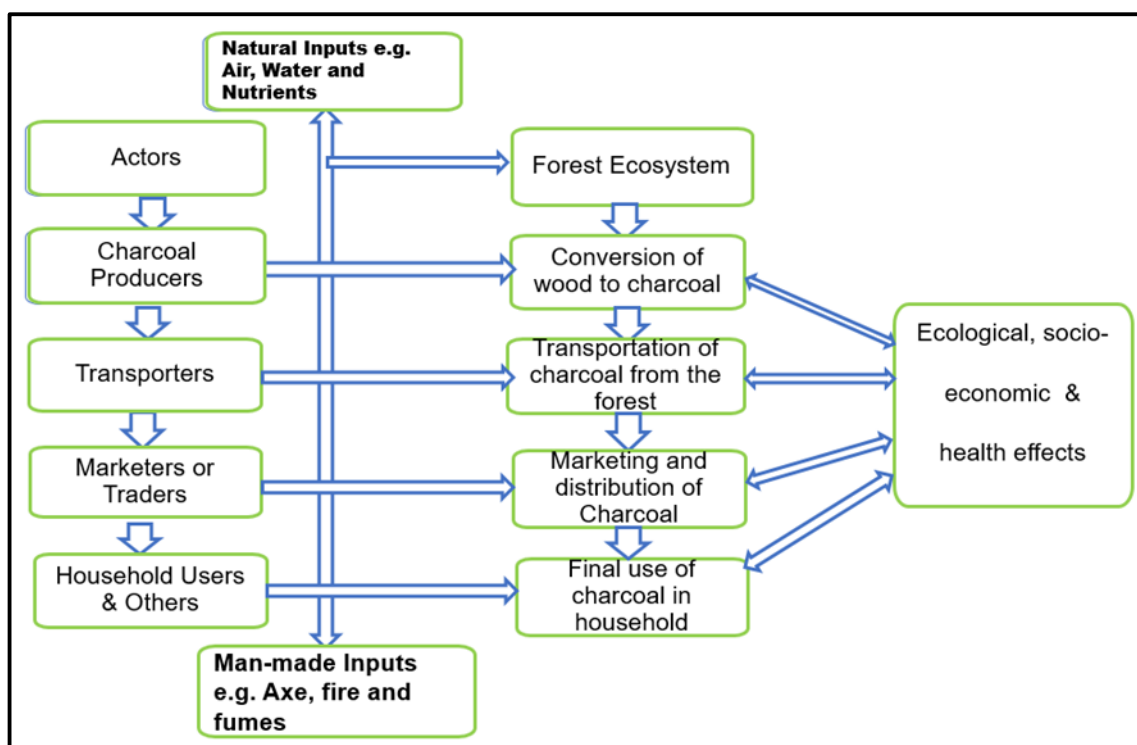


Figure 2 - 2:Diagram showing Charcoal Energy Production and Use System. The left Column represents the charcoal production whereas the right column is the charcoal use systems (Serenje et al., 1994).

2.1.4 Impact of charcoal making deforestation and kiln activity on riverine systems and flooding

Rivers are intricate water-flowing systems that drain specific land areas defined by catchments (Grabowski et al., 2022; Meybeck et al., 2006; Nyberg et al., 2018; Twidale, 2004). Rivers supply people with clean water for drinking and cultivation. The characteristics of both rivers and catchments are connected to the catchment's size, form, and geological features, as well as climatic circumstances, which determine the amount of water drained by the river network (Meybeck et al., 2006; Nyberg et al., 2018; Twidale, 2004).

Riverine systems are hydrological-ecological networks characterised by the passage of water, sediment, nutrients, and organisms, as well as the dynamic migration of animals upstream and downstream (Mwaijengo, 2020; Nyberg et al., 2018). Tanzania features ecological hotspots such as the Eastern Arc Mountains, which includes Mount Usambara and is extremely rich in freshwater supplies for community usage. Numerous rivers run through the East Usambara mountains, notably the Zigi and Pangani rivers (Mwaijengo, 2020; Yanda & Munishi, 2007). Several authors studied the influence of deforestation on runoff generation and soil erosion and discovered that removing forest areas and changing land use had a detrimental impact on watershed hydrological conditions (Gholami, 2013; Mwaijengo, 2020; Yanda & Munishi, 2007).

Deforestation has been associated to increased runoff quantity and frequency, as well as decreased base flows, increased pesticide pollution, corrosion, and sedimentation of streams and rivers (Gholami, 2013; Madulu, 2005; Monela et al., 1999; Twidale, 2004). Changes in land cover, such as deforestation, have been shown to have a substantial influence on watershed hydrology, natural resource degradation, and urban growth (Gholami, 2013; Hlásny et al., 2015). Land-use and vegetation are elements that influence soil erosion and runoff production, and changes in these characteristics have a detrimental impact on watershed hydrological conditions (Gholami, 2013; Mwaijengo, 2020)(Forcales et al., 2007; Gholami, 2013; Zhao et al., 2022).

Agricultural expansion, livestock grazing, wildfires, over-exploitation, unsustainable use of wood resources (including charcoal manufacture), and other human activities, largely in general lands, are important factors driving deforestation (Doggart & Meshack, 2017; Kideghesho, 2015; Makunga & Misana, 2017). Deforestation in the context of charcoal production will have an influence on a wide variety of regions exploited for that purpose (Chidumayo & Gumbo, 2013; Sedano et al., 2016). The effects of such deforestation will be like those detailed in section 2.1.2.

2.1.5 Impact of charcoal making on land use and land cover change

Land use change is the process by which human activities transform the natural environment by referring to how land has been utilised, with a focus on land's functional role in economic activity (Msofe et al., 2019; Wu, 2008). Land cover refers to the observed (bio)physical cover on the earth's surface (Gregorio & Jansen, 2005; Msofe et al., 2019). The concepts of land use and land cover change are connected, although there are substantial variances. Land use is characterised by the arrangements (for example, fulfilling society's preferences for ecosystem service supply), actions (for example, farming and construction), and inputs that humans undertake on a certain land cover type to develop, change, or sustain it (Gregorio & Jansen, 2005; Rogger et al., 2017; Swetnam et al., 2011). Human activities and natural forces are driving land use and cover change (LUCC), which has resulted in the global loss of native biodiversity and the altering of ecological processes and services across diverse ecosystems (Msofe et al., 2019). Figure 2.3 demonstrates the forces driving land use change, as well as the need for and reaction to planning.

Ecosystem degradation induced by land use and cover change has led to a rise in catchment damage in many regions of the world, resulting in a lack of water for domestic and industrial use, as well as water for environmental flows (Falkenmark et al., 2007; Yanda & Munishi, 2007). Tanzania's East Usambara Mountains are part of the Eastern Arc mountain chain, which features one of Africa's most diversified vegetations with a high rate of flora and animal endemism (Burgess et

al., 2007; Mbilinyi et al., 2006; Yanda & Munishi, 2007). The mountain is home to impoverished people that rely on the natural resources of the forest to live. Land cover changes have occurred in east Usambara, notably in the Sigi catchment region, over time. Between 1955 and 1995, nearly 37% of the overall catchment area was transformed from natural vegetation to farmland (Yanda & Munishi, 2007). The observed land use changes are driven by the cultivation of bush crops, an increase in population necessitating structure development, and a high settlement density that makes the region prone to environmental deterioration. "Land cover is crucial in the drainage system and conservation of every watershed" (Kitalika et al., 2018). Land use changes may be due to anthropogenic activities that include cutting trees for charcoal making and consequently increase emission into the atmosphere (Chidumayo & Gumbo, 2013; Mengistu & Woldetsedik, 2018). These emissions can be quantified through emerging low-cost electrochemical sensors in least developed countries (see section 2.2).

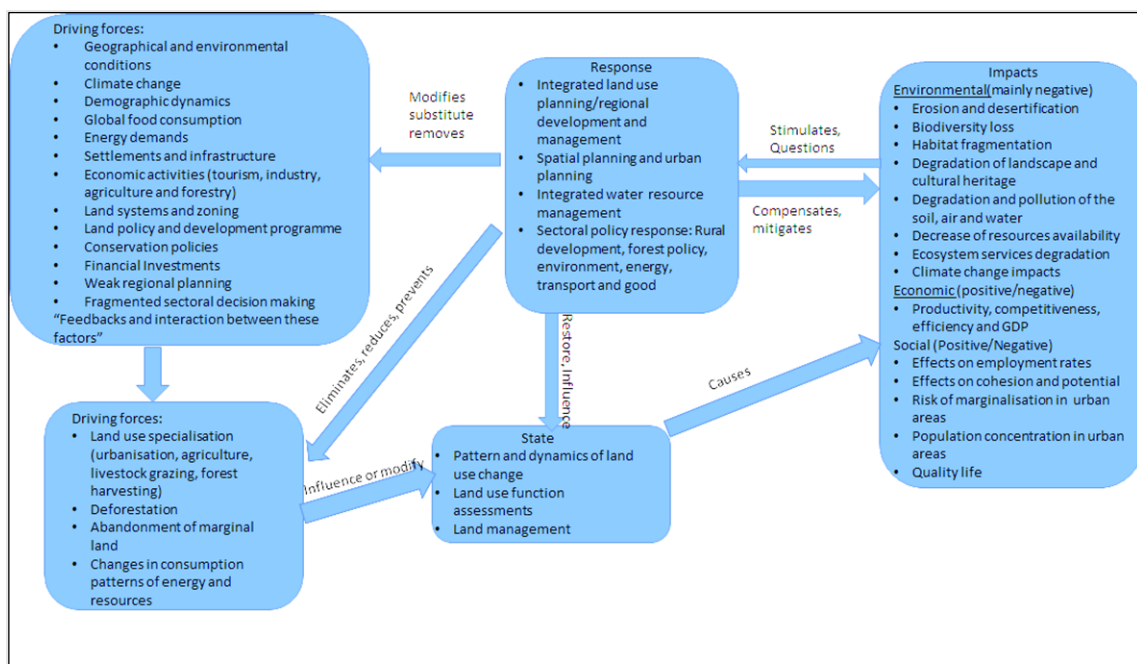


Figure 2 - 3: Drivers and pressures on land use change (Metternicht, 2017)

2.1.6 Charcoal production

Charcoal is the solid residue left after wood has been "carbonised" or "pyrolyzed" under regulated circumstances in a closed environment, such as a charcoal kiln

(Menemencioglu, 2013; Nartey & Zhao, 2014). Control is exerted over the entrance of air during the pyrolysis or carbonization process, so that the wood does not totally pyrolyze and convert to ash, as in a traditional fire, but instead partially decomposes to generate charcoal (FAO, 1987b; Nartey & Zhao, 2014; Van Beukering et al., 2007). Africa, particularly Sub-Saharan Africa, accounts for a sizable proportion of charcoal producers. This contributes 24.6 million tonnes (Mt), with the Americas accounting for 9.9 Mt. Tanzania is one of the top 10 charcoal producers in the world, with nine countries producing an average of 1.6 million tonnes of charcoal every year which is the equal of 30 million trees. (Fig.2.4b) (Bergesen et al., 2019; Nabukalu & Gieré, 2019; Njenga, 2018).

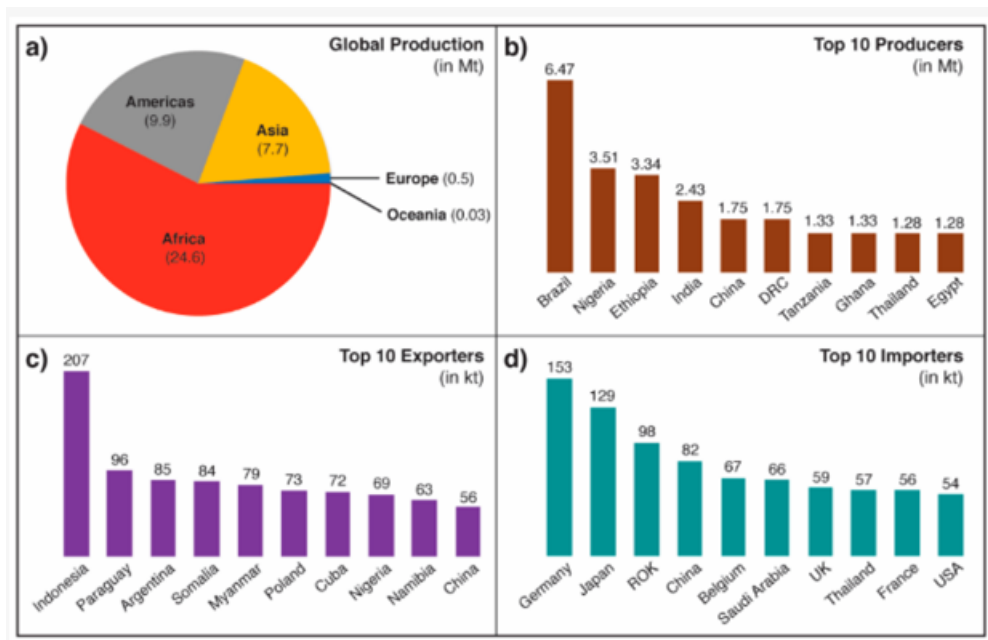


Figure 2 - 4: Global charcoal production and trade. (a) Production by region; (b) top producers; (c) top exporters; (d) top importers. DRC = Democratic Republic of the Congo; China = Mainland China; ROK = Republic of Korea; UK=United Kingdom, USA=United States of America. All data represent annual averages 1993–2017(Nabukalu & Gieré, 2019).

Several writers provided thorough information on charcoal producing processes (Antal & Grønli, 2003; FAO, 1987b; Kammen & Lew, 2005; Mhache, 2012; Msuya et al., 2011; Rolando, 1999). For example, several studies detailed the production and usage of charcoal across most emerging economies (Hofstad, 2017; Idowu et al., 2023; Kļaviņa et al., 2015; Nabukalu & Gieré, 2019; Serenje et al., 1994).

In rural Tanzania, traditional biofuels such as firewood and charcoal are widely used (Hoffmann *et al.*, 2018; Kilahama, 2008; Mabele, 2020; Mhache, 2012; Norconsult, 2002; WB, 2009). Figure 2-5 and 2-6 shows earth kilns type of charcoal production kilns widely used in Tanzania (TFCG, 2020 and Msuya 2011). However, there are other types of charcoal production kilns that includes Casamance and Adams Retorts.



Figure 2 - 5: An image showing preparation for Charcoal production kiln in Tanzania (TFCG, 2020).



Figure 2 - 6: Image of traditional earth kiln showing charcoal production in Tanzania (Msuya, 2011).

Adam and Casamance retorts are two other varieties of kilns used to produce charcoal. The Casamance Kiln (Figure 2-8) is founded on the idea that a low-cost, effective kiln that can effectively adjust to local conditions may be created. Agencies in the Casamance region of Senegal, West Africa, conducted field study for several years before developing the kiln. The local charcoal producers embraced the resulting kiln, which demonstrated a significant increase in production efficiency and financial returns over the conventional approach.

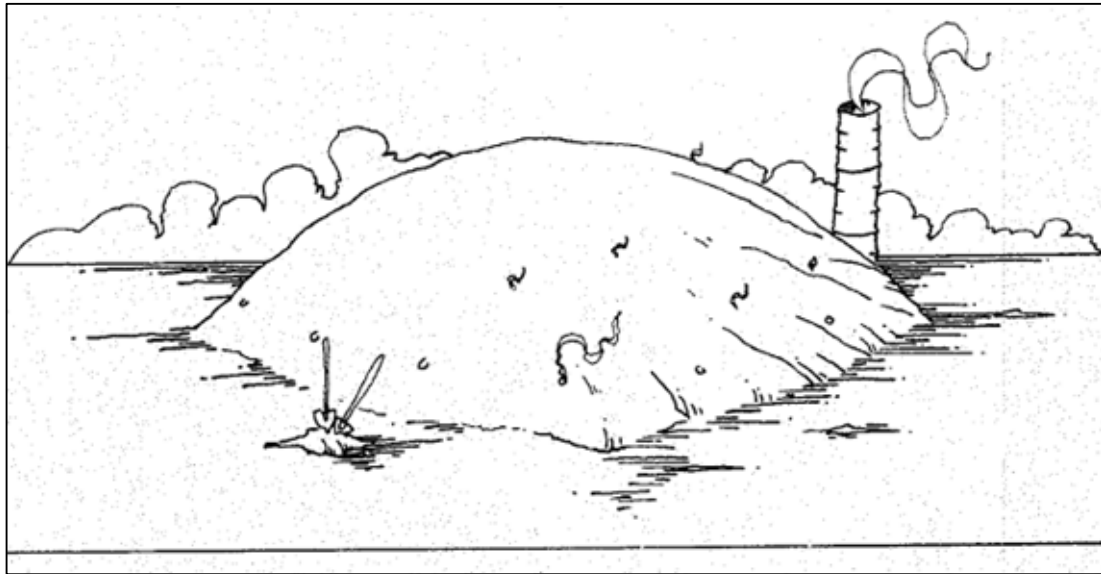


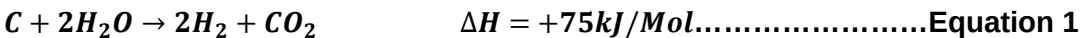
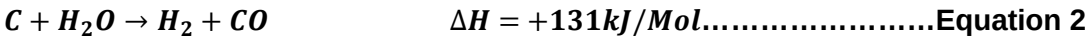
Figure 2 - 7: Casamance type of charcoal Kiln (Karch et al., 1987)

Retort–kilns have a much higher efficiency rating of 35%–40% in comparison with earth-mound kilns (Figure 2-8); Another benefit is that the operating time for the retort– kiln is much shorter – about 12 h (plus about 12 h for cooling) (Adam, 2009).

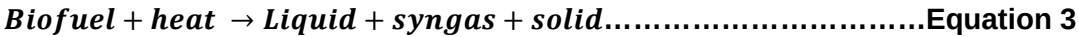


Figure 2 - 8: Adam-retort charcoal kiln type built in Rift valley, Kenya (Adam, 2009).

Charcoal combustion is a very complex phenomenon. It involves both mass and heat transfer processes (i.e., diffusion of oxygen and combustion products), thermodynamics, aerodynamics, and kinetics of several simultaneous and/or competing chemical reactions (i.e., series of oxidation reactions, thermal decomposition of fuel). Fundamentally, combustion requires three important elements: 1) fuels, 2) oxygen and 3) external energy. External energy refers here to ignition sources or a high-temperature environment where combustible vapours can be self-ignited in the presence of oxygen. Equations 1 and 2 indicate the chemical reactions during the pyrolysis process (Meng et al., 2016).



Pyrolysis is typically defined as the thermochemical decomposition of biomass feedstock at medium (300–800°C) to high temperatures (800–1300°C) in an inert atmosphere (Meng et al., 2016). The overall reaction of biomass feedstock can be seen in Equation 3.



Pyrolysis, being a critical phase in charcoal production, is usually monitored closely by someone who is responsible for the outcome of the process (Olujimi et al., 2016).

PM₁, PM_{2.5} and PM₁₀ were considered for analysis because charcoal production releases those pollutants into the atmosphere and they are well known to have an impact on human health (Sola et al., 2017). Particles are commonly classified according to their size as either coarse or fine; fine particles have a diameter of 2.5 µm (PM_{2.5}) or less, and coarse particles are 10 µm or less (PM₁₀). Particulate matter that has a diameter over 10 µm tends not to stay airborne long enough travel far. Coarse particles are commonly the product of mechanical processes but also include naturally occurring wind-blown particles¹¹. A common example of coarse particulate matter is dust containing calcium, iron, silicon and other materials from the earth's crust.

Fine particles are commonly generated through combustion or by secondary gas to particle reactions. Their smaller size means they can penetrate deeper into the lungs and be more easily absorbed into the blood stream. In this way PM can cause multiple health issues (Hime et al., 2018; Meng et al., 2016; Watcharaviton et al., 2013). These fine particles are typically rich in carbon, nitrates, sulphates, and ammonium ions. They can cause respiratory problems such as asthma (Kim, 2017) or act as a vector for the transmission of microorganisms having an impact on human health. It was reported that small particulates can serve as vehicles for the transport of microorganisms such as viruses and bacteria to the lungs and blood stream (Olujimi et al., 2016).

There has long been a question as to whether some components of the PM mixture are of greater public health concern than others, so that the sources that emit the more toxic components could be controlled (Hulanicki et al., 1991). The cause-specific mortality pattern among hospital deaths in Tanzania from 2006 to 2015 was investigated and reported a total of 247,976 deaths of which 10.08% were caused by respiratory diseases were reported (Mboera et al., 2018).

2.2 Emerging low-cost sensors module for measuring atmospheric pollutants

It is now possible to better characterise emissions from charcoal production through the in-situ deployment of miniaturised sensing technologies with appropriate sensitivities. These technologies have seen widespread and increasing use in outdoor air quality studies, particularly in the global North (Magnone et al., 2019). A broad description of this work is beyond the scope of this thesis. For a detailed discussion of emerging small sensor technologies and their usage see (Gameli Hodoli et al., 2020; Latif et al., 2016; Pang et al., 2017; Raysoni et al., 2023). The sensor module description, its overview and potential for their use for this targeted study on charcoal making is described in item 2.2.1 to 2.2.2.

2.2.1 Low-cost atmospheric sensors module

A sensor system is defined as an integration of one or more sensors sub-components with control systems and other supporting components, that can

result in a fully functional and autonomous detection system (Morawska *et al.*, 2019). The world of sensors is broad and expanding quickly because of the increasing demand for them and ongoing technological advancements (Baranwal *et al.*, 2022) and it has many facets (Saputra, 2023). Compared to conventional analytical techniques, electrochemical sensors provide a number of benefits, such as selectivity, sensitivity, robustness, convenience of use, short-time measurement, portability, cheap cost, etc (Alaraifi, 2012; Mead *et al.*, 2013; Saputra, 2023). An electrochemical sensor is an integrated, stand-alone device that converts data related to electrochemical processes into signals suitable for analysis (Kumar *et al.*, 2015; Morawska *et al.*, 2018; Saputra, 2023).

The fundamental concept of an electrochemical sensor is that the electrode surface's fixed receptors identify the target analyte in a sample, which causes a catalytic or binding event. Figure 2-8 portrays the configuration and working principles of electrochemical sensors.

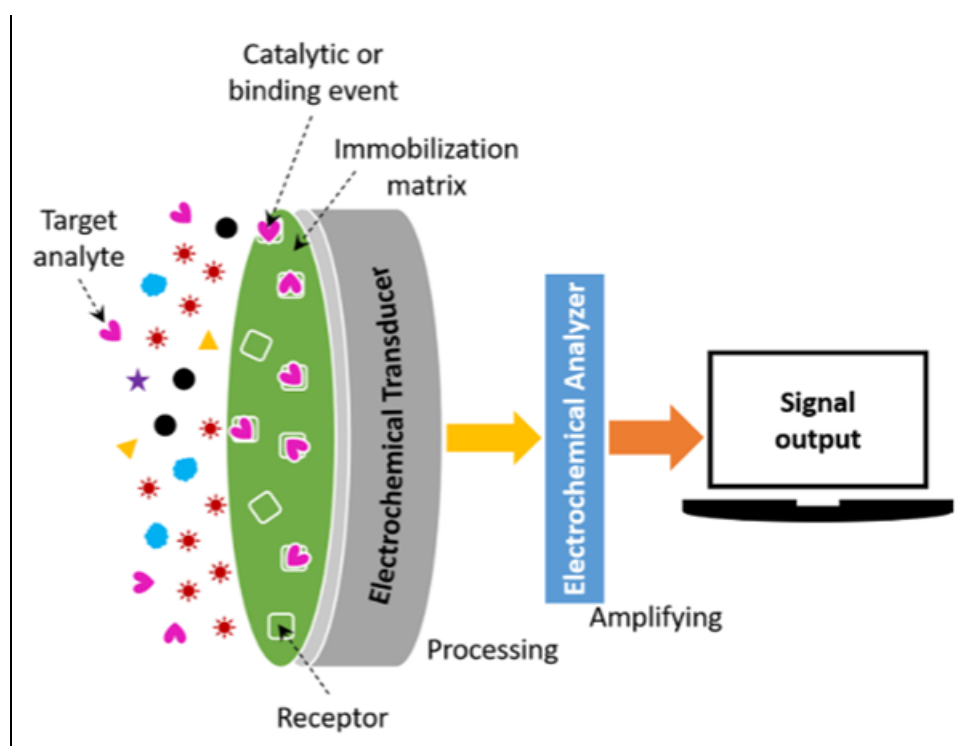


Figure 2 - 9: The configuration and working principles of electrochemical sensors (Saputra, 2023).

Based on the type of measurement, electrochemical sensors are grouped into potentiometric, conductometric, and amperometry/voltametric sensors (Nasir, 2018; Pisoschi, 2016; Saputra, 2023; Stradiotto et al., 2003a). Atmospheric electrochemical sensors transform a target species in the environment into an electrical signal, the magnitude of which is proportional to the atmospheric concentration (Lewis et al., 2018; Saputra, 2023).

Potentiometric sensors may be used to estimate the analytical concentration of certain analyte gas or solution components (Baranwal et al., 2022; Stradiotto et al., 2003a; Wang, 2011; Yin et al., 2012). When no current is flowing, these sensors measure the electrical potential of an electrode. Potentiometric sensors are divided into three types: ion-selective electrodes (IES), coated wire electrodes (CWES), and field effect transistors (FETS) (Baranwal et al., 2022; Stradiotto et al., 2003a). Potentiometric sensors are extensively utilised in the field because of their capacity to selectively respond to specific species of interest but are less effective at monitoring beyond these (Castell et al., 2017; Karagulian et al., 2019).

Conductometric sensors, frequently referred to as impedimetric sensors, on the other hand, measure changes in the surface impedance to detect and quantify a specific impedance-specific recognition event on the electrode (Baranwal et al., 2022). This class of sensors is dependent on variations in the electric conductivity of a film or bulk material, the conductivity of which is influenced by the presence of an analyte (Baranwal et al., 2022; Stradiotto et al., 2003b). Fundamentally, conductimetric techniques lack selectivity. These techniques haven't become more practical for sensor design until the introduction of changed surfaces for selectivity and significantly better instrumentation. Because conductimetric techniques don't require reference electrodes, they are simple and inexpensive, which are two very useful aspects. Analytes may now be quickly and easily determined using merely the conductivity measurement thanks to improved technology (Stradiotto et al., 2003b).

Amperometry electrochemical sensors are sensitive analytical devices that detect current when an electroactive material loses (oxidation) or gains (reduction) an electron during an electrochemical process (Baron & Saffell, 2017; Chang et al., 1993). Amperometry imaging has significant promise for multipoint fast detection and the investigation of target molecule diffusion processes (Baron & Saffell, 2017; Nakazato, 2013). Electrochemical sensors for CO, NO₂, and NO can be robust, have low power requirements, and be relatively very low cost (Karagulian et al., 2019; Mead et al., 2013; Saputra, 2023; Wickham et al., 2018). These amperometry sensor methodologies were originally designed for sensing selected toxic gases at the parts-per-million level in industrial settings (Fig.2.6) (Mead et al., 2013). Electrochemical sensors have the added benefit of having a signal output current that is directly proportional to the measured gas concentration (Baron & Saffell, 2017; Mead et al., 2013; Saputra, 2023).

2.2.2 Global overview of use of low-cost sensors

Low-cost sensors are often defined by comparing the purchase price of a functioning sensor system to the purchase price of a reference instrument measuring the same or equivalent air pollutant or greenhouse species (Morawska et al., 2018). Low-cost air pollution sensors and monitors are technologies that offer a significant potential improvement in air quality monitoring through potentially large gains in spatial and temporal data resolution, bringing solutions to research issues and applications for end users (Morawska et al., 2018). Air pollution and greenhouse gas measurements are needed for a range of applications ranging from academic research to regulatory activities and services for individuals, governments, and commercial organisations (Lewis et al., 2018). Over the last decade, a wide range of sensor technologies have become accessible on the market resulting in a dramatic change in air pollution monitoring and evaluation (Morawska et al., 2019). Furthermore, because of this paradigm change, the number of companies and groups active in the commercialization of low-cost sensors (LCS) to monitor environmental air pollution has expanded (Karagulian et al., 2019). Diagram showing parts of an electrochemical cell for atmospheric measurements (Fig. 2-9).

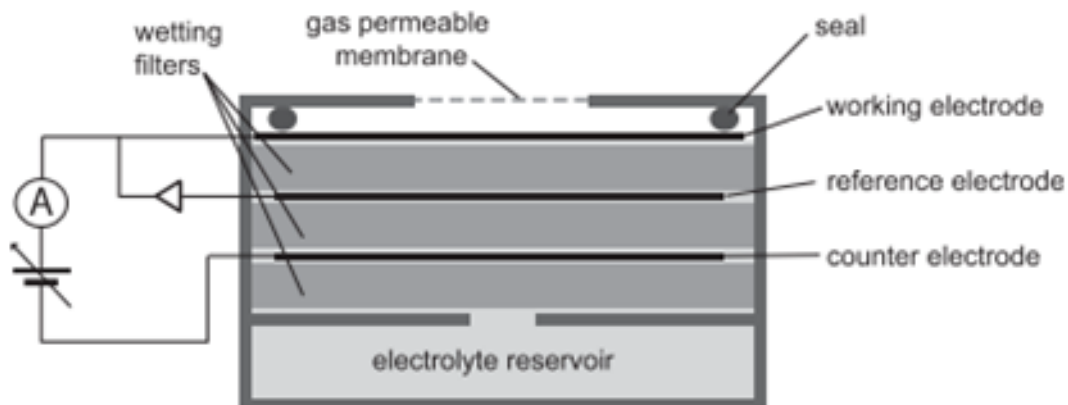


Figure 2 - 10: Diagram showing parts of an electrochemical cell for atmospheric measurements.

Several studies, have demonstrated that, once properly calibrated, this sensor type is capable of monitoring selected target species in rural and urban areas with a range of pollutant concentrations as it can measure pollutants at the parts per billion (ppb) level (Mead et al., 2013; Pang et al., 2017; Rai et al., 2017). Fully autonomous complex multi-parameter sensor systems can cost more than \$10,000 (Morawska et al., 2018). Simple single-pollutant sensors may be purchased for less than \$50 (without any associated required hardware).

The low-cost sensors are capable of detecting CO, CO₂ and particulate matters (PM) particles. The electrochemical sensors are imbedded with optical particle counter (OPC) specifically for detecting particulate matters. For example, the Alphasense OPC-N₂ / OPC-N₃ sensors are optical particle monitors that measure PM_{1.0}, PM_{2.5} and PM₁₀. The Alphasense OPC-N₂ / OPC-N₃ sensors use laser beams to detect particles from 0.38 micron to 17 micron in diameter with 16 bins (0.35 to 40µm with 24 bins for OPC-N₃). Count measurements are converted into mass concentrations of PM_{1.0}, PM_{2.5} & PM₁₀ using embedded algorithms (Alphasense, 2015).

Although there has been substantial study on the use of electrochemical sensors in calculating emissions from various pollutants, their use is limited in emerging economies such as Tanzania.

2.2.3 Assessment on the performance of Low-cost sensors

Several studies reviewed on the performance of low-cost sensors (Kang *et al.*, 2022 and Damanenga *et al.*, 2021). Kang *et al.*, (2022) reported that suggested that low-cost air quality sensors exhibited improved r^2 and RMSE in the experiments with stable environmental settings, in the comparison against non-designated reference instruments, or in the analysis where advanced regression models were used to adjust the sensor readings.

A thorough performance evaluation of eight consumer-grade multi-parameter monitors and eight single-parameter sensors in the areas of relative humidity, dry-bulb air temperature, total volatile organic compounds, and particulate matter detection was also reviewed (Damanenga *et al.*, 2021). According to reports, the majority of the devices underreported measurements of reference particles by as much as 50%. Additionally, the devices gave acceptable responses for carbon dioxide within a 15% range, while the findings for total volatile organic compounds showed varying results with poor quantitative agreement (Damanenga *et al.*, 2021). It was also mentioned that most of the inexpensive devices could identify source events and had a significant correlation with the reference data, indicating that they would be appropriate for measurement-based indoor air quality management even with the observed differences in quantitative agreements. Additionally, most of the evaluated devices have demonstrated the ability to monitor relative humidity (within $\pm 5\%$ RH) and air temperature (within $\pm 0.6^\circ\text{C}$) with competence and stability throughout the two thermodynamic situations (Damanenga *et al.*, 2021).

2.2.4 Use of low-cost sensors in developing economies

The use of low-cost sensor networks (LCSNs) in pollution monitoring has the potential to provide a relatively low-cost and appropriately sensitive solution for

monitoring and managing the air quality in emerging economies. The use of LCSNs in the environmental sciences is becoming increasingly widespread, and the monitoring data provided has enabled research across a wide variety of disciplines and applications (Mao et al., 2019). Non-technical hurdles such as stakeholder participation, the wider socio-economic situation logistics and in some cases country scale capacity can limit the broader development and use of LCSNs.

In the context of monitoring charcoal production, LCSNs could be used to determine levels of directly emitted CO, CO₂, NO₂ and PM. There is very limited data on the contribution of charcoal production to ambient air quality. It is reported that emissions from charcoal manufacturing are frequently overlooked when assessing the wider environment (Sedano et al., 2016). Further studies are needed to understand charcoal making as a source of pollutants and to link any emissions to social, economic, and wider environmental issues. Low-cost sensors can be installed in developing nations to characterise air conditions to identify the extent and contribution of emissions from charcoal producing operations through source apportionment studies in remote locations. Low-cost sensors provide data of an appropriate quality in packages suitable to use in remote areas, allowing for flexible deployments (Morawska et al., 2018). The development of low-cost sensors for environmental monitoring has received a lot of attention (Afshar-Mohajer et al., 2018; Kumar et al., 2015; Lewis et al., 2018; Mead et al., 2013; Rai et al., 2017; Schneider et al., 2017; Spinelle et al., 2014). However, no studies have been conducted to assess the specific implications of emissions from charcoal manufacturing using low-cost sensors, particularly in underdeveloped nations. As part of this investigation, a methodology to quantify charcoal kiln emission plumes will be developed and areas of increased charcoal production will be identified. This will be done using advanced miniaturized gas phase and particulate sensors in the Usambara Mountains region of Tanzania. Areas of high-density charcoal production kilns will be identified and links between charcoal production and forest-catchment degradation will be established.

2.3 Summary

The forests cover 31% of the Earth's land surface (4.06 billion ha) but the area is shrinking, with 420 million ha of forest lost through deforestation between 1990 and 2020 (FAO, 2022). It is estimated that the globe has lost 178 million ha of forest during the 1990s, which is approximately an extent equivalent to Libya (FAO, 2020b). Africa had the highest yearly rate of net forest loss between 2010 and 2020 at 3.9 million ha, followed by South America at 2.6 million ha (FAO, 2020b). Since 1990, the pace of net forest loss in Africa has grown on a decade-by-decade basis. However, it dropped significantly in South America, to almost half the rate between 2010 and 2020 when compared to the 2000-2010 period (FAO, 2020b).

It was reported that Africa had the highest annual rate of net forest loss from 2010 to 2020, at 3.9 million ha, followed by South America, at 2.6 million ha over the same period (FAO, 2020a). Since 1990, the rate of net forest loss in Africa has increased in each of the three decades. Population growth, density, distribution, migration, and urbanisation are key drivers of deforestation (UN DESA, 2019). It was reported on the relationships between population and loss of forest cover, Tanzania ranks among the top ten countries, with an annual forest loss of 372,000 ha (NBS, 2020; Population Action International, 2011).

Forested areas of Tanzania are mostly Miombo woodlands, constituting an estimated 90% of forest cover (Mgaya, 2016). The forests have a high biodiversity value, which helps to reduce poverty as well as increase agricultural stability and improve soil protection (Blomley & Iddi, 2009). Due to the high cost of other energy sources, a high proportion of communities in Tanzania use biomass as a source of energy. Although forests in Tanzania are an essential resource, they are being reduced in overall coverage as well as being degraded in part due to the use of forest products as a fuel source. In rural Tanzania, traditional biofuels such as firewood and charcoal are widely used (Hoffmann et al., 2018). The major areas producing charcoal are predominately found in Tanzania's eastern region

(Mhache, 2012; Msuya et al., 2011), with consumption primarily in major urban areas such as Muheza, Korogwe, Handeni, Dar-es-salaam, and Tanga.

Charcoal consumption contributes directly to deforestation and forest degradation. This is because most households rely heavily on charcoal and firewood to meet their domestic energy needs. In Dar es Salaam, Tanga, and Morogoro, per capita charcoal consumption per day is approximately 0.2 kg. Charcoal production contributes to the emissions of a variety of pollutants, including CH₄ and CO. Charcoal production also generates particulate matter such as PM₁₀ and PM_{2.5} (Msuya et al., 2011). The production and use of charcoal contributes to several health effects in communities, including pneumonia and chronic respiratory disease. During combustion processes such as charcoal production, CO and NO_x are emitted. Exposure to emissions from charcoal making activities for an extended period may cause brain damage and death (Msuya et al., 2011).

Several studies have addressed the impacts of emissions derived from charcoal making on health and loss of biodiversity (Bailis et al., 2003; Green et al., 2013; Kilahama, 2008; Mhache, 2012; Msuya *et al.*, 2011). These studies have been mainly focused on consumption of charcoal and impact at the indoor household level. Most of these studies were undertaken in developed economies that have the infrastructure needed to conduct real time measurements. In contrast, studies on the specific impacts of charcoal making activities in developing economies such as Tanzania have not been undertaken. This study will lead to the development of a methodology for the quantification of charcoal production emission in ambient condition, identifying areas of high-density kiln and changes in charcoal production around East Usambara Mountain and to link the charcoal production impacts on catchments and forest degradation.

CHAPTER 3. Methodology

This chapter summarises the study site and the methodology used in this investigation. Section 3.1 describes the rationale for the selection of the study site as well as its characteristics (e.g., climatic conditions, and vegetation). The instrumentation utilised and the data collected in this study to assess the environmental implications of kiln burning are outlined in section 3.2. Low-cost electrochemical sensors are examples of equipment used and are described within this section. Section 3.3 introduces the methodology (data analysis) used to (i) quantify charcoal production emissions in ambient conditions and (ii) investigate the regional distribution of charcoal production in Tanzania utilising satellite data derived products, as well as land use change and characterisation. These strategies aid in better limiting pollutant emissions into the atmosphere as well as identifying regions of high charcoal production activity and changes in production in Northern Tanzania.

3.1. Study Site

Data were obtained at two separate locations situated in Moshi and the East Usambara mountains (Figure 3-1 and Figure 3-2). Data from the first site (Moshi) addressed objective one that stated, “To develop a methodology to quantify charcoal production emissions in ambient conditions”. Data collected at the second site (East Usambara mountains) was used to address objective 2 “To identify areas of high-density kilns and changes in charcoal production around Usambara Mountain using GIS approaches” and objective 3 “To link charcoal production with forest impact and degradation”.

Moshi is located on the south slopes of Kilimanjaro Mountain at latitude (3.3430° S), longitude (37.3507° E), a height of 985 metres in the north-eastern section of the town and 750 metres in the south (Mhina et al., 2003) with a population of approximately 535,803 people (URT, 2022). The site in Moshi was located at the Forest Industries Training Institute (FITI), in the Kilimanjaro Region which is characterised by the presence of leather workshops and sawmills. There are also

several general waste dumping sites and widespread domestic wood or charcoal burning. These industries, dumping sites, and home burning emit CO₂ (Mavrodin et al., 2015; UNIDO, 2017), as well as PM, NO₂, SO₂, and CH₄ (Oguntoke et al., 2013; Ramasamy et al., 2015).

The FITI site was chosen because it permitted the legal setup of a kiln experiment to obtain the required data for the characterization of charcoal production emissions. Permission had to be requested to cut down a tree in the surrounding area and set up the kiln. Such a permit may not have been available for more rural areas where trees have fallen illegally as part of encroachment activities. The site was also selected based on the availability of an electric network for sensor deployment. The exact location for the installation of the sensors was selected based on the availability of a reliable energy source, a secure installation point as well as it being representative of the wider environment.

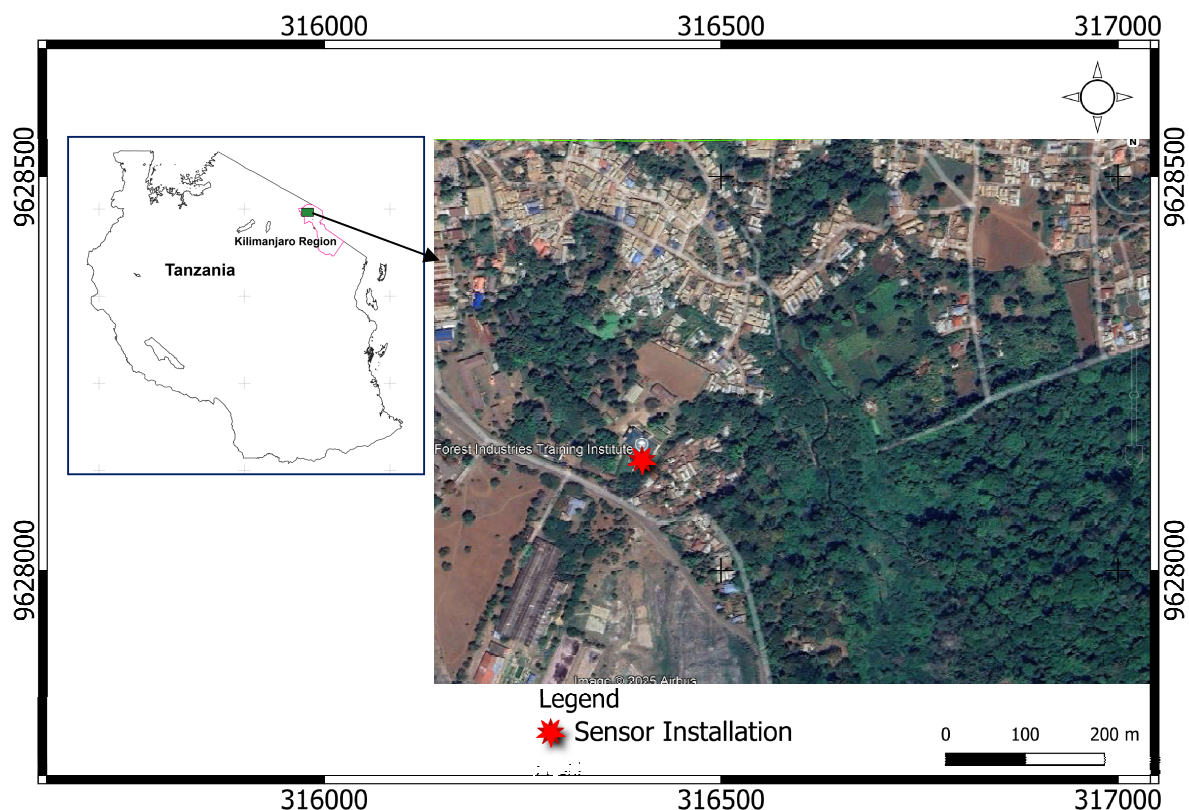


Figure 3 - 1: A map of Tanzania indicating the location of Moshi, the area where Charcoal Kiln experimentation was established.

The East Usambara Mountains, located in the north-eastern region of Tanzania at a latitude and longitude of 4° 58' 53" S and 38° 36' 38" E respectively. The elevation gradient of an area ranging from 200 m to beyond 1200 m with a population of approximately 135,000 people (URT, 2022). The entire East Usambara landscape covers an area of approximately 108,200 ha (Burgess et al., 2007), of which about 31,000 ha is forest. The two main districts of Tanzania comprising the East Usambara landscape are Muheza and Mkinga. The highest point in this mountain range is Mt. Nilo, at 1,506 meters (Mansourian et al., 2019). It has been recognized as one of the forest ecosystems in the world that is facing the highest level of threats due to deforestation (Myers et al., 2013). Deforestation is a widespread issue in the unprotected forests of this region (Hall et al., 2009). The region encompasses a wet tropical montane forest situated at an elevation of around 600 meters and harbors a significant portion of the surviving lowland montane forest in East Africa, which holds ecological significance (Myers et al., 2013). The forests located in the East Usambara region exhibit a range of protection levels, with the majority being situated inside government reserves.

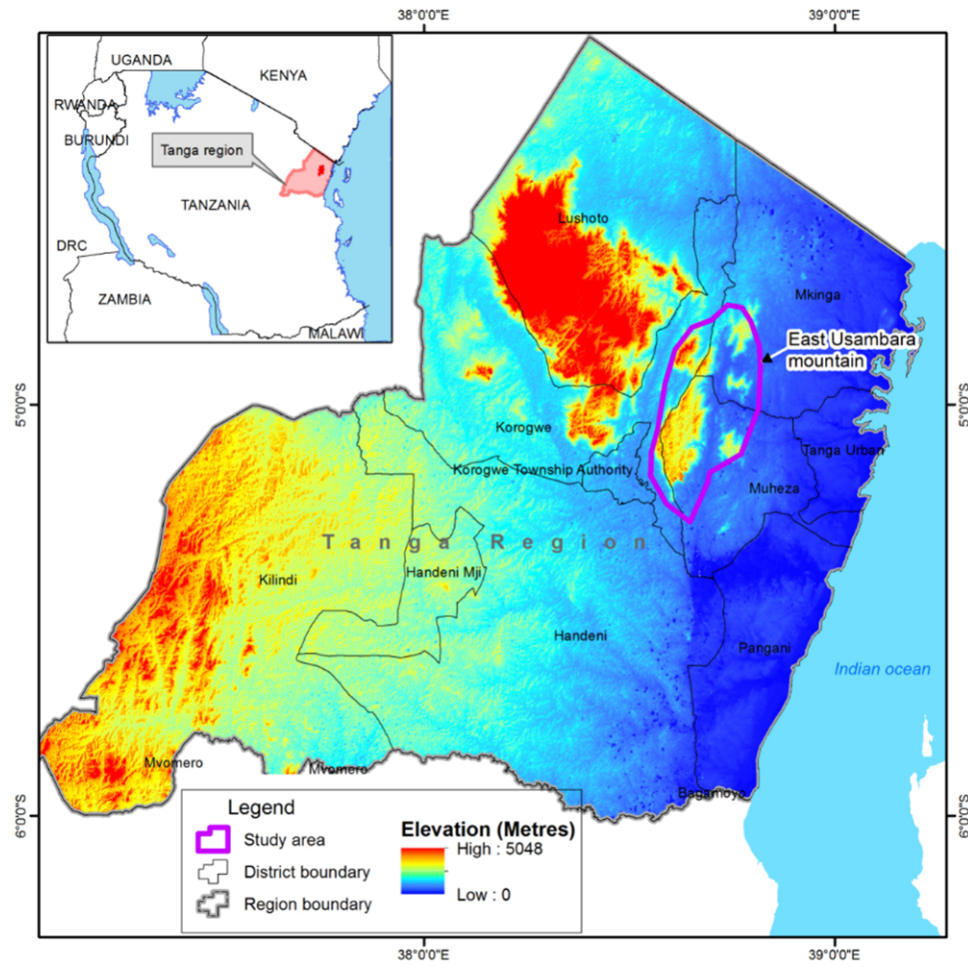


Figure 3 - 2: A map of Tanzania indicating the location East Usambara Mountain, the area where proxy variables on charcoal kiln activities were identified.

The East Usambara region comprises a collection of long-standing protected areas in East Africa. Historically, these areas have implemented policies that have limited the involvement of local communities in matters of administration and decision-making, while also imposing significant constraints on their utilisation. The area is closely guarded to ensure that no unlawful activities take place (mining, tree cutting, and charcoal making). However, the militarisation of conservation holds potentially far reaching consequences for practices, rhetoric, policy, and interactions between conservation actors and other stakeholders (Duffy et al., 2019). Encroachment does occur, though, and charcoal-making activity is observed. The site was selected because the projected population increase in Tanzania, especially in Tanga town, which is just 30 km from the East

Usambara Mountains, is expected to have an impact on the increased production of charcoal within the area. At present, there is a lack of information on the distribution of charcoal production in the area and how increased charcoal making activity will impact encroachment and degradation.

3.1.1 Climatology of the study sites

In this section the general climatic conditions for the study sites chosen are summarised. Tropical wet and tropical dry environments coexist at Moshi district where the study site (FITI) is found (Climate-data, 2019a). Temperature patterns and increased precipitation in April differentiate tropical wet and tropical dry periods (Climate-data, 2019a). Rainfall is highest from November to May and lowest from June to October at the FITI site (Fig.3-2). The average annual temperature and rainfall in the region are 23.4 °C and 856 mm, respectively (Climate-data, 2019a; Hermansen et al., 1985). The monthly average temperature and rainfall in Kilimanjaro's Moshi District are depicted in Figure 3-2 (Climate-data, 2019a).

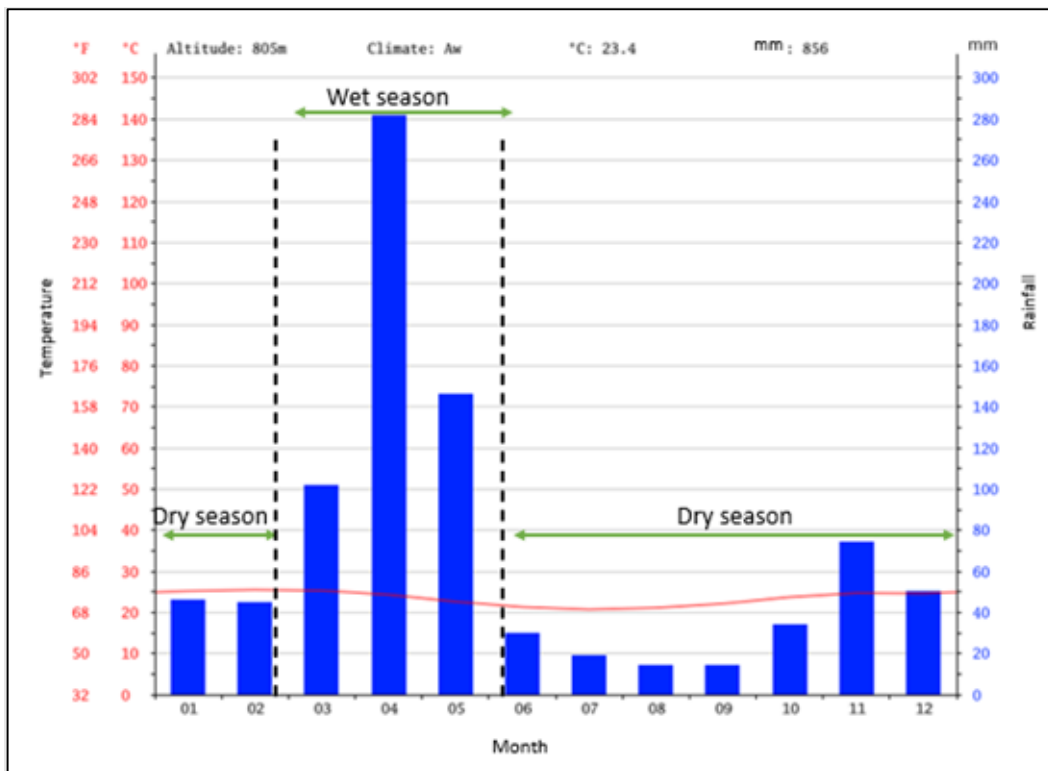


Figure 3 - 3: Representative monthly average for temperature and rainfall (23.4°C and 856mm) within Moshi. Charcoal production within Moshi District is constant all through the year. The months shown in the plot align with the calendar year (01=January). Source: (Climate-data, 2019a).

The East Usambara Mountains are characterised by a tropical climate, with a marked seasonal alternation of wet and dry periods, as well as an average temperature above 18°C throughout the year (Aguado & Burt, 2015). The humid tropical environment that surrounds along east Usambara Mountain is classified as dry winter (Aw) climate by Köppen and Geiger. Based on statistical research, the temperature at this place is roughly 22.7 °C (72.9 °F). In total, there is around 1268 mm of precipitation annually (Fig. 3.3). The end of June marks the start of summer, which lasts until September. June, July, August, and September are summer months (Climate-data, 2019b).

It was previously established that the climatic conditions of a given location will impact the occurrence of air pollution in that area (Kumar et al., 2019). A variety of models have been constructed to examine the relationships between atmospheric chemistry and the climate system (Isaksen et al., 2019). The composition and chemistry of the atmosphere are inextricably linked to the climatic system of the area due to numerous interactions. The climate change is expected to degrade air quality in many polluted areas by altering air pollution meteorology (ventilation and dilution), precipitation, and other removal processes, as well as by triggering some amplifying responses in atmospheric chemistry and anthropogenic and natural sources (Latif et al., 2016). Therefore, the climatic conditions within the study areas will have to be considered when interpreting the results of this study.

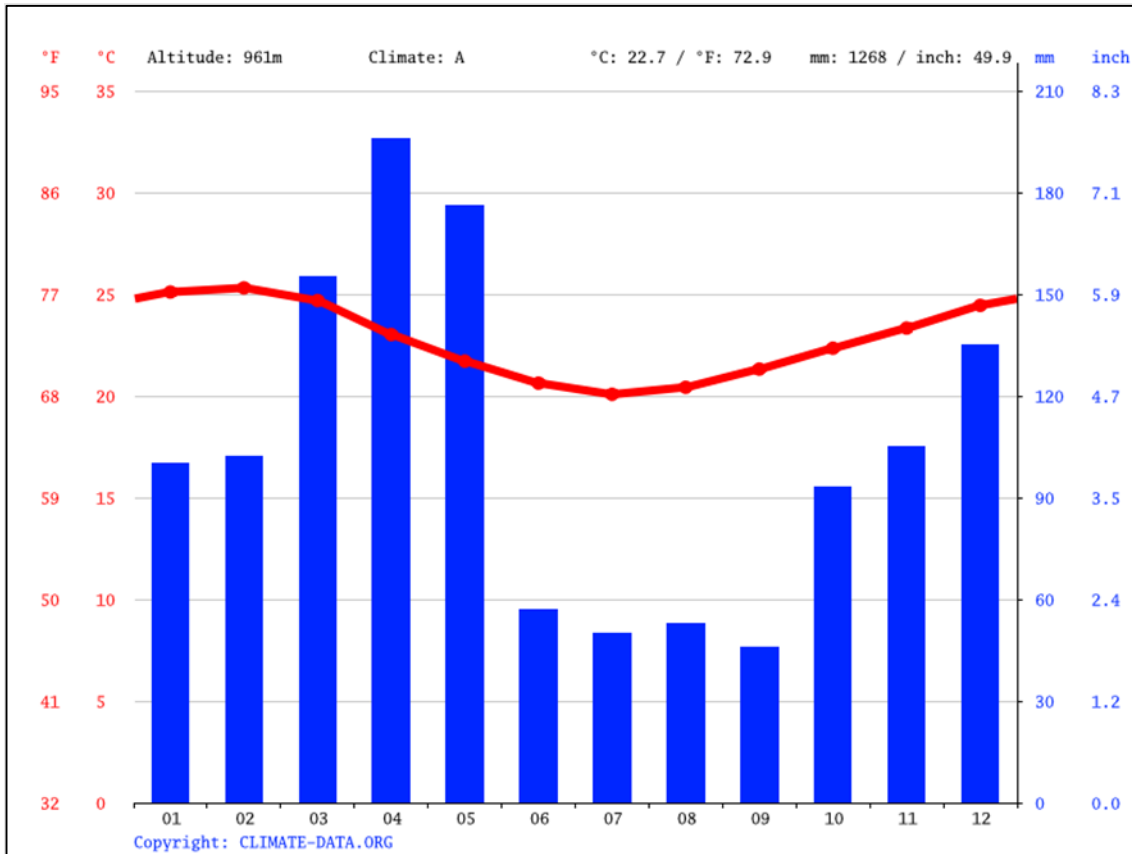


Figure 3 - 4: Plot shows the monthly average temperature and rainfall at the East Usambara Mountains (**based on Mbomole weather station**). The months shown in the plot align with the calendar year (01=January). Source: (Climate-data, 2019a).

3.1.2 Topology and hydrology at the study sites.

The topography and hydrology of the sites are critical for understanding the overall impact of charcoal production on water catchments and freshwater ecosystems within the region. The geography and hydrology of Moshi where the FITI site is located and the East Usambara Mountain are described in the following paragraphs.

The primary physical characteristics of the mountains extending from North-Northwest to South-Southeast determine the hydrology and morphology of Moshi, with the terrain elevation dropping down to 305 meters above sea level on either side. Mount Kilimanjaro's snow-capped peak offers an inexhaustible supply of water to the lower slopes via countless streams. Most rivers in this region dry up after entering the plains, but the Ruvu (Pangani) and Kikuletwa rivers collect water from the higher streams and continue to flow even during the dry season.

The rivers merge 38 kilometres south of Moshi municipality, making a vast manmade lake named *Nyumba ya Mungu*, which stretches about 6 km from north to south. The dam released water originates the Pangani river, which loops around and flows southward of the region.

The East Usambara Mountains (EUMs) are located, mainly in Muheza and Korogwe Districts in Tanga Region in North-East Tanzania. The highest mountain peak reaches 1,506 metres. The Eastern Arc Mountains have a direct geographical connection with the Indian Ocean. The mountains compel the incoming air masses originating from the ocean to ascend, undergo cooling, and then undergo a phase change in precipitation. The occurrence referred to as the orographic effect is accountable for the presence of consistent precipitation, leading to ample runoff and replenishment of groundwater (Yanda & Munishi, 2007). The reduced evapotranspiration rates seen on the slopes of these mountains, due to colder temperatures, contribute to a favourable overall water balance. Typically, the low-lying areas neighbouring these mountain ranges have diminished levels of precipitation and elevated rates of evapotranspiration, leading to an unfavourable water equilibrium. Consequently, the Eastern Arc Mountains serve as the primary water source for the lowlands, which encompass the primary population centres. The Eastern Arc Mountains serve as the primary hydrological source for major rivers in Tanzania, facilitating crucial functions such as power generation, agriculture, and water provisioning. The presence of mountains has a crucial role in sustaining the base flow of rivers, ensuring the availability of water even in periods of low precipitation (URT, 2005).

3.1.3 Vegetation at the study sites

Understanding the flora present in the study sites is critical for determining the possible utilisation of wood for charcoal-making operations. The important plant species in the area are described here.

The FITI is distinguished by dispersed trees that may be divided into two types: cultivated and wild. *Senna siamea*, *Azadirachita indica*, *Mangifera indica*,

Jacaranda mimosifolia, and *Leucaena leucocephala* are among the plants planted. The Rau Forest Reserve, which surrounds the experiment site, has both natural and indigenous trees. The Rau Forest reserve is characterised by lowland groundwater forest and has numerous uncommon tree species, including *Oxystigma msoo* (only known from Rau Forest and only in a 5 ha region) and *Tapura fischere* (rare in East Africa) (Hermansen et al., 1985). As a result, local people gather timber from the surrounding forest, and some are active in charcoal production and firewood collection for domestic energy.

The vegetation in the East Usambara Mountains is typical of a tropical rain forest, with two ecosystem types, mountains and coastal forests. Tropical evergreen forests (*Cephalosphaera usambarensis*, *Allanblankia stuhlmanii*) coexist with tropical submontane rainforests, savanna woods (*Combretum* spp., *Annona* spp.), agroforestry, agroecosystems, grazing, and urban areas. According to Frontier Tanzania (2002)(Frontier Tanzania, 2002), East Usambara is one of Africa's most precious conservation zones. Although the area is preserved, human activities such as charcoal production and firewood gathering are clearly taking place within it (White et al., 2005). The production of charcoal within the forest may lead to deforestation and its derived emission could affect atmosphere.

3.2. Data collection

3.2.1. Data Collection for Objective 1

Atmospheric data was required to address objective 1 (“To develop a methodology to quantify charcoal production emissions in ambient conditions”). Low-cost electrochemical sensor modules were used for that purpose. Their configuration is summarised in section 3.2.1.1. An experiment replicating a traditional kiln for charcoal production was used to collect the required information. The set-up of the experiment is explained in section 3.2.1.2.

3.2.1.1. Atmospheric Instrumentation

Low-cost electrochemical sensor modules (Atmospheric Sensor Model 510, numbers 97 and 98) based on technology developed by the University of Cambridge (Mead et al., 2013) and Alphasense technology were used to collect

the required atmospheric data for the study. Figure 3-4 depicts an exterior and interior view of the components of a low-cost electrochemical sensor. A powerful 32-bit floating-point ARM microprocessor controls the sensor node, which is meant to offer a comprehensive study of local air quality. The device includes four electrochemical sensors for monitoring CO, NO, NO₂, and O₃ levels down to parts per billion (ppb); a NDIR CO₂ sensor; an OPC-N₂ sensor; and a laser particle monitors PM₁, PM_{2.5}, and PM₁₀. These are linked to a temperature and relative humidity sensor. A RTK GPS is utilised for precise position and time stamping. Furthermore, the modules contain gaseous inlets for CO, CO₂ and particulate particles. An optional microphone is available to provide information about ambient noise. Data is saved locally before being uploaded to a centralised administration site.

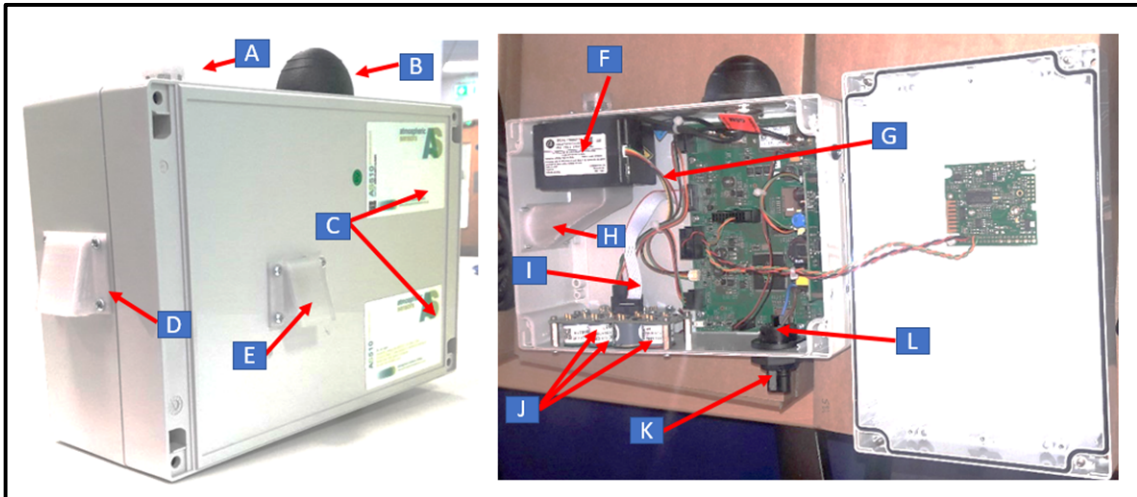


Figure 3 - 5: Deployed sensor Nodes (AS510 Model) showing external and internal main components. The external parts of the sensor nodes include the following; Inlet for species of [e.g. PM₁, PM_{2.5}, PM₁₀] (A), GPS Antenna (B), Label indicating specific board [node] number (C), OPC Exhaust (D), Inlet for species of O₃, NO₂-and CO (E) and the internal parts of sensor nodes includes an Optical Particle Counter-N₂ (OPC) (F), Communication wire between the main PCB and the OPC (G), chimney of OPC (H), Communication wire between the main PCB and the electrochemical cells (I), Electrochemical cells (J), weather tight AC power input (K) and weather proof pin (L).

The atmospheric sensor modules deployed automatically measured multiple parameters as described in this section. However, for the purpose of this study and to address the objectives of the thesis, only CO, CO₂, PM₁, PM_{2.5} and PM₁₀ were considered for analysis. Both CO and CO₂ were considered for analysis

because charcoal production through pyrolysis is accompanied by gaseous emissions into the atmosphere and occupationally exposed workers could be affected (Olujimi et al., 2016). They were also selected because of their latest applicability in measuring pollutants at a low cost and usefulness in climate change studies. CO₂ is the main product of complete combustion and CO, a product of incomplete combustion, is a toxic gas that at high concentrations can overcome exposed persons without warning (Olujimi et al., 2016).

3.2.1.2. Kiln experimental design at the FITI site (Moshi)

The experiment carried out at the FITI site (Moshi) replicated charcoal making activity using the traditional kiln method, mostly adopted by local communities across sub-Saharan Africa. This consists of the placement of mud, soil and grass, amongst other materials, on top of the hump to ensure the right conditions for charcoal making were achieved (Menemencioglu, 2013) and figure 3-5. A single kiln set-up was used in the study due to limited of material and labour. The author understands that a single kiln is not fully representative of all the kilns within the area. However, time and cost constraints did not enable the replication of the kiln set-up. The experimental site is surrounded by households, industrial estates and dumping areas (within a 5 km radius). Emissions from household activities (e.g., cooking) are expected within the area. The site is adjacent to a forest where no charcoal production is conducted. A visual inspection was carried out to ensure that no other kilns were within close (>10 km radius) proximity of the experiment site. This ensured that all the emissions the sensors recorded related to the production of charcoal of the experiment kiln set up and to no other kilns within the area, although emissions from other sources (e.g., households) could not be controlled.

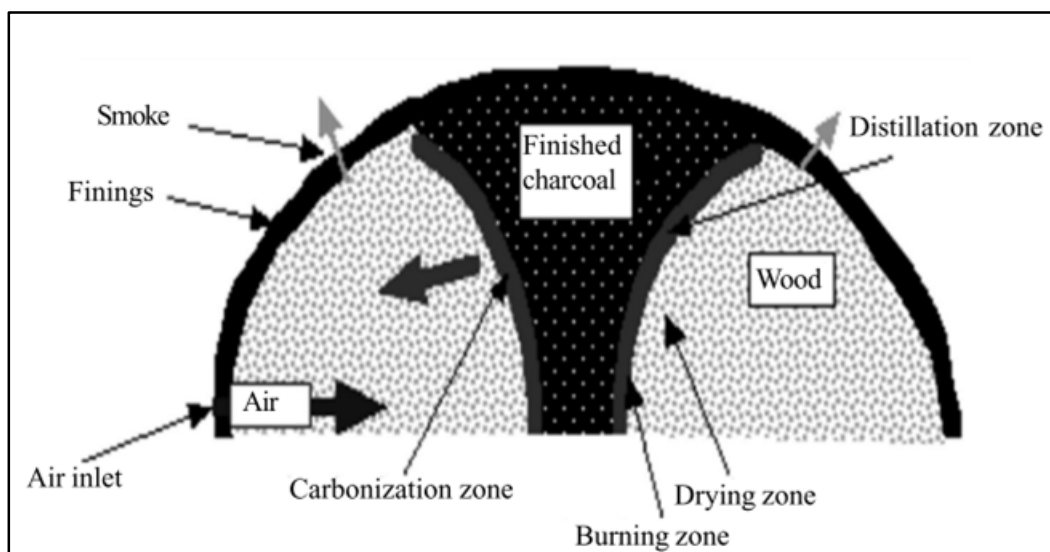


Figure 3 - 6: Diagram of kiln design (Menemencioglu, 2013)

The typical procedures of charcoal making are described in various literatures (Domac et al., 2008; FAO, 1987b; Kammen & Lew, 2005; Msuya et al., 2011). Fig 3.5 shows the workflow followed to set up and run the experimental kiln at the FITI site. The earth kiln was prepared using trees found in Moshi to replicate local methods and materials used in the area for charcoal making. The activity involved cutting down an old tree species known as *Jacaranda mimosifolia* found at FITI compound using chainsaw operators for charcoal making. A total volume of 2.1 m³ of wood (trunk and branches) was used in the kiln for charcoal production. The wood was not left to dry before setting up the kiln. The experimental kiln was hemispherical in shape with a radius of 1 meter. Ignition was facilitated through the burning of dried wood and grasses using matches that lead to burning of logs intended for charcoal production. The pollutants from earth charcoal kiln were recorded using low-cost electrochemical sensors developed by Alphasense, UK

The low-cost electrochemical sensor modules were tested from 05th October 2018 to 22nd January 2019 at the FITI site (Moshi), 300 m away from the exact location where the kiln experiment was set up. The testing period was required to ensure the sensors, which were initially designed in and developed for Northern countries, were able to record information in tropical Tanzania. The sensors recorded information right from testing kiln. The kiln was set up from the 20th March 2019 to

10th April 2019 and ignition took place on the 24th March 2019. Smoke first came out of the kiln on the first day of ignition 24th March 2019. The kiln was opened six days (30th March 2019) after ignition and any charcoal produced (approx. 50 kg) was removed. The kiln was then closed again on 31st March 2019 with the remaining wood and left for another 9 days. On 10th April 2019, the additional charcoal produced (20 kg) was retrieved and the kiln set up was dismantled. The volume of the kiln was estimated to be 2.1 m³ as the radius of the kiln (hemisphere shape) was approximately 1 m (Equation 4). The charcoal produced was calculated using equation 4. Figure 3-6 shows the stacking of logs, covering of logs, area of sensor node deployment and typical emissions derived from the earth kiln.

$V = (2/3) * \pi * r^3$ Equation 4
 where V is the volume of the kiln in cubic meter (m³) and r is the radius (m) of the sphere.

The study aimed to provide information about the emissions from a typical earth kiln and contribute to estimating the extent of emissions that are derived from various earth kilns in general. The results were used to develop a methodology to quantify charcoal production emissions in ambient conditions.

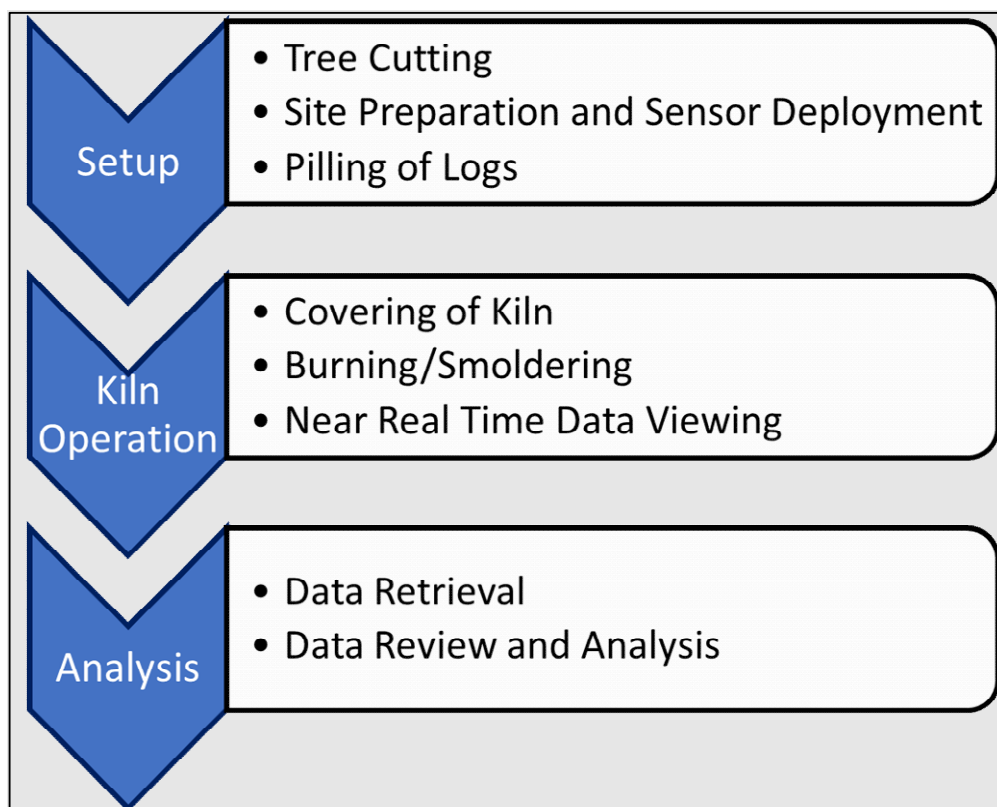


Figure 3 - 7: Workflow of the experimental kiln set up for charcoal production at the FITI site (Moshi).

Figure 3-7 shows an experimental set up at the FITI study site (Moshi), using a typical earth kiln method. The atmospheric sensors were deployed 10 m away from the experimental kiln site from 04th February to 19th March 2019 before setting and ignition process (kiln operations). The 10 m distance was selected because it provided a safety buffer for the sensor and yet ensured the collection of the required measurements. Deployment of the sensors in closer proximities would have resulted in equipment failure due to heat exposure. The six (6) week period provided measurements prior to the kiln ignition to set up the baseline conditions for that area at that time of the year and to enable subsequent quantification of the kiln's emissions of CO, CO₂, NO, and PM_x. Six months was judged to be a long enough period to ensure the characteristics of the site prior to kiln ignition were accurately determined based on the earlier study (Products Lab, 1961).

The efficiency of converting wood to charcoal depends on the skill of the operator and the water content of the wood. Once the ignition process takes place, the deployed sensors are used to detect the changes that are estimated to be caused by the burned charcoal kiln in the area.

The sensors recorded information every second to capture the pollutants derived from the charcoal making activities. Spatio - temporally collocated records for CO, CO₂, and PM_x were collected from 04th February 2019 to 27th August 2019. Two sensors with label number Node 97 and 98 from Alphasense Ltd were collocated. However, data from node 98 was not used in this study as too much dirty data observed, and such noise won't let analyse anything properly. Thus, no intercomparison was possible during this study.

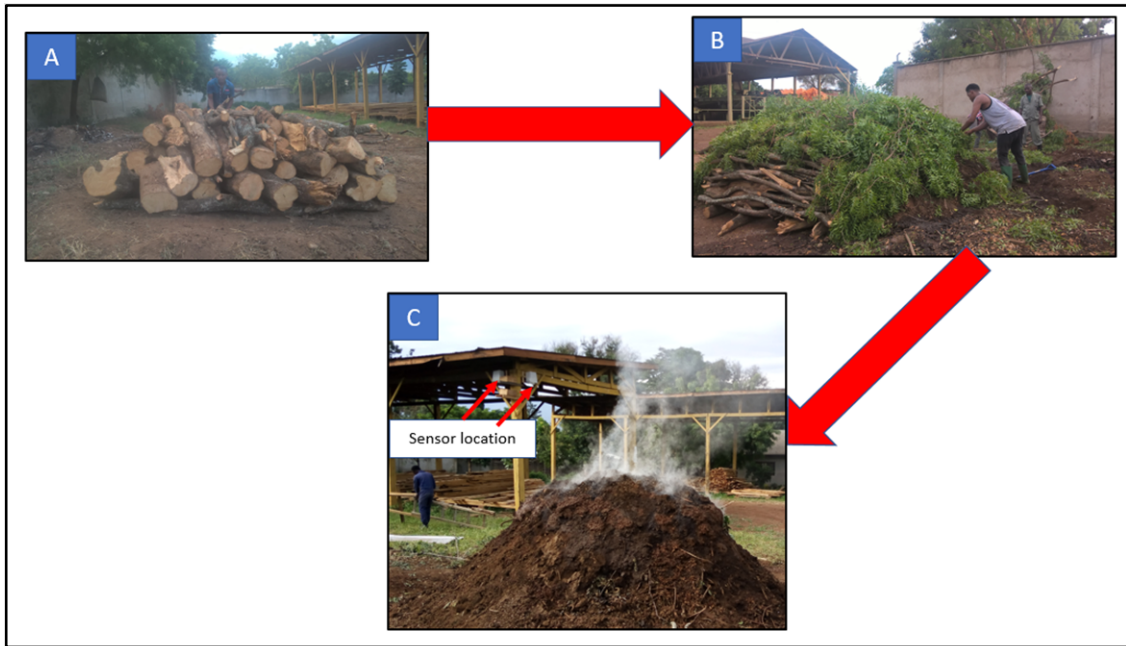


Figure 3 - 8: Experimental set up at the FITI study site (Moshi), using a typical earth kiln method. The process shown in the pictures involved the stacking of logs to enable easy ignition and burning (A), covering of logs with grasses or leaves to prevent the soil entering the kiln and suffocating the burning process (B) and ignition of the kiln (C).

3.2.1.3. Meteorological data

Secondary data sets on meteorological variables of wind speed and direction were downloaded from the Global Forecasting System (GFS) (Fernández-López & Schliep, 2018). The download was done under R software infrastructure using

codes developed in the wind package (Fernández-lópez & Schliep, 2018). The package enabled the download of the basic meteorological parameters, which are wind speed and wind direction, from the testing phase date of low-cost electrochemical sensor node installation (05th October 2018). These variables influence a scope of environmental attributes and dispersal of toxins. It was reported that the meteorological variables and their regular changes control the gravity and power of air contamination in a zone, cause occasional variations and therefore have an impact on the way pollutants separate in the atmosphere (CPCB, 2010)

3.2.2. Data collection for Objective 2

Land use information as well as the locations where charcoal was produced were required to address objective 2 that aimed “To identify areas of high-density kilns and changes in charcoal production around the East Usambara Mountains using GIS approaches”. This section describes the primary and ancillary data collected or collated to address objective 2 and ultimately link to objective 3 “To link charcoal production with forest impact and degradation” (Objective 3).

3.2.2.1. Charcoal production locations

The entire East Usambara landscape covers an area of approximately 108,200 ha (Burgess et al., 2007) of which about 31,000 ha is forest (Mansourian et al., 2019). The East Usambara Nature Reserve (Figure 3-8) is divided into 14 forest patches for management purpose. These patches are defined by governmental boundaries outlining the edge of the forest (Kijazi et al., 2000; The United Republic of Tanzania (URT) & Unfccc, 2016) within the nature reserve. Google Earth imagery from 2008 to 2018 was collated to identify (digitise) charcoal making activity across the Usambara block. The forest patches were used to define discrete boundaries to aid with the visual identification of proxy variables (i.e., dark spots, foot paths, human settlements and charcoal kilns) that indicated charcoal making activity had taken place. In brief, these proxy variables were not expected to be identified within the patches as they represent the presence of

illegal activities within the nature reserve. Any activity of the type occurring within the patches is considered encroachment.

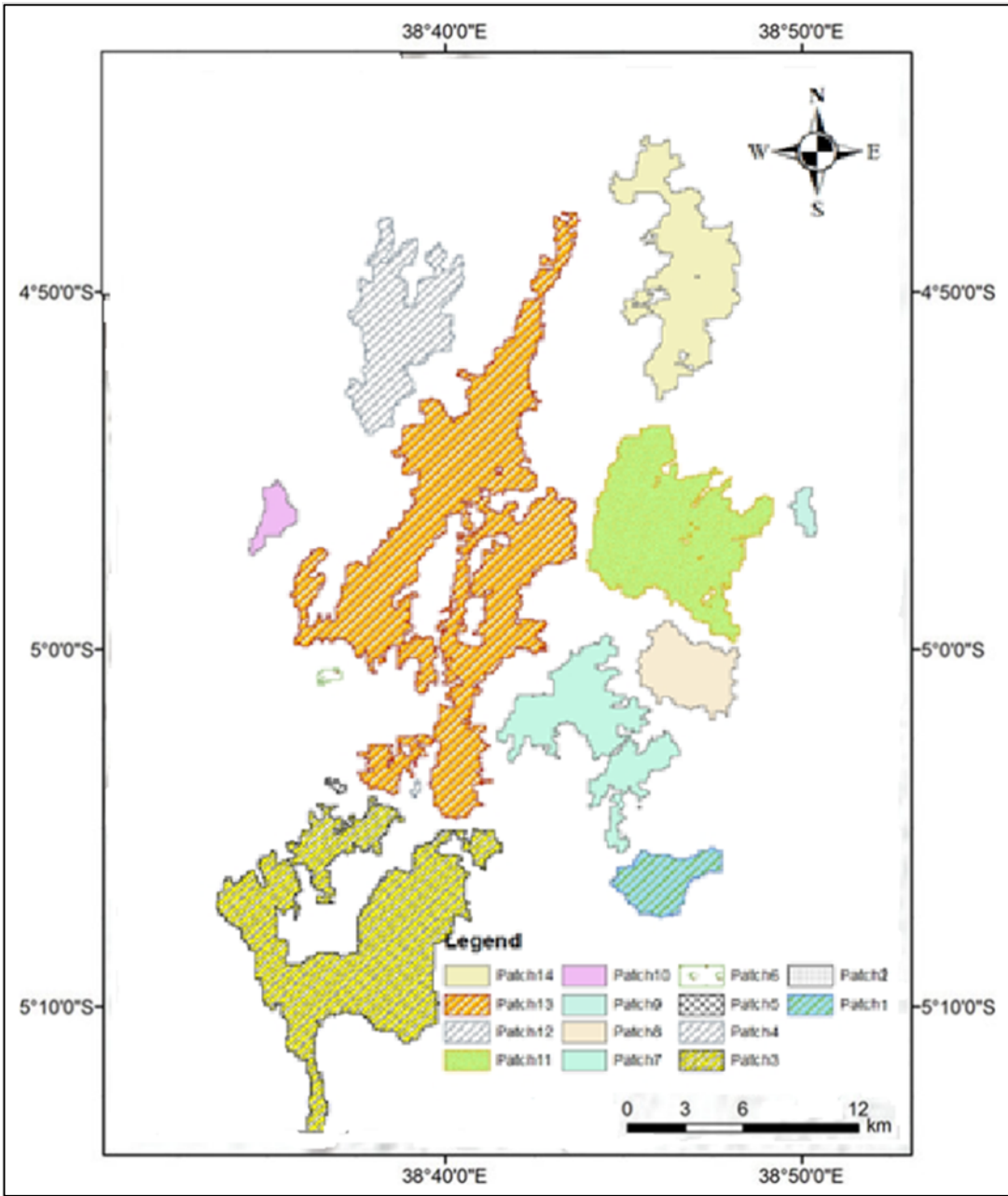


Figure 3 - 9: Map of the East Usambara Mountains depicting the 14 forest patches selected during the identification of proxy variables.

The proxy variables were identified through visual scanning of all the images from Google Earth that comprised all the forest patches. The Google Earth images scanned were divided into four-time intervals: [1995 to 2001], [2002 to 2012],

[2013 to 2015] and [2016 to 2019]. Each forest patch was scanned systematically for each of these periods and all proxy variables (i.e., dark spots, foot paths, human settlements, and charcoal kilns) were identified and labelled for the full extent. Dark spots and charcoal kilns were labelled using the “add placemark” option on Google Earth, human settlements were labelled using the “add polygon” option, whereas foot paths were labelled using the “add path” option. This was done using collect earth software embedded in the google earth pro. Collect earth software is a tool that enables data collection through Google Earth. In conjunction with google earth, Bing Maps and Google Earth Engine, users can analyse high and very high-resolution satellite imagery for a variety of purpose, including quantifying deforestation, reforestation and desertification, validation of existing maps, land use, landuse Change and Forestry (LULUCF) assessment, support multi-phase National Forest Inventory, monitoring agricultural land and urban areas (Openforis, 2024; <https://openforis.org/solutions/collect-earth/>). Examples of images with these types of features are presented in Appendix 1.

3.2.2.2 Land use and land cover data

Land use and land cover data of the East Usambara Mountains were derived from satellite imagery using Remote Sensing (RS) techniques in a Geographical Information System (GIS) environment (Figure 3-9).

Satellite imagery (Landsat) was selected from the dry season to minimise both cloud cover (<10%) and seasonality differences (Caetano, 2009; Liu et al., 2015). Images were downloaded from the United States Geological Survey using the Google Earth Engine Code Editor. The images were obtained from two different Landsat sensors i.e., Landsat Thematic Mapper (2008) and Landsat Operation Land Imager (2018). The images were assumed to accurately represent the land use and land cover within the area for 2008 and 2018.

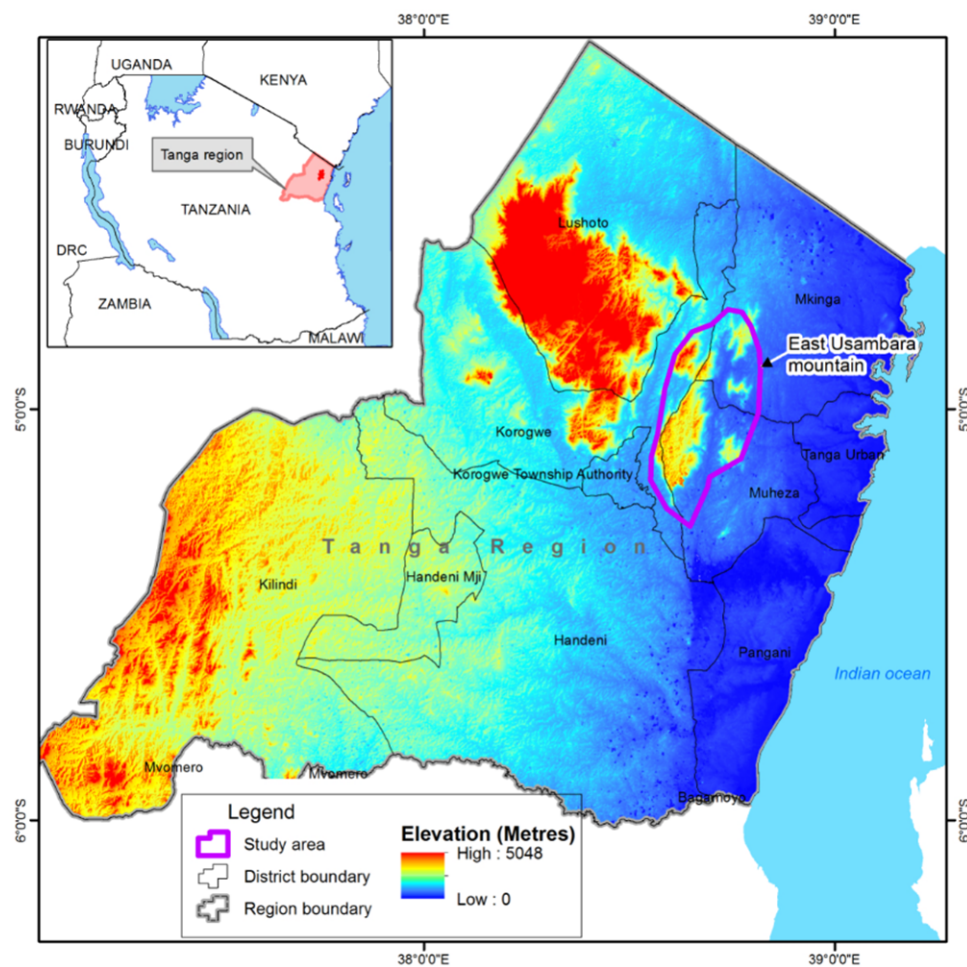


Figure 3 – 10: Map showing the area of the East Usambara Mountains for which satellite imagery were obtained and analysed to assess land use and land cover change.

3.2.2.3. Fuel consumption and environmental changes

Secondary data on charcoal production and usage and, deforestation, changes in riverine systems and flooding events was collected from government institutions and NGO's available in the study area including Tanzania Forest Service (TFS)-Amani Nature Reserve, Tanzania Forest Conservation Groups (TFCG), ONGAWA, Friends of Nature, World Wildlife Fund (WWF)-Tanzania, Umoja wa Wakulima na Mazingira Kihuhwi-Zigi (UWAMAKIZI) Pangani River Basin Authority and Watershed Management for Ruvu and Zigi Project. Also, other data were obtained from different publications, journals and visiting websites.

3.2.3 Data collection for objective 3

The analysis carried out to address objective 3 (i.e., “To link charcoal production with forest impact and degradation”) did not require the collection or collation of any additional data as it relied on the data derived from objective 2.

3.3. Data Analysis

The workflow followed to analyse the data for objective 1 to 3 is summarised in Figure 3-10. Section 3.3.1, 3.3.2 and 3.3.3 provide the additional detail required to understand how each objective was addressed.

3.3.1. Data analysis for objective 1

For objective 1, emissions records obtained for pre- (04th February to 19th March 2019), during charcoal production (20th March 2019 to 10th April 2019 and post-kiln (11th April to August 27th, 2019) were compared for CO, CO₂ and particulate matters. Figure 3-10 shows the timeline of the kiln experiment carried out under objective 1. The pre-kiln activity measurements were treated as the baseline information and were assumed to represent the general atmospheric conditions of the area. The during-kiln data was assumed to provide a general representation of the atmospheric conditions when the area is under influence of charcoal making activity. The post-kiln burning data was assumed to represent the atmospheric conditions after charcoal making activity had taken place.

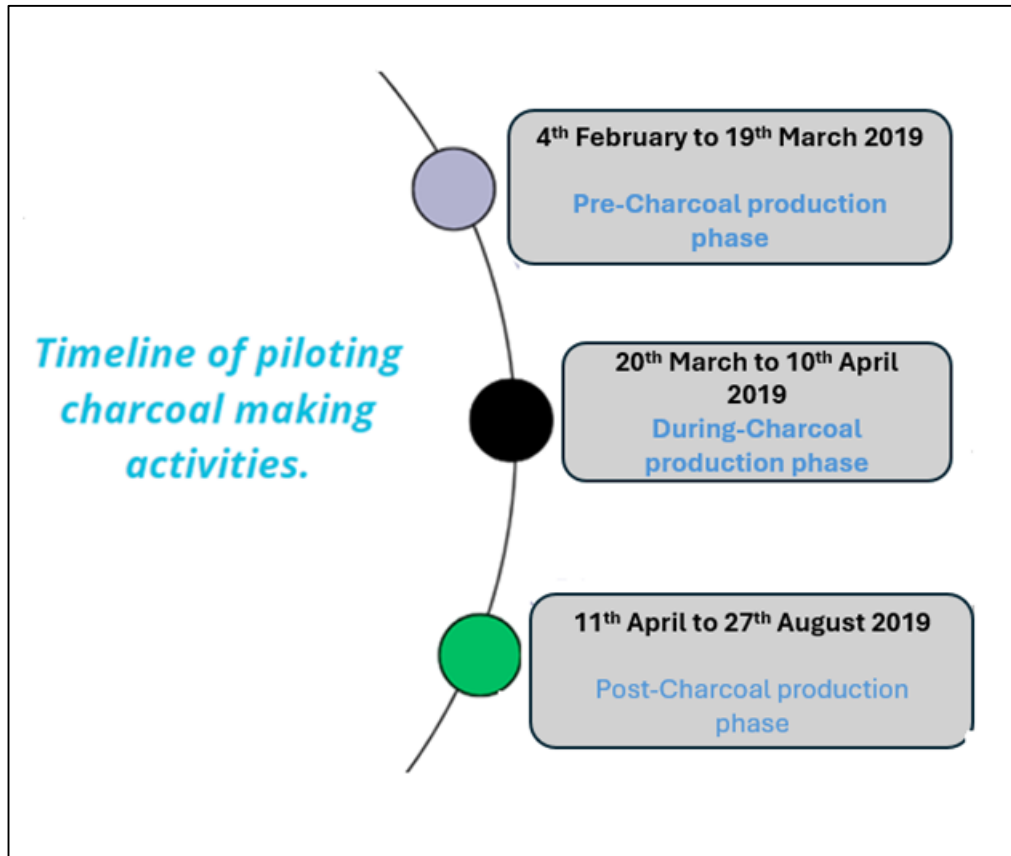


Figure 3 - 11: Timeline of piloting charcoal making activities.

The analysis of objective 1 involves the following steps: (i) data cleaning and data correction, (ii) calculations of descriptive statistics, (iii) time series plots of the cleaned data and estimation of mixing ratios, (iv) local maximum estimation to differentiate background information from peak emissions, (v) scatter plot estimation and (vi) estimate of the total emission derived from the experimental kiln. The workflow diagram in figure 3-11 depicts the analysis followed for objective 1.

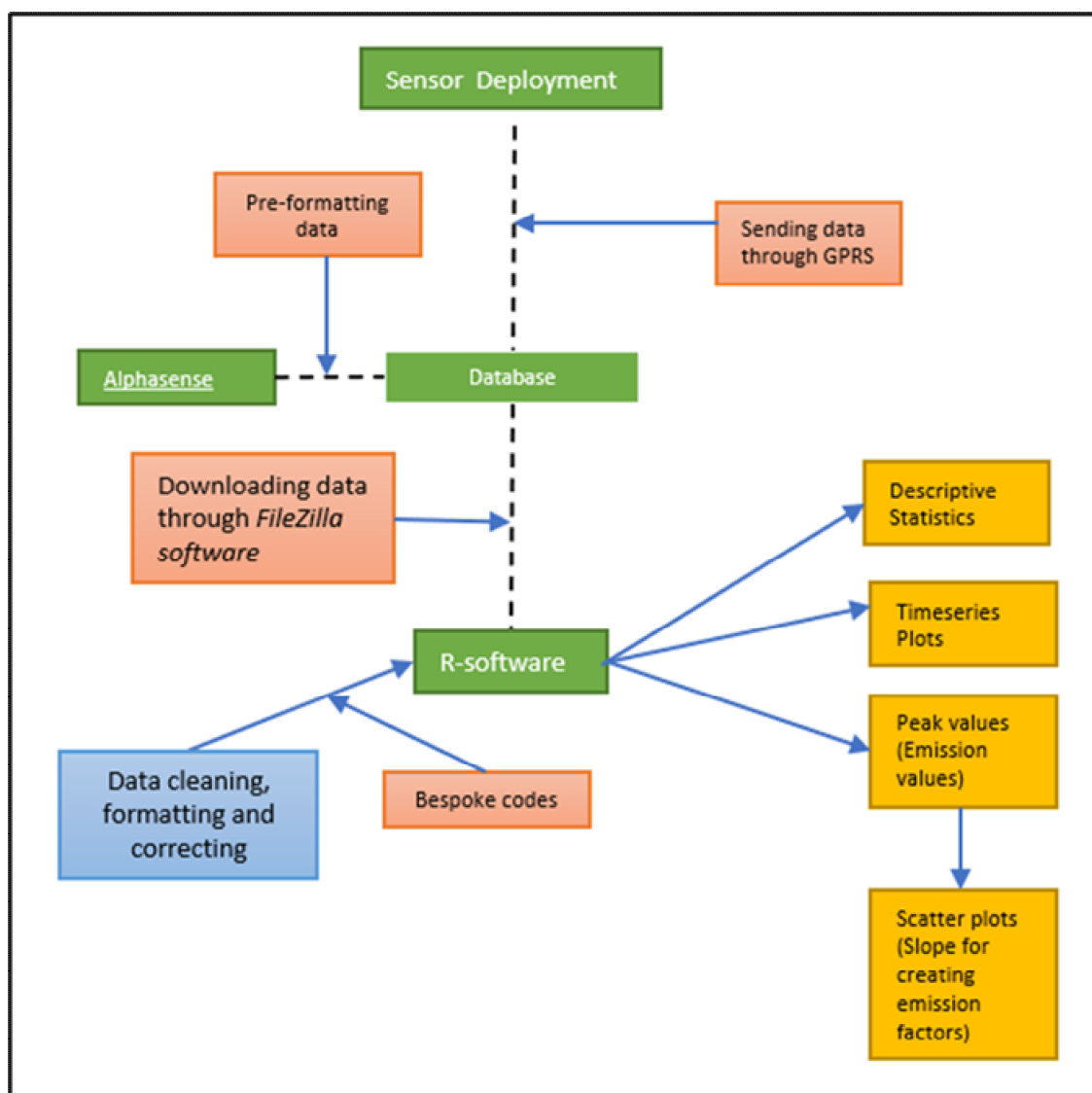


Figure 3 - 12: Workflow of the analysis emission data derived from charcoal making.

The first step of cleaning and correcting the data involved several steps. The first task was to extract raw data from the sensors and prepare it in the right format in R. This was done by: (a) importing raw data into R and applying a bespoke code to format the data, (b) setting the time and date right, (c) verifying the name and number of columns in the data, (d) selecting the preferred columns within the data (especially columns with temperature corrected value) (e) converting the dataset into numeric and (f) removing NA's and zeros within the data. It required the exclusion of missing values (NA's), negative and zeros values. The removal of missing values is important as sometimes a

manufactured sensor breaks or misbehaves, and good readings are obtained only for few measurements on the assembly line and may also lead to missing values for several input parameters. In turn, this can affect the statistical calculations as certain procedures do not handle missing data gracefully (Kwak & Kim, 2017). The be-spoke code applied is shown in Appendix 2 section 1. (Appendix 2 section 1).

The second task involved adding baseline data into the data extracted in task 1 above. This is because, the implementation of the process described above resulted in a cleaned data set without baseline information. This was of paramount importance data, especially for CO. The correction of gases, especially CO, is important as it tackles drifting responses of electrochemical gas sensors due to environmental factors such as temperature and humidity (Liang et al., 2021). Within this context, “baseline” refers to measurements of key conditions (indicators) before the experiment begins, from which change and progress can be assessed (IFRC, 2013). The baseline data helps to assess the measurability of the selected indicators and fine tune the systems for future measurement (IFRC, 2013). This involved exporting dataset into CSV formats and opened into an Excel spreadsheet to help the addition of the estimated baseline values. Baseline information is usually defined by background air quality records. These levels are established for each regulated pollutant and averaging period being assessed. The values are then added to measured observations to obtain total observations which are then compared with applicable ambient air quality standards. Background air quality records are ambient levels of pollutants that are not associated with any of the sources explicitly included in the experiment. The background data for CO was calculated using the formula (Equation 5):

$Xodp = (BV - SB) + Xdp$ Equation 5

In the formula above, (Data point = Xdp, Offset data point = Xodp, Sensor baseline = SB, Background values = BV)

The Sensor baseline (SB) data was determined through the selection of windows in the CO pod data where minimum values of CO were observed. This involved two steps: the first step involved selecting the starting dates from the raw data that helped to understand the minimum values of emissions. This involved plotting the time variation plots to enable the detection of the hours that showed the minimum values. The number of hours obtained was used to determine the minimum values of the sensor baseline (SB).

Figure 3-12 shows an example of the variation's plots obtained. The figure shows the windows in the CO pod data where minimum values are systematically observed. These are used to determine the sensor baseline data. The hours where a minimum value was observed have been highlighted with a green circle (between 10:00 and 14:00 hours) as can be observed. The sensor baseline was estimated to be 220 ppbv.

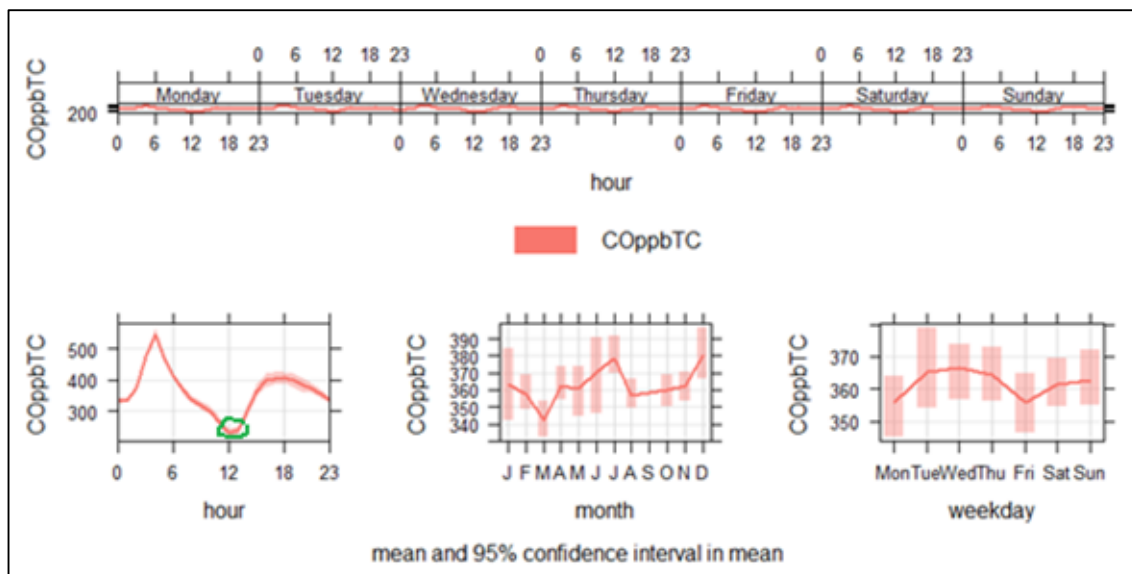


Figure 3 - 13: Windows in the CO pod data where minimum values are observed systematically circled with green color.

The background values (BV) were determined from (Dewitt et al., 2019). The authors conducted a study reporting background concentrations in Rwanda. The Rwandan measurement was preferred because there is few research in the region and the data provided information in similar conditions to the case study

area - i.e., it was in the highlands and in the same region of East Africa. The BV values were extracted by multiplying the monthly CO Normalised ratio with the average value of CO Monthly mixing ratio estimated to be 215ppbv in the area. The total monthly values obtained were averaged to obtain the average concentration of CO in the area (Table 3-1).

Table 3 - 1: Average concentration of CO for East Africa. Adapted from DeWitt (2019).

Months	CO Normalised ratio	Monthly CO Mixing ratio (ppbv)	Mixing ratio CO (ppbv)
January	1.25	215	269
February	1.63	215	349
March	0.75	215	161
April	0.63	215	134
May	0.68	215	146
June	1.13	215	242
July	1.30	215	280
August	1.35	215	290
September	1.00	215	215
October	1.30	215	280
November	1.25	215	269
December	1.40	215	301
Total			2936
Average			244.65

The second step was to estimate the descriptive statistics pre-, during- and post-kiln burning. Measures of central tendency (i.e., means of each phase) and measures of dispersion (i.e., standard deviation) of carbon monoxide and particulate matters (PM's) were calculated to characterise the distribution of the data pre-, during- and post-kiln burning. The mean informs about the average presence of pollutants in the area pre-, during and post-kiln burning. The standard deviation informs about the amount of variation or dispersion of the pollutant (i.e., a low standard deviation indicates that the values tend to be close to the mean, while a high standard deviation indicates that the values are spread out over a wider range). The interpretation of the standard deviation provides information about the persistence by which a pollutant is present in the area: low standard deviations will indicate a high persistence of the pollutant in the

area whereas high standard deviations could indicate variable presence and persistent of the same pollutant (Goldman *et al.*, 2012). Additionally, data identification was carried out to ascertain if the data was regularly distributed or not. A Kruskal-Wallis test was used to test for significant differences in the distribution of concentrations in the pre, during and post periods. The data was not normally distributed so the Kruskal-Wallis test, a non-parametric equivalent to ANOVA for non-normally distributed data, was used.

The third step was to generate the time plots for the cleaned data. It focused on the analysis of the time series for pre-, during- and post- charcoal production to understand the general trends of CO, CO₂ and particulate matters. The time series plots were generated using the bespoke code (Appendix 2 section 3). Also, temporal variations using the bespoke code (Appendix 2 section 4) and sources of pollutants using Hysplit model were determined to help comprehend data moving over time and the relationship between variables. Polar plots were used to assess the sources of CO and CO₂ around the study area.

The fourth step involved identifying filtered peak values from local maximum. This involved differencing the pollution signal (peak values) of CO, CO₂ and PM from the background signals (low values) for pre, during and post charcoal production phases. The *splus2R*, *zoo* and *carddates* R packages were used to find local maxima of the time series (Appendix 3). Each local maxima defines the largest point between 11 consecutive measurements (5 below the peak and 5 after the peak). All points outside the local maximum were considered background readings. A moving window was used to calculate the median per species (bkg column) using a range of 15 data points. The resulting peak values were assumed to be the indicator of pollution signals of CO, CO₂ and particulate matters during charcoal production respectively.

The median values were orientated left (i.e., to the first value in the window), and the window moved one unit at a time. To find overlapping CO and CO₂ local maxima, the background data was subtracted from the corresponding measured value, and all negative differences were recorded as an 8-point NAA buffer (4 left

and 4 right from local maximae). It was presumed that every point in the buffer belonged to the same peak. Values that (i) did not fall within overlapping CO and CO₂ peaks, (ii) displayed NA for either CO or CO₂, or (iii) had a difference of less than 50 units from the background concentration were excluded using a series of filtering stages.

The fifth step involved the creation of correlation plots of maximum values of species vs CO₂ were created; The local maxima obtained in the fourth step would have been used to create scatter plots of each specie vs CO₂ to determine the slopes and correlation coefficients (R²). This would have allowed the estimation of emission ratios of the pollutants under investigation. Within this context, the emission ratio would have been assumed to be CO vs CO₂, PM₁ vs CO₂, PM_{2.5} vs CO₂ and PM₁₀ vs CO₂.

The sixth step would have involved estimating the emission factors of CO and CO₂. This would have involved multiplying the obtained emission ratio in the fifth step by the amount of CO₂ (kg) produced from charcoal production. The amount of CO₂ emitted from a single charcoal kiln would have been obtained through equation 6.

$$CO^{kiln} = \frac{CO}{CO_2} \times F_1 \times F_2 \dots\dots\dots \text{Equation 6}$$

Where CO^{kiln} is the CO in kg produced by a kiln; $\frac{CO}{CO_2}$ is the ratio of CO vs CO₂
 F_1, F_2 is the total quantity of charcoal produced per kiln in kg.

This was done through determining the mass and number of C atoms involved whereby 1 ppb CO contains 1 ppb C atoms and 1 ppm CO₂ contains 1 ppb C atoms. For example, a slope of 4 ppb CO/ 1 ppm CO₂ means that 4 x 10⁻³ molecules of CO are produced for each CO₂ produced. The molecular mass of CO is 12 (for C) + 16 (for O) = 28 and the molecular mass for CO₂ is 44. The mass of CO produced per mass of CO₂ produced can be calculated from Equation 7;

$$CO^{kiln} = \frac{28}{44} \times 4 \times 10^{-3} \text{ equivalent to } 2.54 \times 10^{-3} \frac{gCO}{gCO_2} \dots \dots \dots \text{Equation 7}$$

3.3.2. Data analysis for objective 2

Under objective 2, two groups of variables were required to identify areas of high-density kiln. The first group of variables indicate catchment degradation whereas the second group indicates charcoal making activity. Catchment degradation variables can be identified through land cover land use change detection. Charcoal making activity can be identified from local community activity observed in existing aerial imagery. The flow chart showing the methodology of objective 2 is shown in figure 3-13.

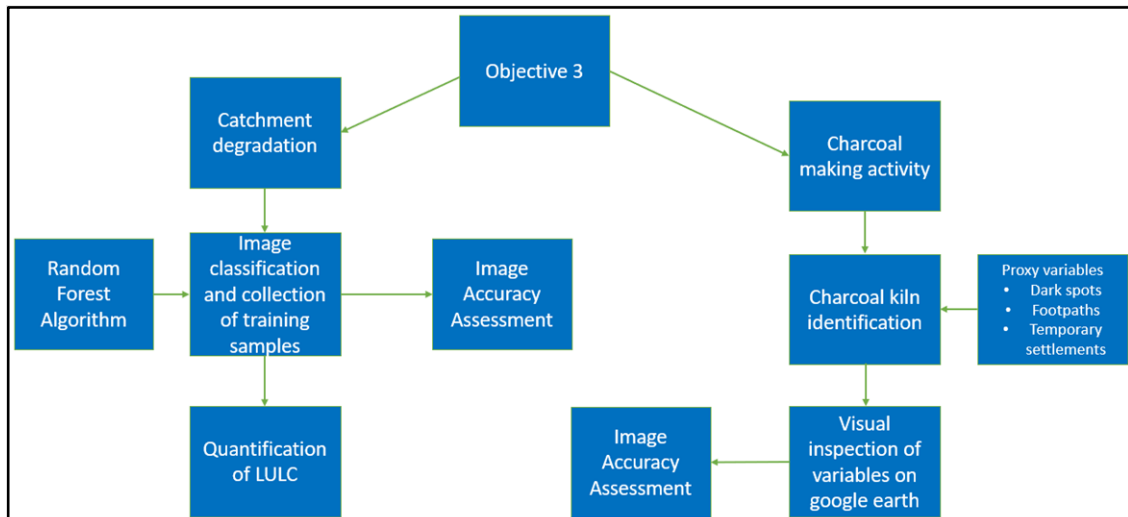


Figure 3 - 14: The flow chart showing the methodology of objective 3. Left panel indicate quantification of land use and cover change and right panel showing proxies for charcoal kiln identification.

The land use from satellite imagery for the study area in east Usambara mountain was classified using ArcGIS software 10.6. Land use land cover change was analysed for the period 2008-2018. Identification of land cover change of the area involved several steps, including the following; identifying land use and land use cover in the study area in 2008 and 2018, assessing the accuracy of the classification for 2008 and 2018 images, estimation of land use land cover change (LULUC) using ArcGIS10 and the identification of charcoal kiln around Usambara Mountain.

The first step to address objective 2 was to identify land use and land use cover in the study area in 2008 and 2018. A 10-year lag was selected to assess land cover change as this was a significant time lag to detect change in the study area. Automatic identification of land cover within the study area was carried out using classification techniques. A Land cover classification system is an abstract framework which provides the tools necessary to describe the bio-physical cover of the earth's surface. Classification systems can be classified in multiple ways; common distinctions between systems are whether they are *a priori* (conditions on the ground are forced to fit a pre-defined classification scheme) or *a posteriori* (conditions on the ground are used to develop the classification scheme); whether they are hierarchical or not (Abburu & Babu Golla, 2015; Lu & Weng, 2007; Yang et al., 2015) and whether the classification is supervised or unsupervised. In this study, the type and number of classes of land cover identified were selected based on the type of forest and activities conducted in the study area. A total of eight classes (Table 3-2) were considered to represent and characterise the land cover and associated degradation processes within the area. These included Humid Forest, Woodland, Bushlands, Grassland, Water, Bare soils, Cultivated land, Urban areas.

Supervised image classification was done for each image using ArcGIS software 10.6. Training samples for various land cover types were collected using ArcGIS 10.6 software. The samples were visually identified within the corresponding class categories and selected randomly. Tools in the training samples manager pane allow to create training samples for each class category in the schema and provide information about the number and size of samples to help improve the accuracy of your classification model.

Table 3 - 2: Detailed description of land use land cover (Raphael, 2018).

LCLU Categories	Description
Humid forest	Closed canopy forests mainly coastal and riverine forests often embedded within larger areas of Miombo woodlands.

LCLU Categories	Description
	They grow along the seasonal and permanent rivers and streams. They are semi or evergreen throughout a year.
Woodland	Closed stand of trees (trees close to each other) with closure of the upper canopy. Mainly Miombo woodlands. Open stand of trees (scattered trees) with open canopy. Mainly Miombo woodlands and <i>Acacia-commiphora</i> woodlands dominated with <i>Brachystegia/Julbernadia spp</i> , <i>Acacia spp</i> , and <i>Combretum spp</i> .
Bushlands	Closed or open stands of bushes (usually between 1 and 3 m tall). Comprised of plants that are multi-stemmed from a single root base.
Grassland	Land covered with grasses and other herbs, generally perennial and sometimes with evergreen or deciduous trees or shrubs, scattered or in small, isolated groups not covering more than 10 percent of the ground.
Water	Include inland water (dams and rivers)
Bare soils	Land which includes bare land and Coastal sands
Cultivated land	Land actively used to grow agriculture crops including agro-forestry systems, wooded crops, herbaceous crops and grain crops
Urban areas	Built up areas especially urban areas

Post processing included recoding and majority filtering. The classified images were recoded to various land cover classes (Table 3-2). Classified images were then recorded again to respective classes (i.e., Humid Forest, Woodland, Urban areas, Bare soil, Bushland, Grassland, Cultivated land and Water). Recoding was necessary because the image was firstly classified using unsupervised methods, of which we see only the colours of classes, but we do not know the numbers corresponding to classes and the relation between classes and objects in the field. Therefore, when we do a supervised classification using ArcGIS software then recoding of those classes must be done to ensure the classes correspond to the specified objects on the ground. Majority filtering involved eliminating noise and smoothing the image. "Filtering" is an operation that changes the observable quality of an image, in terms of resolution, contrast and noises (Dong et al., 2006; Khorram et al., 2013; Manandhar et al., 2009). As expected, numerous isolated pixels or noise pixels appear in classified images.

Smoothing image was necessary to reduce unneeded detail and further improve the classification accuracy (Dong et al., 2006). Other filters that have been frequently used in image processing use functions that highlight differences between pixel values. They are usually used for sharpening the edges of objects in an image (Pelton et al., 2013).

The second step was to assess the accuracy of the classification for 2008 and 2018. Accuracy in the land use land cover classification was measured through a confusion matrix approach (FAO, 2016; Olofsson et al., 2014; Stehman, 2009; Visa et al., 2011) using user classification and reference image (online Google base maps) as ground-truth data. During this process a total of 511 validation points were generated using ArcMap. The confusion matrix was generated, and individual accuracy was obtained following equation 8 and 9 (Stehman, 2009).

$$\text{Individual accuracy} = \frac{\text{Reference value}}{\text{row total}} \dots\dots\dots \text{Equation 8}$$

$$\text{Total(overall)accuracy} = \frac{\text{Number of correct plots(Value)}}{\text{Total number of plots (Value)}} \times 100 \dots\dots\dots \text{Equation 9}$$

During the analysis, producer and user accuracy and kappa coefficient were determined. Producer accuracy refers to the probability that a certain feature of an area on the ground is classified as such. It results from dividing the numbers of pixels correctly classified in each category by the numbers of sample pixels taken for this category (column total). User accuracy refers to the probability that a pixel labelled as a certain class in the map is really this class. It is obtained by dividing the accurately classified pixels by the total numbers of pixels classified in this category. The producer accuracy and user accuracy are not the same typically. For example, the producer accuracy of water is 100% whereas the user accuracy is 93%. Further, the kappa coefficient, a discrete multivariate method of use in accuracy assessment, was estimated. In the classification process, pixels are randomly assigned to classes, which produces a percentage-correct value. Obviously, pixels are not assigned randomly during image classification, but there are statistical measures that attempt to account for the contribution of random

chance when evaluating the accuracy of a classification. The resulting Kappa measure compensates for chance agreement in the classification and provides a measure of how much better the classification performed in comparison to the probability of randomly assigning pixels to their correct categories (Bharatkar & Patel, 2013; Manandhar et al., 2009; Tilahun & Teferie, 2015).

The third step focused on the estimation of land use land cover change (LULUC) using ArcGIS10. The two classified land cover layers i.e. 2008 and 2018 were used for that purpose. The spatial analysis tool in ArcGIS with the zonal tabulate area function was used to generate a land cover change matrix. The function calculates cross-tabulated areas (categorical transition) between two datasets and outputs a table that displays a record for each unique value of the zone dataset and a field for each unique value of the class dataset. Within this context, the zone dataset is ha of land converted in percent for 2008 and 2018 respectively whereas the class data set is landcover/use types that includes humid forest, woodland, bushland, grassland and cultivated land. The off-diagonal entries comprise proportions of the landscape that experienced transition from one category of land use to a different category, while the diagonal entries indicate persistence of categories. The totals denote the proportion of landscape per category (land use).

The “calculate geometry” tool in ArcGIS was used to calculate the areas (in ha) of each land cover in the matrix and to determine the areas that have been changed and the potential drivers for change. These drivers of change include biophysical and socio-economic variables (Kissinger et al., 2012b; Serneels et al., 2007). Special attention was dedicated to changes in land use land cover that could indicate charcoal making activity and catchment degradation, especially in terms of deforestation and forest gain. These are summarised in Table 3-3. The reasons as to why these land use land cover changes indicate charcoal making activity are summarised in Table 3-3. A change from humid forest to woodland indicates catchment degradation because the tree cover will be decreased, and the land will be exposed to various factors that could result into degradation

including soil erosion. A change from woodland to bushland demonstrates catchment degradation because this change assumed to occur after removal of trees in the forest that resulting to area exposure into agents of degradation. Catchment degradation also occurs when land use land cover changes from bushland to grassland because the trees covering the area have been removed in such a large quantity that could result into exposure to agents of degradation. Similarly, grassland to cultivated land changes demonstrate catchment degradation because the cultivated land would have low number of trees covering the area and, as a result, the area could be exposed to agents of catchment degradation. Finally, a change from cultivated land to building results in catchment degradation because the tree cover that protects the land from degradation is completely removed that resulting into exposure at high degree on agents of degradation.

Table 3 - 3: Summary of Land Use Land Cover (LULUC) changes indicating potential charcoal making activity.

LULUC change	Reason
Humid forest to woodland conversion (2008-2018)	Loss of humid forest to woodland indicates thinning of tree density. The assumption is that cut trees are used for felling trees for construction and charcoal activity.
Woodland to bushland conversion (2008-2018)	Loss of woodland forest to bushland indicates the forest density decreased by 50%. Conversion of woodlands into bushland can be associated with felling of trees for charcoal and firewood (Mdemu and Bura, 2016)
Bushland to grassland conversion (2008- 2018)	Loss of bushland to grassland indicates the forest density decreased by 25%. Forest cover changes are results of intensified extraction of forest products from the forest reserves (Mdemu and Bura, 2016)
Grassland to cultivated land conversion (2008- 2018)	Loss of grassland to cultivated land indicates the forest density decreased by 25%. These forest cover changes are results of intensified shifting cultivation in the forest reserve (Mdemu and Bura, 2016)
Cultivated land to building conversion (2008-2018)	Loss of cultivated to building area indicates the forest density decreased by 25%. These forest cover changes are results of

	intensified shifting cultivation and population increase in in the forest reserve.
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The fourth step under objective 2 was the identification of charcoal kilns around Usambara mountain. This was conducted through four tasks outlined below;

Firstly, it involved identifying proxy variables to help recognise charcoal kilns. Proxy variables defining charcoal making activity were defined based on an in-depth literature review (Bolognesi et al., 2014; Nakalema, 2019; Rembold et al., 2013; Žutautas, 2017). These primarily looked at dark spots on the ground, footpaths leading to kilns, presence of kilns and temporary settlements in the area that influence charcoal making (Table 3-4). The dark spots on the ground can be used as proxies to detect charcoal making activity in Somalia (Nakalema, 2019). The local relief and topographic openness variable can be used for charcoal making identification in Sweden (Žutautas, 2017). The dark colour, their round shape and typical size of ca. 10-12m in Somalia were used to identify charcoal making (Rembold et al., 2013) whereas other studies used colour, reflectance and size of the dark spots for the automated recognition of charcoal kilns (Bolognesi et al., 2014).

Table 3 - 4: List and description of proxy variables used to identify kiln making activity.

Variable	Description
Dark spots with round shapes or rectangle shapes (approx.10-12m) (Rembold et al., 2013)	This variable will delineate (polygon shapefile) black spots on the ground that show areas where charcoal making activities are conducted. This will provide the potential concentration of kilns in the area. Tables indicating number of kilns will be created.
Charcoal Kilns	This variable will identify areas with mound or earth kilns on the ground (approx. 10-12 m length and 1 m height). The earth type of kilns mostly preferred by local communities in the area. The identification will help to understand the concentration in the area in proximity to the settlements or newly developed footpath or roads.

	Tables indicating the number of kilns in the field site will be created.
Temporary settlements	<p>This variable identifies the location of temporary settlements (point shapefile) and measures the distance of the forest to the local settlements. The distance from the centre of each settlement to the nearest forest was estimated in ArcGIS using the NEAR analysis tool. The nearest tool calculates the distance between each point of a feature class and the nearest point or line of another feature class (Carmeron et al., 2004; Crosier et al., 2005). The nearby tool was used to find the temporary settlements that were closest to the forest (ESRI, 2016). The Near tool added the property identifier and, optionally, coordinates and angle to the nearest property (Carmeron et al., 2004).</p> <p>It provided information about the potential involvement of local communities in charcoal making activities for income generation. For a small study, it was suggested that ten (10) households to be clustered and termed as settlement (Bhattarai et al., 2020).</p>
New exploitation roads or presence of narrow footpaths within forested areas.	<p>This variable will detect new exploitation roads and narrow footpaths in the forested area. The footpaths will be delineated (polyline shapefile) and, using the Euclidean distance tool in ArcMap, the distance between the newly developed roads and the forest will be determined. The Euclidean distance tool gives the distance from each cell in the raster to the closest source. Euclidean distance is calculated from the center of the source cell to the center of each of the surrounding cells (Carmeron et al., 2004). Therefore, here we will connect center source cells located in the digitised path with the cells center of the forest and near temporary settlements. This will provide information on possibility of using the footpath, bicycle or motorcycle for transporting charcoal from the field.</p>

The second task focused on the visual inspection of Google imagery for years 2008, 2010, 2011, 2013, 2015, 2017 and 2018. The imagery was inspected systematically using a regular grid approach to identify these proxy variables. The regular grid was defined by random squared cells of 404.56 m by 404.56 m (Fig 3-14). This cell side was considered adequate because the covered area by grids is sufficient for visual identification of kilns on the ground. It was generated in Google Earth by activating the “grids” options. Squares were selected at random

and independently inspected for proxy variables to avoid detection of features by association between consecutive cells. All squares generated were digitised on completion of this second task.

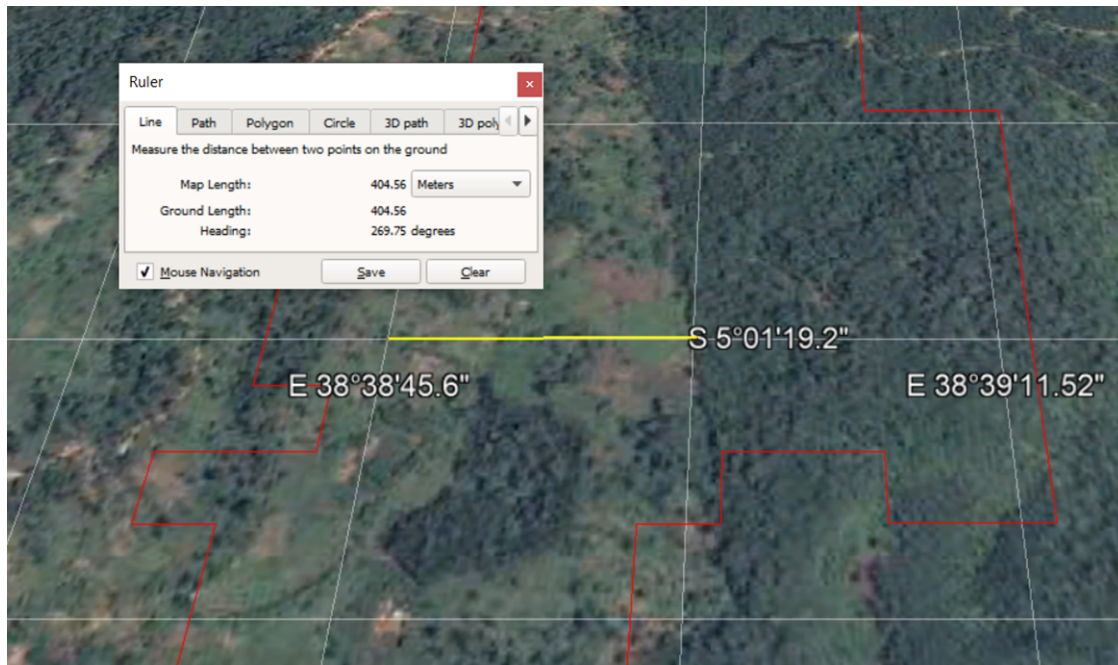


Figure 3 - 15: Sample of squared grid cells with 404.56 Meters by 404.56 Meters created to help locating charcoal kiln around east Usambara Mountain (Britt et al., 2020). Within each grid, in-depth investigation was done to identify proxy variables charcoal kiln from 2008 to 2018.

The third task focused on plotting the number of proxy variables identified per year to understand the level of concentration and charcoal making activity in the area over time. The number of proxy variables detected per year was recorded and tabulated, with the number of hits per variable versus time.

The fourth task involved digitising of the proxy variables on the image to obtain shapefiles. The digitised proxy variables from Google Earth were exported as a shapefile into ArcMap. Settlements and identified charcoal kilns were digitized as polygons. The newly developed footpaths or roads were digitised using paths. For the digitized image in Google Earth, the data were saved as *.kml file and the file were imported to ArcMap through the import function. The digitised image from the Goggle Earth was overlayed to the land cover change shapefile created previously to assess the link between charcoal making and catchment

degradation. The relationship between the two shapefiles was established through spatial analysis and statistical analysis under objective 3.

3.3.3. Data analysis for objective 3

Objective 3 focused on quantifying the link between charcoal making activity and forest degradation. The relationship between land use land cover change (i.e., forest degradation) and the proxy variables indicating charcoal making activity derived in objective 2 was established. This involved identifying the relationship between the shapefiles developed under objective 3 through spatial analysis and then through statistical analysis. The flow chart showing the methodology of objective 3 is shown in Figure 3-15.

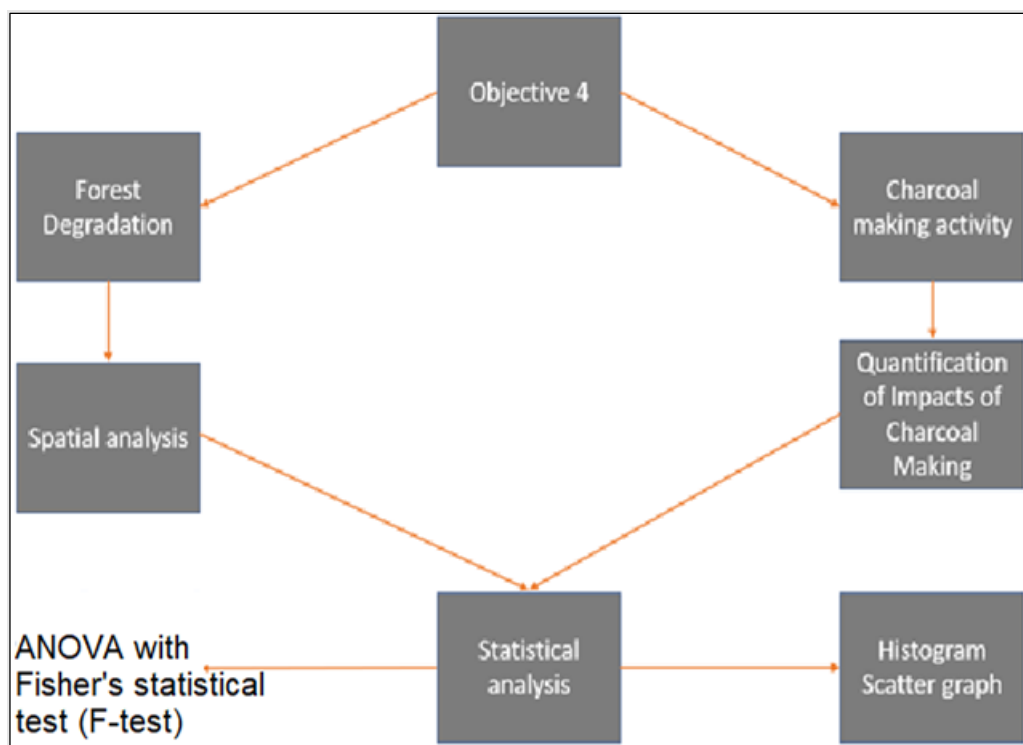


Figure 3 - 16: Workflow showing the analytical methodology followed for objective 3. The left side of the panel shows the analysis carried out to identify catchment degradation and the right panel shows the analysis of the impacts of charcoal making.

The first step involved the analysis of the spatial distribution and collocation between variables indicating charcoal making activity and the land use land

cover change (i.e., forested/non-forested areas), in addition to the analysis of the spatial distribution of charcoal making proxy variables across different forest patches within East Usambara Mountain. Forest patches were selected to identify differences in proxy variables because they are distinct units of management.

The spatial analysis focused on the visual identification of the number of charcoal making variables that fell within and out polygons where land use land cover change had been detected over time. A map showing the location of the proxy variables was generated and compared to the land use land cover classified map. The identification of proxy variables was conducted for three periods: 2002-2012, 2013-2015 and 2016-2019. These three periods were selected due to availability of google images in the selected area. Google imagery was used to identify areas of high charcoal kiln density and temporal changes in charcoal production around Usambara Mountain. Tables summarising the number of counts per variable were generated. The number of counts of each variable indicating charcoal making activity was also determined per land use land cover change (including forested and non-forested areas) as well as per forest patch.

The second step was to find statistically significant differences between the number of proxy variables indicating charcoal making activity and the forest patch they fell in, as well as the type of land use and land cover change identified in objective 2, including forested and non-forested areas, and (ii) the different forest patches within the area, as well as the number of proxy variables indicating charcoal making activity. General linear models (GLM) and post-hoc analysis was used to find statistically significant differences for the dependent variables indicated (dark spots, settlements, walkways, and charcoal kiln).

At a confidence level of 95%, a repeated analysis of variance in GLM (ANOVA with Fisher's statistical test F-test) was used to determine statistically significant differences between components (e.g., forest/non-forest, kinds of land use and

land cover change) and their interaction (Armstrong et al., 2002). Land use and land cover change categories, patches, and forest/non-forest categories are used to describe factors. Because the time intervals were independent, they were regarded repetitions of proxy variable measurements, and the analysis tried to discover variations that happened across time. The ANOVA assumptions were tested using a residual analysis. The ANOVA analysis is based on several assumptions: The population from which samples are taken should be evenly dispersed, and the samples should be distinct from one another.

To test the validity of the assumptions and the robustness of the entire analysis, a residual analysis was performed in *Statistica* software. The variation that is not explained by the model is represented by residuals, which are disparities between observed values and the equivalent values predicted by the model. The lower the residual values, the better the model fits. The i^{th} residual (e_i) equals $e_i = (y_i - \hat{y}_i)$, where y_i represents the i^{th} actual value and $\hat{y}_i$ represents the matching forecasted value (Zhou, 2008). The link between the independent variable (charcoal kiln) and the dependent variables was investigated using residual analysis (location of temporary settlements and new roads or foot paths).

The third step entails the quantification of emissions from charcoal production as well as the impact of charcoal production on forests. The number of charcoal kilns within the area derived from the proxy variables obtained in objective 2 provided information on the total emissions derived from charcoal production, when using the emission factors obtained in objective 1 and global emission estimates reported by (Andreae, 2019; Rembold et al., 2013).

The approach was used to calculate the effect that the production of charcoal had on the woods (Rembold et al., 2013). In their study, they suggested that each dark spot digitised produced 40 bags of charcoal (27 kg). The production of 2 bags of charcoal requires 1 large acacia tree and as a result each site requires 20 acacias trees. Under this scenario, the number of trees cut was estimated based on the number of dark spots and applied as a measure of forest

degradation in addition to the land use land cover change and the statistical analysis carried out investigated under objective 2.

3.4. Summary

This chapter describes the methodology used to address objective 1-3. This involved controlled observational studies around an experimental earth kiln set-up replicating traditional charcoal making techniques to develop a methodology to estimate emission from charcoal production in ambient condition. It also included the deployment of low-cost atmospheric sensors and the analysis of the resulting data.

Areas of high-density kilns and changes in charcoal production around Usambara Mountain were identified using GIS approaches. This involved several steps using image classification techniques in a GIS environment to identify land use and land cover change. Google imagery was used to identify areas of high charcoal kiln density and temporal changes in charcoal production around Usambara Mountain.

Linking charcoal production with catchment impact and degradation involved identifying areas of high charcoal kiln density around the Usambara Mountain using GIS based tools and linking charcoal production with increased deforestation in the region. Lastly, the emissions derived from charcoal kilns and impact to forests around Usambara mountain were quantified.

CHAPTER 4: FINDINGS

This chapter reports the findings of this study. Figure 4-1 illustrates the structure of this chapter and the interconnections between different sections. The workflow addresses the objectives presented in Chapter 1. The first section of chapter 4 describes the measurements from the kiln experiment design and presents an analysis to quantify charcoal production emissions in ambient conditions. The second section reveals the areas of high-density kilns and identifies the changes in land use and cover due to charcoal production around the Usambara Mountain in a GIS environment. Lastly, section three details the links between charcoal production, catchment impact and degradation.

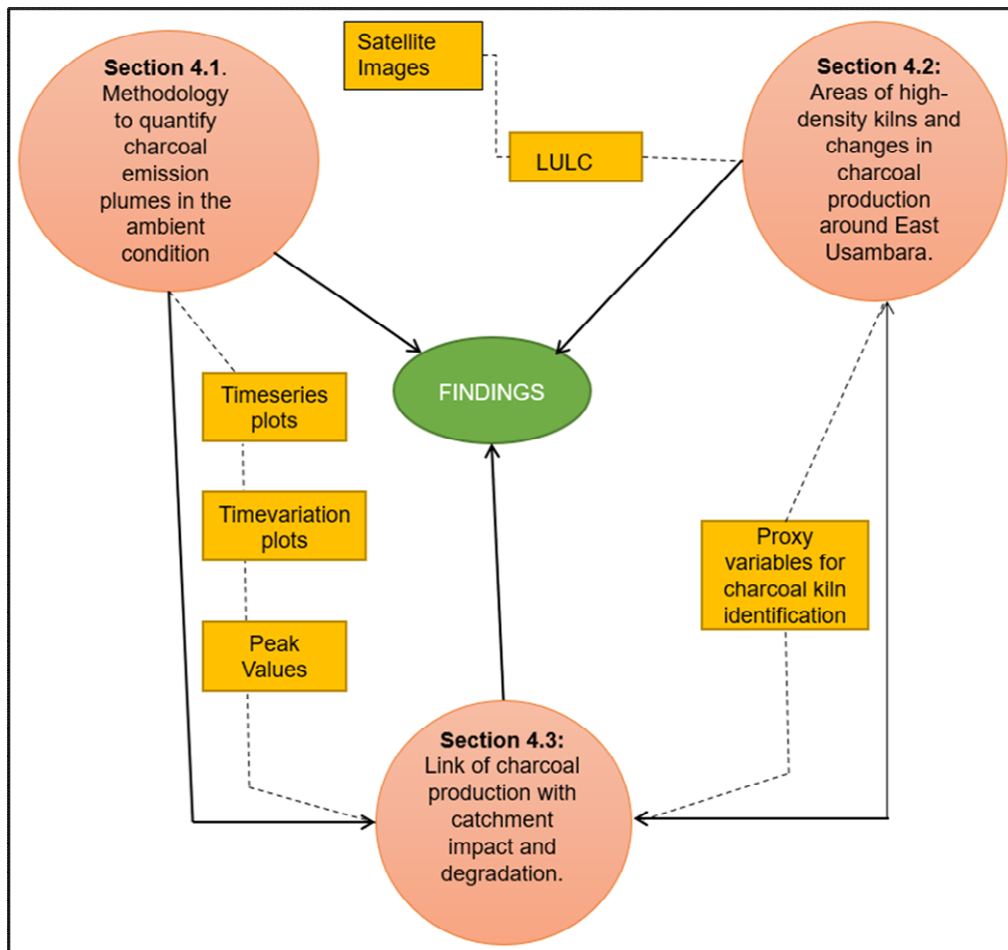


Figure 4 - 1: Diagram illustrating the organisation of chapter 4 and the interconnections between the different sections. Solid lines indicate the main link between the sections whereas the dashed lines indicate the main elements within the sections.

4.1 Kiln experiment design at the FITI site

This section presents the results from the kiln experimental design at FITI for the quantification of charcoal production emissions in ambient conditions. Results for the cleaned data sets are presented for all phases. The section includes the results of the descriptive statistics for each of the selected gases (CO and CO₂) and particulate matter pre-, during and post charcoal production, as well as general and monthly timeseries plots. Temporal variations (intra-annual, weekly, and diurnal cycles), sources of pollutants using Hysplit model and polar plots are also presented to help interpret the measurements and the relationship between variables. Lastly, the section presents the analysis to estimate the total emissions derived from charcoal production.

4.1.1 Pollutants descriptive statistics for pre, during and post charcoal production.

This section presents the results of the descriptive statistics of the selected pollutants pre-, during and post- charcoal production. Table 4-1 presents the descriptive data pertaining to the pollutants observed throughout all stages (combined) of the experimental process.

Table 4 - 1: Background statistics of CO (ppb), CO₂ (ppm), PM₁(μgm^{-3}), PM_{2.5} (μgm^{-3}) and PM₁₀ (μgm^{-3}) for three phases of the experiment (pre, during and post). SD stands for standard deviation. Min and Max describe the minimum and maximum values recorded, ppb, ppm and μgm^{-3} stands for part per billion, part per million and micro-gram per cubic meter.

Variable	Mean			Minimum			Maximum			Std. Dev.		
	Pre	Dur	Post	Pre	Dur	Post	Pre	Dur	Post	Pre	Dur	Post
COppbTC	404	418	464	7	32	102	1198	1364	1737	162	223	290
CO ₂ ppm	457.2	456.6	452	417	423	416	573	568	566	31	30	25
PM ₁ (μgm^{-3})	8	9	9	1	1	1	59	127	199	6	13	12
PM _{2.5} (μgm^{-3})	12	14	12	1	1	1	83	353	398	8	28	21
PM ₁₀ (μgm^{-3})	18	25	19	2	2	1	90	1335	945	13	93	41

Results in table 4-1 shows that the average CO₂ concentrations for before, during, and after the charcoal production periods were 457.2 ppm, 456.6 ppm, and 452 ppm, respectively. At the pre-, during-, and post-charcoal production stages, the monthly average PM₁ levels were 8 ug m⁻³, 9 ug m⁻³, and 9 ug m⁻³, respectively (Table 4-1). The results from the Kruskal-Wallis showed that there were no statistically significant differences for CO and CO₂ pre-, during- and post-event (Appendix 4). All the Particulate matter tests highlighted statistically significant differences between pre- and during, as well as during-and post-burning activities. A Kruskal-Wallis test is considered highly sensitive to differences in the medians, especially when there is departure from normality (Ramachandran et al., 2020). The presence of outliers and skewness make the Kruskal-Wallis test more powerful at detecting differences among treatments than ANOVA analysis normality (Ramachandran et al., 2020). When observing the mean and median values reported in Table 4-1, the statistically significant differences detected by the Kruskal-Wallis test for PM_x are too small to be meaningful from an atmospheric context and would not be considered as representative in this study.

4.1.2 Timeseries plots for pre, during and post charcoal production.

Figure 4-2 shows the general timeseries plot and identifies the phases of charcoal production for the specific case of CO. The time series plot displaying the hourly CO (ppb) during all the phases of the kiln experiment conducted from February to August 2019 at FITI site (Moshi) for pre, during and post charcoal production. The plot shows the periods within which measurements were not captured (missing data) due to an unstable power supply in the area, or lack of calibration or instrumental error. It was reported that end users must thoroughly calibrate low-cost sensors in the field to overcome their reduced accuracy, precision, sensitivity, and specificity (Zuidema et al., 2021). That was not possible in this experiment due to a lack of calibration expertise in Africa, specifically the least developed countries like Tanzania, and particularly to travel restrictions imposed due to the global COVID outbreak. However, the results presented do not affect its applicability for the intended purpose, as the deviation from the baseline is

used here (Fig. 4-2). Further, the operational challenges encountered highlight that the usage of low-cost sensors in developing countries might be hindered by an unreliable supply of electricity, a lack of a calibration laboratory, and the need for production equipment with batteries capable of storing power for about 2 days. Figure 4-2 also shows results for pre-, during, and post-charcoal production phases, which are detailed in subsequent paragraphs. Plots for other species are presented in Appendix 5.

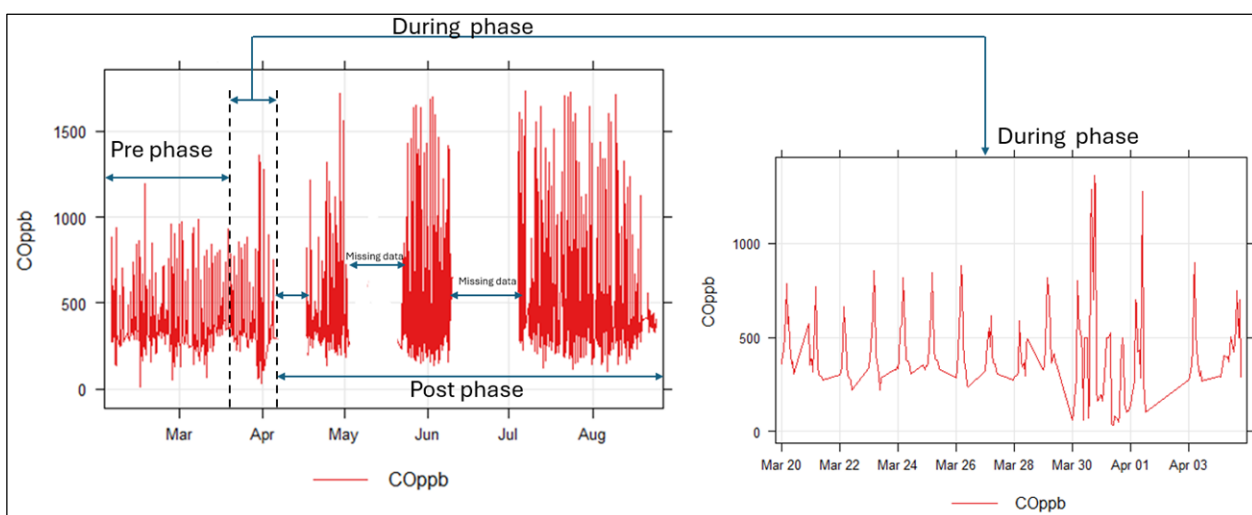


Figure 4 - 2: Time series plot displaying the hourly CO (ppb) during all the phases of the kiln experiment conducted from February to August 2019 at FITI site (Moshi): Pre, during and post charcoal production. The plot indicates the presence of missing data most probably due to unreliable power supply in the area causing interruptions in pollutants data capture.

Figure 4-3 shows the results of CO and CO₂ during the pre-charcoal production phase at the experimental site. Both CO and CO₂ results show cyclic patterns throughout the pre-charcoal production phase. The maximum concentrations of CO and CO₂ for pre-charcoal production were 1198 ppb and 573 ppm (Table 4-1), respectively. The maximum concentration of CO₂ in the area is slightly higher than the global CO₂ estimates based on the annual report from NOAA's Global Monitoring Laboratory, which was equal to 417.06 ppm in 2022 (Lindsey, 2023).

Also, the CO concentration obtained in the area is higher than the results obtained when investigating seasonal and diurnal variations of pollutants in Rwanda, which were 663 ppb (Dewitt et al., 2019). Other timeseries plots of gases for during and post charcoal production are presented in Appendix 6.

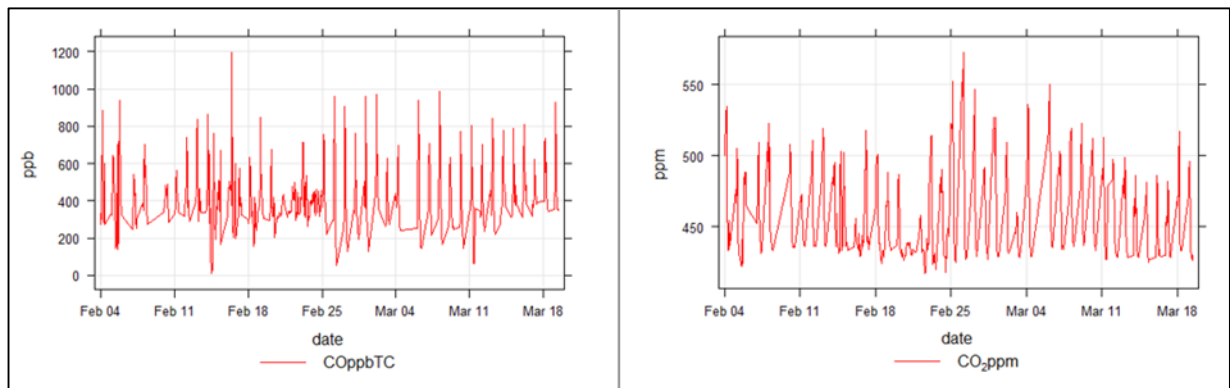


Figure 4 - 3: A monthly timeseries plot shows CO and CO₂ measured two weeks after installation of the sensor at the experimental site (04th February 2019 to 19th March 2019) (using low-cost electromagnetic sensors (AS 510 Multi Sensor unit). Other phases are presented in appendix 7.

Figure 4-4 indicates the concentration of PM_s in the area during the pre-charcoal production phase. In earlier February, the concentration was slightly higher while the rest of the period observed to have average cyclic pattern, with all pollutants rising at the same time. The hourly data from pre-charcoal production demonstrate cyclic movements of PM₁, PM_{2.5} and PM₁₀ with all constant values from mid-February to mid-March. All PM cycles are similar and do not recur at regular intervals. Other timeseries plots of particulate matter for during and post charcoal production are presented in Appendix 8.

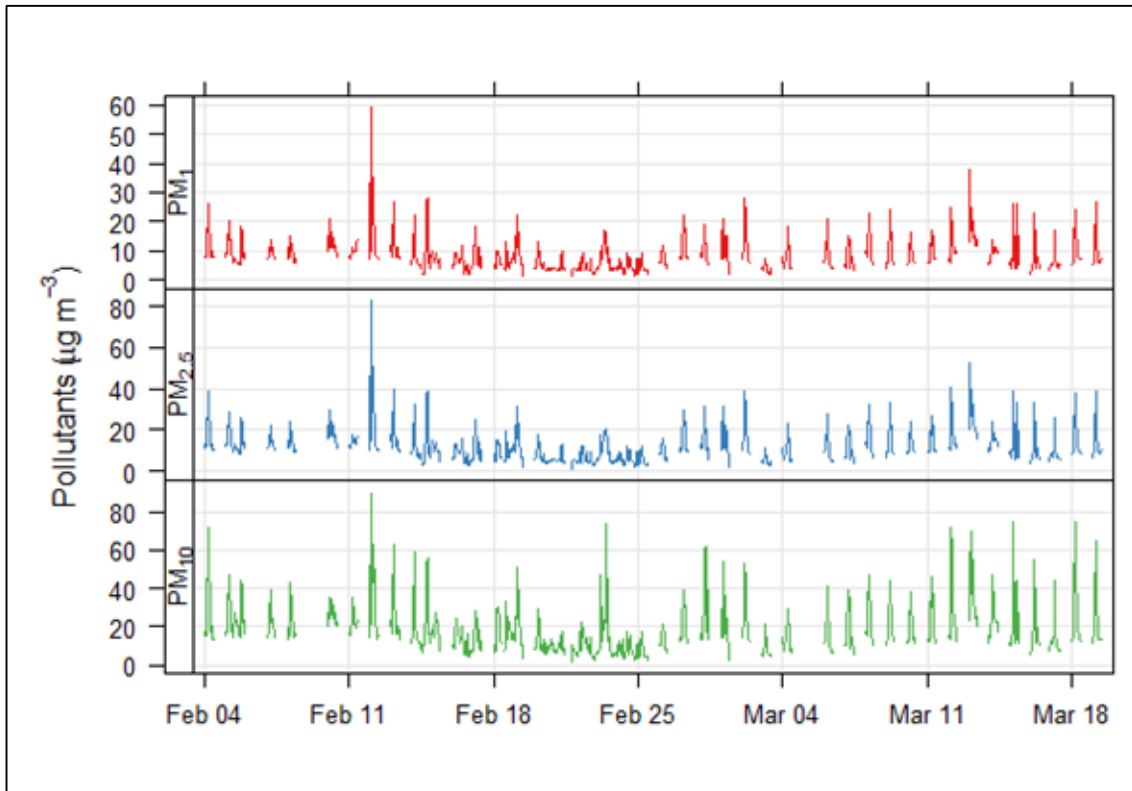


Figure 4 - 4: A timeseries plot showing the particulate matter measured at the experimental site from (04th February 2019 to 19th March 2019) during the pre-charcoal production phase using low-cost electromagnetic sensors (AS510- Multisensory Unit). PMx are reported in $\mu\text{g m}^{-3}$.

Figure 4-5 depicts the temperatures (T) and relative humidity. According to the findings, the typical diurnal cycle for T ranges between 20 and 40 degrees. Further data show distinct behaviour in early April, perhaps due to a strong boundary layer.

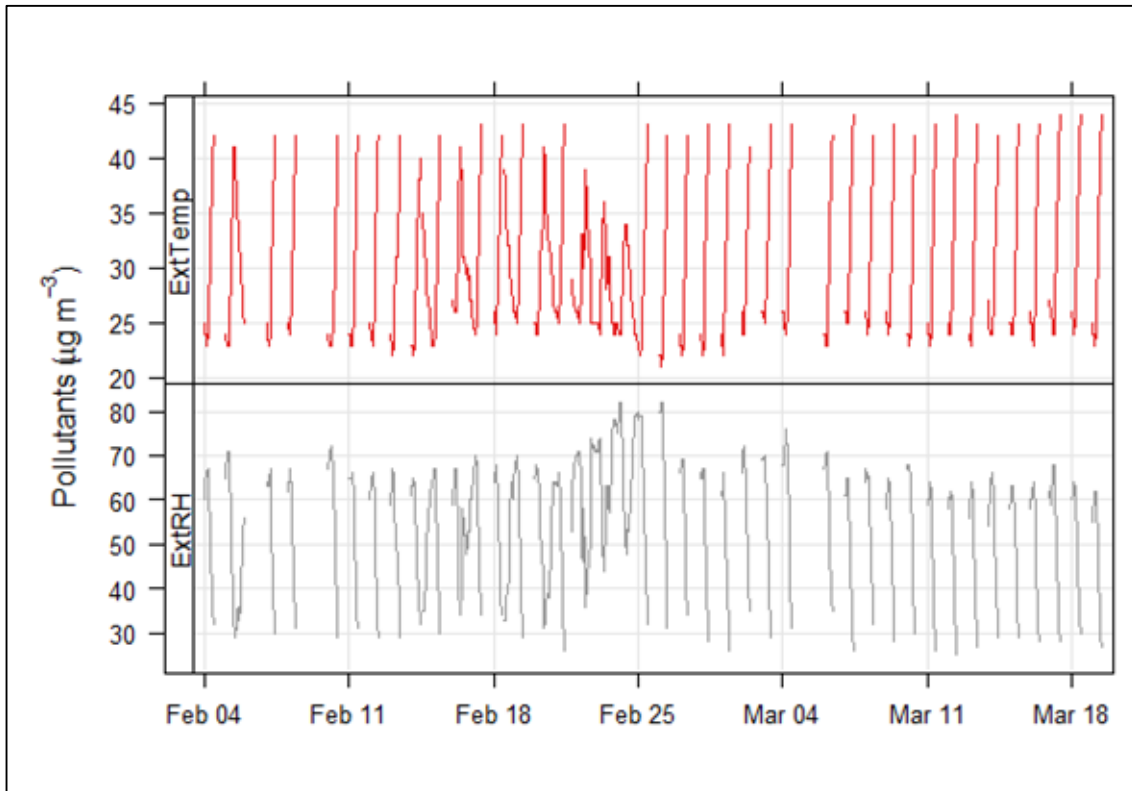


Figure 4 - 5: A timeseries plot showing the external temperature (ExtTem in °C) and relative humidity (ExtRH in %) measured during the pre-charcoal production phase from (04th February 2019 to 19th March 2019) using low-cost electromagnetic sensors (AS510-Multisensory Unit).

4.1.3 Temporal variation of air pollutants in the trial site.

Figure 4-6 indicates the temporal variation of CO in the kiln experimental site for the periods before, during, and after charcoal burning. The plot shows the mean daily fluctuation in concentrations (in the lower left corner). For instance, it demonstrates that CO concentrations often peak during the evening, with an estimated concentration of 880 ppb during the charcoal production phase and about 890 ppb during the post-charcoal production phase (Table 4-1). This suggests the presence of other human-induced activities in the area, as higher concentrations are observed during post-charcoal production. Thus, the peak observed during post-charcoal production may be due to various anthropogenic activities in the area, such as burning debris around the compound, which is a

typical activity during summertime, and household wood energy consumption for cooking and heating.

Further, the lower right corner plot indicates the mean CO concentrations according to the day of the week. The plot shows lower concentrations of CO during pre-charcoal production and higher CO observed during post-charcoal production. On average, higher CO was observed during the weekend, especially on Saturday during the post-charcoal production phase. This finding coincides with the results of the lower left-hand corner, which displays the hourly trends. This increase could be attributed to emissions derived from cooking and heating done within households, as most dwellers remained in the house during the weekends and mostly used charcoal as the source of energy for cooking and heating. According to (Dewitt et al., 2019), who studied the seasonal fluctuation of pollutants in Rwanda, including CO, it is challenging to discern between human and biomass burning emissions in this area because both produce BC, CO, and PM into the atmosphere.

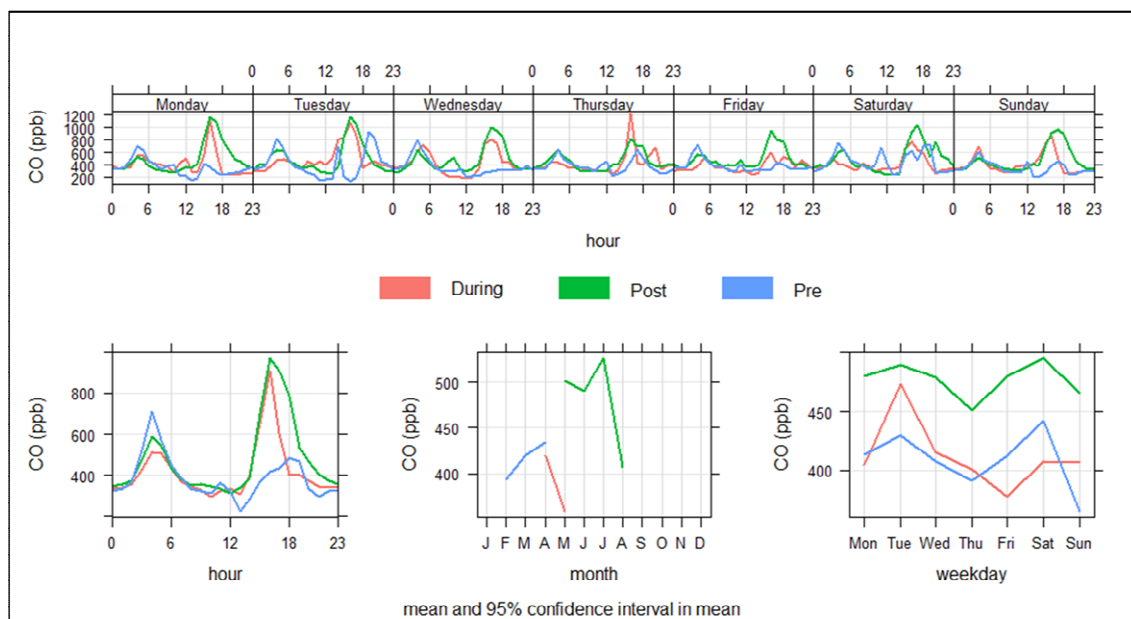


Figure 4 - 6: Mean CO concentrations (ppb) pre-, during, and post-charcoal production on an intra-annual, weekly, and diurnal cycle at the kiln experimental site. CO stands for carbon monoxide.

Figure 4-7 indicates the temporal variation of CO₂ in the kiln experimental site for the periods before, during, and after charcoal burning. The plot in the lower left corner displays the mean daily fluctuation in CO₂ concentrations. It demonstrates that CO₂ concentrations often peak for pre-charcoal production during the morning and evening, with an estimated concentration that ranges from 417 ppm to 573 ppm (Table 4-1). This suggests the presence of other human-induced activities in the area, as a higher concentration of CO₂ was observed during the pre-charcoal production phase.

Further, the plot in the lower right corner displays the mean CO₂ concentrations according to the day of the week. The plot shows a higher concentration of CO₂ during pre-charcoal production, while lower CO₂ concentrations are observed during charcoal production. On average, higher CO₂ was observed during the weekdays, suggesting the presence of emissions from farmland or nearby households and industries.

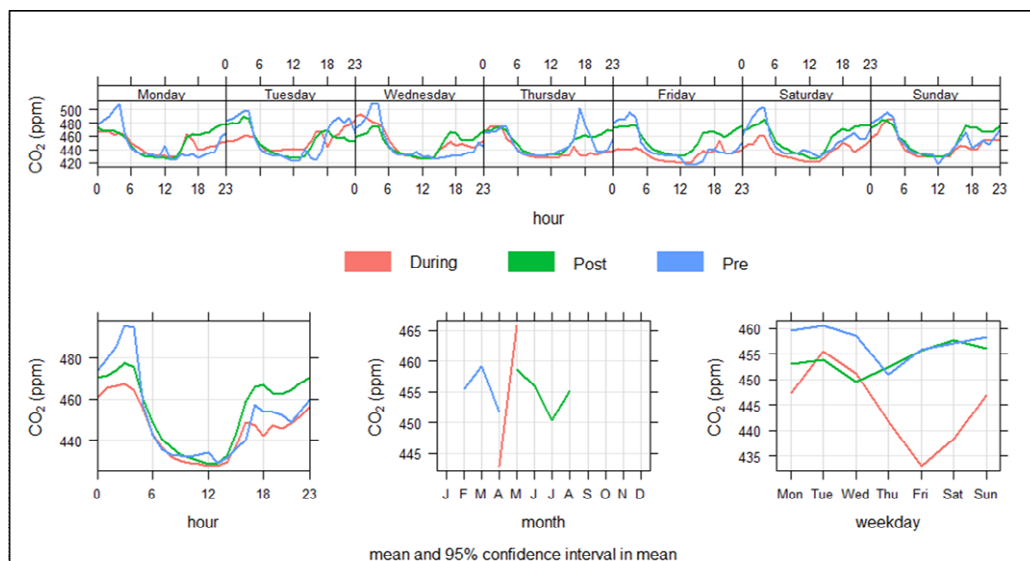


Figure 4 - 7: Mean CO₂ concentrations (ppm) pre-, during, and post-charcoal production on an intra-annual, weekly, and diurnal cycle at the kiln experimental site. CO₂ stands for carbon dioxide.

Figure 4 - 8 show the variations in the intra-annual, weekly, and diurnal cycles of PM_{10} at the trial location. The diurnal cycles of PM_{10} (bottom-left panel) showed greater concentrations during pre-charcoal production at 0400 hrs and 1600 hrs. The decreased concentrations emerged during noon (around 1200hrs). The results coincide with those presented in Figure 4-6 and Figure 4-7, which suggests that as pre-charcoal production occurred during the dry season then particulate matters could be emerged from other anthropogenic activities.

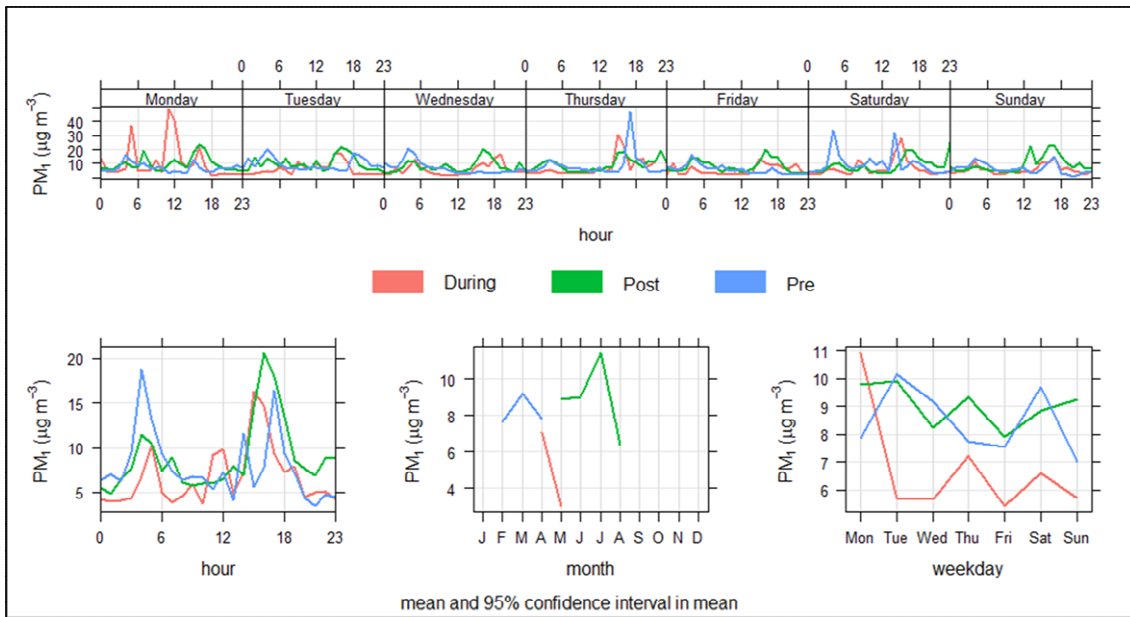


Figure 4 - 8: Mean PM_{10} concentrations ($\mu g m^{-3}$) pre-, during, and post-production charcoal production on an intra-annual, weekly, and diurnal cycle at the kiln experimental site. PM_{10} stands for particles $<10\mu m$ in diameter.

Figures 4-9 and 4-10 display the results for $PM_{2.5}$ and PM_{10} for pre, during and post charcoal production respectively. The trend patterns observed in those plots are similar to those observed for PM_{10} in Figure 4-8.

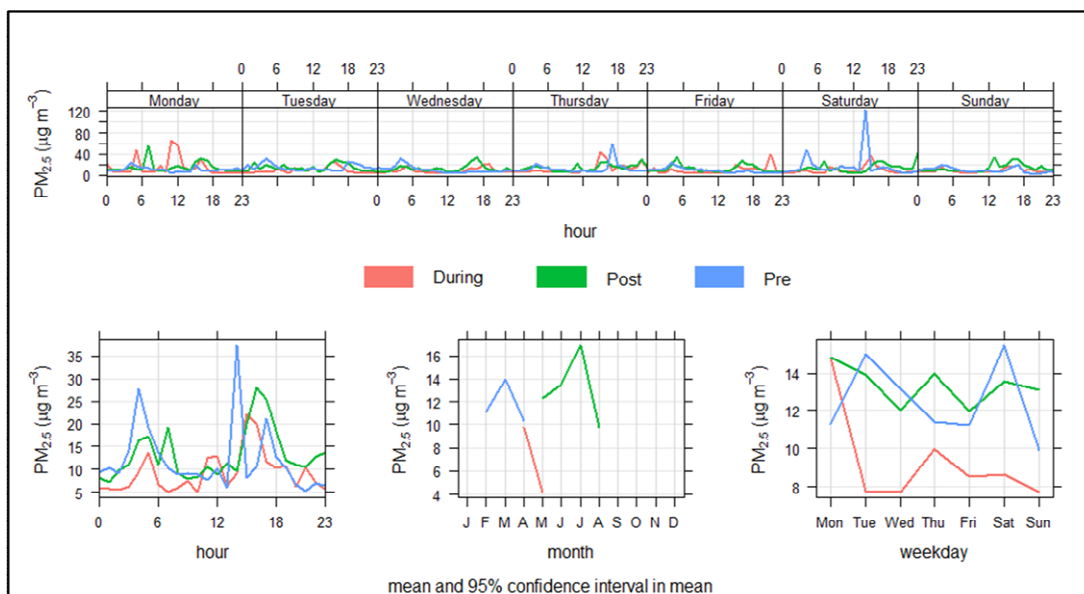


Figure 4 - 9: Mean PM_{2.5} concentrations (ugm⁻³) pre-, during, and post-charcoal production on an intra-annual, weekly, and diurnal cycle at the kiln experimental site. PM_{2.5} stands for tiny particles or droplets in the air that are two- and one-half microns or less in diameter.

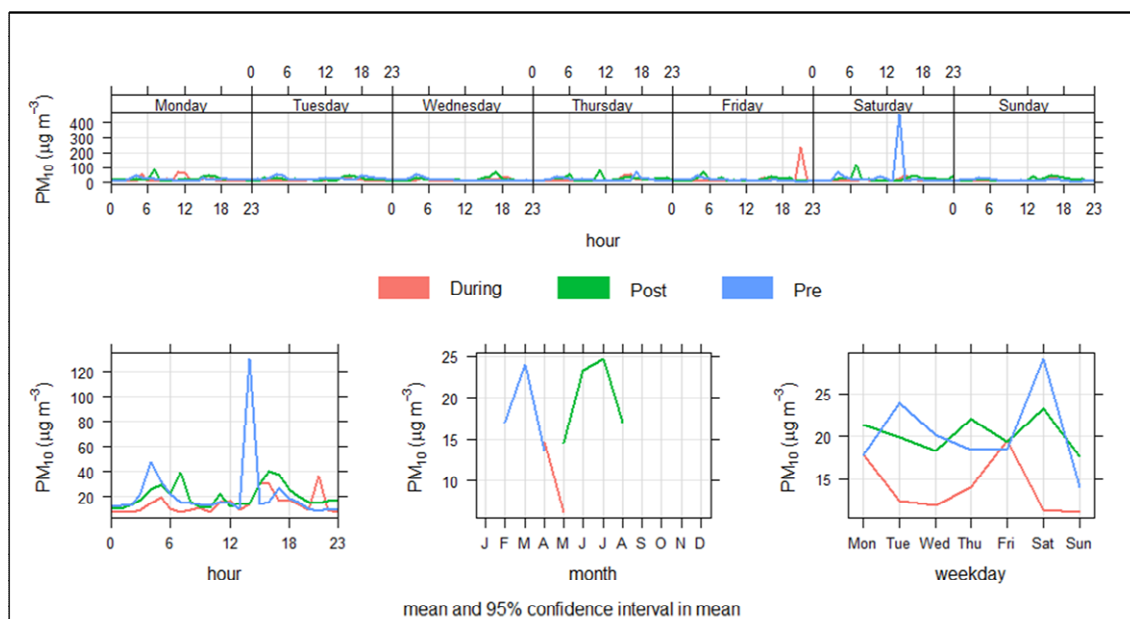


Figure 4 - 10: Mean PM₁₀ concentrations (ugm⁻³) pre-, during, and post-charcoal production on an intra-annual, weekly, and diurnal cycle at the kiln experimental site. PM₁₀ stands for particulate matter with a diameter of 10 microns or less (PM₁₀) and are inhalable into the lungs and can induce adverse health effects.

Figure 4-11 shows the mean wind speed (m/s) at the trial location before, during, and after charcoal production for intra-annual, weekly, and diurnal cycles. The wind speed indicates the presence of wind, with a low speed during the morning and evening and a higher speed observed during the afternoon. The late afternoon wind speed was the highest of the day, which resulted in faster removal of PMs and lower concentrations. When the wind slowed down after 16:00, PM concentrations in all phases increased. On the other hand, slower wind speeds during the charcoal production stage contributed to a greater accumulation of PM₁₀.

Further, sources of pollutants in the experimentation site were determined using Hysplit back trajectories and polar plots and these are presented in the following sections. The sources of pollutants complemented the temporal variations of pollutants in the area.

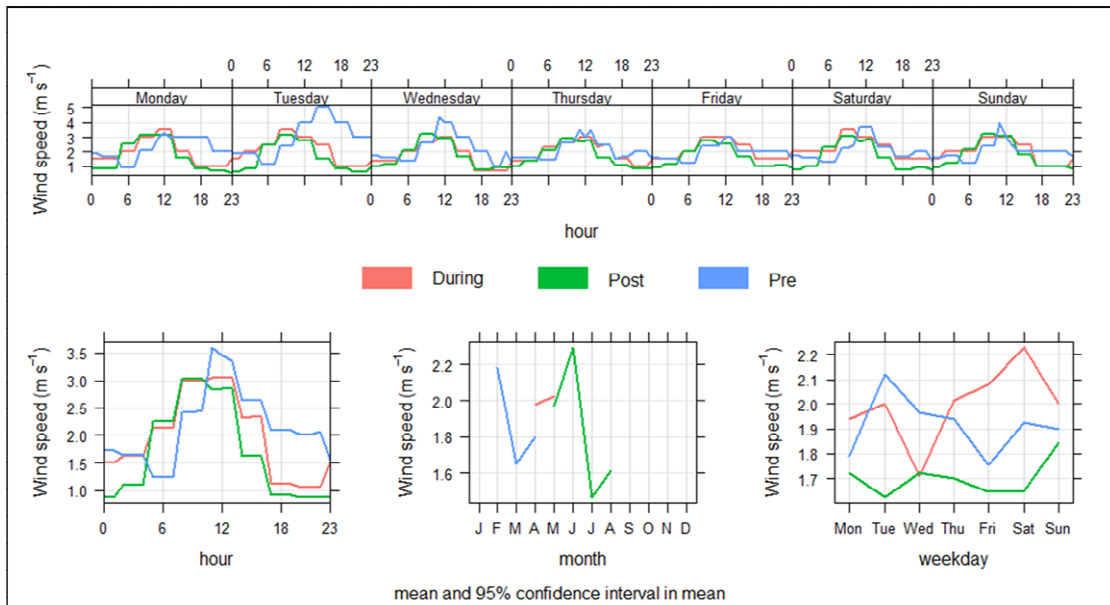


Figure 4 - 11: Intra-annual, weekly, and diurnal cycles of mean wind speed (m/s) at trial site for pre, during and post-charcoal production

4.1.4 Sources of pollutants in the trial site

The findings of the NOAA-developed Hysplit model employing a backward trajectory (Draxler & Hess, 2018) and the polar plots produced using local

emission recorded by inexpensive sensors during charcoal production are summarised in the following paragraphs. Researchers used the Hysplit model to identify long-range sources of emission that might impact the trial site (Item 4.1.4.1). The polar plots enable the identification of sources of local pollutants in the vicinity and help interpret intra-annual, weekly, and diurnal cycles of pollution (Item 4.1.4.2).

4.1.4.1 Hysplit back trajectories

Figures 4-12, 4-13, and 4-14 indicate a backward trajectory of sources of pollutants at the trial site before, during, and after charcoal production. Figure 4-12 (a, b, c) shows that the area was influenced by north-easterly trade winds during pre-charcoal production and southern-eastern winds (Figure 4-12b, c). Figure 4-13 (a, b, and c) show that during charcoal making, the area was influenced by south-easterly trade winds. Furthermore, Figure 4-14 (a, b, c) indicates that after charcoal production, the area was predominantly influenced by south-eastern winds. Generally, all the trajectories observed for pre-, during, and post-charcoal making come from the north-eastern and south-eastern side of the monitoring site. The area is influenced by wind from both north -eastern and south-eastern side due to the monsoon wind blowing from the Indian Ocean. It is reported that Tanzania, due to its proximity to the equator, has a climate shaped by trade winds that are controlled by the position of the intertropical convergence zone (ITCZ) and include north-easterly, easterly, and south-easterly winds (Duane et al., 2008). The north-easterly trade winds are parallel to the Great Horn of Africa and diverge along the coastal areas of Tanzania (Borhara et al., 2020).

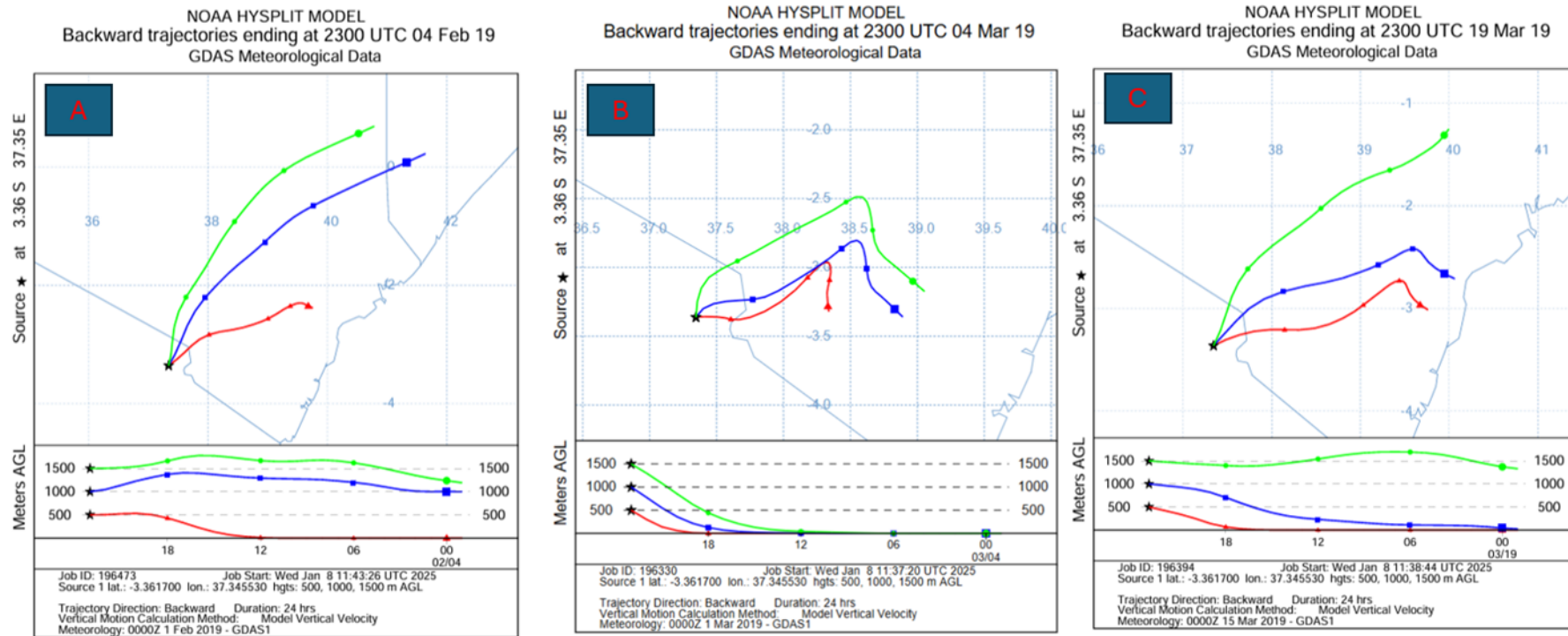


Figure 4 - 12: 24-hour HYSPLIT back trajectories centred on the kiln experimental site ending 2300 UTC 04 Feb, 04 March and 19 March 2019 during pre-charcoal making. The red, blue and green lines show sources of pollutants at 500m, 1000 m and 1500 m above ground level (AGL) at the experimentation site. The trajectory model indicates that north-easterly wind prevailing the area during the pre-charcoal production phase.

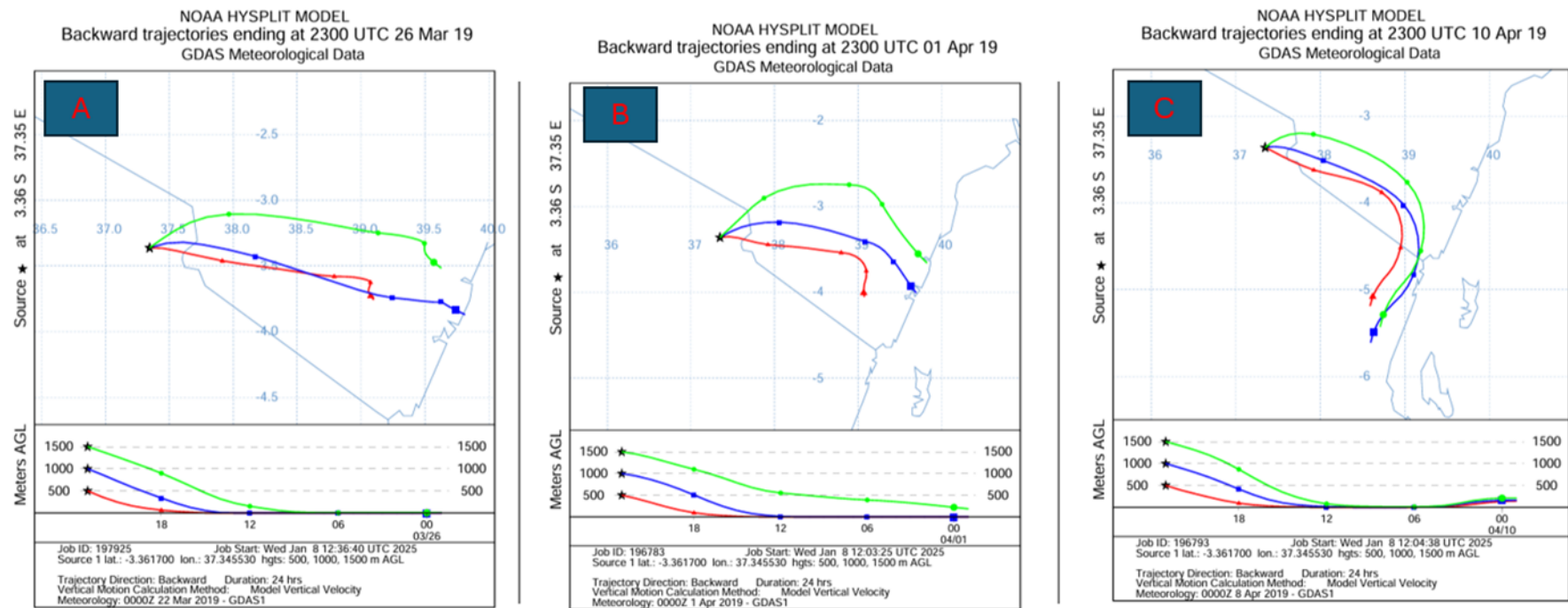


Figure 4 - 13: 24-hour HYSPLIT back trajectories centred on the kiln experimental site ending 2300 UTC 07 April, 21 April and 02 May 2019 during pre-charcoal making. The red, blue and green lines showing sources of pollutants at 500 m, 1000 m and 1500 m above ground level (AGL) at the experimentation site.

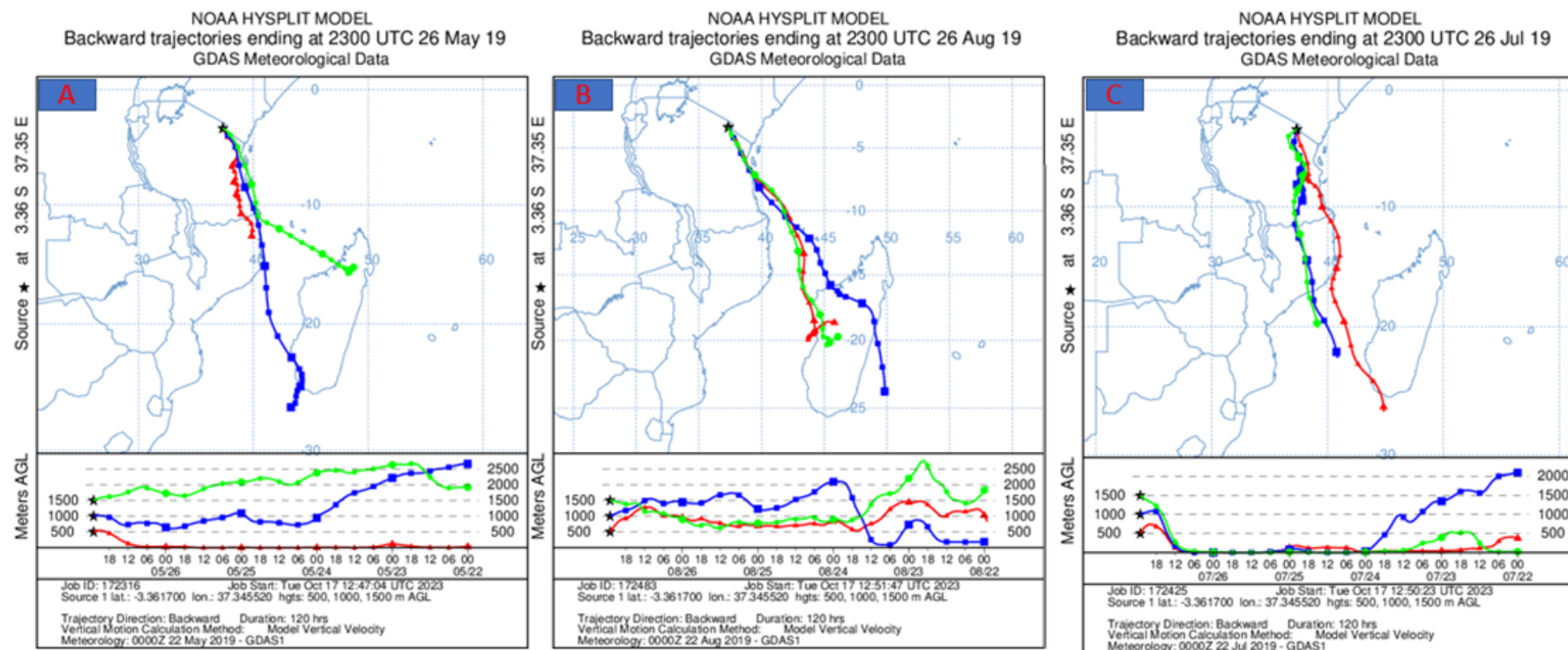


Figure 4 - 14: 120-hour HYSPLIT back trajectories centred on the kiln experimental site ending 2300 UTC on 26 May, 26 July and 26 August 2019 during pre-charcoal making. The red, blue and green lines showing sources of pollutants at 500 m, 1000 m and 1500 m above ground level (AGL) at the experimentation site.

4.1.4.2 Polar plots of the pollutants

Figure 4-15 shows the sources of reactive gases that includes CO and CO₂, in the surroundings of the kiln experiment site for pre charcoal production. Northern-eastern winds and Southern-eastern winds strongly affect the concentrations of both CO and CO₂ in the area. Further, the results are consistent with those obtained in the hybrid model (Figs. 4-12, 4-13, and 4-14), which suggest that the sources of pollutants in the area are influenced by the southern-eastern wind and other winds that influence the region.

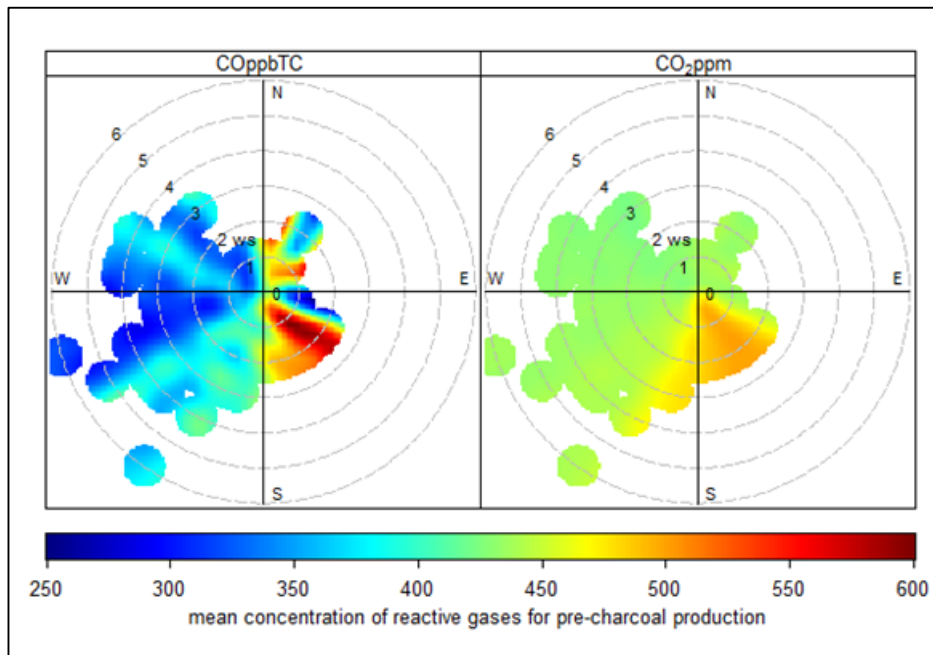


Figure 4 - 15: Polar plot of CO and CO₂ around the kiln experiment site for pre charcoal production. The red colour depicts the direction of the areas with higher concentration of CO₂. The wind data used for the analysis were obtained from Global Forecast System (GFS) of the USA's National Weather Service (NWS) using bi-spoke code (Appendix 8).

Figure 4-16 shows the sources of reactive gases that includes CO and CO₂, in the surroundings of the kiln experiment site for during charcoal production. Northern- eastern winds and Southern-eastern winds strongly affect the concentrations of both CO and CO₂ in the area. Further, the results are consistent with those obtained in the hysplit model (Figs. 4-12, 4-13, and 4-14), which suggest that the sources of pollutants in the area are influenced by the southern-eastern wind and other winds that influence the region.

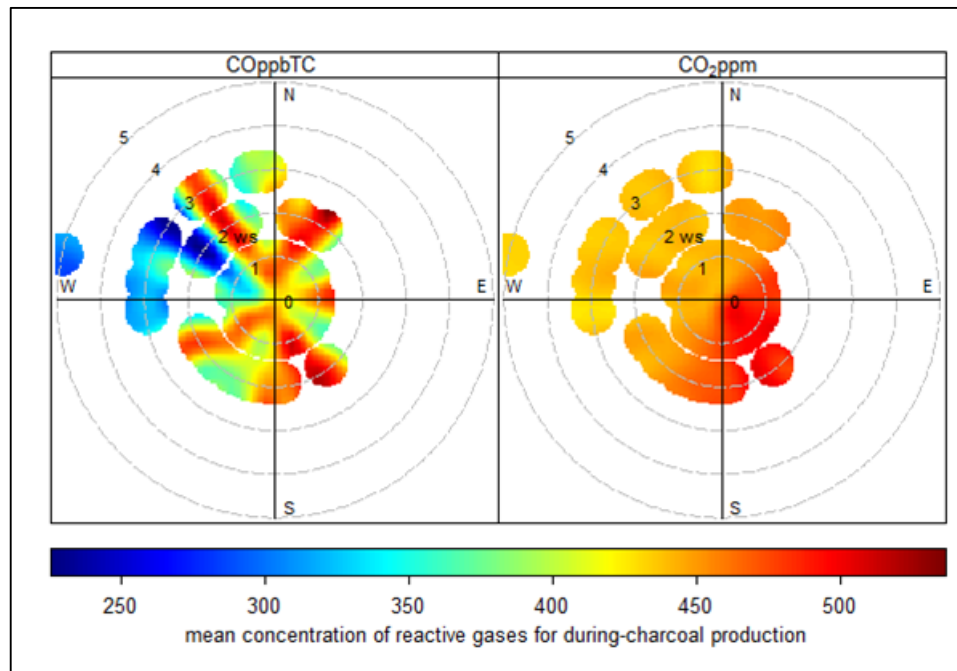


Figure 4 - 16: Polar plot of CO and CO₂ around the kiln experiment site for during charcoal production. The red colour depicts the direction of the areas with higher concentration of CO and CO₂. The wind data used for the analysis were obtained from Global Forecast System (GFS) of the USA's National Weather Service (NWS) using bi-spoke code (Appendix 8).

Figure 4-17 shows the sources of reactive gases that includes CO and CO₂, in the surroundings of the kiln experiment site for post charcoal production. Results shows that Northern- west and Southern-eastern winds strongly affect the concentrations of CO in the area.

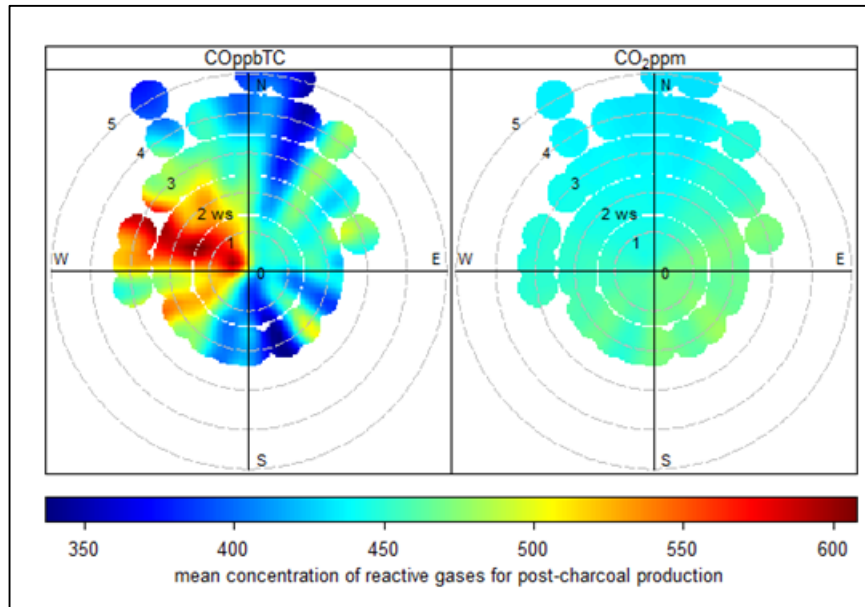


Figure 4 - 17:: Polar plot of CO and CO₂ around the kiln experiment site for post Charcoal production. The red colour depicts the direction of the areas with higher concentration of CO and CO₂. The wind data used for the analysis were obtained from Global Forecast System (GFS) of the USA's National Weather Service (NWS) using bi-spoke code (Appendix 8).

Figure 4-18 shows the sources of reactive gases that includes PM₁, PM_{2.5} and PM₁₀ in the surroundings of the kiln experiment site for during charcoal production. Northern- eastern winds and Southern-eastern winds strongly affect the concentrations of both PM₁₀ in the area. Further, the results for sources of PM₁₀ are consistent with those obtained in the hysplit model (Figs. 4-12, 4-13, and 4-14), which suggest that the sources of pollutants in the area are influenced by the southern-eastern wind and other winds that influence the region.

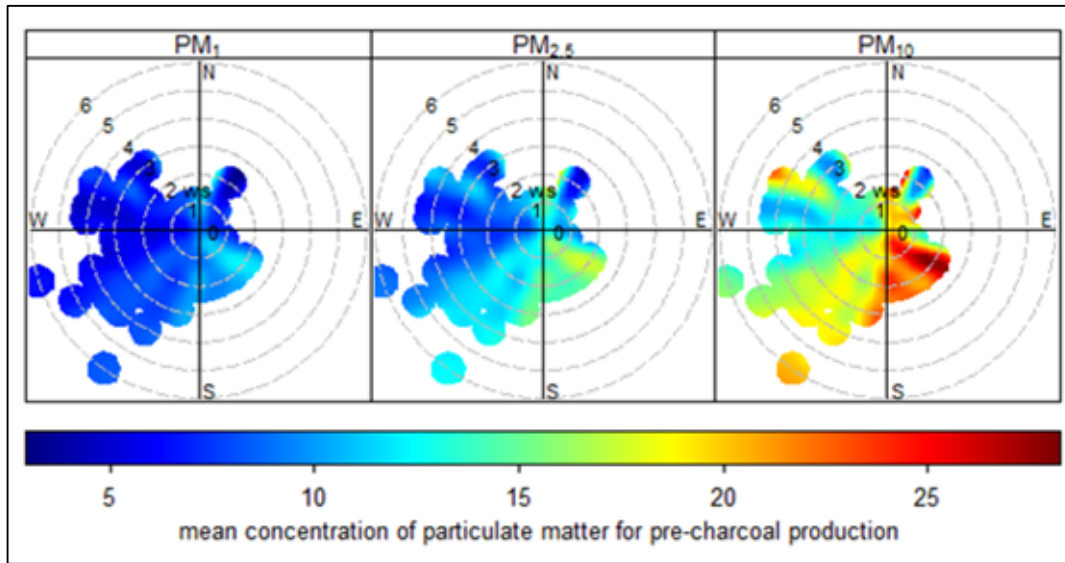


Figure 4 - 18: Polar plot of PM_{10} , $PM_{2.5}$ and PM_1 around the kiln experiment site for pre charcoal production. The red colour depicts the direction of the areas with higher concentration of PM_{10} . The wind data used for the analysis were obtained from Global Forecast System (GFS) of the USA's National Weather Service (NWS) using bi-spoke code (Appendix 8).

Figure 4-19 shows the sources of reactive gases that includes PM_{10} , $PM_{2.5}$ and PM_{10} in the surroundings of the kiln experiment site for during charcoal production. Results shows that Northern - western winds are strongly affect the concentrations of both PM_{10} for during charcoal production.

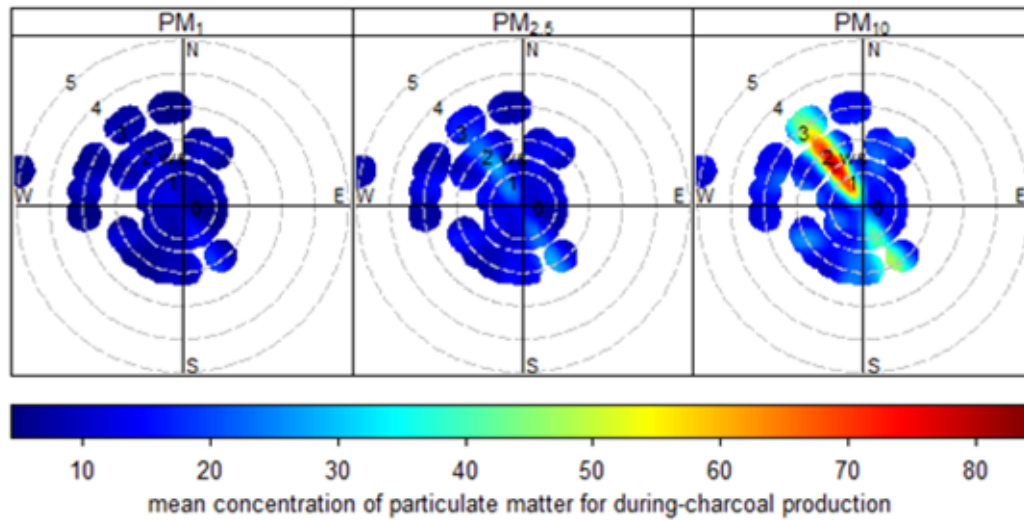


Figure 4 - 19: Polar plot of PM_{10} , $PM_{2.5}$ and PM_{10} around the kiln experiment site for during charcoal production. The red colour depicts the direction of the areas with higher concentration of PM_{10} . The wind data used for the analysis were obtained from Global Forecast System (GFS) of the USA's National Weather Service (NWS) using bi-spoke code (Appendix 8).

Figure 4-20 shows the sources of reactive gases that includes PM_{10} , $PM_{2.5}$ and PM_{10} in the surroundings of the kiln experiment site for post charcoal production. Results shows that Northern - eastern and northern-western winds are strongly affect the concentrations of PM_{10} for post charcoal production.

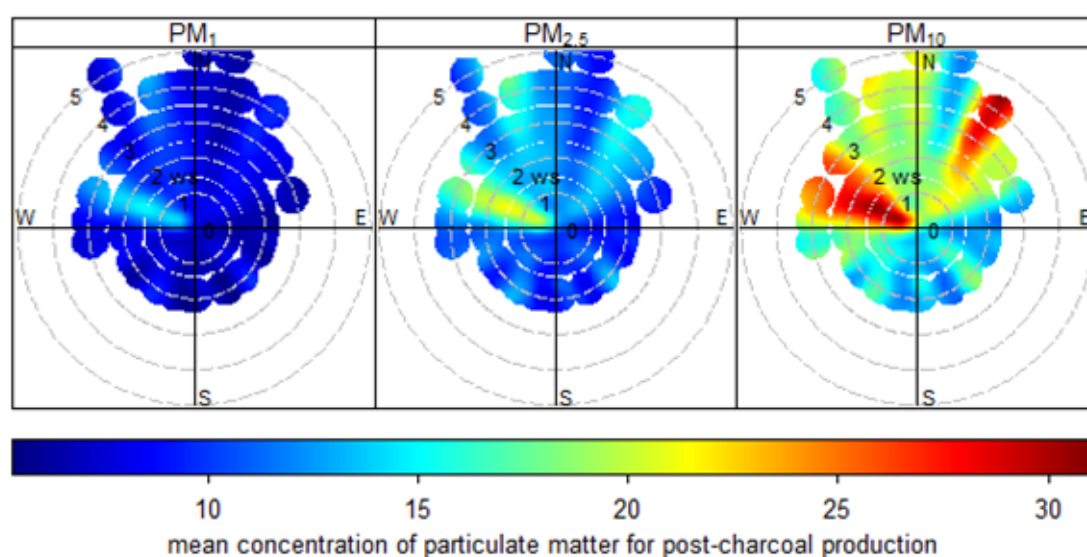


Figure 4 - 20: Polar plot of PM_{10} , $PM_{2.5}$ and PM_1 around the kiln experiment site for post charcoal production. The red colour depicts the direction of the areas with higher concentration of PM_{10} . The wind data used for the analysis were obtained from Global Forecast System (GFS) of the USA's National Weather Service (NWS) using bi-spoke code (Appendix 8).

4.1.4.3 Identified peak values from local maximum and correlation of common peaks for pre, during and post charcoal production

The following section presents the results of the analysis conducted to detect peak values of emissions that highlight the pollution signals of gases and particulate matter during charcoal production. Results in Figures 4–20 show plots of CO that highlight pollution signals of reactive gases for pre, during and post charcoal production, respectively. Other plots for CO₂ and particulate matter are presented in appendix 11. Results show that for pre-, during and post-charcoal production, there were no common peaks detected. This indicates the lack of signals for the during all phases and limits the estimation of emission factors for the charcoal kiln experiment. The results coincide with kruskal-walis test (item 4.1.1) that showed that there were no significant differences between phases and hence no correlation of pollutants between pre, during and post charcoal production.

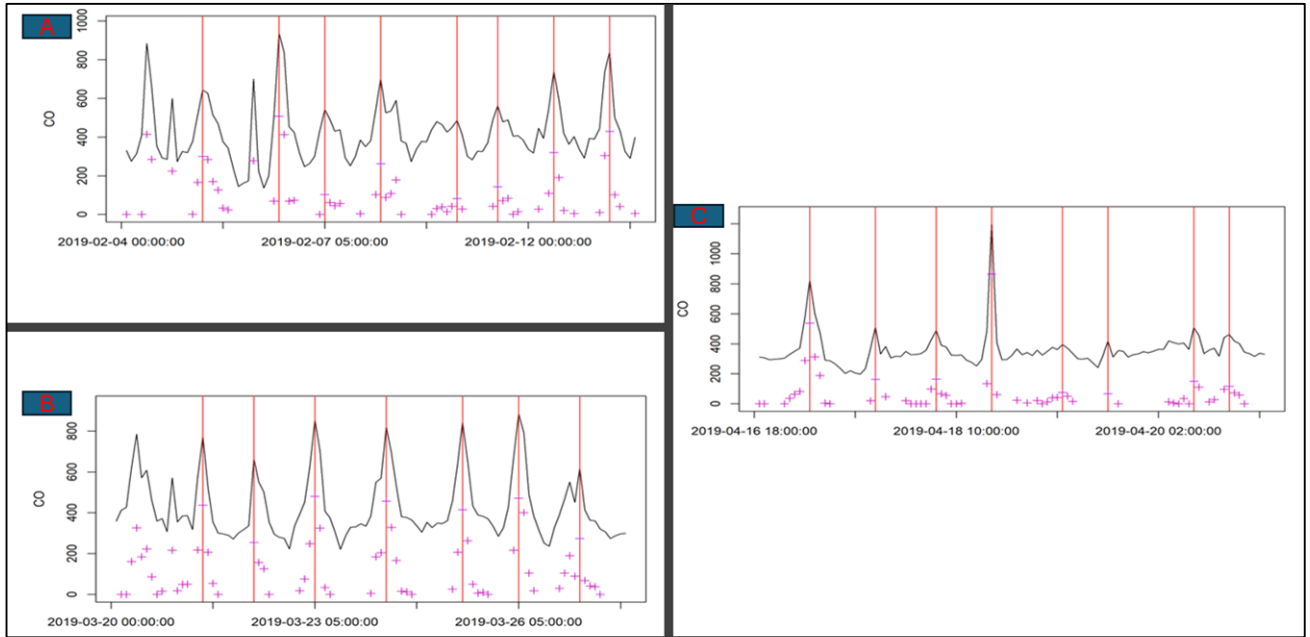


Figure 4 - 21: Timeseries plot showing peak values of CO for pre, during and post charcoal production phase depicting pollution signals. The red lines show specific peak values per each specie. There were no common peaks for all pollutants detected that highlighted lack of correlation between pre, during and post phases.

4.1.5 Summary results of objective 1.

This item indicates the summary results for objective 1. The study found no significant variations in CO₂ concentrations before, during, or after charcoal production periods. PM₁ levels were lower in pre-charcoal production and showed similar trends during and after charcoal production. PM_{2.5} and PM₁₀ concentrations also showed similar patterns, with greater concentrations recorded during charcoal production. Also, the statistical testing for significant difference in the distribution of concentrations in the pre, during and post periods was identified to comprehend the variation in the observed mean across phases of the testing procedure. The results suggest that there were no differences between pre, during and post periods.

Further, the graph in Figure 4-2 shows a time-series graph of charcoal production for CO, demonstrating the sensor's ability to identify pollutants in tropical regions. The sensor was calibrated in temperate regions and tested under climatic

conditions. Results showed its efficacy in identifying pollutants between October and December 2018. However, calibration in this study was hindered by unreliable power, calibration process faults, and travel restrictions due to the COVID pandemic. Operational issues in underdeveloped countries include inconsistent electricity, lack of calibration laboratories, and manufacturing equipment with batteries capable of holding power for 48 hours. The experimental site's pre-charcoal production phase showed cyclic patterns in CO and CO₂ concentrations, with maximum concentrations of 1198 ppb and 573 ppm, respectively. These concentrations are slightly higher than global estimates and seasonal and diurnal variations in Rwanda, with CO concentrations of 663 ppb.

Furthermore, the Hysplit model, developed by NOAA, uses a backward trajectory to identify long-range emission sources impacting a trial site. Polar plots produced using local emission data from inexpensive sensors during charcoal production, help identify local pollutants and interpret pollution cycles, identifying potential sources of long-term impact. The study shows a backward trajectory of pollutants at the trial site, influenced by north-eastern and southern-eastern winds. The climate in Tanzania is shaped by trade winds, controlled by the intertropical convergence zone. During charcoal production, south-eastern winds were predominant, while after, they were predominantly south-eastern. The trajectories mostly come from the eastern side of the site, influenced by monsoon winds from the Indian Ocean.

Nonetheless, the results reveal that the sources of the pollutant gases, particularly CO₂, in the vicinity of the kiln experiment site are strongly influenced by southern-eastern winds. This is consistent with the Hysplit model results, suggesting that the region's pollutants are influenced by these winds and other influences. The presence of buildings, including factories, workshops, and households, around the site suggests that human-induced activities could also contribute to the pollution.

Objective 2.

This section presents the results identifying the areas of high concentration of charcoal making activities around East Usambara mountain. These results were obtained through several steps, including satellite image acquisition and classification. Findings in this section provide information on the land use and cover change between 2008 and 2018 (Fig 4-22) and identifies the associations between proxy variables identified in the area depicting charcoal production and land use land cover change.

4.2.1 Land use land cover change identification using classification techniques.

Figure 4–22 presents the map of land use and land cover change for 2008 and 2018 at East Usambara Mountain as detected from Landsat imagery from the dry season. The land use and cover identified fell under five classes: bushland, cultivated land, grassland, humid forest, and woodland. The humid forest class occupied a large part of the forest, whereas bushland and cultivated land occupied a small share of the forest along East Usambara Mountain. A large proportion of the humid forest is influenced and protected by management interventions as it lies within the protected area of Amani Nature Reserve. The nature reserve, under the law of Tanzania, discourages the utilisation of trees found within the area for timber and charcoal production. The small share of cultivated land observed within the nature reserve may be due to illegal harvesting or burning of forest in search of areas for cultivation and grazing. The accuracy of the classification is presented in Table 4-2.

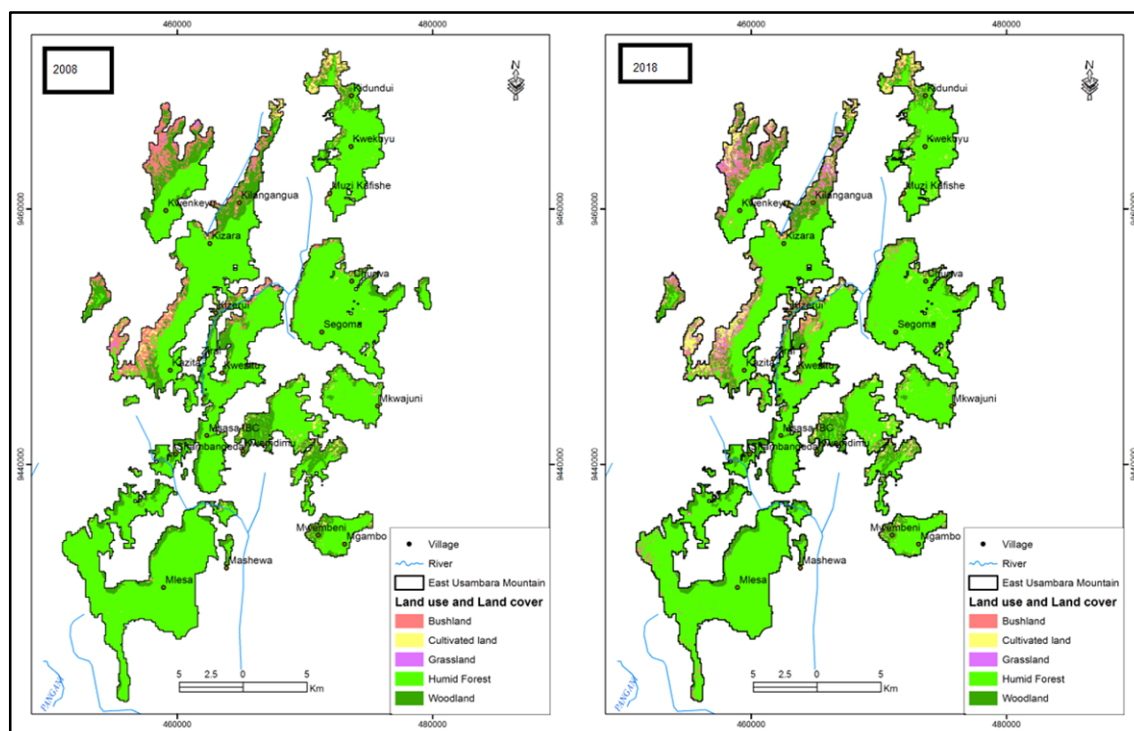


Figure 4 - 22: Land use and land cover map for East Usambara mountain, Muheza District for 2008 and 2018 respectively.

4.2.2 Accuracy assessment of classified images

Accuracy assessment is fundamental to thematic mapping from remotely sensed data (Foody, 2008). Results (Table 4-2) show that the total overall accuracy for the classified image was 81%. This implies a good representation of the classified images. Findings show that the humid forest class was accurately classified as the producer's and user's accuracy was 99.3% and 87.5%, respectively. However, findings show that woodland forest class was not so well classified, with producer's and user's average accuracy of 76.6% and 56.3% accurate, respectively. The Kappa coefficient estimated the accuracy of the classified images to be 0.75, indicating acceptability.

Table 4 - 2: Confusion matrix showing the accuracy assessment for the land use land cover classification.

	True Value (Reference Data)						
Predict Value	Bushland	Cultivated land	Grassland	Humid Forest	Woodland	Row Total	User Accuracy
Bushland	84	16	3	0	1	104	80.8%
Cultivated land	1	77	18	1	3	100	77.0%
Grassland	1	4	70	0	0	75	93.3%
Humid Forest	3	11	0	147	7	168	87.5%
Woodland	12	9	7	0	36	64	56.3%
Column Total	101	117	98	148	47	414	
Producer Accuracy	83.2%	65.8%	71.4%	99.3%	76.6%		
Total accuracy							81.0%

4.2.3 Land cover Change for east Usambara Mountain

The average annual rate of change for cultivated land was 76 ha per year (Table 4-3). This reflects an increase in agricultural activities, as well as other human activities, in the area. The increase in cultivated land led to an increase in grassland of 63 ha, which further led to a decrease in woodland, bushlands, and humid forests of 88 ha, 26 ha, and 25 ha, respectively. The increase in cultivated land may also be due to an increase in population that depends on the cultivation of the land to secure their livelihood.

Table 4 - 3: Land cover change for East Usambara mountain from 2008 to 2018.

Land Use/ Cover Types	Land cover				Annual change rate (Ha)
	Year:2008		Year:2018		2008-2018
	Ha	%	Ha	%	Ha
Bushland	2,774	7	2,515	7	-26
Cultivated land	1,065	3	1,820	5	76
Grassland	118	0	752	2	63
Humid forest	27,475	72	27,221	71	-25
Woodland	6,973	18	6,097	16	-88
TOTAL	38,405	100	38,405	100	

4.2.4 Gross Gains, Gross Losses, and Persistence of LULC

Results (Table 4-4) show that the cultivated and grassland classes have increased by 786ha and 591ha, respectively. Woodland, bushlands, and humid forest decreased 843 ha, 238 ha, and 295 ha, respectively. This could be explained by the fact that local communities, which mostly depend on agriculture and other development activities, utilised the grassland and woodland for their activities such as charcoal making and fuelwood production.

Table 4 - 4: Gross Gains, Gross Losses and Persistence of LULC.

Land Cover	Overall change for land use/cover classes (in Ha), 2008-2018		
	Gain	Loss	Change
Bushland	1,338	1,576	-238
Cultivated land	1,152	366	786
Grassland	691	100	591
Humid forest	347	643	-295
Woodland	706	1,549	-843

4.2.5 Deforestation and forest gains

Findings in Figure 4-24 show the land use and cover change map for 2008–2018. Results indicate that disturbances that include deforestation are observed along the boundary of the forest as it is near the community that depends on forest products, including charcoal and firewood. Communities adjacent to the forest utilise the forest through logging for fuelwood (firewood and charcoal production) and construction of buildings (Mansourian et al., 2019; Monela et al., 1999; Nabukalu & Gieré, 2019; Ract et al., 2023). The terrain is inhabited by around 135,000 individuals, who are dispersed among 35 communities (URT, 2022). They rely directly on the ecosystem's products and services offered by the forest, such as medicinal plants, food, construction materials, and, most importantly, the management and safeguarding of water supplies (Luz et al., 2015; Mansourian et al., 2019; Schaafsma et al., 2012; Turpie et al., 2005; Zulu & Richardson, 2013).

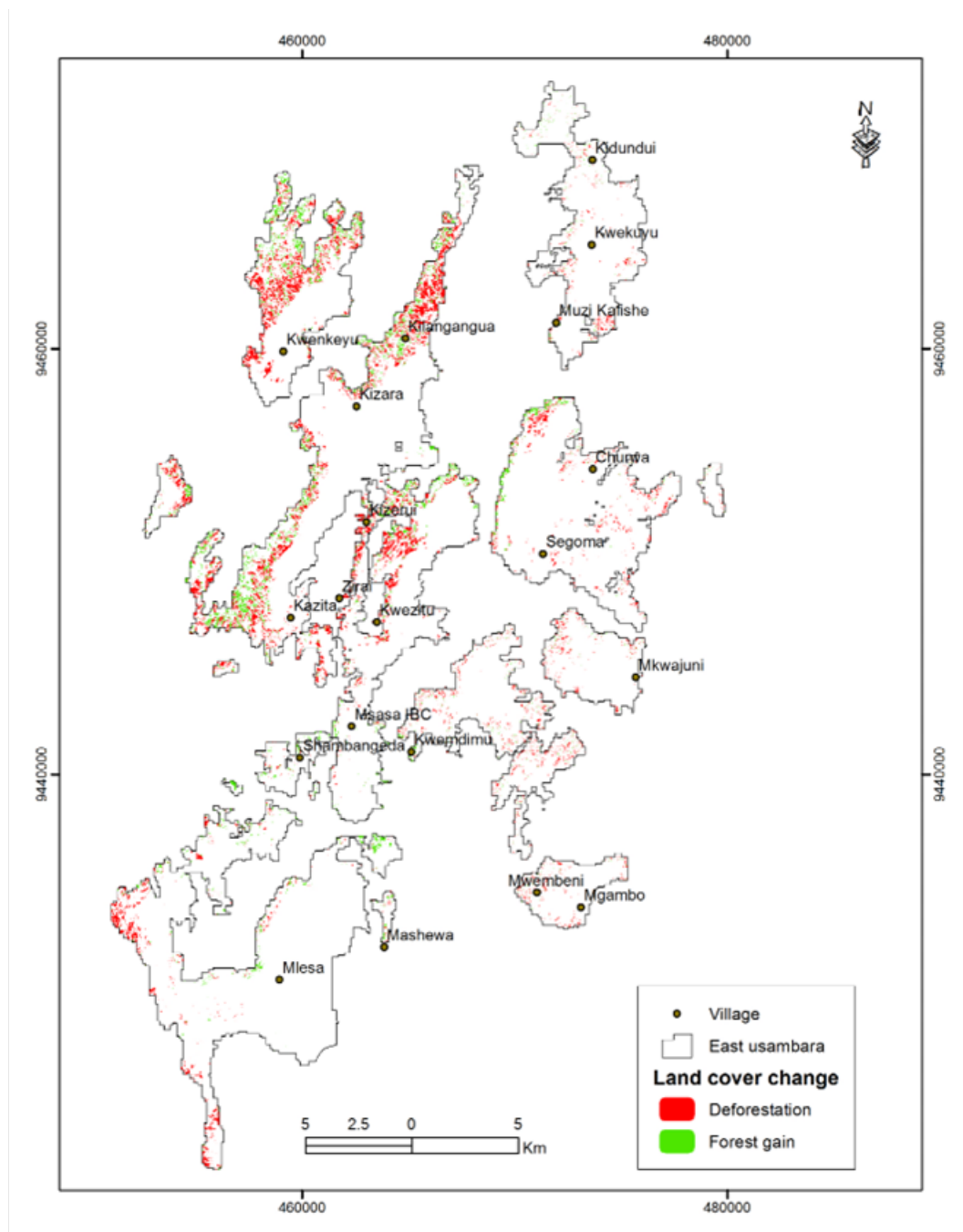


Figure 4 - 23: Map showing the land cover change in terms of deforestation and forest gain from 2008 to 2018 around east Usambara Mountain.

Figure 4-25 reveals the increase in cultivated and grassland areas. This may be due to an increase in human activities such as shifting cultivation and charcoal making that leads to a decrease in woodland and bushlands around the Usambara Mountains.

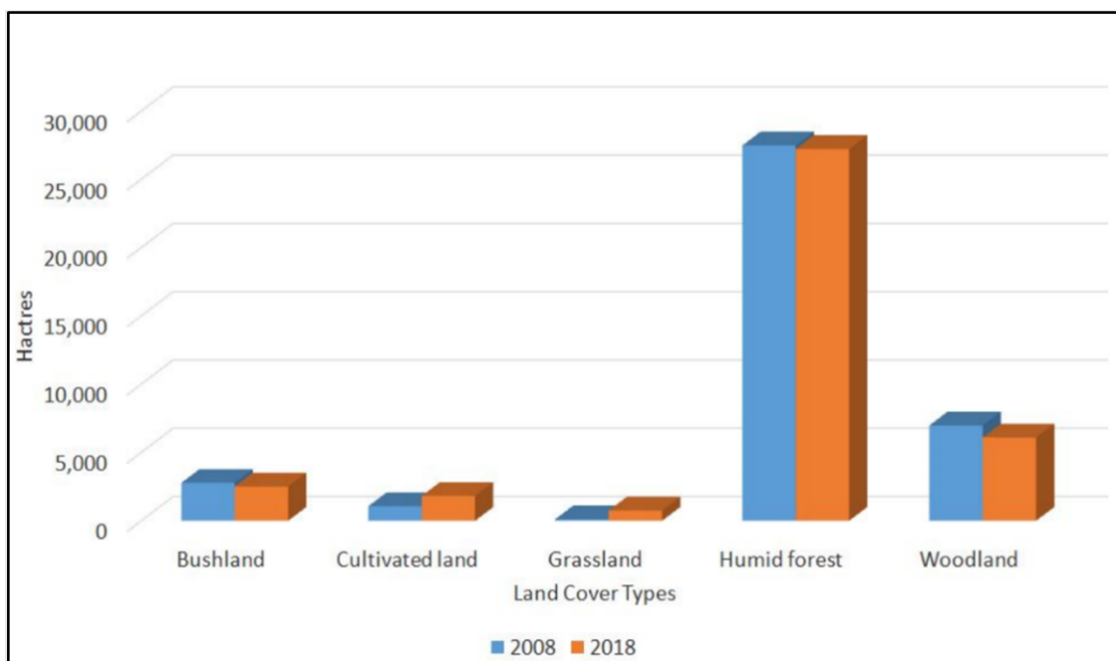


Figure 4 - 24: Bar plot showing the land cover changes that have occurred around the Usambara mountain from 2008 to 2018.

4.2.6 Summary results of objective 2

The analysed map shows land use and land cover changes at East Usambara Mountain between 2008 and 2018, categorized into five classes: bushland, cultivated land, grassland, humid forest, and woodland. The humid forest occupies a significant portion of the forest, while bushland and cultivated land are small. Most of the forest is protected by management interventions within the Amani Nature Reserve, which discourages tree use for timber and charcoal production. The study analysed the accuracy of thematic mapping from remotely sensed data, revealing an overall accuracy of 81%. The humid forest class was the most accurate, with 99.3% and 87.5% accuracy from producers and users, respectively. However, the woodland forest class was less accurate, with an average accuracy of 76.6% and 56.3% from producers and users respectively.

On deforestation issues, it was revealed that the annual rate of change for cultivated land in the area is 76 ha per year, indicating an increase in agricultural activities and human activities. This leads to a 63-ha increase in grassland, but

decreases in woodland, bushlands, and humid forests. The increase in cultivated land may be due to a growing population relying on land cultivation for livelihood. The study reveals that cultivated and grassland classes have grown by 786 and 591 ha, respectively, while woodland, bushlands, and humid forest have decreased by 843, 238 and 295 ha, respectively, due to local communities' agricultural activities.

Results on land use and cover change maps spanning from 2008 to 2018 on the area illustrate the occurrence of deforestation in areas adjacent to forests and communities that depend on forest resources such as charcoal and firewood. These communities utilise the forest for the purpose of producing fuelwood and engaging in building activities. The landscape, home to over 135,000 people, is partitioned into 35 villages that depend on the ecosystem's resources and services, including medicinal plants, food, building materials, and water supply management. Charcoal production was determined along the landscape through proxy variables techniques.

Lastly, results of the investigated distribution of proxy variables from described charcoal-making activity in different forest patches over time. Each forest patch represents an individual forest management unit, helping determine if specific decisions promote or limit charcoal production. The results show that the count of variables for dark spots, footpaths, temporal settlement, and charcoal kilns oscillates between 0-44, 0-38, and 0-29 for 2002-2012, 2013-2015, and 2016-2019, respectively. The average count of proxy variables for each patch is estimated to be 5.428, 4.803, and 4.375 for 2002-2012, 2013-2015, and 20216-2019, respectively.

4.3 Objective 3

This section presents the results obtained for objective 3, which aimed to link charcoal production with catchment impacts and degradation around East Usambara Mountain. Results presented in this section by following the several steps identified in the methodology.

4.3.1 Identification of proxy variables

Table 4-5 shows the distribution of proxy variables describing charcoal-making activity identified for different forest patches over time. Each forest patch defines an individual forest management unit. The concept of a forest patch has been used as it aids in determining whether specific forest management decisions promote or limit charcoal production. Results indicate that the count of variables oscillates between 0–18, 0-38, and 0-24 of dark spots for 2002–2012, 2013–2015, and 2016–2019, respectively. For footpaths, the count of variables ranges between 0-5, 0-4, and 0-1 for 2002–2012, 2013–2015, and 2016–2019, respectively. Further, temporal settlement counts of variables range from 0-39, 0-24, and 0-15, respectively. Lastly, charcoal kiln counts range from 0-44, 0-9, and 0-8 for 2002–2012, 2013–2015, and 2016–2019, respectively. On average, each patch had a count of proxy variables estimated to be 5.428, 4.803, and 4.375 for 2002–2012, 2013–2015, and 2016–2019, respectively.

Table 4 - 5: Distribution of proxy variables describing charcoal making activity identified for each of the forest patches over time.

		Time period			
Patch	Proxy variable	1995-2001	2002-2012	2013-2015	2016-2019
Patch 1	Dark spots	Not visible	14	9	10
Patch 1	Footpaths	Not visible	0	1	1
Patch 1	Temporal settlement	Not visible	1	2	0
Patch 1	Charcoal kiln	Not visible	1	3	1
Patch 2	Dark spots	Not visible	15	29	20
Patch 2	Footpaths	Not visible	1	0	0
Patch 2	Temporal settlement	Not visible	18	18	7
Patch 2	Charcoal kiln	Not visible	5	0	3
Patch 3	Dark spots	Not visible	11	6	5
Patch 3	Footpaths	Not visible	3	2	0
Patch 3	Temporal settlement	Not visible	21	1	1
Patch 3	Charcoal kiln	Not visible	4	4	4
Patch 4	Dark spots	Not visible	0	38	15
Patch 4	Footpaths	Not visible	2	4	0
Patch 4	Temporal settlement	Not visible	1	1	3
Patch 4	Charcoal kiln	Not visible	1	5	1
Patch 5	Dark spots	Not visible	18	4	13
Patch 5	Footpaths	Not visible	1	0	0
Patch 5	Temporal settlement	Not visible	20	2	0

Patch 5	Charcoal kiln	Not visible	10	0	0
Patch 6	Dark spots	Not visible	0	0	0
Patch 6	Footpaths	Not visible	0	0	0
Patch 6	Temporal settlement	Not visible	0	0	0
Patch 6	Charcoal kiln	Not visible	0	0	0
Patch 7	Dark spots	Not visible	2	2	1
Patch 7	Footpaths	Not visible	0	0	0
Patch 7	Temporal settlement	Not visible	0	1	1
Patch 7	Charcoal kiln	Not visible	0	1	1
Patch 8	Dark spots	Not visible	1	0	3
Patch 8	Footpaths	Not visible	0	0	0
Patch 8	Temporal settlement	Not visible	1	0	0
Patch 8	Charcoal kiln	Not visible	0	0	0
Patch 9	Dark spots	Not visible	4	10	13
Patch 9	Footpaths	Not visible	0	0	0
Patch 9	Temporal settlement	Not visible	2	1	3
Patch 9	Charcoal kiln	Not visible	0	0	8
Patch 10	Dark spots	Not visible	0	14	24
Patch 10	Footpaths	Not visible	0	0	1
Patch 10	Temporal settlement	Not visible	0	0	0
Patch 10	Charcoal kiln	Not visible	0	1	4
Patch 11	Dark spots	Not visible	1	24	20
Patch 11	Footpaths	Not visible	0	2	1
Patch 11	Temporal settlement	Not visible	0	0	0
Patch 11	Charcoal kiln	Not visible	0	1	0
Patch 12	Dark spots	Not visible	3	0	13
Patch 12	Footpaths	Not visible	0	2	0
Patch 12	Temporal settlement	Not visible	0	0	15
Patch 12	Charcoal kiln	Not visible	0	0	4
Patch 13	Dark spots	Not visible	21	21	2
Patch 13	Footpaths	Not visible	0	1	0
Patch 13	Temporal settlement	Not visible	9	4	1
Patch 13	Charcoal kiln	Not visible	44	6	0
Patch 14	Dark spots	Not visible	13	16	29
Patch 14	Footpaths	Not visible	5	0	0
Patch 14	Temporal settlement	Not visible	39	24	13
Patch 14	Charcoal kiln	Not visible	12	9	4

4.3.2 Analysis of collocation of land cover change and proxy variables

Figure 4-26 shows the map of the study area with the location of the proxy variables identified. Visual inspection of the map indicates that the presence of proxy variables seems to align with specific land use and cover changes over time when compared to Figure 4-23 and Figure 4-24. The land cover change of

the area from 2008 to 2018 hinted at a significant presence of human activities that resulted in a decrease in forest and natural cover. This seems to be consistent with Figure 4-25. Areas classified as humid forest seem to have a high density of proxy variable presence from 2002 to 2012, while areas classified as grassland seem to have a low density of proxy variables from 2013 to 2015. The proxy variables indicated that darkspots constituted a large proportion while footpaths represented a small proportion. Dark spots were observed to be more abundant than others, and this could be because during visual identification they may have been mixed up with tree shadows. The fact that dark spots are easy to detect through observation of the imagery could be another factor. Instead, footpath variables account for a small share, as it is difficult to visually identify them on the satellite image.

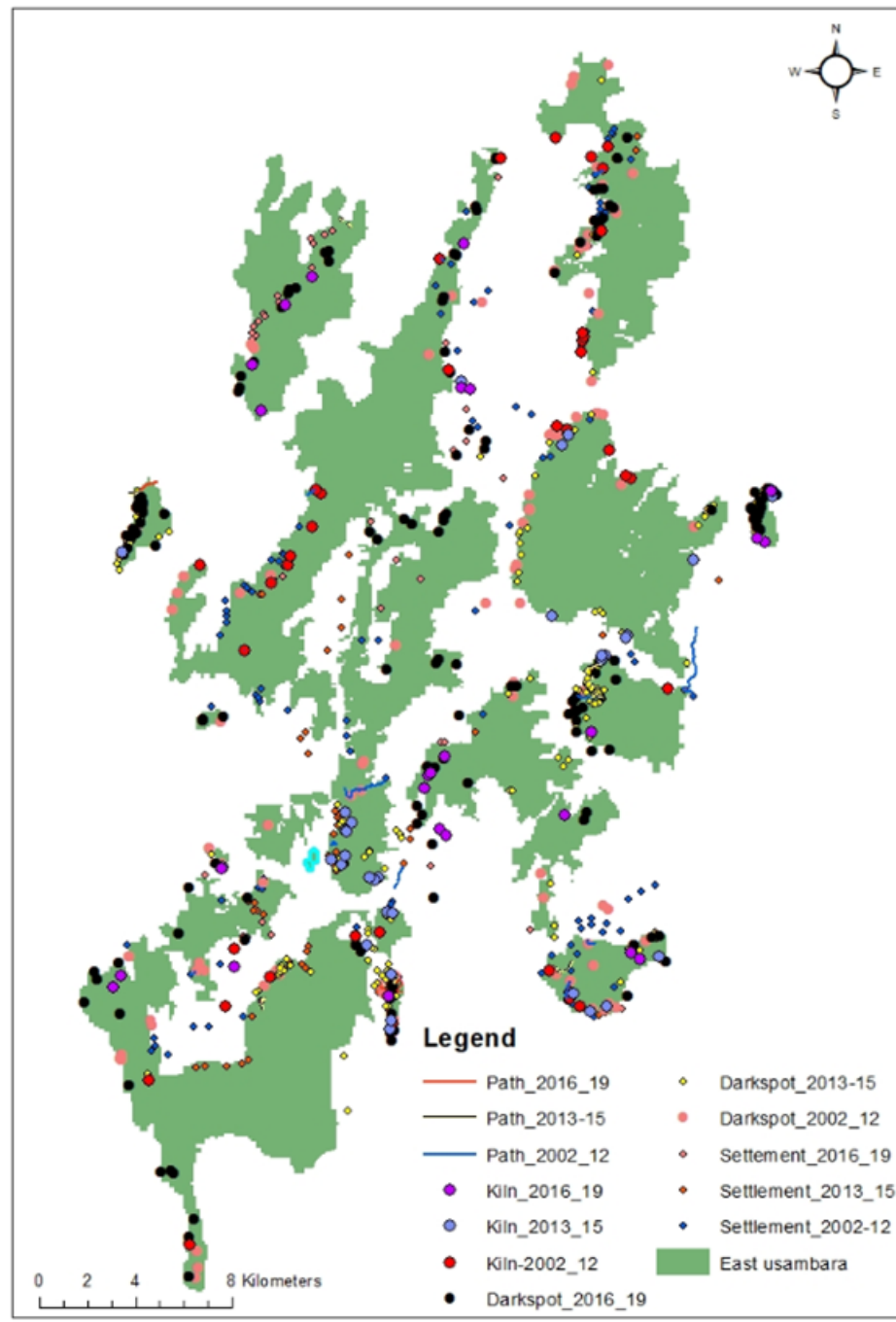


Figure 4 - 25: Map of East Usambara Mountain indicating the distribution of proxy variables describing charcoal making activity identified for different forest patches from 2002 to 2019.

Table 4-5 shows the distribution of proxy variables per land use and land cover type. Results indicate that the count of variables ranges between 6-33, 1-29, and 2-64 for dark spots for 2002–2012, 2013–2016, and 2015–2019, respectively. For

footpaths, the variable ranges from 0–4, 1–5, and 1–2 for 2002–2012, 2013–2015, and 2016–2019, respectively. Further, for the charcoal kiln, the variable ranges from 2–12, 1–9, and 1–9 for 2002–2012, 2013–2015, and 2016–2019, respectively. Lastly, settlement variables range from 4–15, 1–16, and 0–14 for 2002–2012, 2013–2015, and 2016–2019, respectively.

Table 4 - 6: Distribution of proxy variables per land use land cover type identified in the case study area.

Land use land cover	Proxy Variable	2002-2012	2013-2015	2015-2019
Humid forest	Kiln	12	9	9
Humid forest	Settlement	10	5	3
Humid forest	Darkspot	33	9	31
Humid forest	Footpaths	0	5	1
Woodland	Kiln	9	1	9
Woodland	Settlement	14	16	14
Woodland	Darkspot	33	29	64
Woodland	Footpaths	1	2	1
Bushland	Kiln	9	2	1
Bushland	Settlement	15	1	5
Bushland	Darkspot	10	3	14
Bushland	Footpaths	3	1	1
Grassland	Kiln	2	1	3
Grassland	Settlement	4	13	0
Grassland	Darkspot	6	1	2
Grassland	Footpaths	2	4	2
Cultivated land	Kiln	7	1	1
Cultivated land	Settlement	10	1	8
Cultivated land	Darkspot	13	2	9
Cultivated land	Footpaths	4	2	1

Figures 4-27, 4-28, 4-29, and 4-30 show the differences in the number of proxy variables depicting charcoal making activity in each of the land use land cover classes (i.e., humid forest, woodland, bushland, grassland, and cultivated land). The results help identify those land-use land cover classes with a high presence of charcoal-making activity. The results indicate that, from 2002 to 2012, in the humid forest class, there were a high number of proxy variables indicating a high presence of charcoal-making activity. During that period, results also indicate that

for bushland and cultivated land, the number of proxy variables was approximately constant. A similar pattern to that described for 2002–2012 is observed for the period 2016–2019, with woodland classes showing an increase in the number of proxy variables and constant proxy variables in grassland, bushland, and cultivated land. For the period 2013–2015, there has been an increase in the proxy variables indicating charcoal production under the woodland class. This increase in the proxy variable depicting charcoal production may be due to the presence of favourable trees for charcoal making in the area. (Chomba, 2018; Garedew & Simon, 2018; Green et al., 2013; Nduwamungu, 2009) reported that the woodland class consists of closed stands of trees, with the upper canopy closed. It is primarily composed of Miombo woodlands and *Acacia-commiphora* woodlands, which are dominated by *Brachystegia/Julbernadia spp.*, *Acacia spp.*, and *Combretum spp.* It is reported that species that produce high-quality charcoal include trees from woodland land use land cover classes (Chomba, 2018; Hoffmann et al., 2018; Oduor, 2012). The number of proxy variables observed in bushland, grassland, and cultivated land for the period 2013–2015 remains approximately constant compared to that observed for 2002–2012. These similarities between bushlands, grasslands, and cultivated land may be due to the presence of similar anthropogenic activities, such as settlements that increase fuel consumption, in these lands.

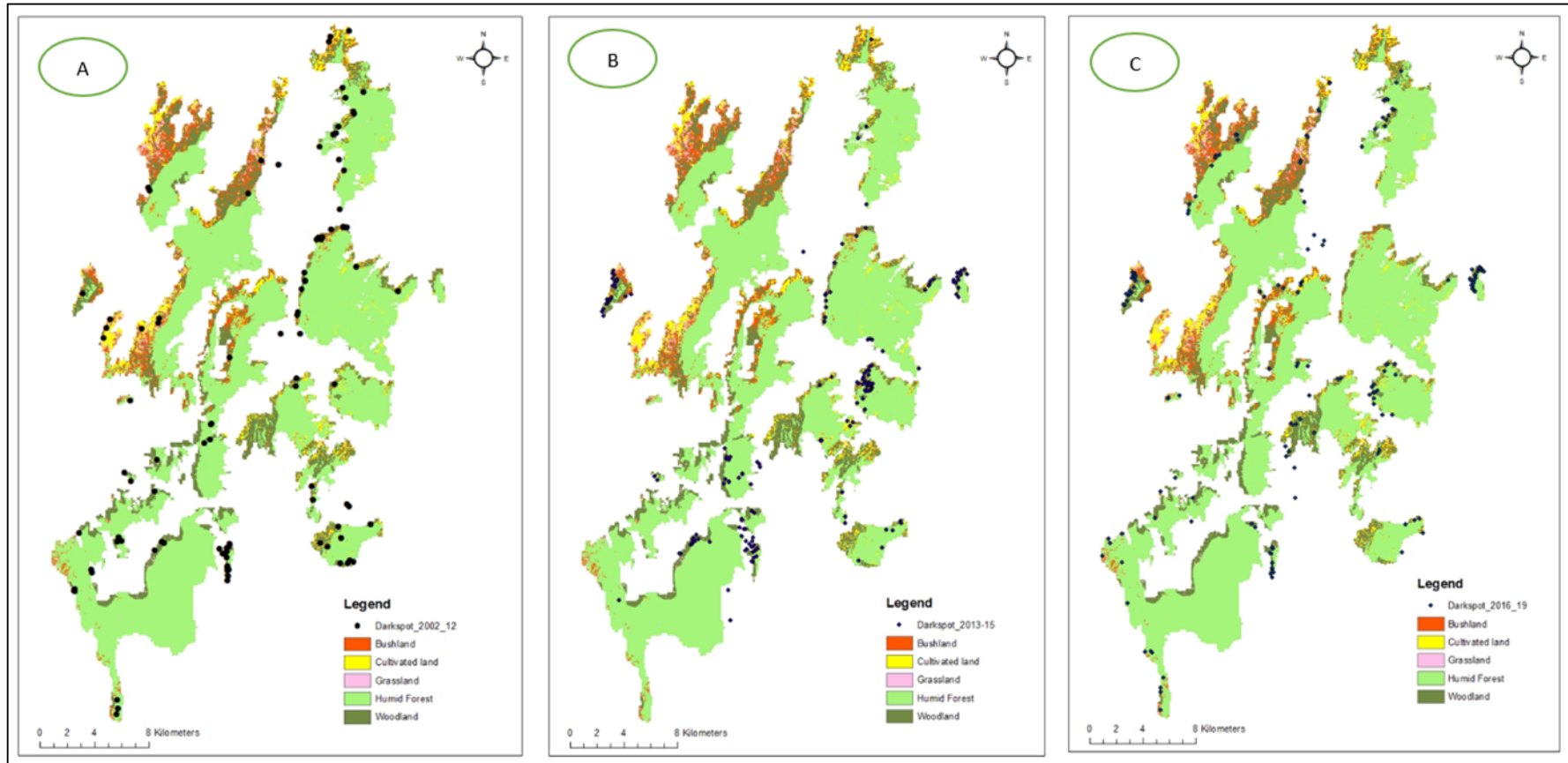


Figure 4 - 26: Maps showing the location of proxy variable (Darkspot) indicating charcoal making activity in relation to forest cover change for East Usambara Mountain from 2002 to 2019. A: Location of darkspot for 2002 to 2012; B: Location of darkspot for 2013 to 2015; C: Location of darkspot for 2016 to 2019.

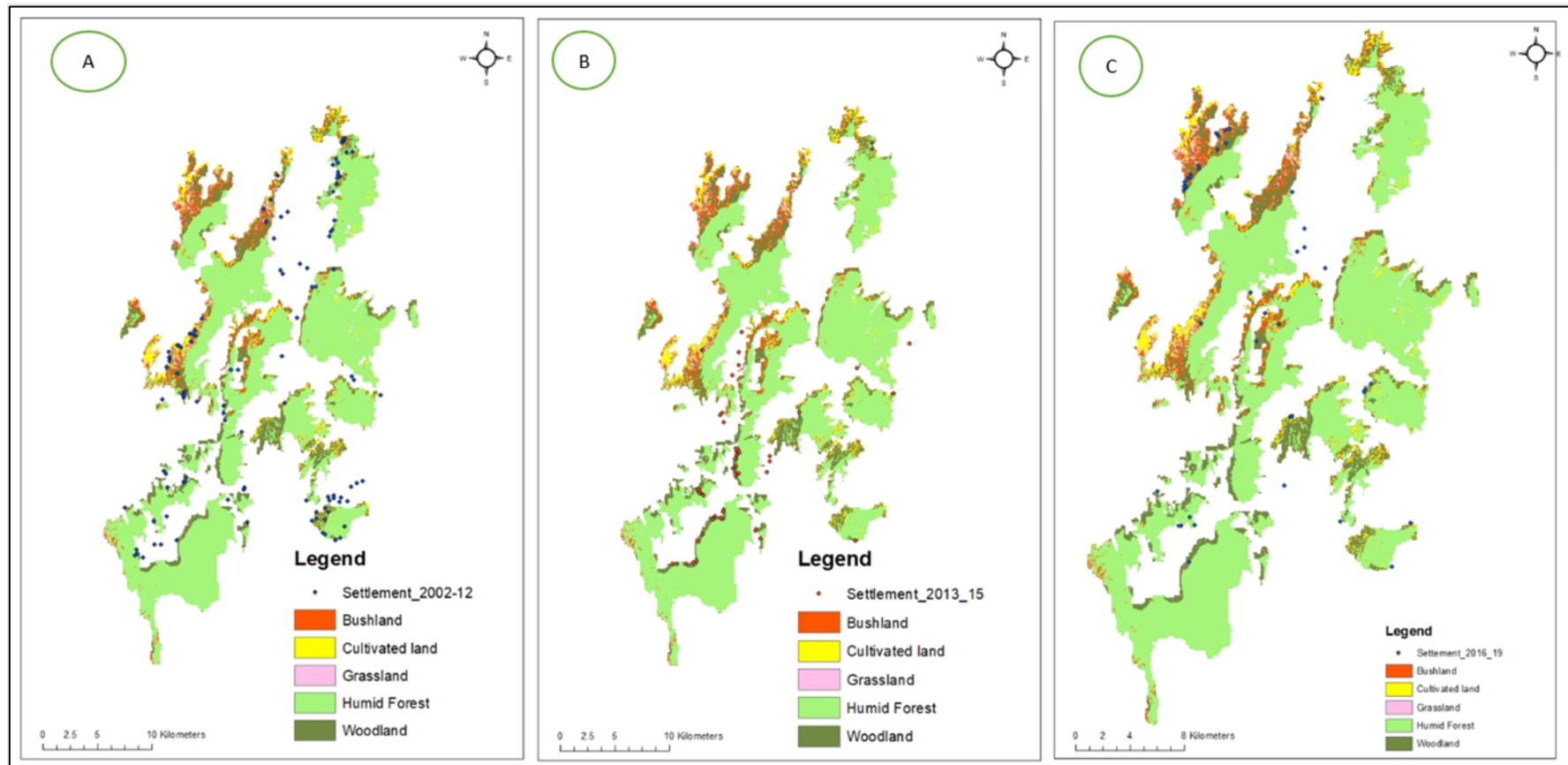


Figure 4 - 27: A map showing the location of proxy variable (settlements) indicating charcoal making activity in relation to forest cover change for East Usambara Mountain from 2002 to 2019. A: Location of settlements for 2002 to 2012; B: Location of settlements for 2013 to 2015; C: Location of settlements for 2016 to 2019.

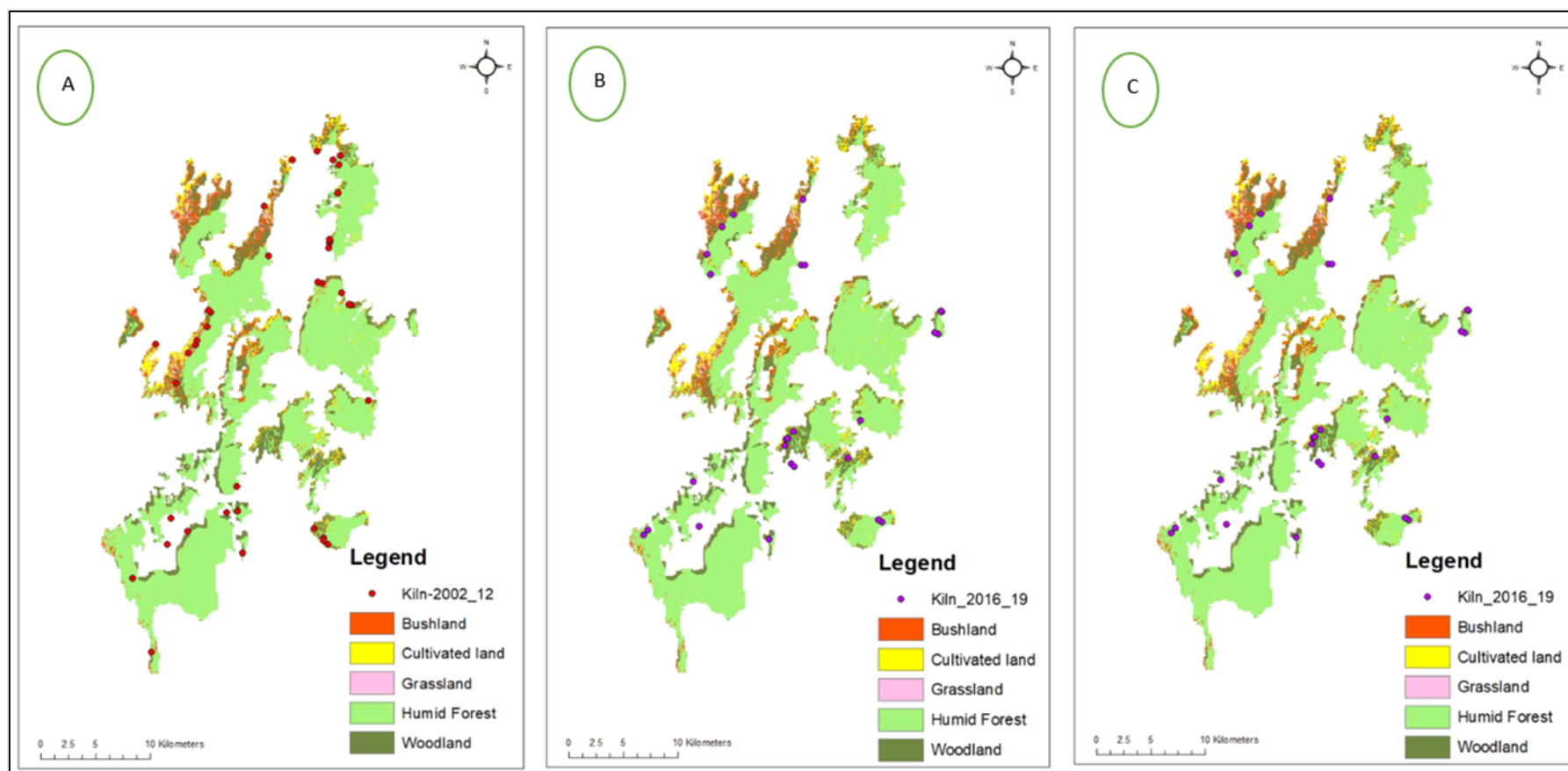


Figure 4 - 28: A map showing the location of proxy variable (Kiln) indicating charcoal making activity in relation to forest cover change for East Usambara Mountain from 2002 to 2019. A: Location of kiln for 2002 to 2012; B: Location of kiln for 2013 to 2015; C: Location of kiln for 2016 to 2019.

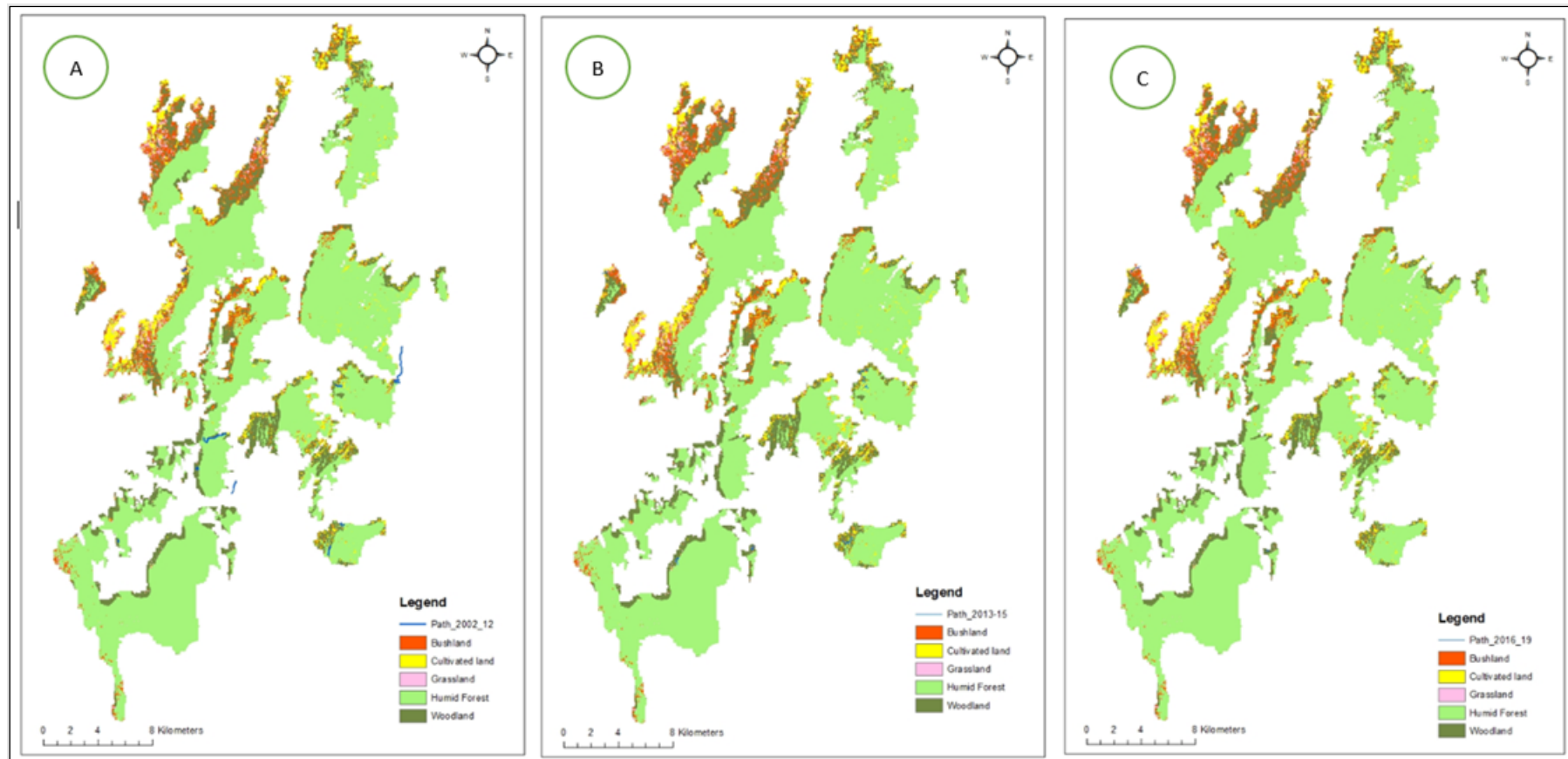


Figure 4 - 29: A map showing the location of proxy variable (Footpath) indicating charcoal making activity in relation to forest cover change for East Usambara Mountain from 2002 to 2019. A: Location of foot path for 2002 to 2012; B: Location of foot paths for 2013 to 2015; C: Location of foot paths for 2016 to 2019.

4.3.3 Detecting Statistically significant differences between forest patches against proxy variables.

Table 4–7 depicts the outcomes of the repeated measure ANOVA conducted to detect the statistically significant differences in charcoal-making activity among various forest areas. The results indicate statistically significant differences (p-value < 0.05) among patches and proxy variables. The differences among patches may arise from their distinct dimensions. The differences across proxy variables may arise from the existence of distinct activities that impact deforestation in the region and the capacity to identify the proxy variables from the image visually. Significant statistical differences (p-value < 0.05) exist both between patches over time and between proxy variables over time. The differences observed in patches throughout time can be attributed to a progressive rise in human activity in the region. The changes in proxy variables over time might be attributed to both increased human activity and satellite images' impact on identifying these variables. The residual analysis conducted has been given in Appendix 12.

Table 4 - 1: Repeated Measure of ANOVA test carried out to identify statistically significant differences between patches and proxy variables. Values in red indicate statistically significant differences (p-values <0.05).

Effect	Repeated Measures Analysis of Variance				
	Std. Error of Estimate: 7.6849				
	SS	Degr. of	MS	F	p
Intercept	3982.881	1	3982.881	67.44016	0.000000
Patch	2274.119	13	174.932	2.96204	0.004347
Proxy	2225.071	3	741.690	12.55868	0.000007
Error	2303.262	39	59.058		
TIME	31.440	2	15.720	0.53321	0.588844
TIME*Patch	1753.560	26	67.445	2.28762	0.002731
TIME*Proxy	488.036	6	81.339	2.75891	0.017450
Error	2299.631	78	29.482		

Figure 4-30 illustrates the variations in the quantity of proxy variables representing charcoal-making activities across the 14 patches. The data aid in identifying areas that have a significant level of charcoal production activity. The findings suggest that between 2002 and 2012, patches 2, 3, 5, 13, and 14

exhibited a significant presence of proxy variables that reflect the occurrence of charcoal-making activities. Patches 13 and 14 have a similar pattern but are somewhat elevated compared to patches 2, 3, and 5. During that time frame, the data also reveal that the number of proxy variables remained relatively stable for patches 6 to 12. The resemblances among these patches may be attributed to their considerable remoteness from human populations and roadways. These patches, including patches 1, 4, 6, 7, 8, 10, 11, and 12, are very significant. Patches 1 and 4 have a comparable pattern but are marginally higher than the pattern found for patches 6, 7, 8, 10, 11, and 12.

Patches 2, 4, and 14 exhibit a rise in the quantity of proxy variables, like the trend seen from 2002 to 2012, during the timeframe of 2013 to 2015. During that time frame, the data suggest that the number of observed proxy variables remained relatively stable for patches 5, 6, 7, and 8. The resemblance between these forest areas may be attributed to the implementation of comparable forest management strategies in the region, which discourage the practise of charcoal burning.

From 2016 to 2019, forest patch 14 had a higher number of variables in comparison to other patches. Forest patches 6, 7, 8, and 13 had a comparable quantity of proxy variables. Charcoal production locations have a distinct clustering tendency along both existing and newly constructed roadways, rather from being uniformly spread over the whole area (Bolognesi et al., 2014; Rembold et al., 2013; Sola et al., 2017). These findings align with the conclusions obtained in this investigation.

During the period from 2016 to 2019 (as shown in Figure 4-30), there was a consistent and unchanging number of proxy variables in patches 6, 7, and 8. However, there was a drop in the number of proxy variables in patch 14 compared to the period from 2002 to 2012. The decrease in proxy variables may be attributed to the implementation of paramilitary practices by the government in 2016 and their participation in forest management. In recent years, Tanzania has experienced a rise in conservation initiatives promoting the adoption of

efficient charcoal stoves that consume minimal amounts of charcoal daily. Additionally, there have been beekeeping projects implemented in the local community to alleviate the demand for charcoal production activities (Camco Clean Energy (Tanzania) Limited, 2014; Conservation & Development, 2014; Gmünder et al., 2014; Mowo et al., 2002; Msofe et al., 2019).

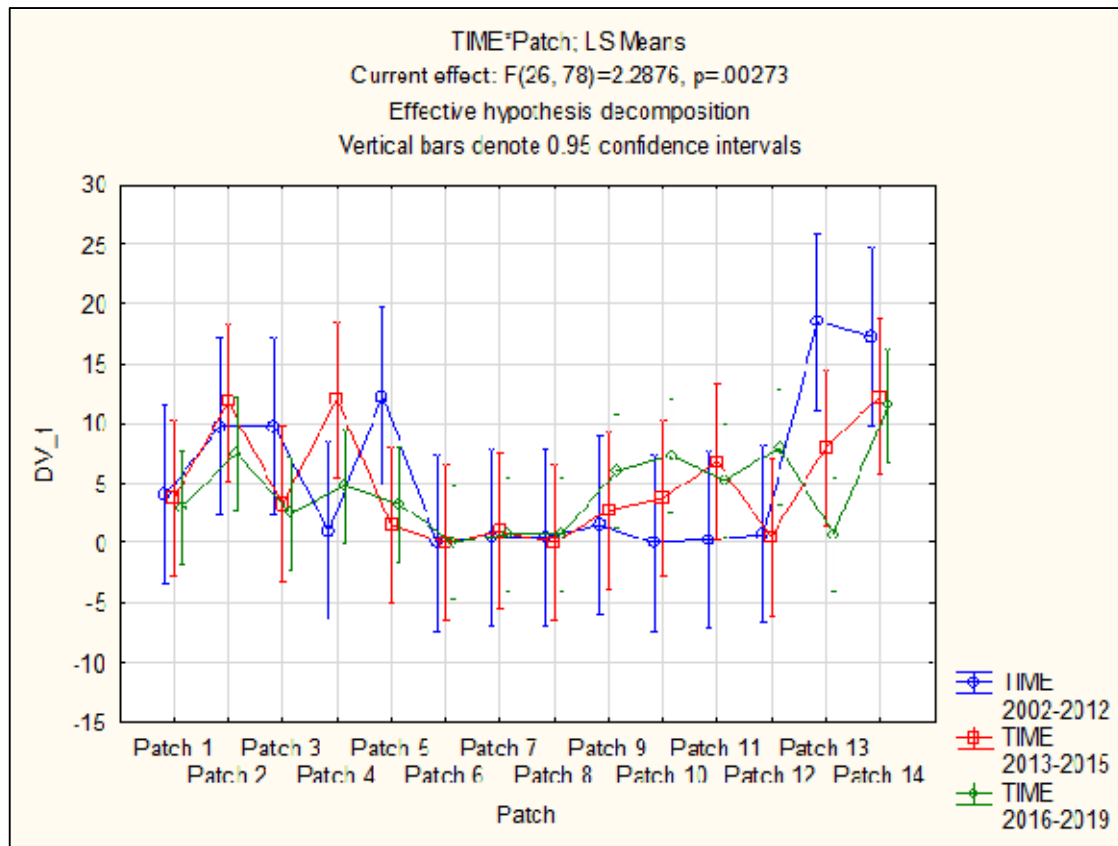


Figure 4 - 30: Plot depicting the presence of proxy variables per forest patch analysed. The blue line indicates the presence of proxy variables for the period 2002 to 2012. The red line shows the presence of proxy variable from 2013 to 2015. The green line shows the presence of proxy variables from 2016 to 2019.

Figures 4–31 and 4–32 illustrate the relative importance of proxy variables in the research area and how their distribution evolves over time. The occurrence of dark patches was more pronounced than any other factor across all time periods (Figure 4-31). Subsequently, there were transitory villages, charcoal kilns, and trails during the whole duration.

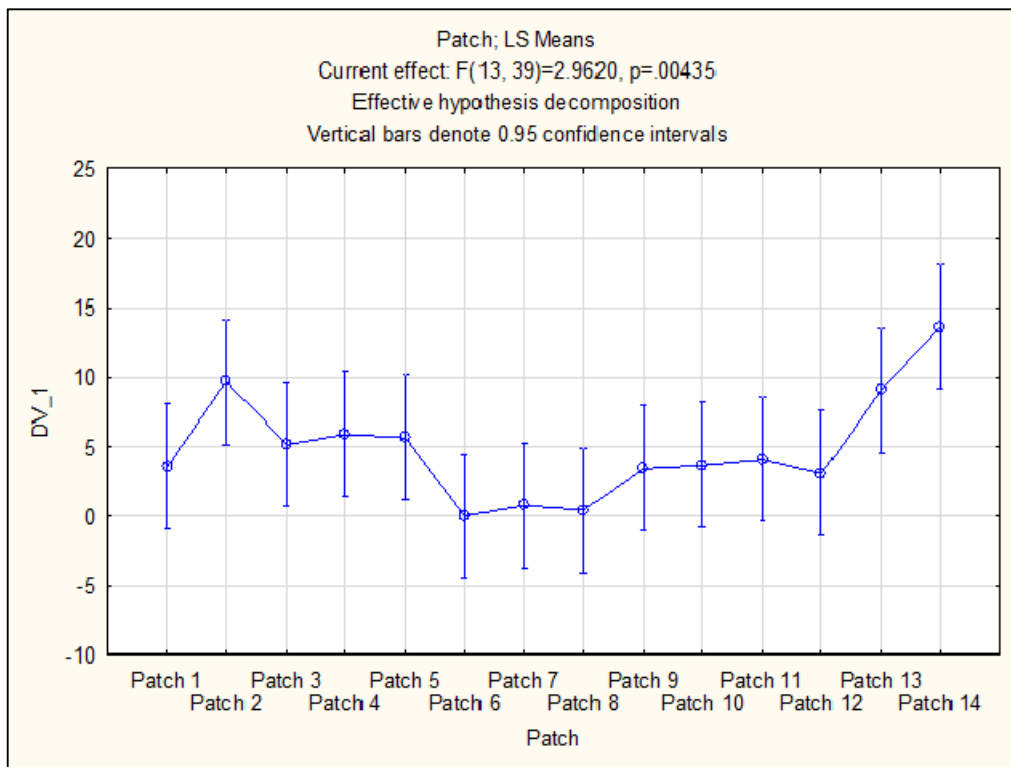


Figure 4 - 31: Shows the presence of proxy variables per patch (all years combined). The results indicate constant variables for patches of 6,7 and 8 while increase in proxy variables observed in patch 14. Further there were slightly similarity on the number of proxy variables observed in patch 2 and 13 for all years combined.

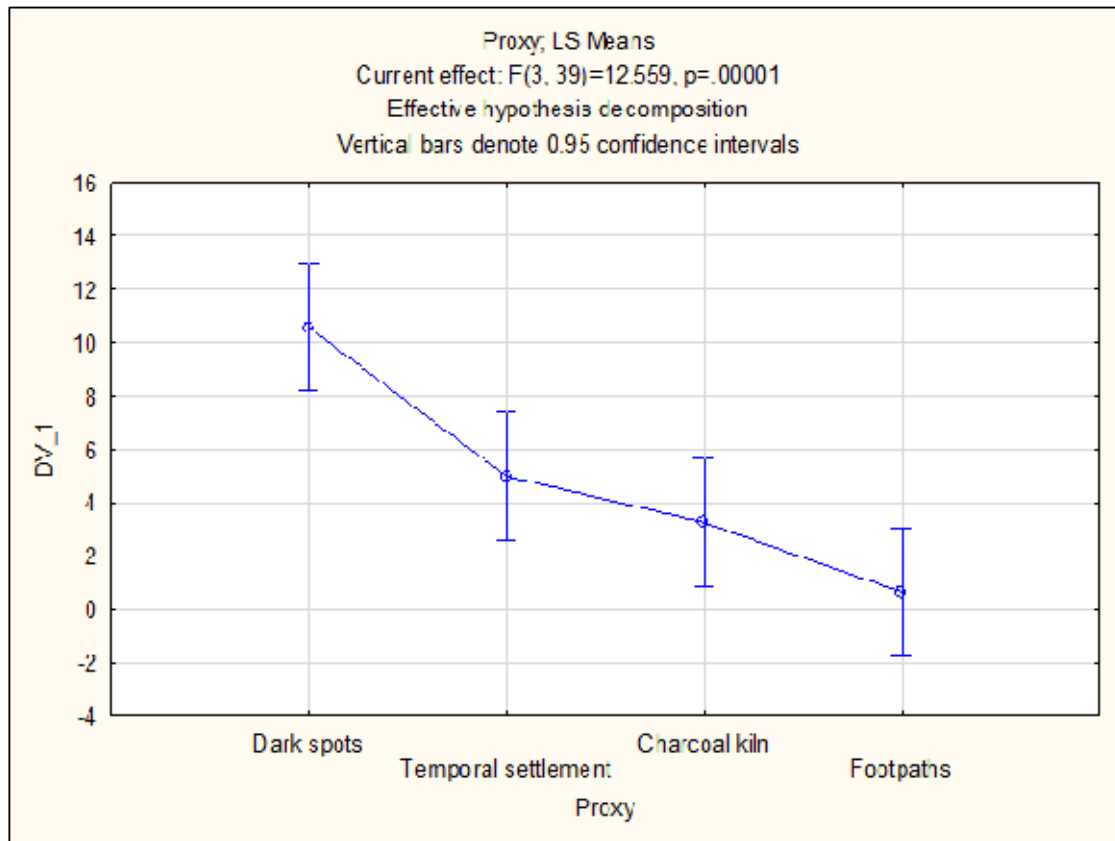


Figure 4 - 32: Plot depicting the presence of total number of proxy variables per proxy variable (all years combined).

Over the course of time, as seen in Figure 4-33, there was a noticeable rise in the number of black patches. This phenomenon may be attributed to heightened human activity, especially the engagement in charcoal production, in the vicinity. The proxy variable "temporal settlements" shows a decline over time. This may be attributed to heightened state initiatives in the forest management of the East Usambara Mountain Forest Block. The proxy variable "charcoal kiln" had the maximum value from 2002 to 2012 and thereafter fell to maintain a consistent level throughout the periods 2013-2015 and 2016-2019. The decline of charcoal kilns may be attributed to an upsurge in conservation initiatives in the vicinity of eastern Usambara Mountain or suitable trees for charcoal production in the area was completely exploited. One example of conservation efforts is the Green Economy in Biosphere Reserve (GEBR) project. This initiative aims to alleviate poverty by using natural resources in a sustainable and controlled manner, while

also promoting alternative livelihoods (UNESCO, 2017). The occurrence of footpaths was the least common proxy variable in the research region and did not change over time. This finding may be attributed to the challenge of discerning the satellite image. The comprehensive post-hoc analysis does not provide any more insights into the findings. Consequently, the detailed tables and outcomes are supplied in Appendix 13.

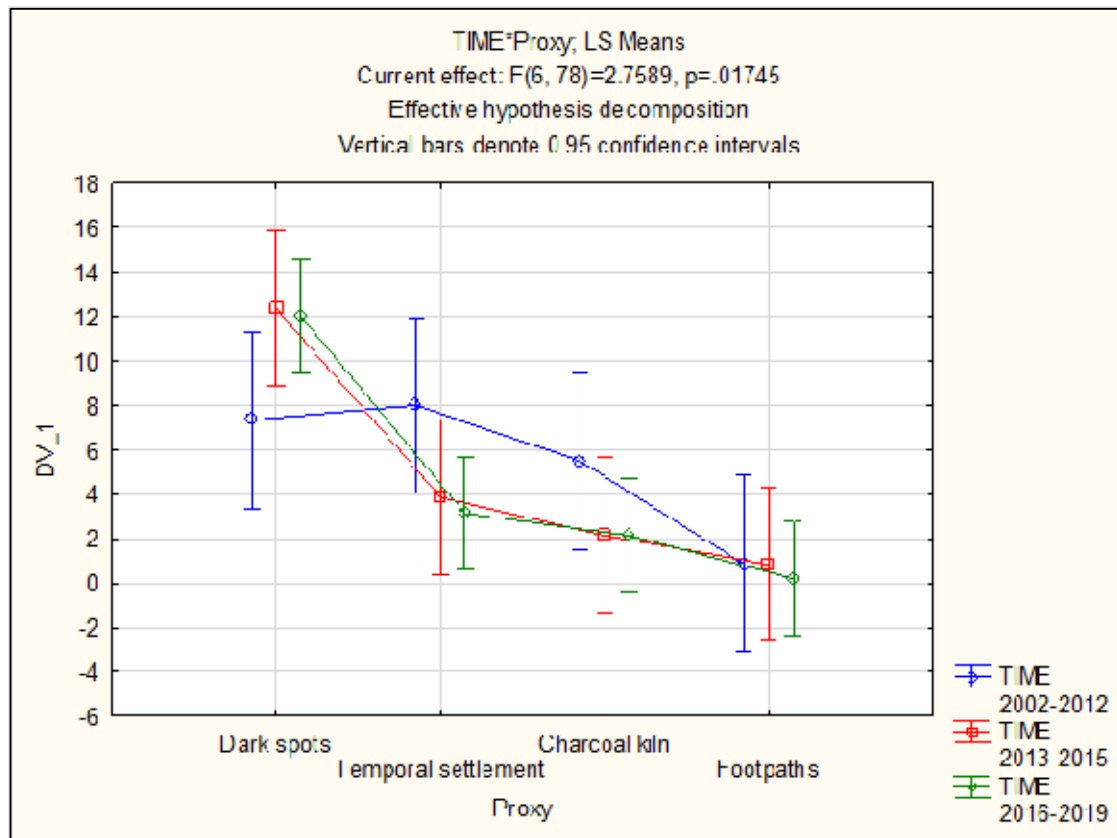


Figure 4 - 33: Plot showing the distribution of proxy variables over time in the study area. The blue line indicates amount and type of proxy variables from 2002 to 2012. The red line shows the distribution of proxy variables from 2013 to 2015. The green line shows the presence of proxy variables in 2016 to 2019.

4.3.4 Detecting Statistically significant differences between land use -land cover and proxy variables.

Table 4–7 displays the outcomes of the repeated measures ANOVA conducted to detect any statistically significant disparities in charcoal-making activity based on land use and land cover. The results indicate that there is no statistically

significant difference (p-value < 0.05) between land use and land cover. However, there are statistically significant differences observed across proxy variables. Statistically significant differences exist both across time periods and among proxy variables throughout time. The differences among proxy variables may arise from the capacity to visually identify proxy variables within the region and the calibre of the retrieved pictures. Additional disparities across historical periods may arise from a gradual growth in population, which might potentially impact shifts in activity and subsequently affect charcoal production and other human-induced activities. The differences in proxy variables over time can be attributed to fluctuations in activities that impact deforestation, such as shifting cultivations and charcoal production, leading to discrepancies in proxy variables representing charcoal production in the region. Appendix 14 presents the findings of the residual analysis.

Table 4 - 7: Repeated Measure of ANOVA test carried out to identify statistically significant differences between land use land cover and proxy variables. Values in red indicate statistically significant differences (p-values <0.05).

	SS	Degr. of	MS	F	P
Intercept	3422.61	1.00	3422.61	18.76	0.00
Land use Land cover	1330.56	4.00	332.64	1.82	0.19
Proxy Variable	1965.58	3.00	655.19	3.59	0.05
Error	2006.98	11.00	182.45		
TIME	258.62	2.00	129.31	5.26	0.01
TIME*Land use Land cover	239.09	8.00	29.89	1.22	0.34
TIME*Proxy Variable	474.20	6.00	79.03	3.21	0.02
Error	541.08	22.00	24.59		

Figure 4–34 illustrates the variations in the quantity of proxy variables representing charcoal-making activities in the specific area under investigation. The results aid in identifying proxy variables that exhibit a high frequency of occurrences within the given area. The findings align with those obtained in Section 4.3.1 and demonstrate that the proxy variable with the lowest occurrence is footpaths, followed by kilns and settlements. The area is predominantly

characterised by the presence of dark patches, which have the highest occurrence rate. Additionally, the findings emphasise a subtle disparity between the quantity of kilns and settlements in the region. An area of increased prominence was detected, maybe caused by the satellite capturing shadows cast by the standing trees. The footpaths in the East Usambara Mountain region may exhibit reduced frequency due to the challenges in visually discerning the foot routes on satellite images caused by the dense forest cover.

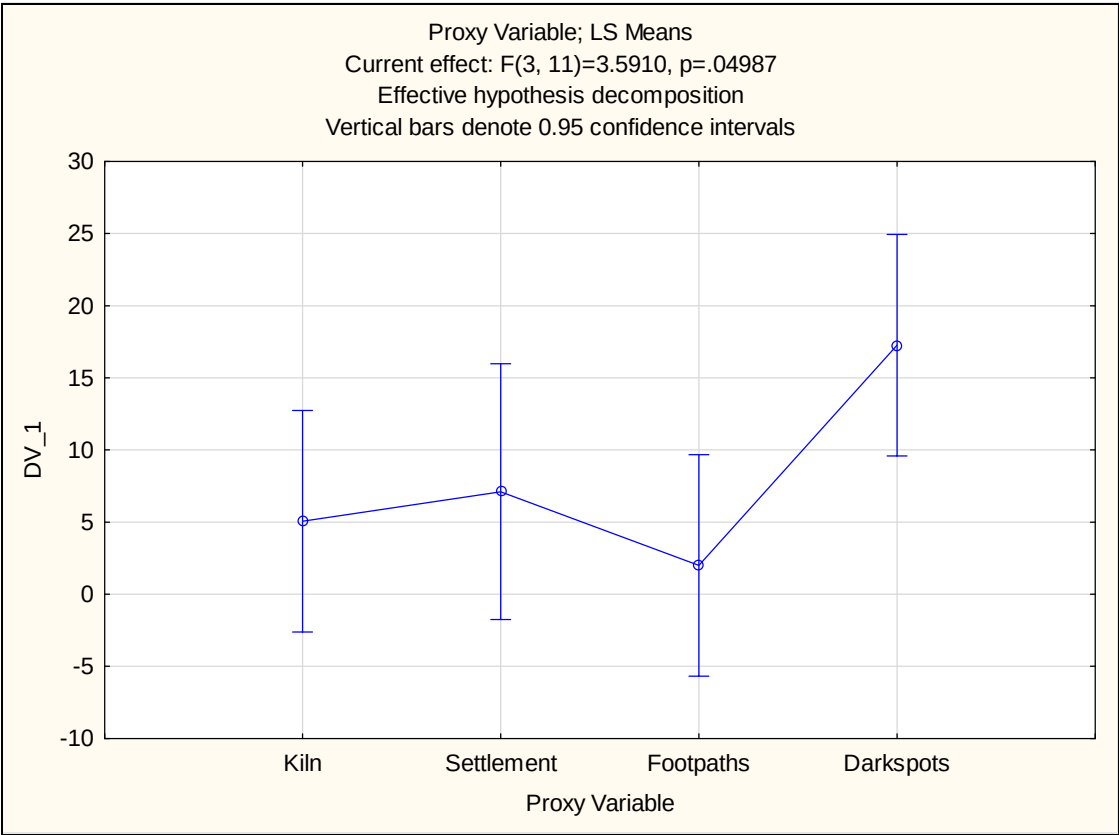


Figure 4 - 34: Plot showcasing the presence of proxy variables within the area.

The presence of proxy variables across time is illustrated by the figures in Figure 4–35. Between 2013 and 2015, the proxy variables that reflect activities related to making charcoal showed a decrease compared to the two preceding periods. The previous chapters have provided a concise summary of the reasons for this. There are similarities between the proxy factors seen from 2002–2012 and 2016–2019.

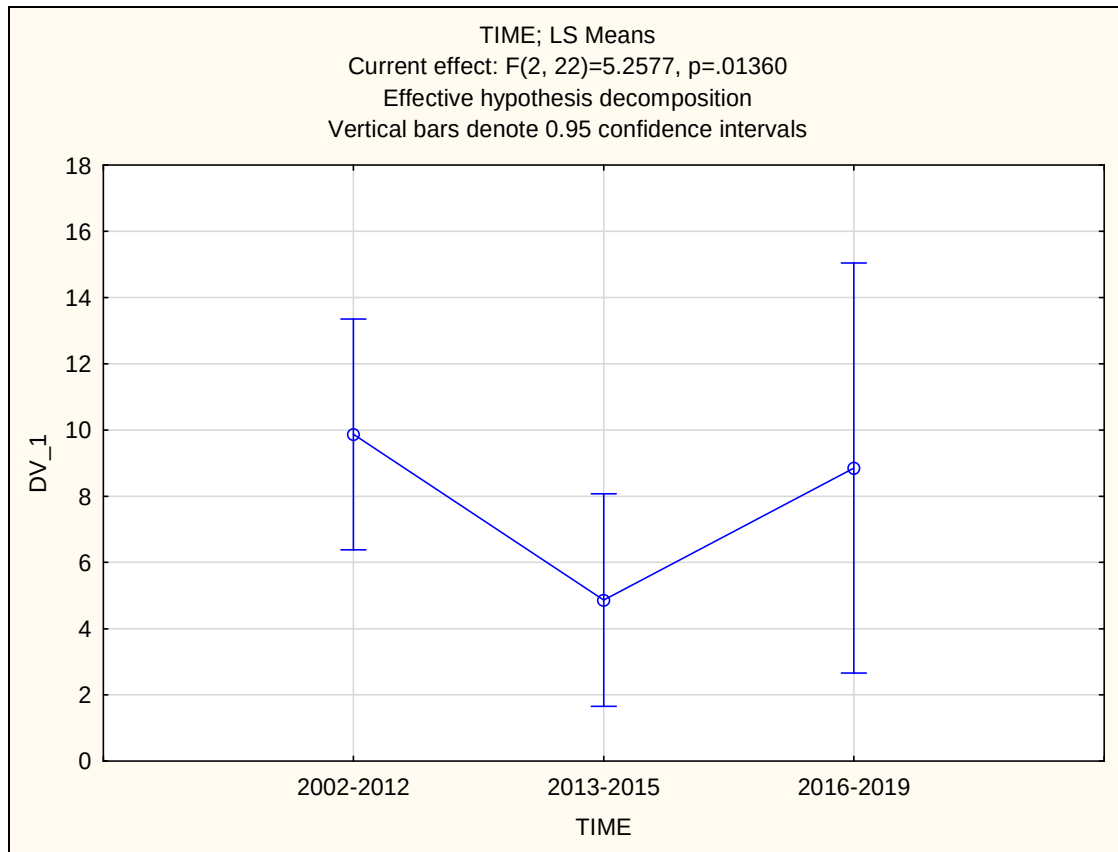


Figure 4 - 35: Plot depicting the presence of total number of proxy variables over time.

The findings in Figure 4-35 demonstrate that the proxy variable indicating paths had consistently low values throughout all time periods in comparison to the other proxy variables. This is likely because the ability to identify paths is impeded by the characteristics of the satellite images obtained and the subsequent processing. An upward trend in the occurrence of dark spots was detected between 2016 and 2019, with the lowest number of instances reported between 2013 and 2015. The occurrences of kilns and villages exhibited comparable frequencies both inside and across different historical periods, as well as across them. The comprehensive findings of the post-hoc analysis does not offer any supplementary data and have been included in Appendix 15.

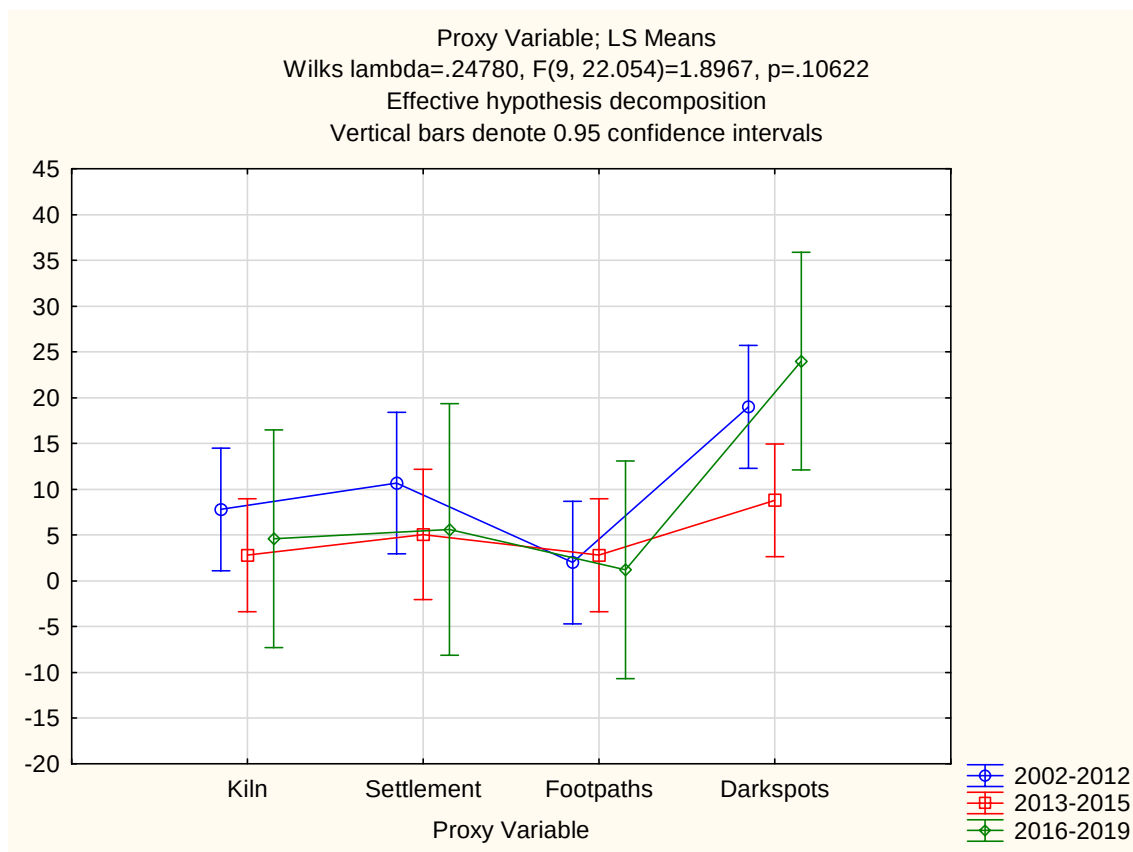


Figure 4 - 36: Plot depicting the presence of proxy variables per land use and cover class analysed. The blue line indicates the presence of proxy variables for the period 2002 to 2012. The red line shows the presence of proxy variable from 2013 to 2015. The green line shows the presence of proxy variables from 2016 to 2019.

4.3.5 Estimating deforestation rate derived from presence of charcoal kiln around Usambara Mountain.

The results indicate that charcoal kiln was extracted from montane forest around Mount Usambara (Fig. 4-25). The montane forest has the highest stem count at 900 trees per ha (Mowo et al., 2002). It was reported that 40 bags (or 27 kg) of charcoal could be produced from each dark spot that was digitalized. Each charcoal kiln site needs 20 trees since it takes one huge tree to produce two bags of charcoal (Rembold et al., 2013). In this scenario, the number of trees felled was calculated based on the number of dark spot and employed as a measure of deforestation. Results indicated that between 2002 and 2012, a total

of 9,920 bags of charcoal were produced, which required the removal of roughly 198,400 trees (equal to an area of around 220 ha). The resulting charcoal weighed an estimated 267,840 kg. It is found that around 30% of the East Usambara terrain is covered in forests, which amounts to a total of 31,000 ha (Mansourian et al., 2019). It was revealed that the overall forest area in Tanzania is expected to be 48.1 million ha (URT, 2015b). Hence, the deforestation in this region accounted for a mere 0.007% of the whole wooded area around East Usambara Mountain and a minuscule 0.0000048% of the entire country.

Further, results indicates that from 2013 to 2015, the output of charcoal amounted to 4,720 bags, which is equivalent to the felling of 94,400 trees and an estimated weight of 127,440 kg. This is results to 105 ha of forest being depleted due to the production of charcoal, accounting for 0.003% of the forested region around east Usambara mountain (31,000ha) and 0.00000023% of Tanzania's overall land area.

Furthermore, results show that between 2016 and 2019, the manufacturing of charcoal led to the generation of 9,800 bags, which is equal to the deforestation of 196,000 trees and a total weight of roughly 264,600 kg. This is led to 218 ha of forest that have been depleted due to activities related to the production of charcoal. This accounts for 0.007% of the forested region and 0.00000047% of Tanzania's overall land area.

4.3.6 Summary results for objective 3

This section aims to establish a connection between charcoal production and the negative effects on the surrounding East Usambara Mountain catchment area, including deforestation. The classified map of the study area shows proxy variables closely associated with changes in land use and cover over time. From 2002 to 2012, regions classified as humid forest had a significant concentration of proxy variables, while areas classified as grassland showed minimal presence

from 2013 to 2015. Darkspots accounted for a significant amount of charcoal, while footpaths represented a small fraction.

The study reveals variable counts for dark spots, footpaths, charcoal kiln, and settlement for 2002-2012, 2013-2016, and 2015-2019, with varying values for footpaths, charcoal kiln, and settlement.

The number of proxy variables in bushland, grassland, and cultivated land over the period 2013-2015 is relatively stable compared to the number recorded during 2002-2012. The presence of comparable anthropogenic activity, such as communities that augment fuel consumption, in these areas may account for these shared features.

The study identifies significant differences in charcoal-making activities among different forest regions, based on repeated measure ANOVA. The differences may be due to unique proportions of patches and differences in proxy variables, which may be influenced by different activities and the ability to visually recognize proxy factors. The observed fluctuations in patches over time can be attributed to the gradual increase in human activities in the region.

The data shows that between 2002 and 2012, patches 2, 3, 5, 13, and 14 showed a notable prevalence of proxy variables indicating the existence of charcoal-making operations. From 2013 to 2015, patches 2, 4, and 14 exhibited a rise in proxy variables, mirroring the pattern observed between 2002 and 2012. Between 2016 and 2019, Forest Patch 14 had a greater abundance of variables compared to other patches.

From 2016 to 2019, patches 6, 7, and 8 exhibited a stable and constant quantity of proxy variables. However, from 2016 to 2019, there was a decrease in the quantity of proxy variables in Patch 14. The prevalence of dark patches was more prominent than any other component over all time periods.

Over time, there was a distinct increase in the quantity of black patches, ascribed to increased human activity, particularly the involvement in charcoal manufacturing in the surrounding area. The proxy variable "temporal settlements" showed a gradual decrease as time progressed, while the proxy variable "charcoal kiln" declined and remained stable throughout the periods 2013-2015 and 2016-2019. Footpaths were the least frequent proxy variable observed in the research region.

The study examines the variation in charcoal production based on land cover and usage. The results show no significant difference between land use and land cover, but significant discrepancies across proxy variables. These discrepancies may be due to the ability to visually discern variables and the quality of the images. The study also reveals that the proxy variable with the least frequency is footpaths, followed by kilns and settlements. The area is primarily distinguished by the prevalence of dark patches, which exhibit the highest frequency.

Lastly, results show that, the total charcoal production in the vicinity of Usambara Mountain between 2002 and 2019 is estimated to be 659,880 kilogrammes equivalent to 488,741 trees. This is results to 543 ha of forest that have been depleted due to the activities of producing charcoal, accounting for 0.018% of the forested region and 0.000001% of Tanzania's overall land area.

Chapter 5: Discussion

This chapter discusses the state of the art of the topics that relate to this PhD and how the study's findings, and their broader implications, contribute to address current gaps in knowledge. The philosophical discussion has been divided in multiple subsections focusing on instrumentation, environmental repercussions, health effects, economic impacts, social aspects, and governance (regulatory/policy) on residents, as well as future implications for Tanzania in general if charcoal making activity remains unregulated. The limitations of the study as well as insights on future research are addressed in chapter 6.

5.1. Instrumentation

Findings indicate the need to consider multiple factors when reflecting upon the instrumentation system used in this study. The most relevant factors are the ability of current state of the art low-cost sensors to detect pollutants in tropical environments as well as emissions from charcoal activities. The low-cost sensors used in this study were designed in the United Kingdom (cold environment) and their suitability for tropical environments had not been tested to date. These factors are key to identifying charcoal plumes signals observed during charcoal production and to quantify their emissions into the atmosphere. There is also a need to consider the accuracy of GIS-based techniques to locate charcoal kilns.

5.1.1 Capability of low-cost sensors to detect pollutants in tropical countries.

Results of the time-series graphs portraying emitted CO and PMs from charcoal kiln activities demonstrated the sensor's ability to identify pollutants in tropical regions. Results showed the sensor was able to detect pollutants between October 2018 and August 2019. The experimental site's pre-charcoal production phase showed cyclic patterns in CO and CO₂ concentrations, with maximum concentrations of 1364 ppb and 573 ppm, respectively. These concentrations are slightly higher than global estimates and seasonal and diurnal variations in Rwanda, with CO and CO₂ concentrations of 663 ppb (Dewitt et al., 2019) and

417.06 ppm in 2022 (Lindsey, 2023) respectively. These findings indicate that the region saw more human activity, as seen by the ongoing increase in pollutant indicators after the production of charcoal and that the sensors were able to capture the pollution signal.

Multiple studies (Carotenuto et al., 2023; Hodoli et al., 2023; Liang et al., 2021; Morawska et al., 2018) have indicated that inexpensive sensors are appropriate for monitoring air quality in settings where there are few or no official air quality monitoring stations. Nevertheless, tropical nations have a restricted implementation of sensors. The main contributing factors include the high cost of individual sensors, a scarcity of proficient technicians capable of installing the sensors, and a lack of governmental determination to allocate resources towards atmospheric monitoring systems. In 2022, Tanzania received advice from specialists to allocate resources towards the establishment of air pollution monitoring systems. This recommendation was prompted by the country's precarious health conditions, which were further worsened by a lack of comprehensive studies and data (Ubwani, 2022). To alleviate the adverse effects of pollution, it is essential to enact anti-pollution measures, such as the installation of air quality sensors (Ubwani, 2022).

The study's findings support the idea that the sensors used in this study, or equivalent low-cost miniaturised sensors are an economically efficient approach for industrialised countries to monitor air contaminants, especially in tropical regions. The findings indicate that compact sensors (specifically, the Atmospheric Sensor Model 510, assigned to node number 97, and created by Alphasense UK) are able to be collected pollution data in tropical nations such as Tanzania.

Nevertheless, it is necessary to create a light calibration scheme that is suitable for the specific local circumstances (Hodoli et al., 2023). The end user needs to be aware that the process of adjustment in this situation should involve adjusting for specific local circumstances, for which a system or plan has not yet been created. Due to their compact size, portability, and GPS tracking capabilities,

these sensors may be easily deployed wherever necessary. Remote sensor calibration, such as the technical correction of readings, can be performed. The use of low-cost sensor networks (LCSNs) in the field of environmental sciences is increasingly prevalent (Borghi et al., 2017; Heimann et al., 2015; Hodoli et al., 2023; Mead et al., 2013; Morawska et al., 2018). These networks offer distinctive monitoring data, which facilitates research across many domains and applications (Mao et al., 2019).

5.1.2 Developing a technique to estimate emission factors from Charcoal production.

Results in figure 4-19 shows the earth kiln experiment pollution signals of CO, CO₂ and particulate matter during charcoal production. Common peak signals were not detected for any of the plots, this indicating that there were no joint local sources in the area (e.g., pollutants from charcoal production). The sensor was calibrated in temperate regions and tested under the same climatic conditions and no re-calibration was conducted when deployed in tropics. The sensor's calibration was hindered by travel restrictions due to the COVID pandemic. However, previous studies conducted in Ghana found and stated that factory calibrated OPC's sensors can be used to monitor PM in Sub-Saharan countries (Hodoli et al., 2023).

5.1.3 Remote sensing capability for the detection of kilns in Tropical countries.

Results show a slight discrepancy in the quantity of charcoal kilns. Between 2013 and 2015, the proxy variables representing charcoal-making activities showed a decrease compared to the preceding two seasons. From 2016 to 2019, the frequency of black patches increased, with the fewest occurrences reported between 2013 and 2015. The study also reveals that between 2002 and 2012, 9,920 bags of charcoal were produced, equivalent to the harvesting of 198,400 trees. This study used proxy factors to identify plausible charcoal kilns on the ground. The use of such proxy variables for the intended purpose was not validated and therefore there is a level of inherent uncertainty associated to the

results presented. It is suggested that the use of proxy variables to evaluate forest degradation activities can be used as alternative techniques of remote sensing as it is cost-effective and uncomplicated (Bhattarai et al., 2020). This method is particularly important for countries with arid forests, like Tanzania, that aim to utilise carbon finance mechanisms to tackle climate change mitigation (Bhattarai et al., 2020).

5.2. Environment

The production of charcoal results in a multitude of environmental repercussions. This encompasses the extent of deforestation and the detrimental impact on cultural values, such as recreational and tourist qualities, resulting from the practise of charcoal burning in the surrounding ecosystem. The impact of charcoal production extends to water quality and the surrounding watershed; a land use practise that leads to changes in land use in the region, and to potential future consequences for Tanzania if these activities are not regulated.

5.2.1 Magnitude of the impact of deforestation due to charcoal burning to the surrounding environment

Various stakeholders, such as governments, public forestry institutions, and non-governmental organisations, have expressed concerns over the detrimental ecological and environmental effects linked to charcoal production in tropical regions of the world (Chidumayo & Gumbo, 2013). The issue of charcoal-related difficulties has received significant attention from governments, public forestry institutions, and non-governmental organisations (Chidumayo & Gumbo, 2013). The primary consequence commonly cited is deforestation, which refers to the removal of trees and vegetation. However, on a larger scale, the production of charcoal nearly invariably leads to the deterioration of forest ecosystems (Chidumayo & Gumbo, 2013). Tanzania saw a reduction of 2.86 million ha of forest cover from 2001 to 2021, representing an 11% fall compared to the year 2000. This loss resulted in the release of 972 million metric tonnes of CO₂ emissions (Bailis et al., 2002; Kļaviņa et al., 2015; Smith et al., 1999). Charcoal

incurs expenses beyond the nominal amount paid for a day's worth of cooking fuel. Tanzanians bear the cost of their natural resource depletion due to charcoal production, as most of households depends on charcoal for cooking. which is an unquantifiable price they pay or the value of missed opportunities. Therefore sustainable charcoal

5.2.2 Magnitude of degradation of recreation/touristic value (cultural ecosystem services) in charcoal making areas

Tanzania ranks among the top ten nations globally in terms of total charcoal production (FAO, 2010a; Moses, 2017). Unrestrained utilisation of resources, namely wood and forests, directly affects the worth of ecosystem services. The ecosystem comprises several services, such as the provision of resources like food and fuel wood, the management of climate and pollination, the cultural aspects like spiritual and recreational benefits, and the support services like soil formation and the hydrological cycle (Folke et al., 2005). Forest degradation will adversely affect both cultural and recreational ecological services. Regrettably, the unregulated use of the environment is negatively impacting cultural services, such as spiritual and historical services that include using nature for religious or heritage purposes (Watcharaviton et al., 2013). The unregulated use of the environment is also negatively impacting recreational activities such as ecotourism, outdoor sports, and general leisure (Arquitectura et al., 2015; Kilahama, 2008; Serenje et al., 1994).

Provisioning services, such as genetic resources, raw materials, energy, and decorative resources, are affected. Supporting services, such as primary production, habitat supply, and soil formation, are also impacted. Charcoal production is a major driver of land use change in Sub-Saharan Africa (SSA), a region where such changes can lead to considerable land degradation and desertification (Chidumayo & Gumbo, 2013). It is asserted that forest cover enhances surface water quality through the reduction of soil erosion, the decrease of sediment in water, and the retention or filtration of water pollutants in forest litter (Piaggio & Siikamäki, 2021). It is reported that both human actions,

such as charcoal production, and natural causes are responsible for land use and cover change (LUCC), leading to the worldwide decline of indigenous biodiversity and the modification of ecological processes and services in diverse ecosystems (Msofe et al., 2019). Tropical forests, like other forest ecosystems, offer commodities and amenities to mankind. Tropical forests provide tangible products such as timber, wood fuel (firewood and charcoal), as well as non-wood items like bush meat, honey, beeswax, edible insects, fruits, tubers, and medicines (FAO, 2010b). Additional advantages encompass the regulation of water flow, the capture and storage of carbon, the avoidance of soil erosion, and the creation of habitats for animal species (Bauhus et al., 2010; Turpie et al., 2005). Forests play a crucial role in preserving wetland ecosystems such as swamps and floodplains, as well as the fish populations that inhabit these wetlands, by controlling the flow of water.

Regulating services are compromised when forests are unable to effectively filter water and air as a result of unregulated tree clearance. Additionally, forests lose their capacity to regulate climate and perform carbon sequestration. Ayodele *et al.* (2009) found that the heating process involved in charcoal manufacture altered many soil characteristics, including colour, bulk density, hue, chroma value, and infiltration ability. The modification in bulk density and the rise in sand content resulted in changes to the overall porosity, infiltration, and flow characteristics of the soils in the vicinity of charcoal kilns (Ayodele et al., 2009).

Charcoal production exacerbates deforestation by intensifying the need for wood biomass energy (Wurster et al., 2010). Additionally, it leads to habitat fragmentation and degradation of forests at the local level (Haddad et al., 2013). Charcoal manufacturing has detrimental effects on both local lives and national economies, particularly in tropical forests where a substantial amount of deforestation and forest degradation occurs (Chidumayo & Gumbo, 2013; Makunga & Misana, 2017). The production of charcoal has resulted in a gradual decline in the ability of tropical forest ecosystems to recover from disturbances over a period of time (Chidumayo & Gumbo, 2013; Hosier, 1993; Msuya et al.,

2011). In addition, there is a growing scepticism towards the significance of total forest clearances, while the importance of employment and service inputs has been downplayed (FAO, 2010b). It is contended that market-based approaches, such as eco-tourism, the trade of certified forest products, and payments for environmental services, are similarly affected (Hosonuma et al., 2012; John et al., 2014; Piaggio & Siikamäki, 2021; Turpie et al., 2005). The manufacture of charcoal has been recognised as a leakage in the context of REDD+ initiatives, undermining any potential co-benefits that may be derived from such programmes (Gizachew et al., 2017; Lupala et al., 2015; Morita & Matsumoto, 2023). To benefit from REDD+ payments, tropical nations engaged in charcoal production would need to establish sustainable methods of charcoal production and develop rigorous monitoring and evaluation systems that effectively track and address any instances of leakage (Chidumayo & Gumbo, 2013).

5.2.3 Magnitude of the impact of charcoal making on river catchments and water quality

Charcoal production has detrimental consequences such as deforestation, resulting in soil deterioration due to heightened soil erosion, contamination of water sources, and alteration of rainfall patterns, including droughts (Msuya et al., 2011). Land use and cover change, as described by (Hoffmann et al., 2018; Yanda & Munishi, 2007), has caused ecosystem degradation, leading to increased damage to watersheds in many parts of the world. This has resulted in a scarcity of water for both domestic and industrial purposes, as well as for maintaining environmental flows.

It was indicated that the location of the study site in the East Usambara Mountains is a component of the eastern arc mountain chain, renowned for its exceptionally diverse vegetation and significant prevalence of unique plant and animal species (Mansourian et al., 2019; Mbilinyi et al., 2006; Yanda & Munishi, 2007). The mountain harbours destitute individuals who depend on the forest's natural resources for sustenance (Burgess et al., 2007; Kijazi et al., 2000; Mbilinyi et al., 2006; Yanda & Munishi, 2007). It is reported that land cover changes have taken

place in the east Usambara region, particularly in the Sigi catchment area, over a period. Their findings indicate that from 1955 to 1995, about 37% of the whole catchment area underwent a conversion from natural vegetation to farming (Mbilinyi et al., 2006; Yanda & Munishi, 2007). These results are consistent with the land use land cover estimates obtained in this study, where the higher land cover land use change rate observed on cultivated land class with 76 ha per year than other classes (Table 4-3). This indicates a rise in human activity in the region, including agricultural activity. A growth in the population that depends on land cultivation for their subsistence may also cause a rise in cultivated land.

5.3. Health Impacts

The health consequences of charcoal burning are explored in terms of indoor/outdoor charcoal burning, environmental deterioration on ecosystem health and the extent of erosion and water quality degradation owing to deforestation, which in turn affects drinking water (potable water-related illnesses).

5.3.1 Impact of charcoal burning indoor/outdoor households.

Results indicate that the maximum concentrations of CO and CO₂ for during-charcoal production were 1720 ppb and 556 ppm (Table 4-2). The maximum concentration of CO₂ in the area during charcoal production is slightly higher than the global CO₂ estimates based on the annual report from NOAA's Global Monitoring Laboratory, which was equal to 417.06 ppm in 2022 (Theodoridis & Kraemer, 2023). Also, the CO concentration obtained in the area is higher than the results obtained when investigating seasonal and diurnal variations of pollutants in Rwanda, which were 663 ppb (Dewitt et al., 2019). Further, the typical concentration of CO in the Earth's troposphere is around 100 parts per billion (ppb), although clean air can have concentrations as low as 50 ppb. Hence, it is apparent that the production of charcoal releases a significant amount of carbon dioxide into the atmosphere (Iverson & Dervan, 2017).

Residents utilise charcoal as a primary energy source within their households for the purposes of cooking and heating. Residents in the area prefer charcoal as a fuel source due to its affordability and easy accessibility. Nevertheless, the use of charcoal within residential settings might potentially lead to health complications such as nausea, headaches, loss of consciousness, obstructive lung illness, or even fatality (Ahmed et al., 2019; Hamatui et al., 2016). It was asserted that charcoal poses a risk to human health due to its exposure to harmful compounds, such as carbon monoxide (CO) (Alfaro & Jones, 2018; Hamatui et al., 2016; Idowu et al., 2023; Onekon & Kipchirchir, 2016; Zulu & Richardson, 2013).

5.3.2 Impacts of charcoal making on degradation of the environment and associated impact on human health.

Around 33% of the overall illness burden in Africa, Caribbean and Pacific (ACP) is linked to environmental causes, which is shown in the significant occurrence of mortality connected to the environment (McGranahan et al., 1999). The illness load in all ACP nations disproportionately affects the impoverished population. Diseases such as Tuberculosis (TB) acute respiratory tract infections, and diarrheal illness are intimately associated with the environmental conditions commonly found in impoverished communities. These illnesses are exacerbated by additional factors associated with poverty and perpetuated by the uneven allocation of resources (Idowu et al., 2023; McGranahan et al., 1999). Inadequate nutrition of substandard quality heightens the susceptibility to illness. Impoverished individuals frequently lack the means to shield themselves from the consequences of both natural and man-made calamities, hence potentially intensifying the cycle of poverty and sickness. This is especially worrisome when considering the impacts of global warming (Ahmed et al., 2019; Hamatui et al., 2016; Idowu et al., 2023; Madulu, 2005; McGranahan et al., 1999; Zulu & Richardson, 2013).

It is recognised that human activities and natural factors are driving land use and cover change (LUCC), which has resulted in the global loss of native biodiversity and the alteration of ecological processes and services across varied ecosystems

(Msofe et al., 2019). Charcoal production has an important role to play in this context as it can be regarded as a significant source of deforestation. This also seen in the results obtained in this study that highlight those disturbances such as deforestation are detected along forest edges (e.g., Fig. 4.23) because of their proximity to inhabited areas that heavily rely on forest products (e.g., charcoal and firewood). According to (Pimentel et al., 2007) exposed soil due to charcoal making is extremely prone to wind and water erosion. The studies further describe that wind erosion may be dangerous to one's health since it blows soil particles and germs into the air, irritating the respiratory system and eyes and exacerbating allergies and asthma. Further, (Ngwira & Watanabe, 2019) reported that degradation of a certain ecosystem might have numerous health consequences at the same time. For example, deforestation can lead to increased malaria exposure and loss of access to wild foods (Ngwira & Watanabe, 2019). Moreover, environmental deterioration can result in major health advantages for local people.

5.3.3 Erosion and water quality impacts and derived impacts on drinking water

Results on deforestation in the study area revealed that the annual rate of change for cultivated land in the area is 76 ha per year, indicating an increase in agricultural activities and human activities. The research done by (Mapulanga & Naito, 2019) revealed that a 1% rise in deforestation led to a roughly 1% reduction in access to safe water. Furthermore, it was noted that the availability of source water did not necessarily translate into an increased supply of safe water for individuals. Deforestation leads to a rise in soil erosion, which in turn causes elevated levels of dirt, silt, and turbidity in the water. This therefore raises the demand for drinking water treatment. Moreover, the presence of source water did not automatically lead to a rise in drinkable water for persons. Deforestation results in an increase in soil erosion, which then leads to higher levels of soil particles, fine sediment, and cloudiness in the water. Consequently, this increases the need for water purification. In addition, (Gholami, 2013) examined the influence of deforestation on the generation of runoff and the erosion of soil.

The author's conclusion was that deforestation and land use alteration had an adverse effect on the hydrological conditions of the watershed in Kasilian watershed, Iran.

It was reported that alterations in land cover, such as deforestation, exert a substantial influence on the hydrology of watersheds, deterioration of natural resources, and growth of urban areas (Gholami, 2013; Hlásny et al., 2015; Msofe et al., 2019; Sola et al., 2017). Further, soil erosion and runoff production are influenced by land use and vegetation, and alterations in these characteristics have an adverse effect on the hydrological conditions of a watershed. Deforestation also amplifies water runoff and silt generation in the area (Gardner et al., 2009; Gholami, 2013; Msofe et al., 2019; Serneels et al., 2007).

Many studies (FAO, 2020a; Hosonuma et al., 2012; Kideghesho, 2015; Ndyamukama, 2015; Ngwira & Watanabe, 2019; URT et al., 2015) reported that deforestation in Tanzania is primarily caused by agricultural expansion, livestock grazing, wildfires, overexploitation, unsustainable use of wood resources (including charcoal production), and other human activities, particularly on general land. The production of charcoal will have a significant influence on various areas designated for this activity, leading to deforestation. Annually, the charcoal industry utilises up to 160,000 traditional earth kilns, averaging 438 kilns per day, for charcoal production. The charcoal industry is accountable for an average yearly depletion of forest land totalling around 100,000–125,000 ha (World Bank, 2009a). (Njenga, 2018) Tanzania is ranked seventh globally in terms of total charcoal production, contributing around 3% to the whole global charcoal output, which amounts to over 1.6 million metric tonnes (Mt) (Njenga, 2018). Wood fuel constitutes 85-90% of Tanzania's energy supply (URT et al., 2015; World Bank, 2009a). Charcoal is generally utilised in urban areas, whereas firewood is predominantly utilised in rural locations. A significant majority of Tanzanian households, namely 71%, depend on charcoal as their primary source of fuel in urban regions (Doggart & Meshack, 2017).

Environmental changes, specifically the escalation of water pollution, have facilitated the proliferation and elevated occurrence of malaria. In certain parts of Africa, the process of deforestation has resulted in the exposure of the ground to sunlight. This exposure has led to the creation of temporary pools of water that have a more neutral pH compared to the puddles seen in wooded regions, where there is an abundance of organic waste, and the pH is acidic (pH 4.5–5.5) (Pimentel et al., 2007). The presence of extra ponds amplifies the proliferation of mosquitoes that feed on humans and transmit malaria (Asigau & Parker, 2018; Dworrak et al., 2022; Githeko et al., 2000; MOSES, 2017).

5.4.Future condition of Tanzania if the level of charcoal making activity continues to be unregulated.

5.4.1 Economy

There are multiple factors to be considered when reflecting upon the economic impacts of charcoal making (Doggart & Meshack, 2017; Kilahama, 2008; Mabele, 2020). These include impacts around sudden restrictions of charcoal production and changes of the level of economic resources. Such impacts will affect the economy at country and community level and could jeopardise the livelihoods of communities depending upon the availability of forest resources.

5.4.1.1 Impacts of sudden restrictions of charcoal production to the country economy

Local communities and internal commerce in Tanzania are currently subject to limitations on the use and trading of charcoal (Mabele, 2020). In 2016, the most prevalent measures to regulate charcoal production were state-wide prohibitions that banned the production, transport, and trade in Tanzania (Harries et al., 2004; Mabele, 2020; Sola et al., 2017). The restriction was implemented due to the significant contribution of charcoal production to deforestation and its negative impact on hydroelectricity (van Beukering et al., 2007). There were other limits that were more particular to certain geographical areas, such as restrictions on creating and trading charcoal outside of a district, but not within the district (Mabele, 2020; Vollmer et al., 2017).

The policymakers in Tanzania do not openly acknowledge the significance of charcoal sales for government income (Mabele, 2020; Nabukalu & Gieré, 2019) and thus its restrictions could reduce government revenue. It reveals that the forestry sector made a significant contribution of approximately 1.2 trillion Tanzanian shillings (TZS) or US\$510 million to the country's GDP. This accounts for a total contribution of 4.01% (Mabele, 2020). Charcoal represented TZS 867 billion (about \$370 million), or 2.89 % of the overall contribution made by the forestry industry. Moreover, the Tanzania Forest Service greatly benefits from the substantial income generated by the sale of charcoal, which serves as a crucial source of cash. Of all the income collected by the agency, 40% is allocated to the national treasury, which collaborates with the forest service (Gmünder et al., 2015) to determine yearly revenue collection goals. It was reported that the total amount of benefits derived from charcoal production in the 45 surrounding communities is estimated to be US\$14 million per year. This money is crucial for the villages (Mabele, 2020; Schaafsma et al., 2012).

5.4.1.2 Impact of sudden restrictions in the livelihoods of communities dependent upon forests

Local communities depend much on charcoal as energy for heating and cooking in urban areas (Doggart et al., 2020; Kilahama, 2008; Mabele, 2020). A restriction on the use of charcoal in Tanzania (a developing country) could impose more poverty to local communities. Charcoal production helps alleviate poverty by providing alternate sources of income (Zulu & Richardson, 2013). Doggart *et al.* (2020) reported that charcoal is the most affordable (excluding firewood) and extensively used fuel, indicating the significant impact of price on consumer fuel preferences (Doggart et al., 2020; FAO, 2010a; Garedew & Simon, 2018; Mabele, 2020; Mangi, 2011).

Further, any attempt to eliminate the use of charcoal for cooking in the urban sector in the framework of improving forest and woodland conservation will fail or meet great hostility (Kilahama, 2008). Perhaps what is needed is to increase

efforts to enhance charcoal production and use efficiency, as well as to plant additional trees for wood energy reasons. It should be noted that the importance of traditional fuels in Tanzania's socio-economic setting is not diminishing, but the challenges faced in meeting demand for wood energy are difficult to manage, as there are no simple or quick solutions due to persistent and widespread poverty conditions in both rural and some urban areas (Kilahama, 2008).

5.4.2 Social

Findings indicated that there are multiple factors to be considered when reflecting upon the social impacts of charcoal making. These include impacts of charcoal making on child labour, accidents rates, land use conflicts and governance. There is also a need to reflect on the management guidance that needs to be provided to agencies on how to address challenges related to charcoal production.

5.4.2.1 Impacts of charcoal making on child labour in Tanzania

A study investigating the impacts of charcoal production in Ethiopia, which presents similar condition to the study area of Tanzania, showed that producers were using more than one labourer in their production, and some of them were child laborers (Tassie et al., 2021). It was reported that among other things, children are involved in tasks such as brick manufacturing, tree cutting for charcoal production and sale, building materials, pursuing, and hunting animals for food and profit, and honey extraction (Kyengo, 1998; Rwamahe, 2008). In this study, the increase in deforestation from 2016 to 2019 of approximately 0.007% and the increased charcoal production rate from 4,720 bags from 2013 – 2015 to 9,800 bags to 2016-2019 indicate that there would be an increase in manpower needed to meet the increasing production and demand rates especially child labour. Since charcoal production in Tanzania is improperly regulated, there are no controls that prohibit the use of child labour. As a result, the use of child for charcoal production around east Usambara mountain is widespread due to its wide area outreach and no possibilities of enforcing rules of involving only matured people in all produced charcoal (Kowero et al., 2003; Tassie et al., 2021).

5.4.2.2 Relationship of accident rate with charcoal production in rural areas (especially charcoal transporters)

The study area is a mountainous region with subject to higher slopes and slippery. The sporadic distribution of charcoal kiln observed in the area (Fig. 4-25), coupled with the use of motorcycles (Fig. 2-7) to transport charcoal out from the forest or to the market, will likely result in road accidents and sometimes casualties. Also, people transporting charcoal during night-time to escape from taxes (Malimbwi & Zahabu, 2008) could result in road accidents. Further, most labourers engaged in charcoal production don't wear personal protective equipment that mitigates the potential hazards and health risks (Tassie et al., 2021). In this study, an increase in the number of charcoal bags produced was detected, from 4,720 bags between 2013-2015 to 9,800 bags between 2016 and 2019. This means that 5,080 additional bags were transported from rural areas to urban areas. Improper trafficking of the charcoal product along highways is the reason behind the increasing number of road traffic accidents. Some charcoal traders have begun utilising motorbikes to deliver their goods to markets in cities. The numbers also reveal that the charcoal traffickers utilise at least 3000 motorbikes and 1500 motorcycles every day to carry charcoal over the Morogoro-Dar es salaam Road network (National Media Group, 2020).

5.4.3 Governance (Regulatory/Policy)

Forest policy through its statement No.1 states that “to ensure sustainable supply of forest products and services and environmental conservation, all types of forest reserves will be managed for production and/or protection based on sustainable management objectives defined for each forest reserve. The management of all types of forest reserves will be based on forest management plans” (URT, 1998). An act to regulate forest products in Tanzania under the name of Forest (Sustainable Utilization of Logs, Timber, Withies, Poles or Charcoal) Regulations was gazetted in Tanzania (URT, 2019). However, the observed spatial distribution of charcoal kiln in the area may hamper its effectiveness (Fig. 4-25). The act clearly specifies a person is allowed to carry up to 50 kg of charcoal for household consumption, but the actual results of charcoal produced in the area

suggest improper consideration of the act. The ability to enforce these laws is faced with the challenges of the dispersion of people in these mountainous areas as well as the challenge of people's understanding of these laws.

5.4.3.1 Advice on charcoal management to agencies

The spatial distribution of kilns around Usambara mountain coincides with arguments presented by (Msuya et al., 2011; World Bank, 2009a) that described the extent and impacts of charcoal production. The results of this PhD research project show that the spatial distribution of charcoal kilns around the Usambara mountain could be a limiting factor in implementing proper charcoal production monitoring in the area and consequently the whole country at large. Although the government imposes sanctions of harvesting natural forest without any legal permit (URT, 2019), the sporadic distribution of charcoal shows illegal harvesting of charcoal in the reserved area and around the forest boundary. This study suggests that there is a need to strengthen and extending the services around the local communities and other areas to create awareness about the impact of illegal harvesting so vividly present in the area.

5.4.3.2 Implications for governance and best practice guidelines

In Tanzania, the charcoal trade is marked by poor governance, law enforcement, and other regulatory capacities (World Bank, 2009a). Corruption at checkpoints along charcoal distribution routes exacerbates the government's inability to enforce laws and successfully collect taxes (World Bank, 2009a). The charcoal trade is driven by a small group of influential and politically connected businesses who can use their clout to avoid and escape paying taxes and obtaining permits (World Bank, 2009a). The study area around Usambara mountain includes the Amani Nature Reserve. The Amani nature gazetted by the Government of Tanzania under the declaration order GN Nos 152 of 1997 and 162 of 1998 earmarked the forest boundary. The area is totally protected and human activities that include cultivation and charcoal making are prohibited. The results of this study indicate sporadic distribution of kilns in the area thus conforming with (World Bank, 2009b) work suggesting that illegal harvesting of charcoal persist

and is run by influential people who sometimes conduct the business illegally. This study suggests that there is a need to increase resources required to enforce existing and future regulations that includes human resources, transport systems and good governance. Further to create awareness on the impacts of corruption on the managing the natural resources on the surrounding communities.

5.5. Scientific contribution to knowledge

The findings presented in this study demonstrate a mechanism that enables the characterisation of and differentiation between charcoal burning and production signatures. Airborne emissions from charcoal production are inadequately described in the available greenhouse gas emission database (Pennise *et al.*, 2001; Sun *et al.*, 2019; Yazdani *et al.*, 2021). The mechanism presented in this study for characterising charcoal burning signatures could contribute to addressing the knowledge gap as described by Pennise *et al.* (2001), Sun *et al.* (2019) and Yazdani *et al.* (2021). However, results of this study were hampered by a lack of local training data enabling the unambiguous measurement and quantification of the plumes from charcoal production and combustion. This work highlights the need for further research into (i) making focused observations of charcoal burning; (ii) deploying sensors in more than one village in the region; and (iii) repeating and improving the in-situ analysis established here when estimating the emission profile from charcoal burning.

Chapter 6: Conclusion and Recommendations

This chapter provides the conclusion and further recommendation to future works based on the findings and discussion provided under Chapter 4 and 5.

6.1 Conclusion

The aim of the PhD was to advance current knowledge on environmental impacts, specifically emissions derived during charcoal production and links to deforestation in Tanzania. Overall, the study has contributed to address multiple gaps in knowledge around the impact of charcoal making in the East Usambara mountain region.

Under objective 1: “To develop a methodology to quantify charcoal production emissions in ambient conditions”, the study has shown that the sources of atmospheric pollution are complex in the vicinity of the charcoal kiln used here. Similar findings are likely to be found at other kilns as they tend to be found near or in human settlements. This can be shown in the finding that no significant differences in pollutants (CO_2 , CO and particulate matter) was observed between pre, during and post charcoal production period. This is thought to be due to the dominant influence of domestic charcoal burning and other pollution sources in nearby buildings and was supported by wind-rose analyses of the local winds. Measurements made closer to the kiln itself should provide a way to estimate the emission factors relative to CO_2 .

It was found that the low-cost sensors used in this study recorded pollutants signatures in tropical conditions, but it was not possible to check their calibration due to a lack of well-equipped laboratories. However, the results presented here, showing one of the earliest deployments of such sensors in the Tropics are promising regarding more widespread use in warm and humid conditions. In other deployments, techniques have been developed to provide a certain level of calibration at least where networks of sensors are used (Gameli Hodoli et al., 2020; Mead et al., 2013; Pang et al., 2017; Yin et al., 2012). These should be

exploited if low-cost sensors are to be deployed more widely in Tanzania, sat at regional or national scales.

The larger scale flow was investigated using 5-day Hysplit back-trajectories. This study showed that at the start of the year the air had been transported from over the northwest Indian Ocean and that the winds then turned so that they came from the south, either over land or over the Indian Ocean around Madagascar. No difference in the pollutant concentrations was obvious in the measurements, suggesting that local emission sources were hiding any difference between the northern and southern hemispheres.

Under objective 2: “To identify areas of high-density kilns and changes in charcoal production around the East Usambara Mountains using GIS approaches”, the study analysed land use and land cover changes in the East Usambara Mountain region between 2008 and 2018. The annual rate of change for cultivated land indicated an increase in agricultural activities and anthropogenic activities, leading to a decrease in woodland, bushlands, and humid forests. The study also highlighted the dependence of local communities on forest resources for fuelwood and building materials. Additionally, the investigation of proxy variables showed fluctuations in charcoal-making activity over time. Overall, the study provided insights into deforestation issues and the impact on the ecosystem and local communities in the East Usambara Mountain region.

Under objective 3 “To link charcoal production with forest impact and degradation, the study established a connection between charcoal production and negative effects on the East Usambara Mountain catchment area using GIS approach technique that include use of proxy variables in identifying areas of higher density kiln concentrations. This is the first study that employed proxy variables in detecting areas of charcoal kiln and its associated negative effect on catchment degradation in Tanzania. The research findings showed that humid forest regions had a significant concentration of proxy variables associated with charcoal production. The study also identified differences in charcoal-making activities

among different forest regions. The prevalence of dark patches indicates a high frequency of charcoal production in the area. The study also revealed a decrease in the quantity of charcoal-making activities between 2013 and 2015, followed by an increase from 2016 to 2019. The study estimates that a significant amount of charcoal was produced, resulting in the harvesting of many trees and the emission of CO and CO₂. Overall, the findings highlight the need for sustainable charcoal production practices to mitigate land use change and deforestation.

6.2 Limitation of this research

- a) Unreliable supply of electricity in the area that caused discontinuous data collection by electrochemical sensors. The response and recovery times ranging from 1.36 min and 9.11 min of electrochemical sensors (Zhu et al., 2024). The area was affected by regular power cuts from National grid due to shortage of electric supply. The data were not captured continuously. This can be mitigated in future research through constructing battery that can store energy for at least 48 hours.
- b) Lack of reference data, especially on atmospheric data, curtailed the accurate estimation of background information. The lack of proper reference values of atmospheric emission in the study site likely resulted in improper determination of pollutants emitted from charcoal production and emission factors. Determination of pollutants emitted from charcoal production. Reference levels could be determined through installing local sensors in different location for a longer time to try to characterise the emission level present in ambient condition prior to any experimentations. The observed ambient atmospheric emission from different sensors located in different areas were supposed to be averaged and obtain the emission reference levels.
- c) Only one type of kiln was tested. The type of kiln tested was earth kiln. The sensors collected emission in ambient condition thus limiting the actual collection of pollutant information from the kiln due to the presence of wind that caused pollutants dispersions. Robust capture of emissions from kiln

charcoal production could be done using Casamance and Adam retort type of Kilns (described in page 19-20). Pollutants derived from these types of kilns are easier to capture as the plume is centrally located and easier to target.

- d) The kiln experiment was run once only. There is a need to generate more replicates of the same type of kiln to assess whether the results are representative. The lack of replicates resulted in improper characterisation of the sources of pollutants in the area. It is unclear whether these pollutants were the result of nearby households or other anthropogenic activities. The use of replicate kilns could enable the validation of the results obtained in this study.
- e) No information about the humidity content of the wood, the kgs of wood and the kgs of charcoal produced was obtained. It is therefore difficult to know the impact per kg of charcoal produced. This limited estimation of amount of charcoal produced in relation to smokes or pollutants emitted from the kiln. This would have been done through measuring the moisture contents of woods to be ignited for charcoal making, measuring the weight of wood and charcoal produced in one kiln to establish the relation to the pollutants emitted in the area.
- f) Emissions from other sources could have been picked up by the sensors as the sensors were deployed in ambient condition without any control. The experimentation was conducted in open areas (ambient condition) with no control of other sources rather than the kilns. To address this limitation, the sensors would have been installed in a confined area near the chimney (especially when using Casamance or Adam retort type of Kiln) to enable easy sensing plumes from charcoal production instead of mixing up with other pollutants from different sources.
- g) The deployed sensors were developed for cold countries (not made for tropical countries like Tanzania) and presented a lack of calibration information for Tanzania. The sensors were tested in cold countries as the

result of high temperature observed during sensing in Tanzania, the cross sensitivity between pollutants could have occurred and that might have caused measurement errors. Further, the lack of a calibration laboratory in Tanzania for regular calibration reduces knowledge in the uncertainties associated with the observed concentrations.

- h) A windmeter and a video camera would have been useful to identify whether the smoke from the kiln was moving towards/over the sensors so that only the data corresponding to the kiln emissions was considered for analysis. The wind direction information gathered in the current experiment cannot be used for that purpose because it was not actually recorded by the sensors while it was gathered by global monitoring. Thus, the probability of having simulated data of wind is high that reduce the accurateness of the obtained wind data. This could be supplemented by initially having someone in the field to provide on-site checking and improvement of the experimental set-up.
- i) The lack of ground truthing data during kiln identification and the use of proxy variables to detect kiln distribution around Usambara mountain. Ground truthing was planned to be conducted through surveying around the Usambara mountain to identify the exact position of charcoal kilns in the field. The ground truth data could help in mapping the distribution of charcoal in the area accurately. The use of the GIS based approach without ground truthing could have resulted on possible errors such as misidentification of tree shadow from darkspot proxy of charcoal kiln in the area. This could be done through using GPS that could help to locate the kiln and the obtained coordinated could help in mapping accurately charcoal kiln distribution around Usambara mountain.
- j) Lack of higher resolution satellite image for classification that could help easier identification of charcoal kiln on the ground. The area located in mountainous region with high amount of cloud that could limit visualization of ground for easy identification of charcoal kiln spots on the ground. This could be improved through purchasing of higher resolution images to enable

classify the images and identification of charcoal kiln in the area to reduce any possible errors.

6.3 Further recommended works.

- a) A more focussed study on one or more charcoal-making kilns should be able to produce emission factors for CO, particulate matter and potentially NO_x relative to CO₂. This would be done by having more than one sensor unit and by having someone local able to move one sensor into the kiln's plume to ensure that emissions from the kiln are sampled. This could be carried out over the course of one or more cycles of charcoal production and for more than one type of kiln. The influence of the temperature and the efficiency of the charcoal making could be studied with a view to optimising the system for charcoal production and for air quality.
- b) Deploying enough sensors within the region (due to insufficient representative spatial distribution of atmospheric condition) within the full country/region. The country is lacking monitoring centres for various pollutants in the environment. The presence of a sensor network in the area could help in obtaining the air quality in the area as well as identifying emission sources. The number of sensors would be deployed in areas with high concentration of charcoal making to characterise the condition of atmosphere and identify more plumes, with the rest in areas with no charcoal activities that could help to establish the differences.
- c) Using low-cost miniaturised sensors to detect the level of emission derived when burning charcoal for household activities. That would show any differences in the emissions from charcoal production and from charcoal burning.
- d) Develop citizen scale techniques for the detection of emissions, as well as the identification and assessment of consequences of charcoal making into the community. Using ground-truthing for satellite data during image classification as part of land use land cover change and reduce possibility errors.

- e) Studies around the development of strategies for the uptake of charcoal making guidelines in Tanzania.
- f) Studies investigating strategies to move toward non-fossil fuel sources in Tanzania to reduce pressure on the use of forest.
- g) Studies around setting up sound regulation around charcoal making activities in Tanzania.
- h) Studies on the development of approaches for sustainable charcoal production in Tanzania.

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8.0 Apéndices

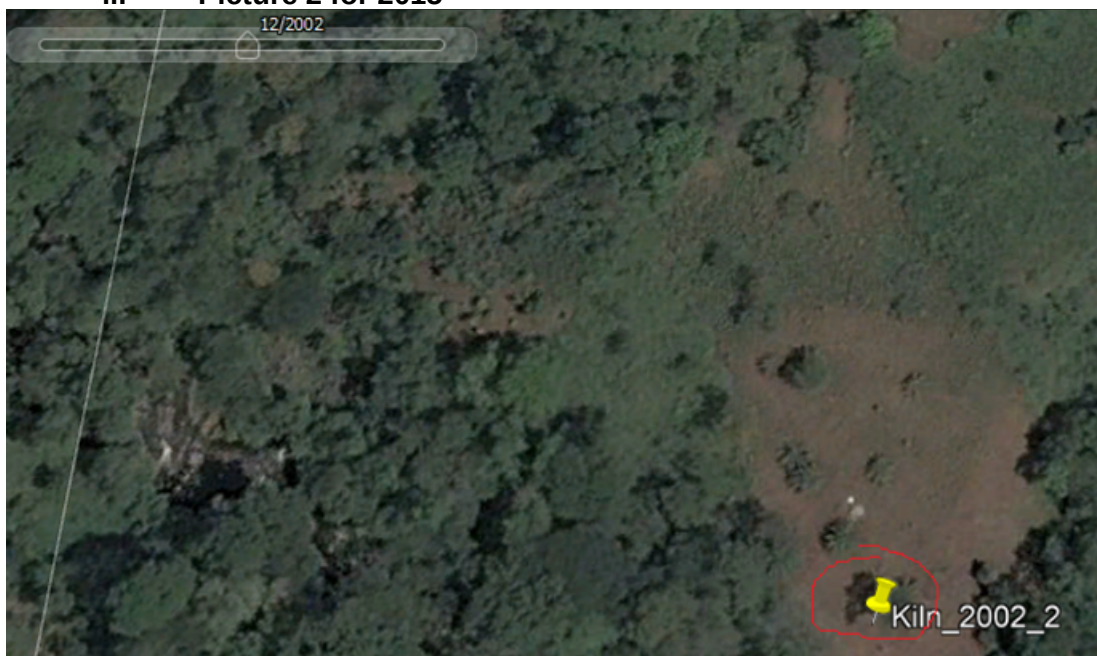
Appendix 01: Images for kilns, darkspot, temporary settlements and footpaths as charcoal making features from collect earth software imbedded into google earth pro.

a. Kiln

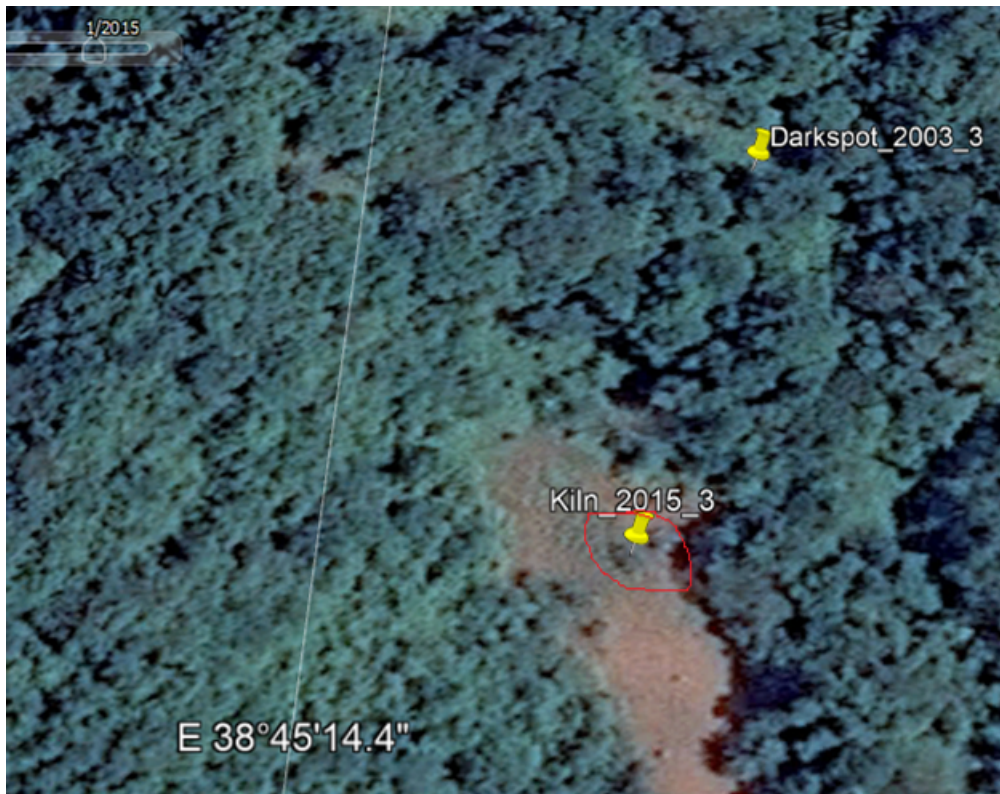
i. Picture 1 for 2003



ii. Picture 2 for 2015



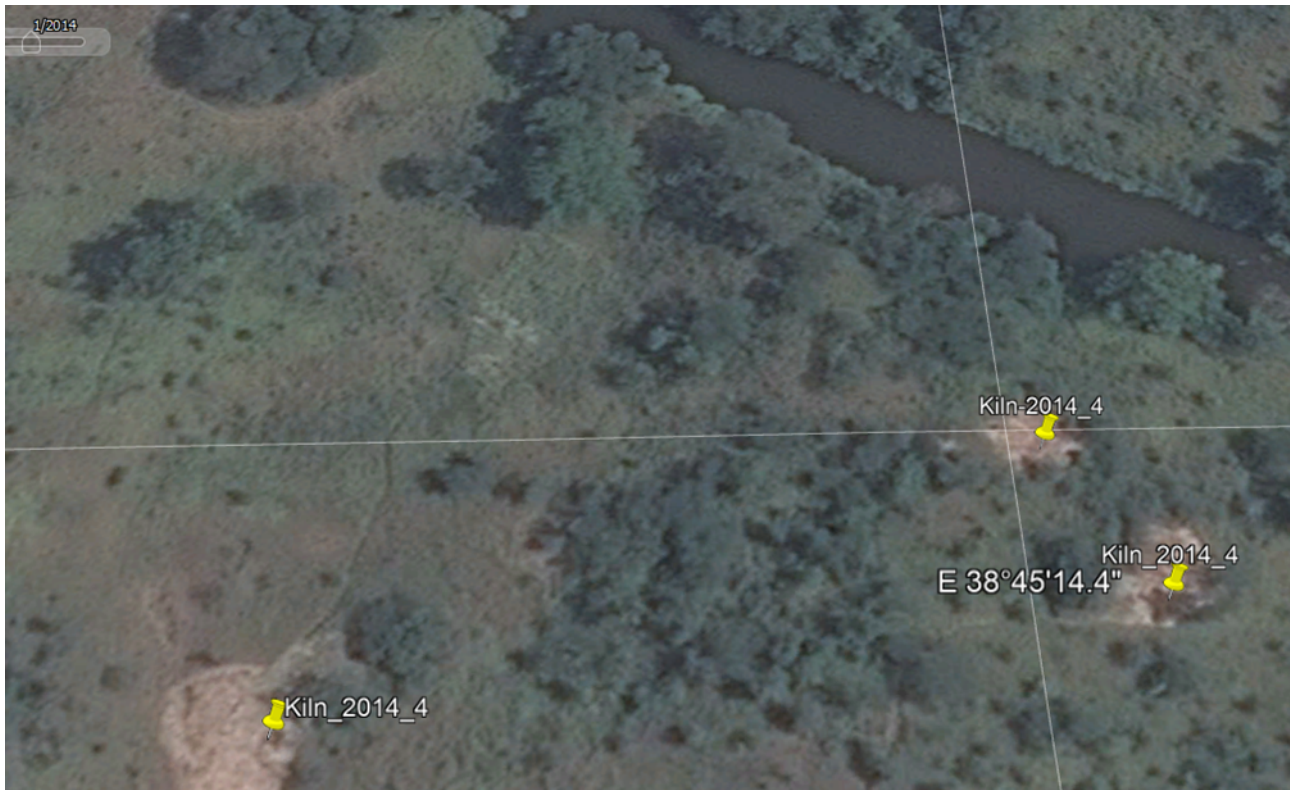
iii. Picture 3



iv. Picture 4



v. Picture 5

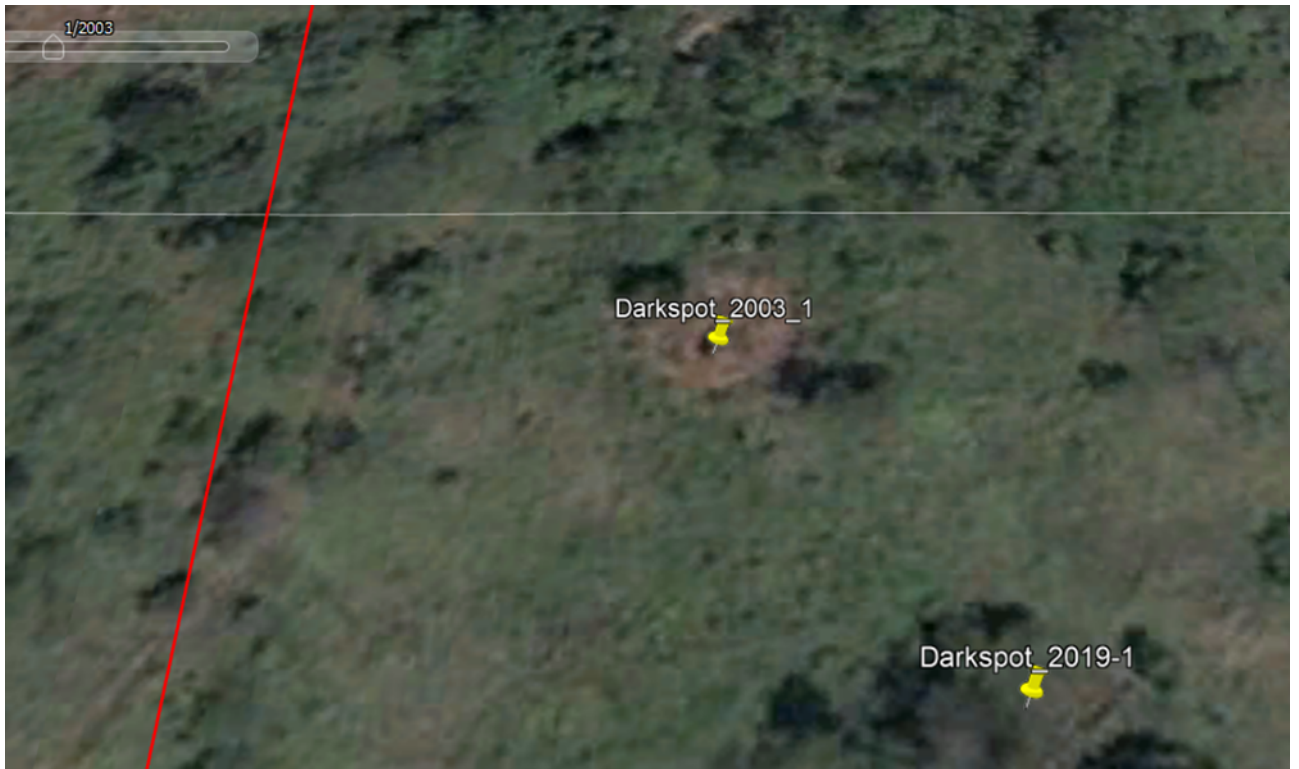


b. Dark spots

i. Picture 1



ii. Picture 2



iii. Picture 3



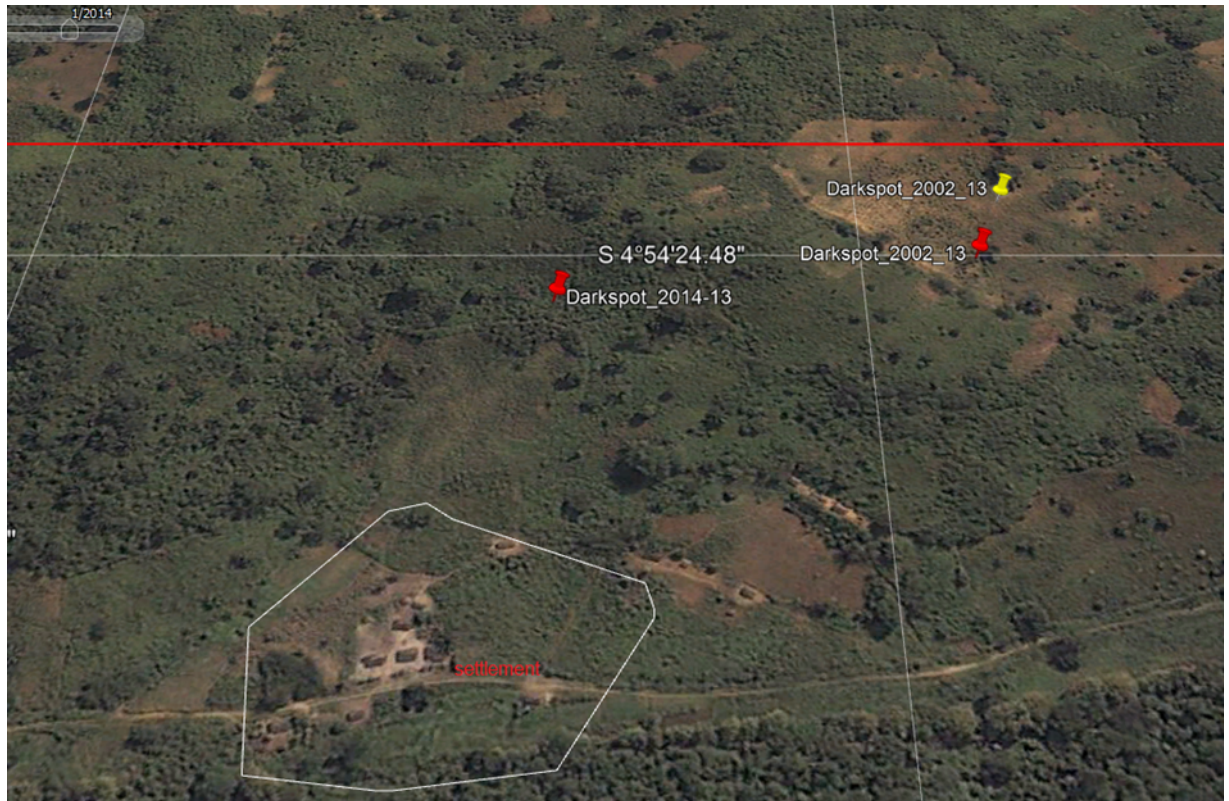
iv. Picture 5



c. Temporary settlement
i. Picture 1



ii. Picture 2



iii. Picture 3



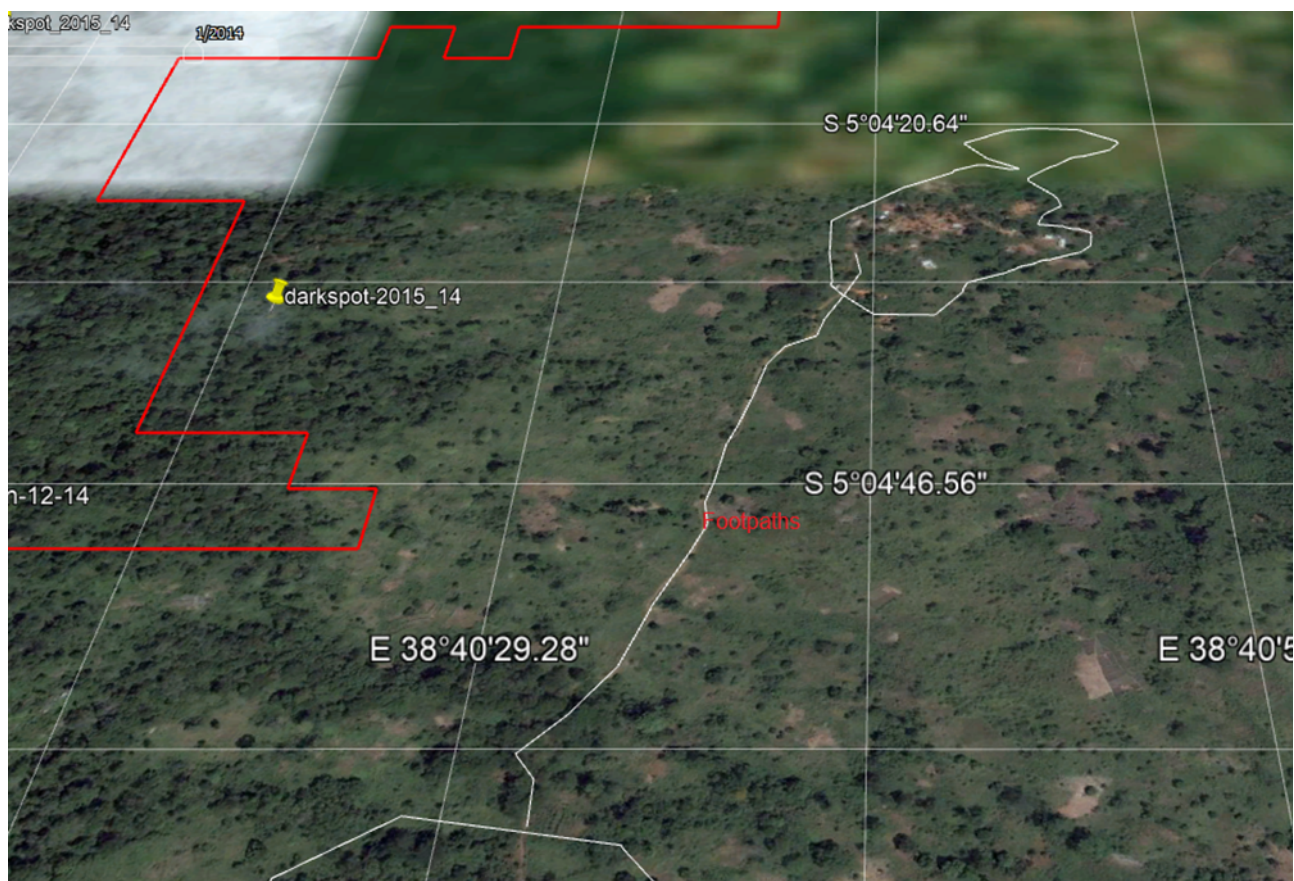
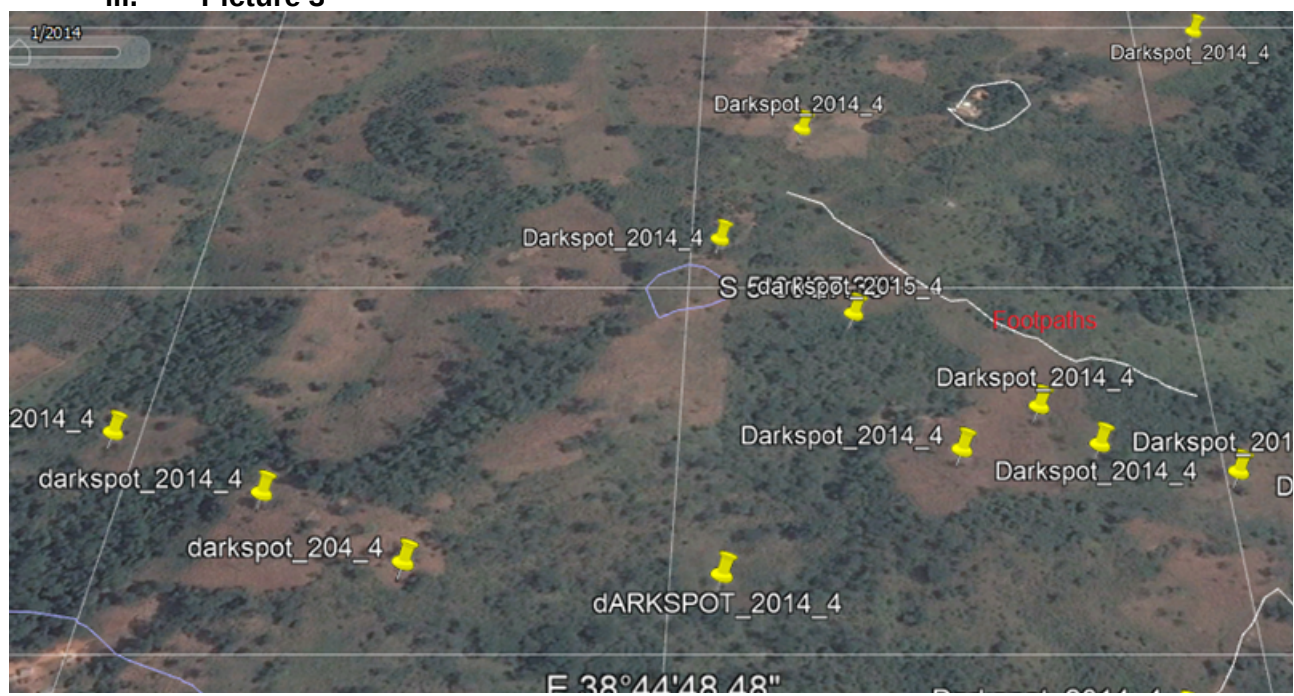
iv. Picture 5



d. Footpaths
i. Picture 1

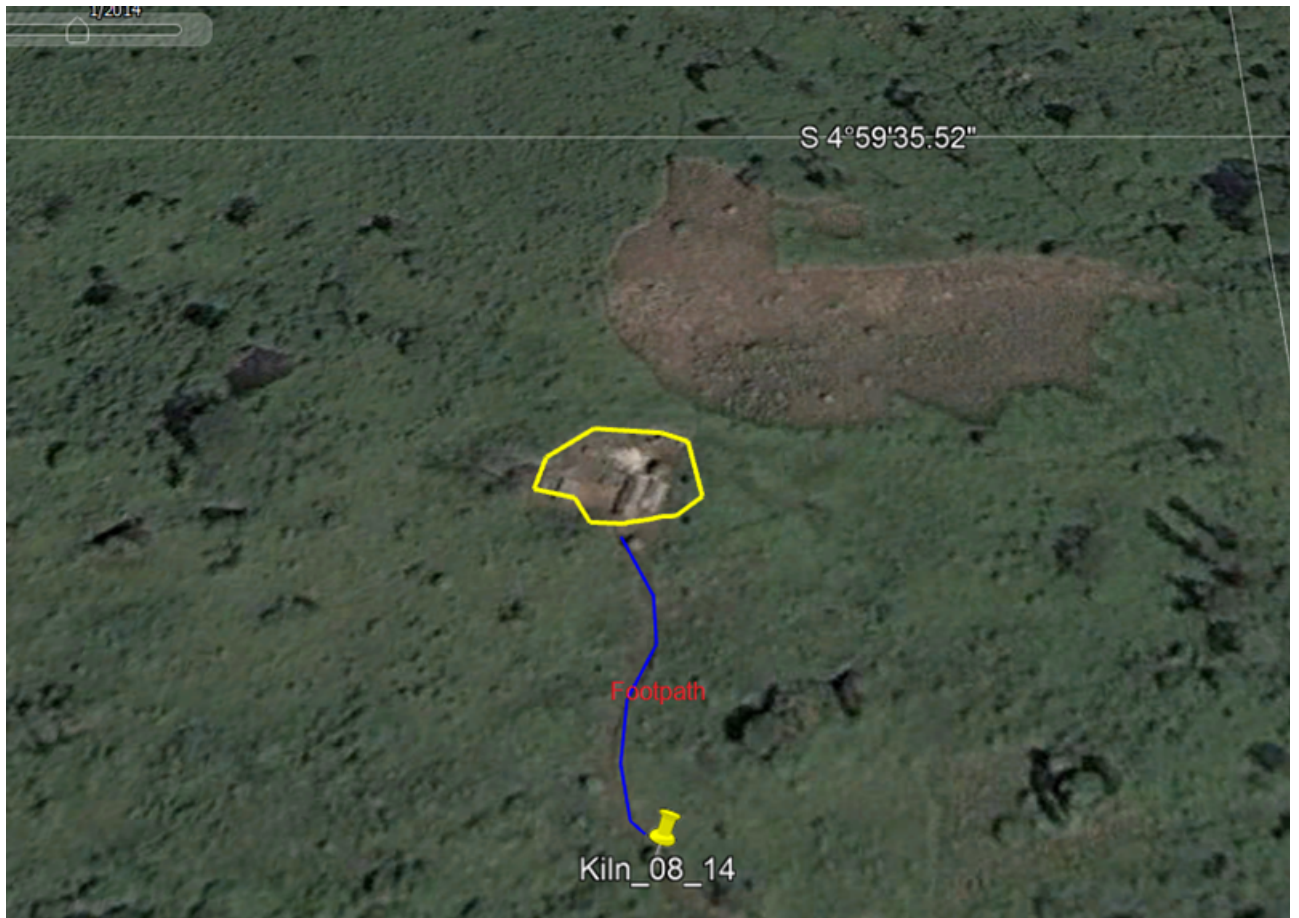


ii. Picture 2





v. **Picture 5**



Appendix 2: The bespoke code during analysis of pollutants

Section 1: The be-spoke code Data cleaning.

```
1.  ##Import data into R##
2.  setwd("C:/Users/s273473/OneDrive - Cranfield University/Desktop/Shule/Data work &
    analysis_v1/analyse_06112021/node97/raw/pre")
3.  temp = list.files(pattern="*97all*")
4.  for (file in temp){
5.    # if the merged dataset doesn't exist, create it
6.    if (!exists("dataset")){
7.      dataset <- read.table(file, header=FALSE, fill = TRUE, sep=",")
8.    }
9.    # if the merged dataset does exist, append to it
10.   if (exists("dataset")){
11.     temp_dataset <-read.table(file, header=FALSE, fill = TRUE, sep=",")
12.     dataset<-rbind(dataset, temp_dataset)
13.     rm(temp_dataset)
14.   }
15. }
16.
17. ##set system time to UTC
18. Sys.setenv(TZ='UTC')
19.
20. ##list the file names
21. filename <-list.files(pattern="*.OutputFile")
22. node97pr <-import_list(filename, rbind = TRUE)
23.
24. ###how does my data look like?
25. View(node97pr)
26.
27. node97pr$time <- format(as.POSIXct(Sys.Date() + node97pr$DecDay), "%H:%M:%S", tz="UTC")
28. node97pr<- within(node97pr, {date=(paste(Day, Month, Year, time))})
29. node97pr$date<- as.POSIXct(strptime(node97pr$date, format = "%d %m %y %H:%M:%S"))
30. View(node97pr)
```

Section 2: The be-spoke code for setting time and date right;

```
31. ##Changing time format into a workable one
32. node97pr$time <- time(node97pr$DecDay)
33. node97pr$time <- format(as.POSIXct(Sys.Date() + node97pr$DecDay), "%H:%M:%S", tz="UTC")
34. node97v1<- within(node97pr, {date=(paste(Day, Month, Year, time))})
35. node97v1$date<- as.POSIXct(strptime(node97v1$date, format = "%d %m %y %H:%M:%S"))
36.
37. view(node97v1)
```

```

38. ##Verify name and number of columns
39. names(node97v1)
40. view(node97v1)
41.
42. ##Select preferred columns (remember we are selecting columns with TC-temperature corrected)
43. node97v2 <- node97v1[c(62,13,15,16,17,18,19,20)]
44. View(node97v2)
45.
46. data3 <- node97v2
47. colnames(data3) <- c("date","COppbTC","CO2ppm","ExtTemp","ExtRH", "PM1", "PM2.5", "PM10")
48. ##Convert dataset into numeric
49. data3$COppbTC <- as.numeric(as.character(data3$COppbTC))
50. data3$CO2ppm <- as.numeric(as.character(data3$CO2ppm))
51. data3$PM1 <- as.numeric(as.character(data3$PM1))
52. data3$PM2.5 <- as.numeric(as.character(data3$PM2.5))
53. data3$PM10 <- as.numeric(as.character(data3$PM10))
54. view(data3)
55.
56. datapr <- data3
57.
58. ## REMOVING NAs ##
59. datapr = datapr[complete.cases(datapr),]
60.
61. #####Export files##
62. write.csv (datapr, file = "node97pre_unadded.csv")

```

Section 3: The be-spoke code for creating timeseries plots;

```

63. #####
64. timePlot(selectByDate(prechav1, start = "2019-02-04", end = "2019-08-30"),
65.           pollutant = c("COppb"))
66. timePlot(selectByDate(foye3, start = "2019-02-04", end = "2019-08-30"),
67.           pollutant = c("CO2ppm"))
68. timePlot(selectByDate(foye3, start = "2019-02-04", end = "2019-08-30"),
69.           pollutant = c("PM1"))
70. timePlot(selectByDate(foye3, start = "2019-02-04", end = "2019-08-30"),
71.           pollutant = c("PM2.5"))
72. timePlot(selectByDate(foye3, start = "2019-02-04", end = "2019-08-30"),
73.           pollutant = c("PM10"))

```

Section 4: The be-spoke code for creating temporal variation plots.

```

74. timeVariation (selectByDate(foye3, start = "2019-02-04", end = "2019-08-30"), pollutant = "split.by")
75. timeVariation (selectByDate(foye3, start = "2019-04-12", end = "2019-05-02"), pollutant =
    "COppbTC")

```

```
timeVariation (selectByDate(foye3, start = "2019-05-03", end = "2019-08-30"), pollutant = "COppbTC")
```

Appendix 3: Be-spoke code for determination of peaks (local maximum);

a. Background determination;

```
1. #Create a set of new functions to link to word
2. #plot to word appendix.
3. #function to create a new word doc
4. new.word.doc=function(){
5.   my.doc=read_docx()
6.   return(my.doc)
7. }
8. # function to add a title
9. add.title=function(doc, my.title){
10.  my.prop=fp_text(font.size = 14, bold = TRUE, font.family = "Times")
11.  the.title=fpar(ftext(my.title, prop=my.prop))
12.  body_add_fpar(doc, the.title)
13.  body_add_par(doc, " ")
14.  return("title added")
15. }
16. ##function to add empty line
17. add.empty.line=function(doc){
18.  body_add_par(doc, " ")
19.  return("empty line added")
20. }
21. ##function to add.page.break
22. add.page.break=function(doc){
23.  body_add_break(doc, pos="after")
24.  return("page break added")
25. }
26. #function to add new image
27. add.image=function(doc, image, h=5, w=5){
28.  body_add_img(doc, src=image,
29.               height=h, width=w,
30.               style="centered")
```

```

31. return("image added")
32. }
33. Kabura2<-foye3
34. view(Kabura2)
35. #identify peaks
36. doc=new.word.doc()
37. add.title(doc,"Appendix 1 : Local Maximum")
38. add.empty.line(doc)
39. Kabura1<-selectByDate(Kabura2, start = "2019-04-05", end = "2019-05-02")
40. view(Kabura1)
41. for (i in seq(1, (length(Kabura1$date)-100),100)){
42.   j<-i+100
43.   print(j)
44.   #CO
45.   peaks_CO<-peakwindow(Kabura1$date[i:j],Kabura1$COppbTC[i:j])
46.   z_CO<-peaks(Kabura1$COppbTC, span=10)
47.   z1_CO<-z_CO[i:j]
48.   nm<-paste("CO",i,j,".png")
49.   png(filename=nm,width=6,height=5,units="in", res=300)
50.   plot(Kabura1$COppbTC[i:j],type="l",xaxt="n",xlab="Time", ylab="CO (ppb)") #adjust visualisation
   window to display more data by increasing value 100
51.   abline(v=which(z1_CO), col="red")
52.   axis(1,at=c(0,20,40,60,80,100),labels                                =
   c(Kabura1$date[i],Kabura1$date[i+20],Kabura1$date[i+40],Kabura1$date[i+60],Kabura1$date[i+8
   0], Kabura1$date[i+100]))
53.   dev.off()
54.   add.title(doc,nm)
55.   add.image(doc,nm,h=4,w=6)
56.   #CO2
57.   peaks_CO2<-peakwindow(Kabura1$date[i:j],Kabura1$CO2ppm[i:j])
58.   z_CO2<-peaks(Kabura1$CO2ppm, span=10)
59.   z1_CO2<-z_CO2[i:j]
60.   nm<-paste("CO2",i,j,".png")
61.   png(filename=nm,width=6,height=5,units="in", res=300)
62.   plot(Kabura1$CO2ppm[i:j],type="l",xaxt="n") #adjust visualisation window to display more data by
   increasing value 100
63.   abline(v=which(z1_CO2), col="red")
64.   axis(1,at=c(0,20,40,60,80,100),labels                                =
   c(Kabura1$date[i],Kabura1$date[i+20],Kabura1$date[i+40],Kabura1$date[i+60],Kabura1$date[i+8
   0], Kabura1$date[i+100]))
65.   dev.off()
66.   add.title(doc,nm)
67.   add.image(doc,nm,h=4,w=6)

```



```

68. #PM1
69. peaks_PM1<-peakwindow(Kabura1$date[i:j],Kabura1$PM1[i:j])
70. z_PM1<-peaks(Kabura1$PM1, span=10)
71. z1_PM1<-z_PM1[i:j]
72. nm<-paste("PM1",i,j,".png")
73. png(filename=nm,width=6,height=5,units="in", res=300)
74. plot(Kabura1$PM1[i:j],type="l",xaxt="n") #adjust visualisation window to display more data by
increasing value 100
75. abline(v=which(z1_PM1), col="red")
76. axis(1,at=c(0,20,40,60,80,100),labels                                     =
c(Kabura1$date[i],Kabura1$date[i+20],Kabura1$date[i+40],Kabura1$date[i+60],Kabura1$date[i+8
0], Kabura1$date[i+100]))
77. dev.off()

78. add.title(doc,nm)
79. add.image(doc,nm,h=4,w=6)

80. #PM2.5
81. peaks_PM25<-peakwindow(Kabura1$date[i:j],Kabura1$PM2.5[i:j])
82. z_PM25<-peaks(Kabura1$PM2.5, span=10)
83. z1_PM25<-z_PM25[i:j]
84. nm<-paste("PM25",i,j,".png")
85. png(filename=nm,width=6,height=5,units="in", res=300)
86. plot(Kabura1$PM2.5[i:j],type="l",xaxt="n") #adjust visualisation window to display more data by
increasing value 100
87. abline(v=which(z1_PM25), col="red")
88. axis(1,at=c(0,20,40,60,80,100),labels                                     =
c(Kabura1$date[i],Kabura1$date[i+20],Kabura1$date[i+40],Kabura1$date[i+60],Kabura1$date[i+8
0], Kabura1$date[i+100]))
89. dev.off()
90. add.title(doc,nm)
91. add.image(doc,nm,h=4,w=6)
92. #PM10
93. peaks_PM10<-peakwindow(Kabura1$date[i:j],Kabura1$PM10[i:j])
94. z_PM10<-peaks(Kabura1$PM10, span=10)
95. z1_PM10<-z_PM10[i:j]
96. nm<-paste("PM10",i,j,".png")
97. png(filename=nm,width=6,height=5,units="in", res=300)
98. plot(Kabura1$PM10[i:j],type="l",xaxt="n") #adjust visualisation window to display more data by
increasing value 100
99. abline(v=which(z1_PM10), col="red")

```

```

100. axis(1,at=c(0,20,40,60,80,100),labels                                =
      c(Kabura1$date[i],Kabura1$date[i+20],Kabura1$date[i+40],Kabura1$date[i+60],Kabura1$date[i+8
      0], Kabura1$date[i+100]))
101. dev.off()
102. add.title(doc,nm)
103. add.image(doc,nm,h=4,w=6)
104.}
105.print(doc, target="My report_peak_during.docx")

106.#CALCULATE LOCAL BACKGROUNDS#####
107.#####
108.k2<-cbind(Kabura1,z_CO,z_CO2,z_PM1, z_PM25,z_PM10)
109.bkg_CO<-rollapply(Kabura1$COppbTC,15,FUN=median, align="left")
110.bkg_CO2<-rollapply(Kabura1$CO2ppm,15, FUN=median, align="left")
111.bkg_PM1<-rollapply(Kabura1$PM1,15, FUN=median, align="left")
112.bkg_PM25<-rollapply(Kabura1$PM2.5,15,FUN=median, align="left")
113.bkg_PM10<-rollapply(Kabura1$PM10,15,FUN=median, align="left")
114.vec<-vector("numeric",nrow(k2)-length(bkg_CO))
115.#exclude those values for which a median was not calculated when the window was outside of the
      time series (towards the end).
116.#####
117.bkg1_CO<-c(bkg_CO, vec)
118.bkg1_CO2<-c(bkg_CO2, vec)
119.bkg1_PM1<-c(bkg_PM1, vec)
120.bkg1_PM25<-c(bkg_PM25, vec)
121.bkg1_PM10<-c(bkg_PM10, vec)
122.
123.k3<-cbind(k2,bkg1_CO, bkg1_CO2, bkg1_PM1, bkg1_PM25,bkg1_PM10)
124.
125.NoBakg_CO<-k3$COppbTC-k3$bkg1_CO
126.NoBakg_CO2<-k3$CO2ppm-k3$bkg1_CO2
127.NoBakg_PM1<-k3$PM1-k3$bkg1_PM1
128.NoBakg_PM25<-k3$PM2.5-k3$bkg1_PM25
129.NoBakg_PM10<-k3$PM10-k3$bkg1_PM10
130.
131.k5<-cbind(k3,NoBakg_CO,NoBakg_CO2, NoBakg_PM1, NoBakg_PM25, NoBakg_PM10)
132.k5[,"NoBakg_CO"][k5[,"NoBakg_CO"]<0]<-NA
133.k5[,"NoBakg_CO2"][k5[,"NoBakg_CO2"]<0]<-NA
134.k5[,"NoBakg_PM1"][k5[,"NoBakg_PM1"]<0]<-NA
135.k5[,"NoBakg_PM25"][k5[,"NoBakg_PM25"]<0]<-NA
136.k5[,"NoBakg_PM10"][k5[,"NoBakg_PM10"]<0]<-NA
137.
138.k6<-k5[1:(nrow(k5)-15),]

```

```

139.
140.#Looking for common peaks
141.#####
142.
143.ComPeak<-k6$NoBakg_CO+k6$NoBakg_CO2+k6$NoBakg_PM1
144.Exclude<-ComPeak
145.k7<-cbind(k6,ComPeak, Exclude)
146.#perhaps use na.omit?
147.
148.for(g in seq(1,nrow(k7),1)){
149.
150.  if(is.na(k7$NoBakg_CO[g])==TRUE){
151.    k7$Exclude[g]<-0}
152.
153.  else{
154.    if(is.na(k7$NoBakg_CO2[g])==TRUE){
155.      k7$Exclude[g]<-0
156.    }
157.    else{
158.      if(is.na(k7$NoBakg_PM1[g])==TRUE){
159.        k7$Exclude[g]<-0
160.      }
161.      else{
162.        if(k7$Exclude[g]>(k7$NoBakg_CO[g]+10)){
163.          k7$Exclude[g]<-k7$ComPeak[g]
164.        }
165.        else{k7$Exclude[g]<-NA}
166.      }
167.    }}}
168.
169.summary(k7)
170.k8<-subset(k7,Exclude>0)
171.view(k8)
172.
173.#SCATTERPLOTS WITH HEXBIN
174.#####
175.
176.doc=new.word.doc()
177.add.title(doc,"Appendix 1 : Scatter plots for during charcoal production phase")
178.add.empty.line(doc)
179.
180.
181.png(filename="CovsCO2.png",width=8,height=4,units="in", res=300)

```

```

182.scatterPlot(k6, x ="NoBakg_CO2" , y ="NoBakg_CO", ylab ="CO", xlab="CO2", type = "month",
      smooth = FALSE,
183.      linear = TRUE, layout = c(2,1), method="hexbin", par.settings=list(fontsize=list(text=5)))
184.dev.off()
185.add.title(doc,"COvsCO2.png")
186.add.image(doc,"CovsCO2.png",h=4,w=8)
187.
188.png(filename="PM1vsCO2.png",width=8,height=4,units="in", res=300)
189.scatterPlot(k6, x = "NoBakg_CO2", y = "NoBakg_PM1", ylab ="PM1", xlab="CO2", type = "month",
      smooth = FALSE,
190.      linear = TRUE, layout = c(2,1), method="hexbin", par.settings=list(fontsize=list(text=5)))
191.dev.off()
192.add.title(doc,"PM1vsCO2.png")
193.add.image(doc,"PM1vsCO2.png",h=4,w=8)
194.
195.png(filename="PM25vsCO2.png",width=8,height=4,units="in", res=300)
196.scatterPlot(k6, x = "NoBakg_CO2", y = "NoBakg_PM25", ylab ="PM2.5", xlab="CO2", type =
      "month", smooth = FALSE,
197.      linear = TRUE, layout = c(2,1), method="hexbin", par.settings=list(fontsize=list(text=5)))
198.dev.off()
199.add.title(doc,"PM25vsCO2.png")
200.add.image(doc,"PM25vsCO2.png",h=4,w=8)
201.
202.png(filename="PM10vsCO2.png",width=8,height=4,units="in", res=300)
203.scatterPlot(k6, x = "NoBakg_CO2", y = "NoBakg_PM10", ylab ="PM10", xlab="CO2", type =
      "month", smooth = FALSE,
204.      linear = TRUE, layout = c(2,1), method="hexbin",par.settings=list(fontsize=list(text=5)))
205.dev.off()
206.add.title(doc,"PM10vsCO2.png")
207.add.image(doc,"PM10vsCO2.png",h=4,w=8)
208.
209.print(doc, target="Scatter plots.docx")
210.
211.#SCATTERPLOTS WITHOUT HEXBIN
212.#####
213.
214.doc=new.word.doc()
215.add.title(doc,"Appendix 1 : Scatter plots for charcoal production phase without hexabin_32082022")
216.add.empty.line(doc)
217.
218.
219.png(filename="CovsCO2.png",width=8,height=4,units="in", res=300)

```

```

220.scatterPlot(k6, x ="NoBakg_CO2" , y ="NoBakg_CO", ylab ="CO", xlab="CO2", type = "month",
      smooth = FALSE,
221.      linear = TRUE, layout = c(2,1),par.settings=list(fontsize=list(text=5)))
222.dev.off()
223.add.title(doc,"COvsCO2.png")
224.add.image(doc,"CovsCO2.png",h=4,w=8)
225.
226.png(filename="PM1vsCO2.png",width=8,height=4,units="in", res=300)
227.scatterPlot(k6, x = "NoBakg_CO2", y = "NoBakg_PM1", ylab ="PM1", xlab="CO2",type = "month",
      smooth = FALSE,
228.      linear = TRUE, layout = c(2,1),par.settings=list(fontsize=list(tet=7)))
229.dev.off()
230.add.title(doc,"PM1vsCO2.png")
231.add.image(doc,"PM1vsCO2.png",h=4,w=8)
232.
233.png(filename="PM25vsCO2.png",width=8,height=4,units="in", res=300)
234.scatterPlot(k6, x = "NoBakg_CO2", y = "NoBakg_PM25", ylab ="PM2.5", xlab="CO2", type =
      "month", smooth = FALSE,
235.      linear = TRUE, layout = c(2,1),par.settings=list(fontsize=list(tet=7)))
236.dev.off()
237.add.title(doc,"PM25vsCO2.png")
238.add.image(doc,"PM25vsCO2.png",h=4,w=8)
239.
240.png(filename="PM10vsCO2.png",width=8,height=4,units="in", res=300)
241.scatterPlot(k6, x = "NoBakg_CO2", y = "NoBakg_PM10", ylab ="PM10", xlab="CO2", type =
      "month", smooth = FALSE,
242.      linear = TRUE, layout = c(2,1),par.settings=list(fontsize=list(tet=7)))
243.dev.off()
244.add.title(doc,"PM10vsCO2.png")
245.add.image(doc,"PM10vsCO2.png",h=4,w=8)
246.
247.print(doc, target="Scatter plots No hexabin.docx")
248.
249.
250.#SCATTERPLOTS FOR COMMON PEAKS ONLY NO HEXBIN
251.#####
252.
253.doc=new.word.doc()
254.add.title(doc,"Appendix 1 : Scatter plots for charcoal production phase with common peaks
      only_31082022")
255.add.empty.line(doc)
256.
257.

```

```

258.png(filename="CovsCO2.png",width=4,height=8,units="in", res=300)
259.scatterPlot(k8, x ="NoBakg_CO2" , y ="NoBakg_CO", ylab ="CO", xlab="CO2", type = "month",
      smooth = FALSE,
260.      linear = TRUE, layout = c(2,1),par.settings=list(fontsize=list(tet=7)))
261.dev.off()
262.add.title(doc,"COvsCO2.png")
263.add.image(doc,"CovsCO2.png",h=4,w=8)
264.
265.png(filename="PM1vsCO2.png",width=8,height=4,units="in", res=300)
266.scatterPlot(k8, x = "NoBakg_CO2", y = "NoBakg_PM1", ylab ="PM1", xlab="CO2",type = "month",
      smooth = FALSE,
267.      linear = TRUE, layout = c(2,1),par.settings=list(fontsize=list(tet=7)))
268.dev.off()
269.add.title(doc,"PM1vsCO2.png")
270.add.image(doc,"PM1vsCO2.png",h=4,w=8)
271.
272.png(filename="PM25vsCO2.png",width=8,height=4,units="in", res=300)
273.scatterPlot(k8, x = "NoBakg_CO2", y = "NoBakg_PM25", ylab ="PM2.5", xlab="CO2", type =
      "month", smooth = FALSE,
274.      linear = TRUE, layout = c(2,1),par.settings=list(fontsize=list(tet=7)))
275.dev.off()
276.add.title(doc,"PM25vsCO2.png")
277.add.image(doc,"PM25vsCO2.png",h=4,w=8)
278.
279.png(filename="PM10vsCO2.png",width=8,height=4,units="in", res=300)
280.scatterPlot(k8, x = "NoBakg_CO2", y = "NoBakg_PM10", ylab ="PM10", xlab="CO2", type =
      "month", smooth = FALSE,
281.      linear = TRUE, layout = c(2,1),par.settings=list(fontsize=list(tet=7)))
282.dev.off()
283.add.title(doc,"PM10vsCO2.png")
284.add.image(doc,"PM10vsCO2.png",h=4,w=8)
285.
286.print(doc, target="Scatter plots for common peak only.docx")
287.
288.#SCATTERPLOTS FOR COMMON PEAKS ONLY WITH HEXBIN
289.#####
290.
291.doc=new.word.doc()
292.add.title(doc,"Appendix 1 : Scatter plots for charcoal production phase common peaks
      only_31082022")
293.add.empty.line(doc)
294.
295.

```

```

296.png(filename="CovsCO2.png",width=8,height=4,units="in", res=300)
297.scatterPlot(k8, x ="NoBakg_CO2" , y ="NoBakg_CO", ylab ="CO", xlab="CO2", type = "month",
      smooth = FALSE,
298.      linear = TRUE, method="hexbin", layout = c(2,1),par.settings=list(fontsize=list(text=5)))
299.dev.off()
300.add.title(doc,"COvsCO2.png")
301.add.image(doc,"CovsCO2.png",h=4,w=8)
302.
303.png(filename="PM1vsCO2.png",width=8,height=8,units="in", res=300)
304.scatterPlot(k8, x = "NoBakg_CO2", y = "NoBakg_PM1", ylab ="PM1", xlab="CO2",type = "month",
      smooth = FALSE,
305.      linear = TRUE, method="hexbin", layout = c(2,1),par.settings=list(fontsize=list(text=5)))
306.dev.off()
307.add.title(doc,"PM1vsCO2.png")
308.add.image(doc,"PM1vsCO2.png",h=4,w=8)
309.
310.png(filename="PM25vsCO2.png",width=8,height=4,units="in", res=300)
311.scatterPlot(k8, x = "NoBakg_CO2", y = "NoBakg_PM25", ylab ="PM2.5", xlab="CO2", type =
      "month", smooth = FALSE,
312.      linear = TRUE, method="hexbin", layout = c(2,1),par.settings=list(fontsize=list(text=5)))
313.dev.off()
314.add.title(doc,"PM25vsCO2.png")
315.add.image(doc,"PM25vsCO2.png",h=4,w=8)
316.
317.png(filename="PM10vsCO2.png",width=8,height=4,units="in", res=300)
318.scatterPlot(k8, x = "NoBakg_CO2", y = "NoBakg_PM10", ylab ="PM10", xlab="CO2", type =
      "month", smooth = FALSE,
319.      linear = TRUE, method="hexbin", layout = c(2,1),par.settings=list(fontsize=list(tet=5)))
320.dev.off()
321.add.title(doc,"PM10vsCO2.png")
322.add.image(doc,"PM10vsCO2.png",h=4,w=8)
323.
324.print(doc, target="Scatter plots Hexbin ComPeak.docx")
325.
326.
327.#####
328.#Ploting time series with NoBackg points
329.doc=new.word.doc()
330.add.title(doc,"Appendix 1 : Local Maximum & No Backg points")
331.add.empty.line(doc)
332.
333.for (i in seq(1, (length(Kabura1$date)-100),100)){
334.  j<-i+100

```

```

335. print(j)
336.
337. #CO
338. peaks_CO<-peakwindow(Kabura1$date[i:j],Kabura1$COppbTC[i:j])
339. z_CO<-peaks(Kabura1$COppbTC, span=10)
340. z1_CO<-z_CO[i:j]
341. nm<-paste("CO",i,j,".png")
342. png(filename=nm,width=8,height=5,units="in", res=300)
343. plot(Kabura1$COppbTC[i:j],type="l",xaxt="n", ylab = "CO",
      ylim=c(0,max(Kabura1$COppbTC[i:j]+50))) #adjust visualisation window to display more data by
      increasing value 100
344. abline(v=which(z1_CO), col="red")
345. points(k5$NoBakg_CO[i:j],pch=3, col=6)
346. axis(1,at=c(0,20,40,60,80,100),labels =
      c(Kabura1$date[i],Kabura1$date[i+20],Kabura1$date[i+40],Kabura1$date[i+60],Kabura1$date[i+80],
      Kabura1$date[i+100]))
347. dev.off()
348.
349. add.title(doc,nm)
350. add.image(doc,nm,h=4,w=8)
351.
352.
353.
354. #CO2
355. peaks_CO2<-peakwindow(Kabura1$date[i:j],Kabura1$CO2ppm[i:j])
356. z_CO2<-peaks(Kabura1$CO2ppm, span=10)
357. z1_CO2<-z_CO2[i:j]
358. nm<-paste("CO2",i,j,".png")
359. png(filename=nm,width=8,height=5,units="in", res=300)
360. plot(Kabura1$CO2ppm[i:j],type="l",ylab = "CO2",xaxt="n",
      ylim=c(0,max(Kabura1$CO2ppm[i:j]+50))) #adjust visualisation window to display more data by
      increasing value 100
361. abline(v=which(z1_CO2), col="red")
362. points(k5$NoBakg_CO2[i:j],type="p", pch=3, col=6)
363. axis(1,at=c(0,20,40,60,80,100),labels =
      c(Kabura1$date[i],Kabura1$date[i+20],Kabura1$date[i+40],Kabura1$date[i+60],Kabura1$date[i+80],
      Kabura1$date[i+100]))
364. dev.off()
365.
366. add.title(doc,nm)
367. add.image(doc,nm,h=4,w=8)
368.
369. #PM1

```



```

370. peaks_PM1<-peakwindow(Kabura1$date[i:j],Kabura1$PM1[i:j])
371. z_PM1<-peaks(Kabura1$PM1, span=10)
372. z1_PM1<-z_PM1[i:j]
373. nm<-paste("PM1",i,j,".png")
374. png(filename=nm,width=8,height=5,units="in", res=300)
375. plot(Kabura1$PM1[i:j],type="l",xaxt="n",ylab      ="PM1",ylim=c(0,max(Kabura1$PM1[i:j]+50)))
      #adjust visualisation window to display more data by increasing value 100
376. abline(v=which(z1_PM1), col="red")
377. points(k5$NoBakg_PM1[i:j],type="p", pch=1, col=6)
378. axis(1,at=c(0,20,40,60,80,100),labels              =
      c(Kabura1$date[i],Kabura1$date[i+20],Kabura1$date[i+40],Kabura1$date[i+60],Kabura1$date[i+8
      0], Kabura1$date[i+100]))
379. dev.off()
380.
381. add.title(doc,nm)
382. add.image(doc,nm,h=4,w=8)
383.
384.
385. #PM2.5
386. peaks_PM25<-peakwindow(Kabura1$date[i:j],Kabura1$PM2.5[i:j])
387. z_PM25<-peaks(Kabura1$PM2.5, span=10)
388. z1_PM25<-z_PM25[i:j]
389. nm<-paste("PM25",i,j,".png")
390. png(filename=nm,width=8,height=5,units="in", res=300)
391. plot(Kabura1$PM2.5[i:j],type="l",xaxt="n",ylab  ="PM2.5",ylim=c(0,max(Kabura1$PM2.5[i:j]+50)))
      #adjust visualisation window to display more data by increasing value 100
392. abline(v=which(z1_PM25), col="red")
393. points(k5$NoBakg_PM25[i:j],pch=3, col=6)
394. axis(1,at=c(0,20,40,60,80,100),labels              =
      c(Kabura1$date[i],Kabura1$date[i+20],Kabura1$date[i+40],Kabura1$date[i+60],Kabura1$date[i+8
      0], Kabura1$date[i+100]))
395. dev.off()
396.
397. add.title(doc,nm)
398. add.image(doc,nm,h=4,w=8)
399.
400.
401. #PM10
402. peaks_PM10<-peakwindow(Kabura1$date[i:j],Kabura1$PM10[i:j])
403. z_PM10<-peaks(Kabura1$PM10, span=10)
404. z1_PM10<-z_PM10[i:j]
405. nm<-paste("PM10",i,j,".png")
406. png(filename=nm,width=8,height=5,units="in", res=300)

```

```

407. plot(Kabura1$PM10[i:j],type="l",xaxt="n",ylab  ="PM10",ylim=c(0,max(Kabura1$PM10[i:j]+50)))
      #adjust visualisation window to display more data by increasing value 100
408. abline(v=which(z1_PM10), col="red")
409. points(k5$NoBakg_PM10[i:j],pch=3, col=6)
410. axis(1,at=c(0,20,40,60,80,100),labels                                =
      c(Kabura1$date[i],Kabura1$date[i+20],Kabura1$date[i+40],Kabura1$date[i+60],Kabura1$date[i+8
      0], Kabura1$date[i+100]))
411. dev.off()
412. add.title(doc,nm)
413. add.image(doc,nm,h=4,w=8)
414.}
415.
416.print(doc, target="My report & NoBackg points.docx")
417.
418.
419.#CLUSTERING TO GET TWO REGRESSION MODELS
420.#Ploting two regression with NoBackg points
421.
422.
423.k8<-subset(k7,Exclude>0)
424.k9<-as.matrix(subset(k8,select=NoBakg_PM10:NoBakg_CO2))
425.group<-kmeans(k9,2,10)
426.k10<-cbind(k9,group$cluster)
427.k11<-as.data.frame(subset(k10,k10[,3]==1))
428.k12<-as.data.frame(subset(k10,k10[,3]==2))
429.model_g1 <- lm(NoBakg_PM10 ~ 0+ NoBakg_CO2, data = k11)
430.model_g2 <- lm(NoBakg_PM10 ~ 0+ NoBakg_CO2, data = k12)
431.plot(k8$NoBakg_CO2, k8$NoBakg_PM10,col=factor(group$cluster))
432.abline(model_g1, col=1)
433.abline(model_g2, col=2)
434.model_g1
435.model_g2
436.
437.
438.dev.off()
439.add.title(doc,"COvsCO2.png")
440.add.image(doc,"COvsCO2.png",h=7,w=7)
441.print(doc, target="Two regression.docx")

```

Appendix 4: Results for the Kruskal Wallis test

a. Distribution of data (normal or lognormal)

Figure 4-2 is the histogram for COppbTC data set which shows that the distribution of data was not normally distributed for all gases. The analysis carried out using Kruskal-Wallis test a non-parametric test for significant differences between groups i.e. pre, during and post phases.

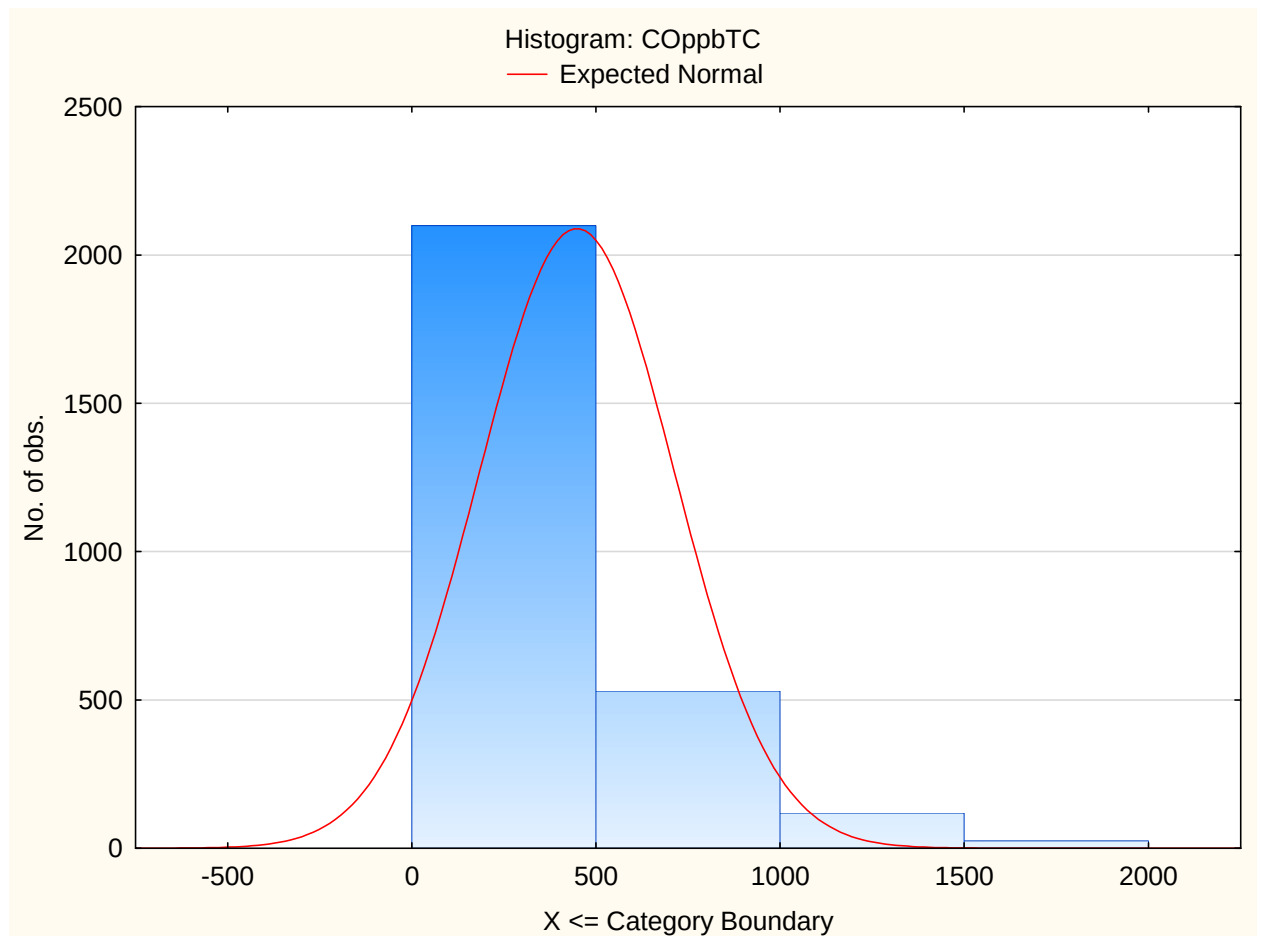


Figure 4-2: Lognormal distribution of COppbTC pollutants in the experimentation area.

b. Statistical testing for significant differences in the distribution of concentrations in the pre, during and post periods

Results in table 4-2 indicated that the Kruskal-Wallis test yields a p-value which was greater than compared to a predetermined significance level (commonly set at 0.05) in each group. If the p-value is greater than the chosen significance level, it indicates that there are no significant differences between at least two groups. Therefore, results shows that no significant differences between of CO ppbTC between different groups.

Table 4 - 2: Multiple comparisons p values (2-tailed); COppbTC (Independent), grouping variable: split.by, Kruskal-Wallis test: H (2, N= 2774) =.0587222, p = 0.9711

Independent (COppbTC)	Pre R:1387.8	During R:1374.8	Post R:1388.8
Pre		1.000000	1.000000
During	1.000000		1.000000
Post	1.000000	1.000000	

Results in table 4-3 indicated that the Kruskal-Wallis test yields a p-value which was greater than compared to a predetermined significance level (commonly set at 0.05) in each group. If the p-value is greater than the chosen significance level, it indicates that there are no significant differences between at least two groups. Therefore, results shows that no significant differences between of CO₂ppm between different groups.

Table 4 - 3: All groups multiple comparisons p values (2-tailed); CO₂ppm (Independent) (grouping variable: split.by, Kruskal-Wallis test: H (2, N= 2774) =2.809345 p = 0.2454

Independent (CO ₂ ppm)	Pre R:1427.3	During R:1430.4	Post R:1371.6
Pre		1.000000	0.429961
During	1.000000		0.920010
Post	0.429961	0.920010	

Results in table 4 - 4 indicated that the Kruskal-Wallis test yields a p-value which was less than compared to a predetermined significance level (commonly set at 0.05) for PM₁ between pre versus during, pre versus post, while higher p-value observed between during versus post phase. If the p-value is less than the chosen significance level, it indicates that there are significant differences. Therefore, significance difference observed between pre versus during, pre versus post while no significant differences observed between during versus post phase for PM₁ (ug^{-m3}).

Table 4 - 4: All groups multiple comparisons p values (2-tailed); PM₁ - Independent, grouping variable: split.by, Kruskal - wallis test: H (2, N= 2774) = 55.51183, p = 0.0000.

Independent (PM ₁)	Pre R:1609.4	During R:1362.2	Post R:1327.1
Pre		0.000358	0.000000
During	0.000358		1.000000
Post	0.000000	1.000000	

Results in table 4 - 5 indicated that the Kruskal-Wallis test yields a p-value which was less than compared to a predetermined significance level (commonly set at 0.05) for PM_{2.5} between pre versus during, pre versus post, while higher p-value observed between during versus post phase. If the p-value is less than the chosen significance level, it indicates that there are significant differences. Therefore, significance difference observed between pre versus during, pre versus post while no significant differences observed between during versus post phase for PM_{2.5} (ug^{-m3}).

Table 4 - 5: All Groups multiple comparisons p-values (2-tailed); Independent variable (PM_{2.5}) (grouping variable: split.by, Kruskal - wallis test: H (2, N= 2774) =57.13448, p = 0.0000.

Independent: (PM _{2.5})	Pre R:1613.7	During R:1343.6	Post R:1327.9
Pre		0.000079	0.000000
During	0.000079		1.000000

Post	0.000000	1.000000
------	----------	----------

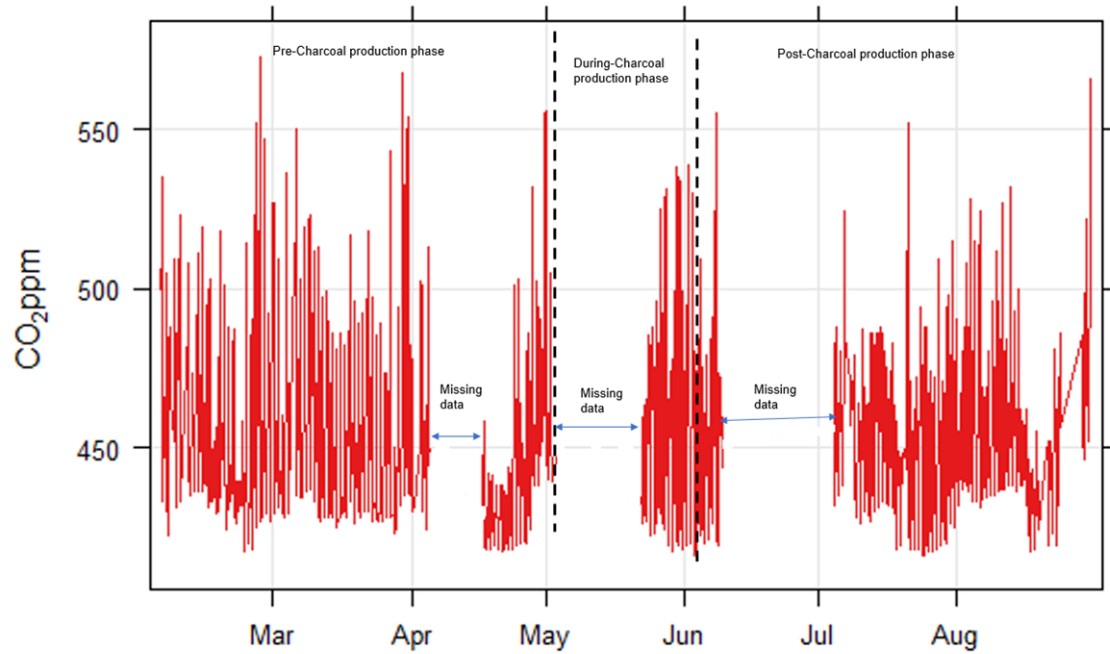
Results in table 4 - 6 indicated that the Kruskal-Wallis test yields a p-value which was less than compared to a predetermined significance level (commonly set at 0.05) for PM₁₀ between pre versus during, pre versus post, while higher p-value observed between during versus post phase. If the p-value is less than the chosen significance level, it indicates that there are significant differences. Therefore, significance difference observed between pre versus during, pre versus post while no significant differences observed between during versus post phase for PM₁₀ (ug^{-m3}).

Table 4 - 6: All Groups multiple comparisons p values (2-tailed); PM₁₀ Independent (grouping) variable: split.by Kruskal-Wallis test: H (2, N= 2774) = 50.51873, p = 0.0000.

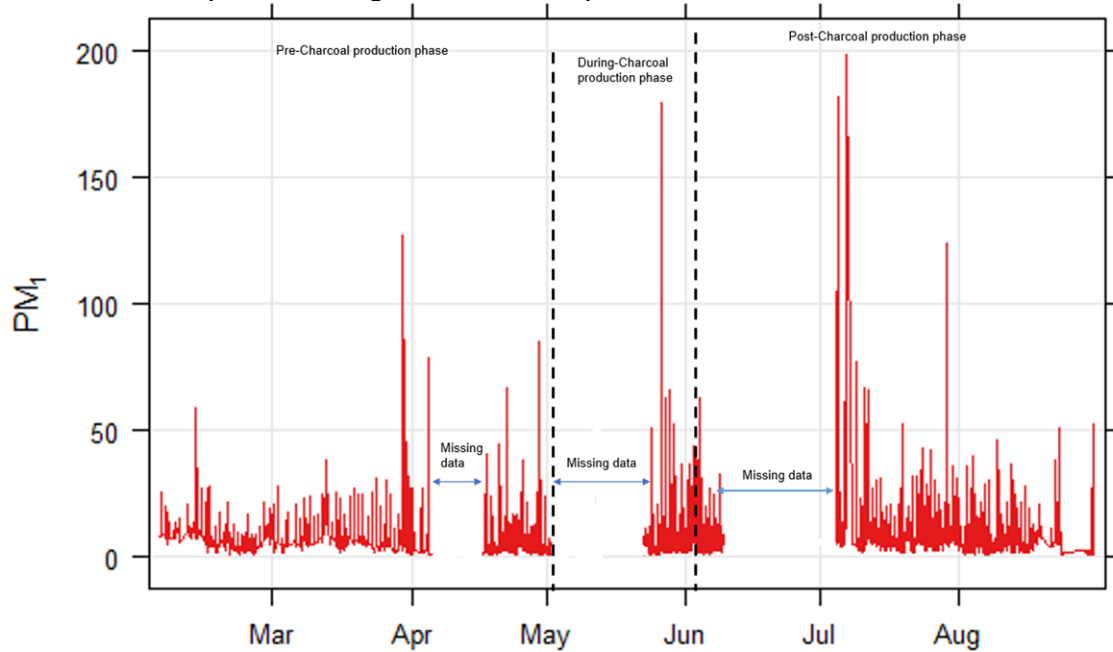
Independent (PM ₁₀)	Pre R:1598.5	During R:1384.5	Post R:1327.8
Pre		0.002599	0.000000
During	0.002599		0.976020
Post	0.000000	0.976020	

Appendix 5: Timeseries plots for CO₂ and particulate matter in the experiment site.

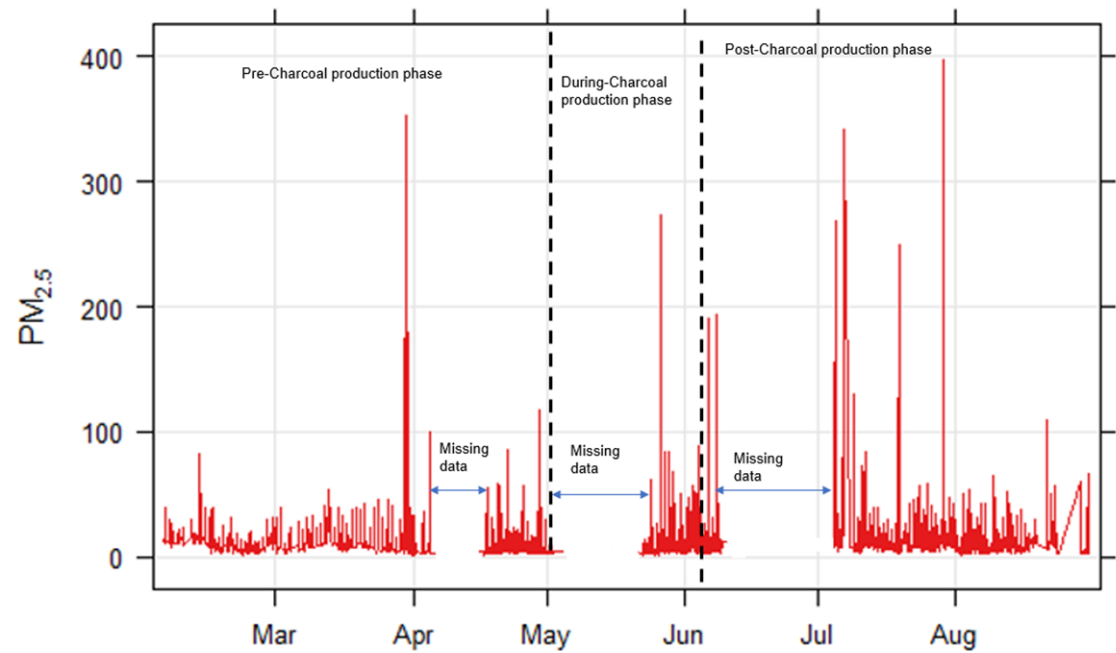
A: Timeseries plot showing CO₂ in the experimentation site



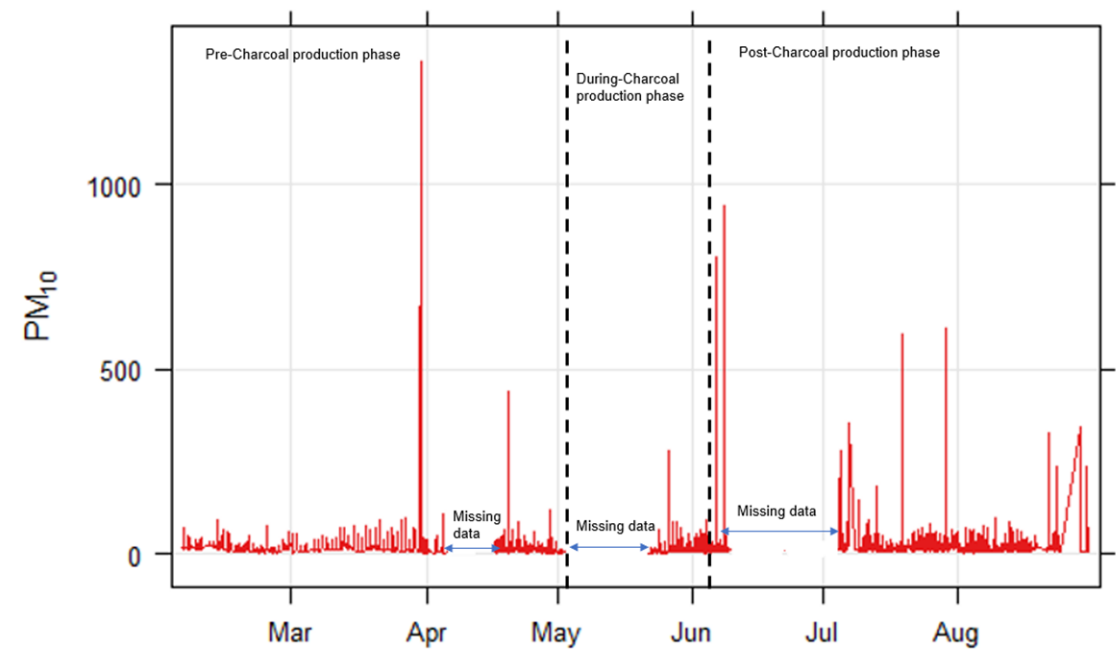
B: Timeseries plot showing PM₁ in the experimentation site



C: Timeseries plot showing $PM_{2.5}$ in the experimentation site

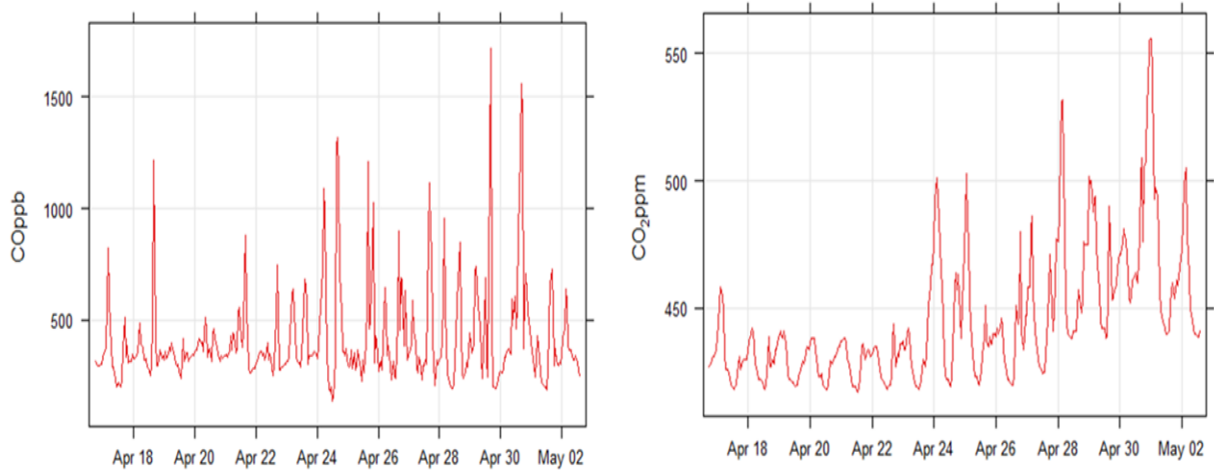


D: Timeseries plot showing PM_{10} in the experimentation site

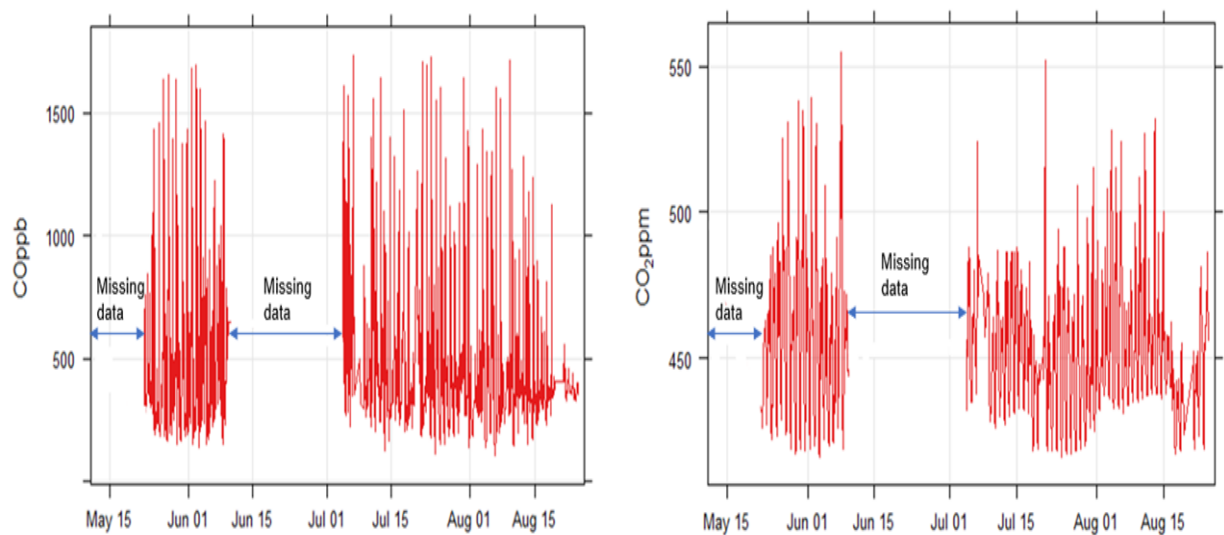


Appendix 6: Other timeseries plots of CO and CO₂ for during and post charcoal production.

A. Timeseries plots of CO and CO₂ during charcoal production phase.

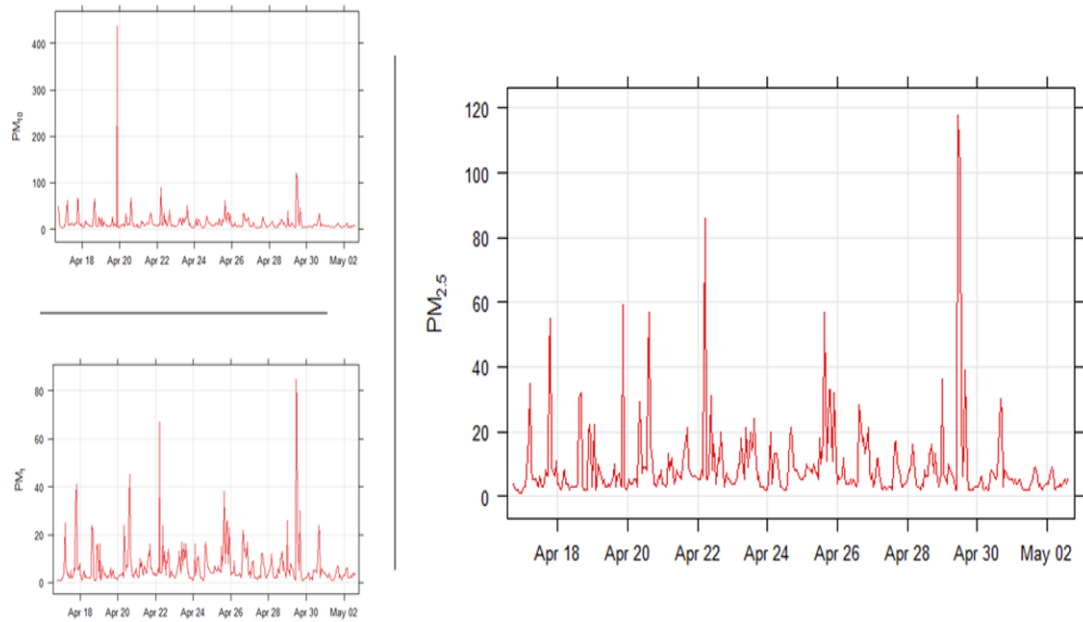


A. Timeseries plots of CO and CO₂ for post charcoal production phase.

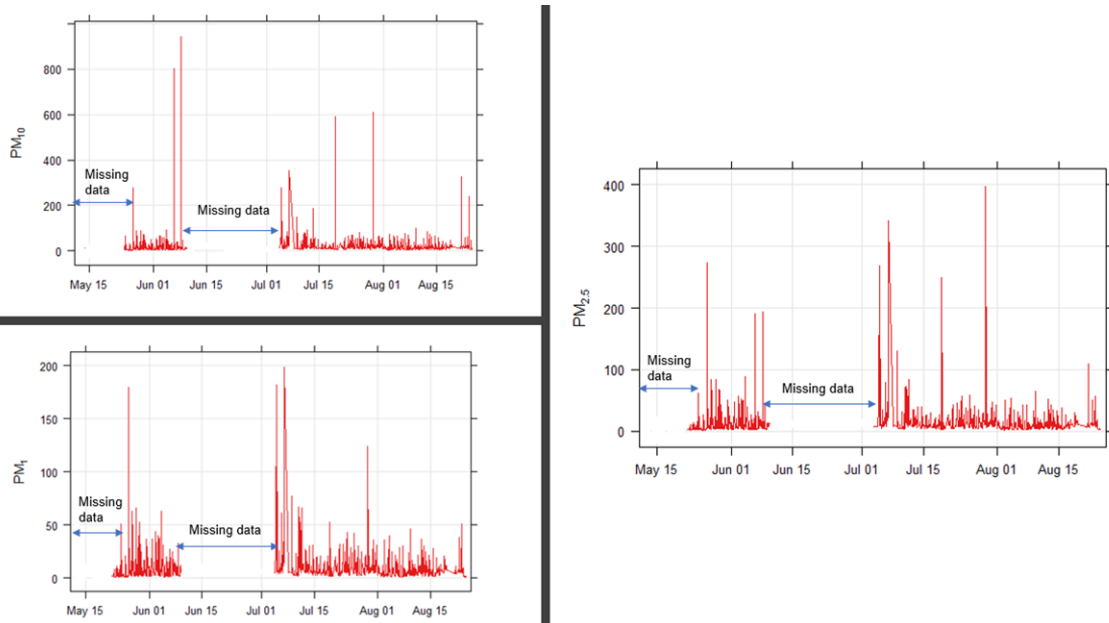


Appendix 7: Other timeseries plots of particulate matter for during and post charcoal production.

A. Timeseries plot of particulate matter for during charcoal production phase;



B. Timeseries plot of particulate matter for post charcoal production phase;

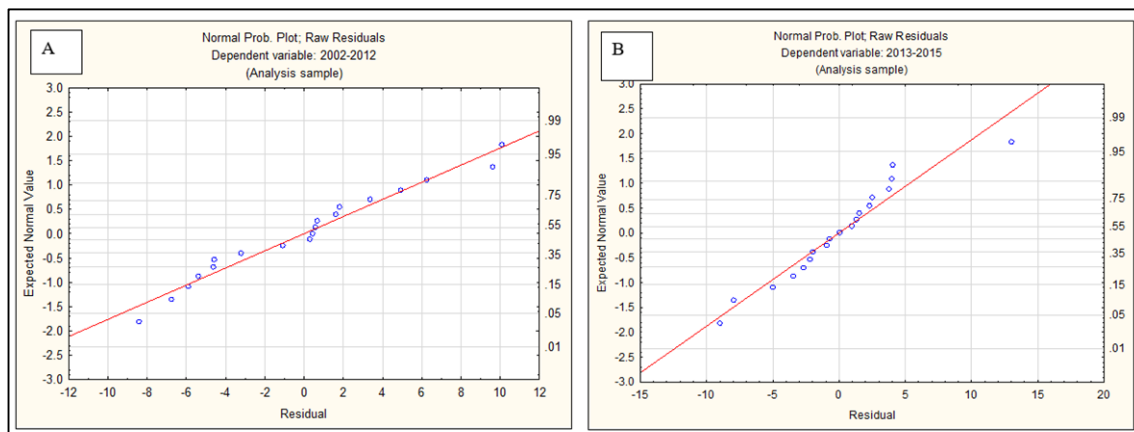


Appendix 8: The be-spoke code downloading wind data used for the analysis that were obtained from Global Forecast System (GFS) of the USA's National Weather Service (NWS).

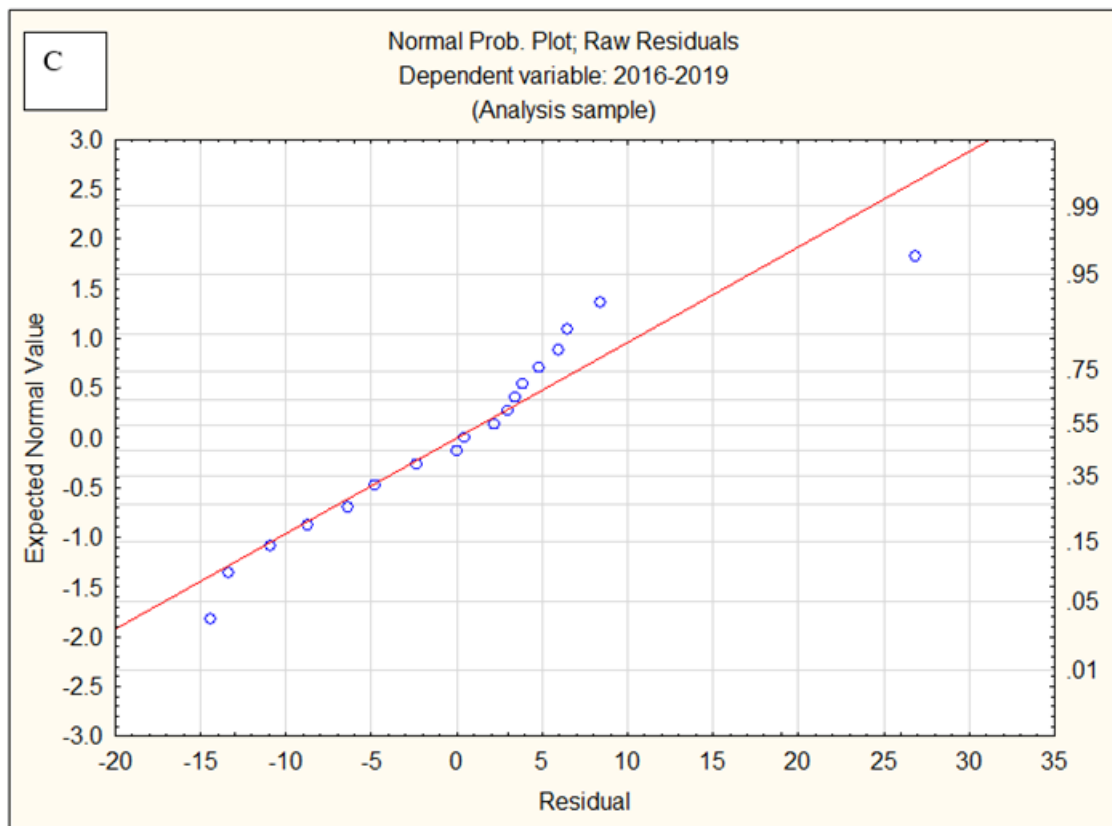
```
43 ## ALL 2018 FOR NOW ##
44 dt <- seq(ymd_hms(paste(2019,01,01,00,00,00, sep="-")),
45           ymd_hms(paste(2019,07,01,00,00,00, sep="-")),by="1 hour")#
46 view(dt)
47
48 ## GENERAL WINDS GET ##
49 ww00 <- wind.d1_2 (dt, 37.34690,37.34692,-3.362469,-3.362484)
50 head(ww00)
51 tidy(ww00)
52 |ww00<-wind.fit(ww00)
53
54
55 view(ww00)
56 names(ww00)
57 ww00v1 <- ww00[c(1,6,7)]
58 names(ww00v1)
59
60 colnames(ww00v1) <- c("date","wd","ws")
61
62 view(ww00v1)
63
64 ###export files#
```

Appendix 9: The residual analysis conducted when detecting statistical significance differences between forest patches against proxy variables.

Figures below showcase the results of residual analysis conducted to test the validity of the analysis. Results indicate that the residuals were normally distributed with 0 mean and constant standard deviation for all the time periods considered (2002-2012, 2013-2015 and 2016-2019). The residual plots showed a slight trend which could indicate the assumption of independence of residuals could have been violated. The plot indicates normal distribution of data over the specified time periods.



(A) and (B): Normal probability plot showing residual distribution of dependent data for 2020-2012 and 2013-205. The plot indicates normal distribution of data over the specified time periods.



(C): Normal probability plot showing residual distribution of dependent data for 2016-2019. The plot indicates normal distribution of data over the specified time

Appendix 10: The comprehensive post-hoc analysis when detecting statistical significance differences between forest patches against proxy variables.

The results in table below show the statistically significant differences between patches. Patch 14 is significantly different ($p < 0.05$) to all the other patches except patches 2 and 13. Other differences detected are between patch 2 and patches 6, 7, 8 and 12. Patch 13 also presents differences when compared to patches 6, 7 and 8. Patch 14 is totally different from other patches maybe due to its large size and the fact that it occupies a large area that lies adjacent the local communities, which quite possibly are involved in charcoal making activities around the area.

Results summarising the post-hoc analysis for patches (LSD test, $\alpha = 0.05$, MSE = 59.058, df = 39.000)

Patch 3	Patch 2	Patch 1	
0.616630	0.059761		Patch 1 3.5833
0.159449		0.059761	Patch 2 9.6667
	0.159449	0.616630	Patch 3 5.1667
0.812315	0.239198	0.461500	Patch 4 5.9167
0.874200	0.209867	0.510571	Patch 5 5.6667
0.107630	0.003772	0.260355	Patch 6 0.0000
0.167121	0.007094	0.372019	Patch 7 0.7500
0.138085	0.005374	0.319032	Patch 8 0.41667
0.580173	0.053391	0.957905	Patch 9 3.4167
0.635241	0.063185	0.978945	Patch 10 3.6667
0.731723	0.082930	0.874200	Patch 11 4.0833
0.510571	0.042399	0.874200	Patch 12 3.0833
0.219328	0.853462	0.087448	Patch 13 9.0833
0.009965	0.209867	0.002628	Patch 14 13.667

Patch 12	Patch 11	Patch 10	Patch 9	Patch 8	Patch 7	Patch 6	Patch 5	Patch 4
0.874200	0.874200	0.978945	0.957905	0.319032	0.372019	0.260355	0.510571	0.461500
0.042399	0.082930	0.063185	0.053391	0.005374	0.007094	0.003772	0.209867	0.239198
0.510571	0.731723	0.635241	0.580173	0.138085	0.167121	0.107630	0.874200	0.812315
0.372019	0.562346	0.477546	0.430363	0.087448	0.107630	0.066775	0.936895	
0.415281	0.616630	0.527538	0.477546	0.102256	0.125162	0.078610		0.936895
0.331773	0.200716	0.249614	0.282826	0.895028	0.812315		0.078610	0.066775
0.461500	0.294559	0.358267	0.400528	0.915931		0.812315	0.125162	0.107630
0.400528	0.249614	0.306628	0.344852		0.915931	0.895028	0.102256	0.087448
0.915931	0.832829	0.936895		0.344852	0.400528	0.282826	0.477546	0.430363
0.853462	0.895028		0.936895	0.306628	0.358267	0.249614	0.527538	0.477546
0.751625		0.895028	0.832829	0.249614	0.294559	0.200716	0.616630	0.562346
	0.751625	0.853462	0.915931	0.400528	0.461500	0.331773	0.415281	0.372019
0.063185	0.119077	0.092171	0.078610	0.008707	0.011390	0.006178	0.282826	0.319032
0.001689	0.004051	0.002827	0.002270	0.000140	0.000193	0.000093	0.014817	0.017982

Patch 14	Patch 13
0.002628	0.087448
0.209867	0.853462
0.009965	0.219328
0.017982	0.319032
0.014817	0.282826
0.000093	0.006178
0.000193	0.011390
0.000140	0.008707
0.002270	0.078610
0.002827	0.092171
0.004051	0.119077
0.001689	0.063185
0.152056	
	0.152056

The results in table below indicate that there are statistically significant differences ($p < 0.05$) between multiple combinations of proxy variables x time. In particular, dark spots for period 2002-12 show differences when compared to dark spots 2013-15, charcoal kiln 2013-15, charcoal kiln 2016-19 and footpaths 2002-12, 2013-16, 2016-19. Dark spots 2002-12 and 2016-19 are different to temporal settlement 2013-15, 2016-19, charcoal kiln 2002-12, 2013-15, 2016-19 and footpaths 2002-12, 2013-15 and 2016-19. Similarly, temporal settlements 2002-12 are also different to temporal settlement 2013-15, 2016-19, charcoal kiln 2013-15, 2016-19 and footpaths 2002-12, 2013-15 and 2016-19. Finally, charcoal kiln 2002-12 showed statistically significant differences when compared to footpaths 2016-19.

Results summarising the post-hoc analysis for the proxy variables against time intervals (LSD test, $\alpha = 0.05$, MSE = 39.341, df = 103.95)

		{1}	{2}	{3}	{4}	{5}	{6}	{7}	{8}	{9}	{10}	{11}	{12}
Proxy	TIME	7.3571	12.357	12.000	8.0000	3.8571	3.1429	5.5000	2.1429	2.1429	0.85714	0.85714	0.21429
Dark spots		2002-2012		0.017116	0.026461	0.786798	0.142868	0.078383	0.435186	0.030059	0.030059	0.007195	0.007195
Dark spots		2013-2015		0.017116	0.862297	0.068929	0.000514	0.000179	0.004656	0.000037	0.000037	0.000004	0.000001

Dark spots	2016-2019	0.026461	0.862297	0.094549	0.000853	0.000306	0.007195	0.000066	0.000066	0.000008	0.000008	0.000003
Temporal settlement	2002-2012	0.786798	0.068929	0.094549	0.046958	0.020427	0.294077	0.015112	0.015112	0.003249	0.003249	0.001394
Temporal settlement	2013-2015	0.142868	0.000514	0.000853	0.046958		0.728742	0.489862	0.471231	0.471231	0.208536	0.208536
Temporal settlement	2016-2019	0.078383	0.000179	0.000306	0.020427	0.728742		0.322391	0.674028	0.337204	0.337204	0.219493
Charcoal kiln	2002-2012	0.435186	0.004656	0.007195	0.294077	0.489862	0.322391		0.105905	0.105905	0.052857	0.052857
Charcoal kiln	2013-2015	0.030059	0.000037	0.000066	0.015112	0.471231	0.674028	0.105905		1.000000	0.588746	0.588746
Charcoal kiln	2016-2019	0.030059	0.000037	0.000066	0.015112	0.471231	0.674028	0.105905	1.000000		0.588746	0.588746
Footpaths	2002-2012	0.007195	0.000004	0.000008	0.003249	0.208536	0.337204	0.052857	0.588746	0.588746	1.000000	0.754932
Footpaths	2013-2015	0.007195	0.000004	0.000008	0.003249	0.208536	0.337204	0.052857	0.588746	0.588746	1.000000	0.754932
Footpaths	2016-2019	0.003249	0.000001	0.000003	0.001394	0.127423	0.219493	0.027924	0.417786	0.417786	0.754932	

The results indicate that there are statistically significant differences ($p < 0.05$) between multiple combinations of forest patches x time. In particular, the three periods describing patch 1 systematically show statistically significant differences

from patch 13 and 14 for period 2002-12, with patch 1 x 2016-19 also showing differences with patch 14 x 2013-15. Patch 2 x 2016-19 also aligns with the general pattern of patch 1. Forest patch 2 for period 2002-12 shows statistically significant differences when compared to forest patch 6 for periods of 2002-12, 2013-15 and 2016-19, forest patch 7 for periods of 2002-12 and 2016-19, for forest patch 8 for periods of 2002-12, 2013-15 and 2016-19, forest patch 10 for period of 2002-12, forest patch 11 for period of 2002-12, forest patch for periods of 2002-12 and 2013-15, forest patch 13 for period of 2016-19. This exact same pattern is observed for patch 3 2002-12. Similarly, forest patch 2 for periods of 2013-15 shows statistically significant different for forest patch 3 for period 2016-19, forest patch 4 for period 2002-12, forest patch 5 for period of 2013-15, forest patch 6,7,8 for periods 2002-12, 2013-15 and 2016-2019, forest patch 9 for periods of 2002-2012 and 2013-15, forest patch 10 and 11 for periods 2002-12, forest patch 12 for period of 2002-12 and 2013-15, for forest patch 13 for period of 2016-19

Differences with patch 13 for 2002-12 and patch 14 for all periods are present across multiple patches, including: patch 3 for 2016-19, patch 4 for 202-12, patch 5 for 2013-15, patch 6 for all periods, patch 7 x all periods, patch 8 x all periods, patch 9 x 2002-12, patch 10 2002-12, patch 11 x 2002-12, patch 12 x 2002-12, 2013-15 and patch 13 x 2016-19. A large proportion of patches (i.e., patch 3 x 2013 x 15, patch 4 x 2016-19, patch 5 x 2016-19, patch 9 x 2016-19, patch 10 x 2016-19, patch 11 x 2013-15, patch 11 x 2016-19, patch 12 x 2016-19, patch 13 x 2013-15) also present differences when compared to patch 13 x 2002-12 and a combination of periods for patch 14. Other differences are also observed across the table but perhaps the most significant left to comment upon is that presented by patch 5 x 2002-12 when compared to path 5 x 2013-15 and 2016 x 19, patch 6 x all periods, patch 7 x all periods, patch 8 x all periods x patch 9 x 2002-12, 2013-15, patch 10, 11 and 12 x 2002-12, patch 12 x 2013-15 and patch 13 x 2016-19

Results summarising the post-hoc analysis forest patches variables against time intervals (LSD test, $\alpha=0.05$, MSE = 39.341, df = 103.95)

Patch x TIME		Patch 1(2002-2012)	Patch 1(2013-2015)	Patch 1(2016-2019)	Patch 2(2002-2012)	Patch 2(2013-2015)	Patch 2(2016-2019)	Patch 3(2002-2012)	Patch 3(2013-2015)	Patch 3(2016-2019)	Patch4(2002-2012)	Patch 4(2013-2015)	Patch 4(2016-2019)	Patch 5(2002-2012)	Patch 5(2013-2015)	Patch 5(2016-2019)	Patch 6(2002-2012)	Patch 6(2013-2015)	Patch 6(2016-2019)	Patch 7(2002-2012)	Patch 7(2013-2015)	Patch 7(2016-2019)	Patch 8(2002-2012)	Patch 8(2013-2015)	Patch 8(2016-2019)	Patch 9(2002-2012)	Patch 9(2013-2015)	Patch 9(2016-2019)	Patch 10(2002-2012)	Patch 10(2013-2015)	Patch 10(2016-2019)	Patch 11(2002-2012)	Patch 11(2013-2015)	Patch 11(2016-2019)	Patch 12(2002-2012)	Patch 12(2013-2015)	Patch 12(2016-2019)	Patch 13(2002-2012)	Patch 13(2013-2015)	Patch 13(2016-2019)	Patch 14(2002-2012)	Patch 14(2013-2015)	Patch 14(2016-2019)
Patch 1 2002-2012			0.95	0.80	0.20	0.08	0.43	0.20	0.87	0.74	0.50	0.07	0.87	0.07	0.57	0.87	0.37	0.37	0.43	0.50	0.47	0.43	0.37	0.47	0.65	0.37	0.96	0.47	0.40	0.54	0.78	0.47	0.43	0.37	0.00	0.37	0.47	0.00	0.37	0.47	0.00	0.07	0.09
Patch 1 2013-2015				0.85	0.18	0.07	0.40	0.18	0.91	0.78	0.54	0.07	0.82	0.06	0.61	0.91	0.40	0.40	0.47	0.54	0.50	0.50	0.61	0.82	0.61	1.00	0.43	0.43	0.50	0.74	0.50	0.50	0.43	0.00	0.34	0.34	0.00	0.26	0.09	0.00	0.06	0.08	
Patch 1 2016-2019					0.13	0.05	0.31	0.13	0.96	0.91	0.65	0.04	0.69	0.04	0.74	0.96	0.50	0.50	0.57	0.65	0.61	0.57	0.74	0.96	0.50	0.50	0.87	0.34	0.54	0.40	0.61	0.57	0.26	0.00	0.00	0.00	0.00	0.00	0.04	0.06	0.06		
Patch 2 2002-2012					0.60	0.56	0.31	0.13	0.96	0.11	0.05	0.61	0.26	0.57	0.07	0.15	0.03	0.03	0.04	0.05	0.61	0.04	0.07	0.12	0.40	0.03	0.18	0.57	0.31	0.61	0.61	0.04	0.05	0.69	0.09	0.04	0.05	0.69	0.09	0.57	0.69	0.69	
Patch 2 2013-2015						0.27	0.65	0.61	0.06	0.04	0.02	0.96	0.12	0.91	0.02	0.06	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.04	0.20	0.01	0.07	0.31	0.26	0.15	0.40	0.40	0.40	0.13	0.40	0.40	0.13	0.40	0.40	0.13	0.40	0.40	
Patch 2								0.61	0.34	0.26	0.15	0.31	0.54	0.29	0.18	0.34	0.09	0.09	0.13	0.12	0.09	0.13	0.18	0.29	0.74	0.09	0.40	0.96	0.11	0.87	0.61	0.87	0.61	0.13	0.12	0.91	0.01	0.91	0.13	0.03	0.29	0.37	0.37

[illegible]

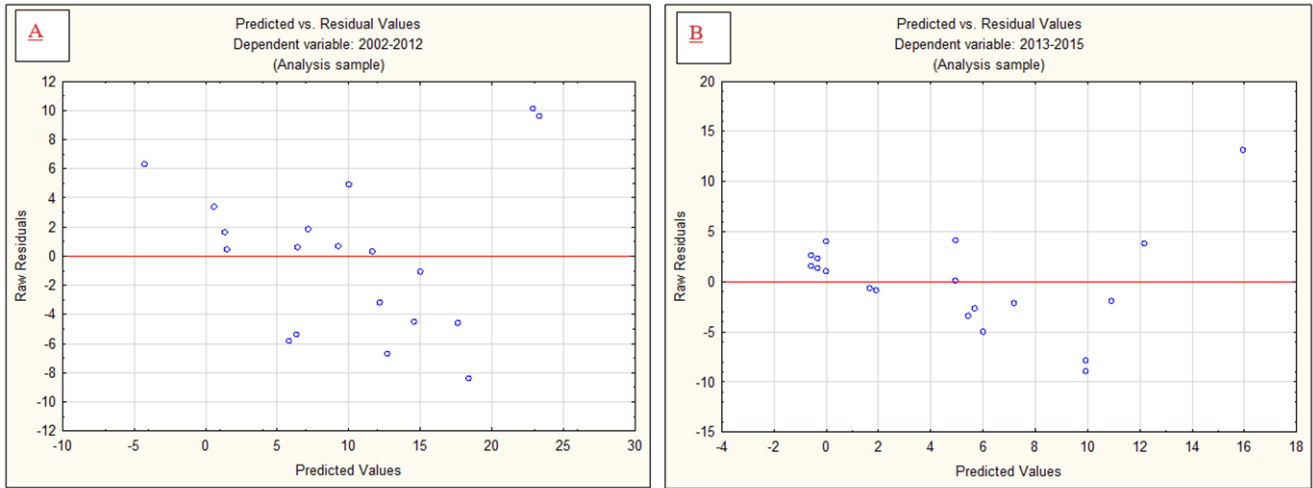
[illegible]

[illegible]

[illegible]

Appendix 10: The residual analysis conducted when detecting Statistically significant differences between land use -land cover and proxy variables.

The result in figure below shows the residual analysis conducted to test the robustness of the ANOVA. Residuals for all time periods considered followed a normal distribution with 0 mean and constant standard deviation. They were randomly distributed and there could be considered independent.



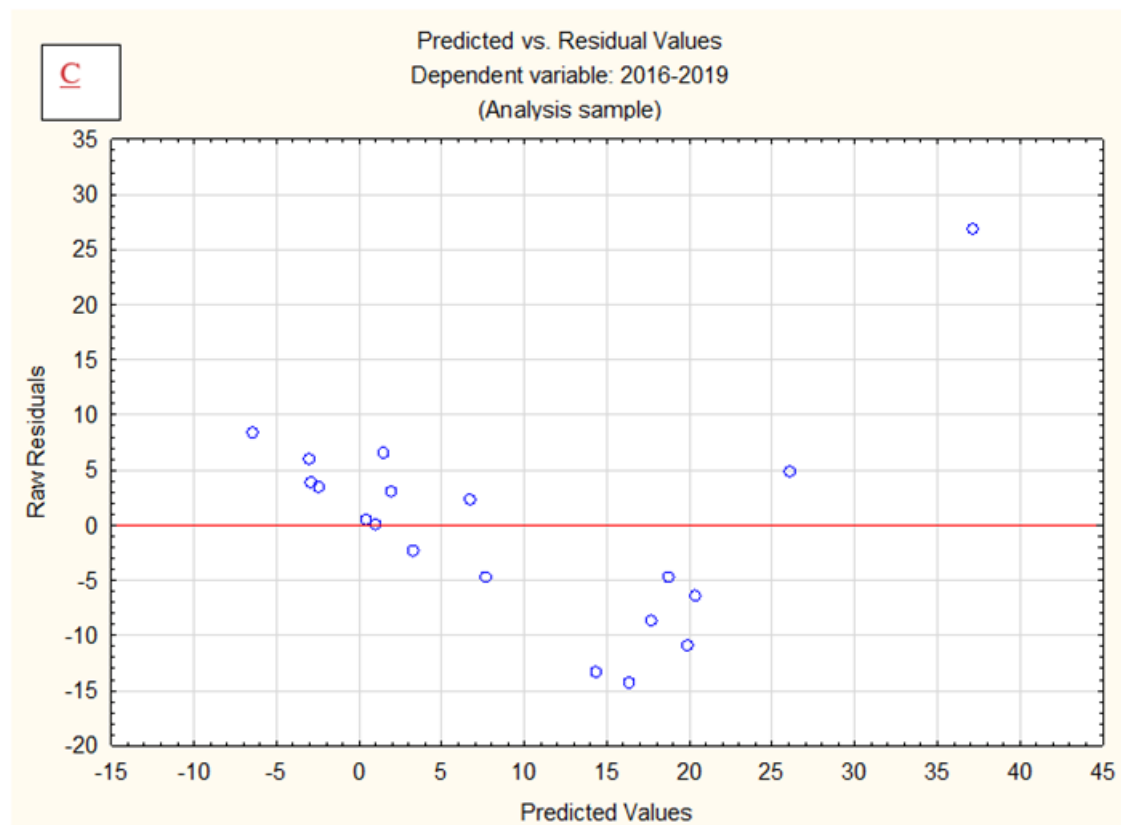


Figure 31 (C): Plot of predicted versus residual values showing independence of data for period of 2016-2019. Results indicates data to be independently over the specified time period.

Appendix 11: The comprehensive post-hoc analysis when detecting statistical significance differences between land use -land cover and proxy variables.

The results in table 4-14 indicate that there are statistically significant differences ($p < 0.05$) between multiple combinations of proxy variables x time. In particular, darkspot variables for 2012-2016 was statistically different from kiln variables for 2013-2015 and 2016-2019, settlement variables for 2013-2015 and footpaths for 2002-2012, 2013-2015 and 2016-2019. Further results indicates that darkspot for 2016-2019 was statistically different from the range of variables that includes kilns variables for 2002-2012, 2013-2015 and 2016-2019, settlement variable for 2013-2015 and 2016-2019, footpaths for 2002-2012, 2013-2015 and 2016-2019, darkspot for 2013-2015. Darkspot for 2012-2012 was statistically different for darkspot of 2013-2015.

Table below shows results summarising the post-hoc analysis proxy variables against time intervals (Between, within, $\alpha= 05$, Pooled MSE = 77.214, df

	Proxy Variable	Kiln (2002-2012)	Kiln (2013-2015)	Kiln (2016-2019)	Settlement (2002-2012)	Settlement (2013-2015)	Settlement (2016-2019)	Footpaths (2002-2012)	Footpaths (2013-2015)	Footpaths (2016-2019)	Darkspot (2002-2012)	Darkspot (2013-2015)	Darkspot (2016-2019)
1	Kiln (2002-2012)		0.125177	0.318706	0.460558	0.73225	0.959999	0.311175	0.380775	0.251222	0.059861	0.859315	0.009604
2	Kiln (2013-2015)			0.571869	0.127199	0.623129	0.43618	0.887222	1	0.776881	0.009604	0.295294	0.001372
3	Kiln (2016-2019)				0.211582	0.847617	0.628989	0.645805	0.749949	0.548722	0.018959	0.460085	0.002777
4	Settlement (2002-2012)					0.07726	0.189316	0.100016	0.127199	0.078026	0.267927	0.565999	0.062418
5	Settlement (2013-2015)						0.622706	0.533081	0.623129	0.450709	0.038057	0.611486	0.006522
6	Settlement (2016-2019)							0.363772	0.43618	0.300019	0.067638	0.82806	0.012273
7	Footpath (2002-2012)								0.801047	0.801047	0.007062	0.237697	0.001003

8	Footpath (2013-2015)									0.615049	0.009604	0.295294	0.001372
9	Footpath (2016-2019)										0.005182	0.189158	0.000734
10	Darkspot (2002-2012)											0.003655	0.125177
11	Darkspot (2013-2015)												0.000077
12	Darkspot (2016-2019)												

Table below shows the results obtained for the post-hoc analysis of time carried out to identify the statistically significant differences in time against land use land cover class. The findings show that there are no statistically significant differences ($p\text{-value} < 0.05$) between variables observed between 2002-2012 and 2016-2019. However, there are statistically significant differences of variables observed between 2002-2012 and 2013-2015 as well as 2013-2015 and 2016-2019. The differences observed between 2002-2012 and 2013-2015 as well as 2013 -2015 and 2019 may be due to paradigm shift of forest management from Central government to agency known as Tanzania Forest Service Agency established in 2009. The agency under Amani nature Conservation developed a management plan that could help to manage the forest. The management of the forest could act as factor for differences observed between land use class and specified time periods.

**Results summarising the post-hoc analysis proxy variables against time intervals
(LSD test, $\alpha = 05$, within MSE = 24.595, df = 22.00)**

Cell No.				
	TIME	2002-2012	2013-2015	2016-2019
1	2002-2012		0.004078	0.651481
2	2013-2015			0.011748
3	2016-2019			

The post-hoc results indicate that there are statistically significant differences ($p < 0.05$) between multiple proxy variables. Specifically, “dark spots” are significantly different to temporal settlements, charcoal kilns and footpaths. Similarly, temporal settlements and footpaths also show statistically significant differences. Results summarising the post-hoc analysis (LSD test, $\alpha = 05$, MSE = 59.058, df = 39.000)

Proxy	Dark spots 10.571	Temporal settlement 5.0000	Charcoal kiln 3.2619	Footpaths .64286
Dark spots		0.001948	0.000092	0.000001
Temporal settlement	0.001948		0.306381	0.013157
Charcoal kiln	0.000092	0.306381		0.126424
Footpaths	0.000001	0.013157	0.126424	

Table below shows the results obtained for the post-hoc analysis of proxy variables carried out to identify the statistically significant differences in proxy variables depicting charcoal making activity between land use land cover class. The findings show that there are no statistically significant differences ($p\text{-value} < 0.05$) between both kiln and footpath proxy variables and dark spots. results summarising the post-hoc analysis of proxy variables against land use class (Test error: $\alpha = 05$, Between MSE = 182.45, df = 11.00)

S/N	Proxy Variable	Kiln 5.0667	Settlement 8.5000	Footpaths 2.0000	Darkspot 17.267
1	Kiln		0.525129	0.546770	0.030928
2	Settlement			0.239891	0.121943
3	Footpaths				0.010190
4	Darkspot				