

**PERI-URBAN AGROSYSTEMS DYNAMICS AND THEIR IMPLICATIONS
ON LAND SUITABILITY FOR VEGETABLE FARMING IN NAIROBI-
MACHAKOS COUNTIES INTERFACE, KENYA**

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Degree of Doctor of Philosophy in Environmental Planning and Management in
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DECLARATION

Declaration by Candidate:

This thesis is my original work and has not been presented for a degree in any other University or for any other award.

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DEDICATION

To my father Ahogle Agassin Hilaire and my mother Ahogle Houessou Paulette for your guidance, wisdom, blessings, and constant support.

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ABBREVIATIONS AND ACRONYMS

AST	: Agricultural Science and Technology
AHP	: Analytic Hierarchy Process
ANOVA	: Analysis of Variance
AR	: Analytical Reagents
AST	: Agricultural Sciences and Technology
ATSDR	: Agency for Toxic Substances and Disease Registry
BCI	: Bacterial Contamination Index
BOD	: Biochemical Oxygen Demand
CDI	: Chronic Daily Intake
CFU	: Colony Forming Units
CI	: Consistency Index
COD	: Chemical Oxygen Demand
CR	: Carcinogenic Risk
CR	: Consistency Ratio
DNA	: Deoxyribonucleic acid
EF	: Enrichment Factor
EPZ	: Export Processing Zone
FAMD	: Factor Analysis of Mixed Data
FAO	: Food and Agriculture Organization
FU	: Farming Unit
GIS	: Geographical Information System
HCPC	: Hierarchical Clustering on Principal Components
HI	: Hazard Index
HQ	: Hazard Quotient
ICP-MS	: Inductively Coupled Plasma Mass Spectrometry
Igoe	: Geo-accumulation index
ISO	: Iterative Self-Organizing
IWQI	: Irrigation Water Quality Index
KEBS	: Kenya Bureau of Standards
KML	: Keyhole Markup Language
KNBS	: Kenya National Bureau of Statistics
LGH	: Large-Scale Greenhouse
LOD	: Limits Of Detection
LOF	: Large-Scale Open Field
LOQ	: Limits Of Quantification
LSA	: Land Suitability Analysis
LULC	: Land Use Land Cover
LWIR	: Long Wave Infrared
MCDA	: Multi-Criteria Decision Analysis
MSAVI	: Modified Soil Adjusted Vegetation Index
MWIR	: Medium Wave Infrared (MWIR),
NACOSTI	: National Commission for Science, Technology, and Innovation
NCWSC	: Nairobi City Water and Sewerage Company
NDVI	: Normalized Difference Vegetation Index

NEMA	: National Environmental Management Authority
OBIA	: Object-Based Image Analysis
PAHs	: Polycyclic Aromatic Hydrocarbons
PCA	: Principal Component Analysis
PCR	: Polymerase Chain Reaction
PI	: Single pollution index
PINemerow	: Nemerow Pollution Index
Pisum	: Sum of Contamination
PLI	: Pollution Load Index (PLI),
PLI	: Pollution Load Index
PS	: PlanetScope
PUA	: Peri-Urban Agriculture
PVI	: Perpendicular Vegetation Index
RG	: Residential Garden
RI	: Ecological Risk
RNA	: Ribonucleic Acid
SAVI	: Soil-Adjusted Vegetation Index
SDGs	: Sustainable Development Goals
SGh	: Small Scale Greenhouse
SOF	: Small-Scale Open Field
SPADNS	: 2-parasulfophenylazo-1,8-dihydroxy-3,6-naphthalene-disulfonate
SVM	: Support Vector Machine
SWIR	: Short-Wave Infrared
TAG	: Trace Analytical Grade
TCR	: Total Carcinogenic Risk
TCU	: True Colour Units
TI	: Thermal Infrared (TI)
TSAVI	: Transformed Soil-Adjusted Vegetation Index
UA	: Urban Agriculture
UPA	: Urban and Peri-Urban Agriculture
USEPA	: United States Environmental Protection Agency
UTM	: Universal Transverse Mercator
UV	: Ultraviolet-Visible Spectrophotometry
VARI	: Visible Atmospherically Resistant Index
VHR-GE	: Very-High Resolution Google Earth
WGS 84	: World Geodetic System 1984
WHO	: World Health Organization
WTP	: Wastewater Treatment Plant

ABSTRACT

Peri-urban agriculture is increasingly becoming important to cities of developing countries for food security, household livelihoods and income generation. However, peri-urban agriculture is often associated with heavy metals, trace elements and bacterial pathogens contamination, which poses serious human and environmental health risks. This study, therefore, assesses the dynamics of peri-urban agrosystems and their implications on land suitability for vegetable farming in Nairobi-Machakos counties interface. The objectives of the study in Nairobi-Machakos counties interface are to 1) to explore the diversity of peri-urban agrosystems and their determinants, 2) to assess irrigation water suitability and the contamination of peri-urban agrosystems, 3) determine the ecological and health risks of peri-urban agro-systems contamination, and 4) model land suitability for vegetable farming. The study used a descriptive correlational research design. Very High Resolution Google Earth imagery analysis and semi-structured questionnaire administered randomly to 130 farming units was used to characterise peri-urban agrosystems. A stratified random sampling method was used to collect irrigation water, soil and vegetable samples in ten vegetable production zones. The samples were processed following standard protocol and tested for water quality parameters, heavy metals and trace elements, and bacterial. Ecological risks were estimated using Hakanson Ecological Index and health risks were estimated using the USEPA framework for human exposure. Land suitability analysis was based on land use, irrigation water quality and accessibility, soil suitability, health risk, landform, and market accessibility considering a current situation (2022) and a future scenario (2030). The findings show that peri-urban farming in Nairobi-Machakos counties interface takes various forms and configurations characterised by different farming scales and diversified resource endowment as influenced by the type of actors, land tenure, irrigation water sources, and market orientations. Irrigation water across the site exhibits high concentrations of dissolved materials and bacterial load, making water quality degraded and thus of marginal suitability for vegetable irrigation. Soil and vegetables show above permissible threshold concentrations of heavy metals and trace elements, with arsenic, cadmium, mercury, and lead exhibiting the highest ecological risks. The potential health risks related to vegetable consumption indicate significant carcinogenic risks. Heavy metals and trace elements contamination in peri-urban farmlands correlate with irrigation water sources and farmland location across the peri-urban interface. Land suitability analysis shows that land use, irrigation water accessibility and quality, and soil suitability are key factors determining land suitability for vegetable farming in the interface. Land suitability modelling show that the current (2022) suitable to highly suitable lands account for 38.3% in dry season and 45.3% in wet season and is expected to drop to 25.2% and 26% in dry season and wet season in the 2030 scenario. The findings imply that there is a non-negligible potential for production of healthy and safe vegetable in Nairobi-Machakos counties interface. However, this potential is undermined by current land development, in which the situation of land use for 2022 has already overruled the expected situation in 2030 for some areas. Considering high peri-urban contamination and increasing reliance on urban hydrological flows for irrigation, there is an urgent need for rational zoning of peri-urban agricultural lands based on land use, water accessibility and quality, and soil suitability, coupled with regular monitoring of public and environmental risks and regulatory enforcement in urban and peri-urban landscapes. Furthermore, the sensitization of the different actors including farmers, urban population, leaders, and experts is important for efficient alleviation of ecological and public health risks.

CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

Agricultural activities in peri-urban landscapes plays a multifunctional and crucial role due to their substantial contribution to urban food systems, employment and income opportunities, ecosystem services and cities' resilience (Zezza & Tasciotti, 2010; Zhu et al., 2018). Peri-urban agriculture (PUA) aids in controlling urban air and thermal temperature generated by expanded impervious land surfaces (Wang et al., 2019). In sub-Saharan Africa, Asia and Latin America, PUA is deeply embedded in citizens' livelihood and not only contributes to urban diet diversification, but also represents an essential source of income from local and international markets (Justus & Yu, 2014; Padgham et al., 2015). Vegetable production from peri-urban landscapes covers more than 60% of the overall vegetable consumed in metropolitan regions (Bellwood-Howard et al., 2015; Artmann & Sartison, 2018).

A growing corpus of literature over the last decade has demonstrated the vital potential of PUA as a transformative asset for food security, cities and communities' resilience, and a framework for climate change mitigation and adaptation (Foeken & Owuor, 2008; Padgham et al., 2015; Ayambire et al., 2019; Gulyas & Edmondson, 2021). Despite these socioecological and economic importance, PUA faces several challenges associated with strong pressure of urbanisation, shaped by diverse human-induced changes characterising peri-urban areas that hinder its productivity and sustainability (Jampani et al., 2020). Rapid urbanization and industrialization in developing countries have led to loss of large-scale farmland and increased land fragmentation in peri-urban areas (Hussain & Hanisch, 2014; Pribadi & Pauleit, 2015). With the surge of intense competitiveness of peri-urban land market,

agricultural lands in peri-urban areas have been increasingly replaced by urban land uses (Kuusaana & Eledi, 2015). Notably, elevated land fragmentation and land speculation in the peri-urban areas of Nairobi has led farmers to abandon farming activities and sell their land (Kinuthia et al., 2020). However, PUA continue to exist in metropolitan areas despite strong urbanisation pressures (Hussain & Hanisch, 2014; Willkomm et al., 2021), residing often on marginal and left over land comprising waste dumping sites, vacant spaces along urban traffics, river reserves, vacant spaces along wastewater treatment plant discharge areas and industrial areas (Nabulo et al., 2010; Ogunkunle et al., 2016; Margenat et al., 2019). In addition, peri-urban farmers rely largely on urban hydrological flows, which are generally subject to substantial contamination with harmful pollutants for farm irrigation (Jampani et al., 2020). Therefore, the consumption of fresh fruit and vegetables from peri-urban agrosystems exposes populations to high intake of harmful contaminants such as heavy metals, trace elements and bacterial pathogens, thus posing severe public health risk concerns (Abass et al., 2015; Tusher et al., 2021; Kumar et al., 2022).

The negative effects of heavy metals and trace elements contamination on human health are numerous, complex to treat, and in severe cases, they can cause death (García-Niño & Pedraza-Chaverri, 2014). Studies have proven that the ingestion of heavy metals and trace elements via food consumption has been correlated with endocrine system diseases, DNA damage, trouble in the immune system, kidney and liver damage, jaundice, and cancer of human the reproductive and nervous systems (Saha et al., 2017). On the other hand, bacterial pathogens' contamination in fresh fruit and vegetables from urban and peri-urban farmlands has been associated with recurrent foodborne disease outbreaks, caused by pathogens like *shigella* spp., *Escherichia coli*, *Salmonella typhi*, *Pseudomonas aeruginosa*,

Enterococcus faecalis and *Vibrio cholerae* (Balali et al., 2020). Bacterial pathogen contamination consequences on human health conditions include personal distress, nausea, vomiting, abdominal pain, diarrhoea, fever and severe outbreaks that can cause widespread deaths (Fung et al., 2018). As result, there is a significant food safety and sustainability concerns related to PUA, especially in metropolitan regions of developing countries (Wynne et al., 2020). Balancing urban development and the preservation of agricultural lands in metropolitan regions is a complex challenge that requires thoughtful planning, policies, and integrated land-use management strategies.

In most developing countries, Kenya included, PUA has remained a transitional land use and overlooked in urban master plans, thus is neglected in land use planning (Ayambire et al., 2019). There are several reasons for this failure in integrating agricultural activities into urban development plans. Land use policies and zoning regulations do not adequately recognize the importance of peri-urban agriculture (Buxton et al., 2016). Priority is often given to expanding urban infrastructure and meeting the demands of the growing urban population. As a result, peri-urban areas are frequently targeted for residential, industrial, and commercial development, leading to the conversion of agricultural land into built-up spaces (Willkomm et al., 2021). The economic potential of these alternative land uses overshadows the significance of PUA, leading to its neglect in the planning process.

Maintaining the potential benefit of PUA in metropolitan regions especially in the developing world need efficient land planning policies and regulations (Pribadi & Pauleit, 2015). Such process needs a spatially explicit understanding of existing forms and arrangements of peri-urban agricultural land uses and their underpinning factors in metropolitan regions (Wynne et al., 2020). There is limited understanding of the dynamic

of peri-urban agriculture around cities and less is known about their underlying factors (Gallaher et al., 2013; Justus & Yu, 2014). These include the prevailing socioeconomic and environmental processes and intertwined factors in place, the state of natural resources such as land and water resources, the extent of health risk and the potential leverage points for suitable policy framework (Poulsen et al., 2015). Furthermore, studies focusing on agricultural land suitability criteria to inform efficient and multi-dimensional peri-urban land use zoning in the global south are strikingly limited (Graefe et al., 2019). There is a need for a new approach to land use planning that can help urban planners and decision-makers incorporate peri-urban agriculture into land use master plans or land use planning. Therefore, two questions that one could ask oneself are: 1) Is it possible to incorporate PUA into urban development plans, not as a transitional but as a permanent land use, despite the risks of contamination in peri-urban areas? 2) Which criteria and approaches could be implemented to do so? This study proposes an integrated and location specific framework for assessing agricultural land suitability in peri-urban areas, considering the complex dynamics of peri-urban land uses, urban hydrologic flows, contamination risks and market opportunities.

1.2 Statement of the Problem

Fresh fruit and vegetable farming constitutes a quick-return economic activity in the Nairobi metropolitan region, given the huge and attractive market opportunity of its high population (Zezza & Tasciotti, 2010; Justus & Yu, 2014). It is noted that peri-urban farming in the region is conducted on marginal lands such as waste dumping sites, vacant spaces along urban traffic, river reserves, vacant spaces along industrial areas, and wastewater

treatment plants, which are potentially contaminated with various pollutants (Karanja et al., 2010). Crop production relies substantially on urban flows including sewage effluent, drainage canal flows, rivers water and industrial effluents, leading to crop contamination with harmful pollutants (Sayo et al., 2020; Tomno et al., 2020). Fresh fruits and vegetables supplied to the metropolitan region of Nairobi are implicitly contaminated with pollutants such as heavy metals, trace elements and bacterial pathogens posing severe public health risks (Koskei et al., 2017). Peri-urban farmland contamination is exacerbated by poor management of urban and industrial waste, poor sanitation and development of informal settlements (Musyoki et al., 2013b; Koskei et al., 2017). Besides, the lack of supportive policies and regulations hampers the growth of PUA in the outskirts of Nairobi (Ayaga et al., 2005; Padgham et al., 2015). Therefore, the sustainability of PUA in the region needs urban planning strategies that recognize and incorporate agricultural activities in policy towards zoning regulations, land tenure security, and incentives for urban farmers.

Research studies have been conducted on environmental contamination in Nairobi metropolitan region (Karanja et al., 2010; Inoti et al., 2012; Mungai et al., 2016; Njuguna et al., 2017; Mungai & Wang, 2019; Njuguna et al., 2019; Tomno et al., 2020) but the understanding of the extent of contamination risks in peri-urban agrosystems is still inadequate. Graefe et al. (2019) pointed out that scientific reports addressing the gap in heavy metals, trace elements and bacterial pathogens contamination in urban and peri-urban agriculture (UPA) is still huge with only 3.6% and 1.7% of the overall literature on UPA, respectively. There is a dearth understanding of metal elements and bacterial pathogens contamination in peri-urban farmlands from which fresh fruits and vegetables are supplied to the Nairobi metropolitan markets (Mng'ong'o et al., 2021). Little is also

known about the spatial distribution of these pollutants at small-scale farmland level, which is important for local planning policy and zoning in the region.

Studies assessing land suitability for vegetable farming in peri-urban areas considering the eccentricity of these landscapes and the potential risks of contaminations are scarce in the body of literature, especially for African metropolitan areas like Nairobi. Most land suitability studies focused on improving crop yield or land productivity at large scale cash crop production. Moreover, the understanding of the specific attributes and complexity of peri-urban agrosystems, which is necessary in informing policy makers and planners on the relevant criteria for agricultural land zoning in peri-urban landscapes has been so far overlooked. Little effort has been directed to the elaboration of a framework for safe and sustainable vegetables farming in Nairobi-Machakos peri-urban interface, which this study focusses on. This study provides valuable data for upscaling decision-making for rational zoning of agricultural land which will help maintain the benefits of PUA in peri-urban landscapes.

1.3 Objectives of the Study

The general objective of the study is to assess the dynamics of peri-urban agrosystems and their implications for land suitability for vegetable farming in Nairobi-Machakos counties interface.

The specific objectives are:

1. To explore the diversity of peri-urban agrosystems and their determinants in Nairobi-Machakos counties interface.

2. To assess irrigation water suitability and the contamination of peri-urban agrosystems in Nairobi-Machakos counties interface.
3. To determine the ecological and health risks of peri-urban agrosystems contamination in Nairobi-Machakos counties interface.
4. To model land suitability for vegetable farming in Nairobi-Machakos counties interface.

1.4 Research Hypothesis

The hypotheses tested in this thesis are:

- H₁: The typology of peri-urban agrosystems is determined by their socioeconomic attributes.
- H₂: Irrigation water across Nairobi-Machakos peri-urban interface is unsuitable for vegetable farming.
- H₃: Concentrations of heavy metals and trace elements and bacterial pathogens loads across peri-urban agrosystems in Nairobi-Machakos counties interface are above the permissible thresholds for agricultural production.
- H₄: Ecological and health risks related to peri-urban agrosystems contamination are significant in Nairobi-Machakos counties interface.
- H₅: Peri-urban land suitability is a function of land use, irrigation water quality, soil contamination, health risks and market accessibility.

1.5 Justification of the Study

PUA plays a multi-functional role, including food security, employment opportunities, poverty alleviation, and environmental sustainability in metropolitan regions (Gallaher et al., 2013; Lwasa et al., 2014). In Kenya, the sector employs directly about 4.5 million people in production, processing, and marketing for the international market, while another 3.5 million people are indirectly engaged through commercial and non-farm-related activities (Justus & Yu, 2014). PUA has gained significant attention in Nairobi metropolitan region in the recent years as a response to the challenges of food insecurity and poverty alleviation (Foeken & Mwangi, 2000; Karanja et al., 2010; Foeken, 2013; Gallaher et al., 2013; Gallaher et al., 2015; Ogendi et al., 2019). As the city grows and the population increases, there is a rising demand for fresh and affordable food. Peri-urban agriculture helps to bridge the gap between food production and consumption by providing locally grown fruits, vegetables, and other agricultural products (Hide et al., 2001; Ayaga et al., 2005). However, vegetable production in peri-urban interface is hampered by land shortage and contamination risks, notably with heavy metals, trace elements and bacterial pathogens (Kaluli et al., 2011; Nyandika et al., 2020). Through daily intake of vegetable, the metropolitan population can be exposed to substantial health risks (Ogunkunle et al., 2016). Addressing the challenges of PUA and ensuring its sustainability in metropolitan regions like Nairobi requires deep understanding of the multi-faceted dynamics of PUA in terms of economic, social, and ecological characteristics.

The peri-urban interface of Nairobi-Machakos counties was purposefully chosen firstly due to its extensive stream network, including Nairobi and Athi Rivers and their tributaries, that favour year-round irrigation of fresh fruits and vegetables that are supplied to Nairobi

metropolitan markets (Langat et al., 2019). Secondly, the area is located on the fast-growing peri-urban interface of Nairobi City, which is substantially influenced by environmental contamination related to poor sanitation and waste management (Ngumba et al., 2016). Thirdly, the major wastewater treatment plants (WTP) in the area Dandora, Kariobangi, and Export Processing Zone (EPZ) discharge 80,000; 11,000 and 61,943 m³/day in the river network (Kilingo et al., 2021). Studies assessing wastewater treatment processes in these WTPs by Maina et al. (2020) and Wafula et al. (2020) concluded that the treatment processes were inadequate and not efficient in reduction of metal elements and bacterial pathogens, hence the effluents discharged to the streams do not comply with the standards for discharge to the environment. Moreover, the sewer coverage in Nairobi and Machakos counties are 51% and 14%, respectively, which is yet to reach the peri-urban interface leading to diversion of large portion of domestic sewage and industrial effluent into the rivers (Kinuthia et al., 2020). Therefore, the urban streams are fed with urban wastewater, raw and partially treated sewage, and industrial effluents (Wichelns et al., 2011; Li et al., 2017a). Despite that advisory, the rivers' water is still used by over four million people downstream for industrial, irrigation and even for domestic purposes (Njuguna et al., 2017). Fourthly, Nairobi is the capital of Kenya with a population estimated about 4.4 million in the 2019 population census (KNBS, 2019), which constitutes a huge market for PUA products.

In recent years, there has been a growing awareness of the importance of PUA for cities resilience and sustainability in most developing countries (Foeken & Owuor, 2008; Gallaher et al., 2013; Ayerakwa, 2018). Despite this increasing awareness, the development and implementation of tangible land use policies supporting PUA has been relatively

limited. Most land use policies primarily focus on urban development, neglecting the importance of integrating agriculture into the urban fabric (Hussain & Hanisch, 2014). This omission often leads to conflicts between urban expansion and agricultural land, resulting in the loss of valuable farmland and a decline in food production (Forkuor & Cofie, 2011; Follmann et al., 2021a). In that context, vegetable farming in metropolitan regions like Nairobi is conducted on marginal lands, which are subject to urban pollution and improper waste disposal, exposing cultivated crops to various contaminants (Ayambire et al., 2019). Maintaining the multifunctionality of peri-urban agrosystems require informed understanding of the dynamics of these farming systems, the extent of prevailing contamination risks and land suitability evaluation approach which can inform efficient land use zoning for healthy and sustainable vegetable farming.

1.6 Significance of the Study

With land and water resources competition and contamination risks in peri-urban regions, vegetable production faces challenges due to lack of supportive land use zoning policies. There is limited empirical data accessible to policymakers at local and regional scales on the potential of PUA and planning approaches that could elucidate PUA integration in planning processes. Without comprehensive information, it becomes challenging to advocate for PUA inclusion in metropolitan master plans and land use policies. The study fills this knowledge gap by providing understanding of the different attributes of PUA in Nairobi-Machakos counties interface including existing forms, their spatial configurations, and the implications of resources such as soil and water contamination for health risks.

Peri-urban farming is considered as a transitional land use and conducted generally on small plots (Ayambire et al., 2019). Therefore, most studies on land suitability evaluation are focused on cash crop, staple crop with large-scale farming or high value horticultural crop production for export market. This research provides a spatially explicit land suitability model for safe and sustainable vegetable farming that gives a framework for rational zoning of PUA in the peri-urban interface. This defines the areas where cultivation of healthy vegetables could be conducted, giving insights for rational land use zoning and implementation of remediation measures.

Land suitability for vegetable farming guides decision-making processes related to land use planning, agricultural development, and sustainable resource management in peri-urban areas and fosters a healthier urban environment. By preserving agricultural land within peri-urban landscapes, cities will benefit from improved air quality, reduced heat island effects, and enhanced aesthetic appeal. The study illustrates a scenarios of land suitability for the year 2030, giving signals on key determinants for sustainable inclusion of PUA in the land use planning process toward resilient cities. It provides upscaling data for harnessing the potential of PUA and maintaining a balance between urban growth and peri-urban farmlands in Nairobi-Machakos counties interface and beyond.

The study provides farmers, policymakers, urban planners, and scientists with valuable data and decision-making tools for sustainable and healthy food production in peri-urban landscapes. The research contributes to increasing agricultural productivity and resilience in peri-urban areas, thereby contributing to improved access to healthy and nutritious food.

For farmers and agricultural practitioners in Nairobi and Machakos counties, this research offers practical guidance on optimizing land use for vegetable farming. By identifying

suitable areas for cultivation and understanding the factors influencing land suitability, farmers can make informed decisions about adequate areas, irrigation methods, and soil management practices. Understanding how peri-urban agrosystems' dynamics affect land suitability can guide decisions related to zoning, infrastructure development, and resource allocation in peri-urban areas.

The study touches on several Sustainable Development Goals (SDGs) 2030 of the United Nations that target sustainable living conditions and a safe and resilient environment. These include SDG 1 (no poverty), SDG 2 (zero hunger), SDG 6 (clean water and sanitation), SDG 11 (sustainable and resilient cities and communities), and SDG 13 (climate action). It also contributes to Goal 5 of the Africa agenda 2063, which desires prosperous agricultural productivity with emphases on agricultural system modernisation for increased productivity and production. Furthermore, the study aligns well with the Chapter 4 of Kenya's Vision 2030 (Government of the Republic of Kenya, 2007), which directs efforts towards achieving food security, affordable housing, manufacturing, and affordable healthcare.

1.7 Conceptual Framework

This study conceptualizes the sustainability of PUA in metropolitan regions as a result of the combined influence of land use zones, irrigation water accessibility and quality, soil suitability, health risks, landform, and market opportunities (Fig. 1.1). The study conceives that peri-urban agrosystem typology (PUA typology) combined with land use determine land use zones, which represent relatively uniform subregions of the study area having the same opportunities and limitations for vegetable farming.

The access to irrigation water and its quality are very important for fresh vegetable production and represent a critical challenge for PUA products safety (Abass et al., 2015; Bozdağ et al., 2016). Peri-urban farmers rely on contaminated urban hydrologic flows for farm irrigation (Randhawa & Marshall, 2014; Jampani et al., 2020). The study conceives irrigation water accessibility and quality as a result of the joint effect of irrigation water accessibility, irrigation water quality index, and bacterial contamination index.

Soil suitability is an important factor for PUA because soil properties influence nutrients availability and contaminants mobility (Akıncı et al., 2013). In addition, peri-urban soils are prone to more disturbance, contamination, and degradation related to urban land uses unlike rural soils (Buxton et al., 2016; Tresch et al., 2018). The study theorises soil suitability as function of soil types and Pollution Load Index (PLI), which is the extent to which heavy metals and trace elements contamination can affect agricultural production. Health risks represent the potential carcinogenic and non-carcinogenic risk factors related to vegetable consumption or soil material ingestion/inhalation/dermal contact, which can have deleterious effects on human health conditions (Bai et al., 2017). The landform, represented by slope and elevation, is important for land suitability for vegetable farming because it influences water flows and infiltration, erosion risk, and nutrients and pollutants' mobility (Memarbashi et al., 2017). Finally, market accessibility is important for peri-urban farmers to sell their products (Khoury et al., 2014). Market accessibility is evaluated as a combined effect of market destinations, road proximity, and the closeness of residential areas.

The independent variables of land suitability for vegetable farming are land use zones, irrigation water accessibility and quality, soil suitability, health risks, landform, and market

accessibility, which exhibits some interrelations (Fig. 1.1). Irrigation water quality and accessibility influences soil suitability and health risks, while land use zones influence soil suitability, irrigation water accessibility and quality and health risks (Bai et al., 2017). Landform influences soil suitability, which also influences health risks.

The intervening variables of land suitability for vegetable farming consists of land use planning policies, regulations, standards, and enforcement measures (Fig. 1.1), that influence land use zones, irrigation water accessibility and quality, soil suitability, health risks and market accessibility (Ma et al., 2020). Planning policies are guidelines and regulations by governments at various levels (local, regional and national) that define how land can be used, what type of development is allowed, and any restrictions or requirements that developers and property owners must follow. Regulations susceptible to influence PUA include regulations for wastewater discharge in the environment (National Environmental Management Authority-NEMA) and regulation irrigation water quality (NEMA, WHO). Standards refer to specific national or international criteria, guidelines, or benchmarks that must be met to ensure quality, safety, and environmental sustainability. Some of the standards used in this study include Irrigation Water Quality Index, Bacterial Contamination Index, Pollution Load Index, Hazard Index and Total Carcinogenic risks. Enforcement is the process of ensuring that land use regulations are adhered to, and that developments and activities comply with the established rules. Effective enforcement mechanisms are necessary to maintain order, protect public interests, and achieve the intended outcomes of planning policies, regulations, and standards.

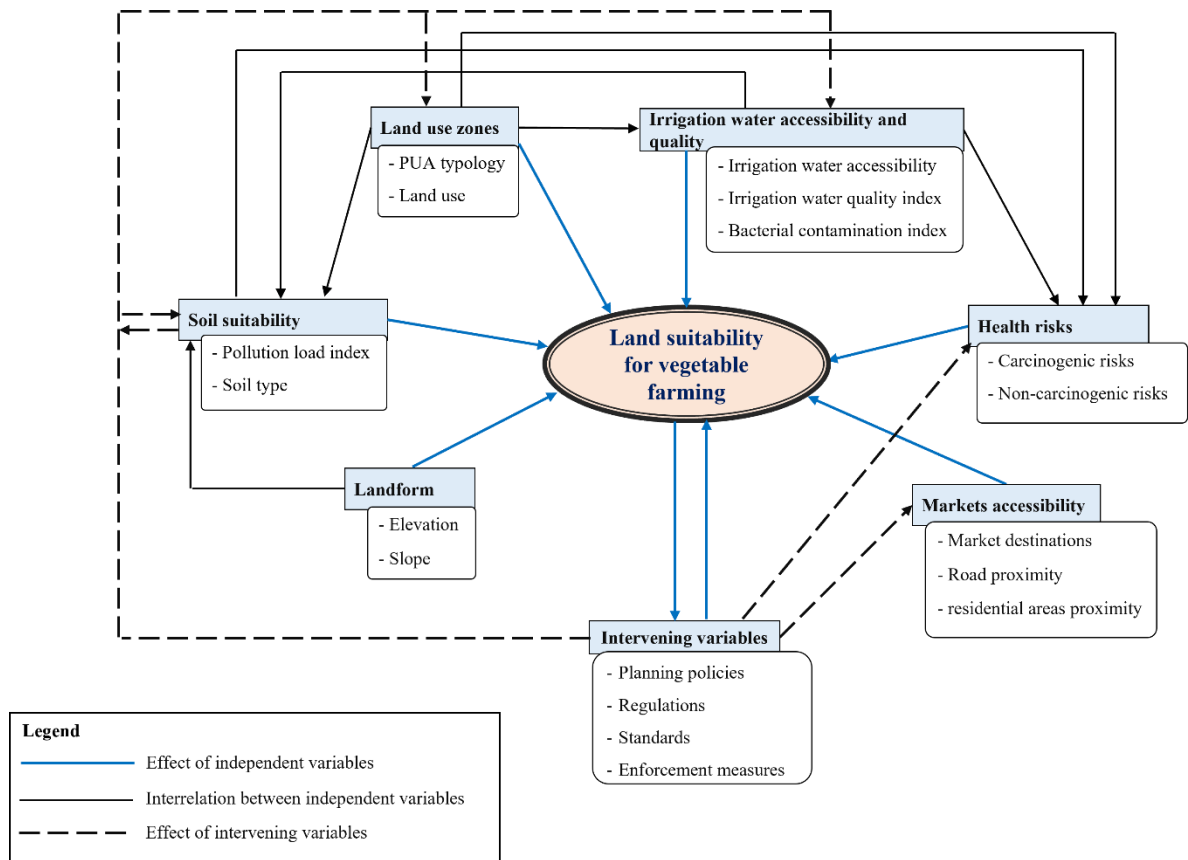


Figure 1.1: Conceptualising land suitability for vegetable farming in Nairobi-Machakos counties interface

1.8 Definition of Terms of the Study

Peri-urban agriculture (PUA) refers to agricultural activities and practices that take place in areas on the outskirts of urban centres, where urban and rural landscapes intersect. This form of agriculture often involves the cultivation of crops, raising of livestock, and other agricultural activities in close proximity to urban areas. PUA faces also various challenges such as land tenure issues, competition for land, environmental degradation, and conflicts between agricultural and urban land uses.

Peri-urban areas refer to areas on the outskirts of urban centres, characterised by a mix of urban and rural features, often undergoing rapid transformation due to urbanization pressures.

Peri-urban agrosystems refer to agricultural systems in peri-urban areas. These agrosystems encompass a complex interplay of agricultural activities, natural resources, infrastructure, and human settlements. Peri-urban agrosystems typically involve a mix of traditional and modern agricultural practices, including crop cultivation, livestock rearing, agroforestry, and aquaculture, or a combination of different type. The study focuses on peri-urban agrosystems for vegetable farming.

The dynamics of peri-urban agrosystems refer to the ever-changing patterns, processes, and interactions within peri-urban agricultural systems. It encompasses factors such as urbanization pressures, land use changes, socioeconomic dynamics, technological advancements, environmental pollution and degradation, and policy influences that shape the functioning and structure of agrosystems on the outskirts of urban areas.

Irrigation water suitability pertains to the appropriateness or fitness of water for use in irrigation purposes. It involves assessing various water quality parameters such as pH, salinity, nutrient levels, heavy metal concentrations, and microbial contamination to ensure that the water meets the requirements for efficient crop irrigation without causing adverse effects on soil, plants, or human health.

Tap water, also known as faucet water or mains water, refers to water that comes directly from a faucet or tap in a building, typically supplied by a municipal water system. It is the primary source of drinking water for many people around the world. Tap water undergoes treatment processes to ensure it meets safety standards and is generally safe for

consumption. The specific treatment methods can vary but often include filtration, disinfection (usually with chlorine or chloramine), and sometimes additional processes to remove contaminants. Although alternative water sources like underground or borehole water can be used as a household water supply, often dispensed through a tap or faucet system installed within houses, in this study the term tap water is restricted to the above definition. In Nairobi tap water is provided by the Nairobi City Water and Sewerage Company (NCWSC).

Health risks are potential hazards to human health or the environment arising from various factors associated with agricultural activities in peri-urban areas. Health risks often include exposure to chemical contaminants from pesticides or fertilisers, microbial pathogens and heavy metals and trace elements from irrigation water or soil, air pollution from agricultural machinery or burning of crop residues, and food safety concerns related to pesticide residues or microbial contamination of vegetables.

Land suitability for vegetable farming refers to the capacity of a plot to support successful and sustainable vegetable cultivation. It involves assessing factors such as soil quality, health risks, climate conditions including temperature, rainfall, and sunlight, topography, access to quality irrigation water, the presence of pests and diseases, and socioeconomic considerations such as market demand and land tenure systems. Land suitability assessments help determine the feasibility and potential productivity of vegetable farming activities in a given area.

Nairobi-Machakos Counties Interface is the transition zone between Nairobi County and Machakos County in Kenya, likely characterised by interactions between urban and rural activities, infrastructure, and land use patterns.

Implications stand for the consequences or effects of peri-urban agrosystem dynamics on land suitability for vegetable farming, including both challenges and opportunities for agricultural production and sustainability in the region.

1.9 Chapter Outline

This thesis is structured in six chapters. Chapter one presents the background of the study, statement of the problem, objectives, hypothesis, justification, significance, and conceptual framework of the study. Chapter two reviews literature on the dynamics and sustainability of peri-urban agricultural production, its multidimensional and multifunctional attributes, the challenges of its subsistence, and health concerns. This chapter also discusses PUA characterisation frameworks and land suitability modelling approaches. Chapter three provides a description of the study area, materials and methods implemented in data collection and analyses. Chapter four presents and discusses the findings per objective. Chapter five presents the summary of findings, conclusion, and recommendations as well as perspectives for further research.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter presents key concepts of peri-urban agrosystems and peri-urban agriculture. It reviews the existing body of literature on the dynamics of peri-urban agro-systems and underlines contamination risks from heavy metals, trace elements, and bacteriological pathogens. It further explores policy and regulations on peri-urban agriculture in Kenya and the techniques and tools used for PUA characterisation and modelling. The key terminologies used in this chapter are represented according to their importance in the word cloud in Fig. 2.1.



Figure 2.1: Key terminologies in Chapter 1

2.2 Concept of Agrosystems in Urban-Rural Continuum

Agrosystems, also known as agroecosystems or agricultural systems, are complex units of agricultural activities that are spatially and functionally coherent, with different

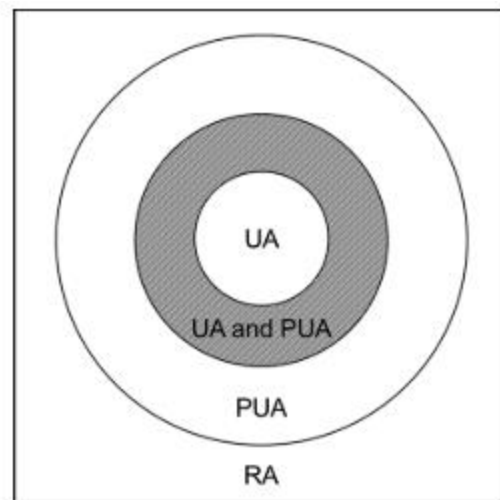
components integrated in diverse interactions (Hodgson, 2012; Loeuille et al., 2013). Agrosystems are in different forms based on purposes of production, resource endowment, species in situ, agro-ecological zones, geographical location, and socioeconomic characteristics of the communities or actors involved (Dossa et al., 2011; Alvarez et al., 2018). Urban agriculture (UA) and peri-urban agriculture (PUA) are two types of agricultural production systems that have gained significant attention in recent years, especially in the context of city resilience and sustainability (Pearson et al., 2011; Orsini et al., 2013; Pribadi & Pauleit, 2016; Ayerakwa, 2017; Nkrumah, 2019). While both forms of agriculture occur in urban areas or metropolitan regions, they differ in terms of their spatial, ecological, and socioeconomic characteristics (Opitz et al., 2016). UA, also referred to as intra-urban agriculture, denotes the cultivation of crops or livestock rearing within the city limits, either on small plots of land or in community gardens (Mougeot, 2000; Lovell, 2010). UA occurs within the developed areas of the city system and is characterised by small farm sizes, and farmland owners live generally close to their farms. Besides, UA is associated with high land use conflicts with non-agricultural land users and substantial evidence of adaptation to space scarcity, such as vertical farming and sack gardening (Gallaher et al., 2013; Thornton, 2018; Ayambire et al., 2019). Individuals or small groups often practice UA for subsistence or local sales in farmers' markets. It can provide fresh produce, create green spaces, and foster community connections (Thornton, 2008).

PUA is also known as urban fringe agriculture or metropolitan agriculture (Heimlich, 1989; Bryant, 1997; Bryant, 2014) and occurs in the transition zone between rural and urban areas, where urban and rural expansion processes meet and interact (Opitz et al., 2016). PUA is typically larger in scale than urban agriculture, can involve both crop production and livestock rearing, and is fully market-oriented production. Also, PUA is

characterised by low land use conflicts due to the relatively legal or transitional status of the farms, their absence, or low space-related issues, even though there is an influence of land fragmentation and speculation (Opitz et al., 2016). Peri-urban areas are generally characterised by lower population densities, less infrastructure development, and limited natural and agricultural resources, and hence are distinct from rural areas (Zasada et al., 2011). PUA faces challenges due to urban pressures but also benefits from its proximity to urban markets, leading to a shift in socio-cultural practices from rural to urban lifestyles (Ayambire et al., 2019). Thebo et al. (2014), while comparing UA and PUA for the purpose of establishing distinct demarcations, suggested that PUA take place within a buffer zone of 10 to 20 km of the urban geographic boundary. However, considering the dynamic variations in urban development and how they are influenced by geographical, historical, political, and socioeconomic variables, UA and PUA types do not exist in completely different geographic places (Opitz et al., 2016). The authors stressed that in many contexts, there is an overlapping zone between the location that could be characterised as the zone of UA and that of PUA (Fig. 2.1). Because of this uncertainty and the highly dynamic attributes of peri-urban environments, the geographic location of farming in the metropolitan environment is not sufficient by itself to distinguish UA from PUA.

Despite these dissimilarities, UA and PUA have both great potential, which makes them vital for urban food systems. Both face comparable challenges, such as the pressures of urbanisation, land use conflicts, water scarcity, pollution, and the associated health risks and soil degradation, which require appropriate policy, planning, and regulation measures to ensure their sustainability (Padgham et al., 2015; Abo-El-Wafa et al., 2017). Lovell (2010) suggested that the advocacy of preserving agricultural land in metropolitan regions in the contest of land competition and rising land prices should be

based not only on its production functions alone but also on its multifunctionality, multiple services, and benefits.



Source: Opitz et al. (2016)

Figure 2.2: Illustration of peri-urban agriculture (PUA) in urban-rural continuum

2.3 Multifunctionality of Peri-urban Agriculture as a Driver of Socio-Ecological Transformation

PUA plays a multifunctional role in urban and peri-urban landscapes (Feifei et al., 2009; Pribadi et al., 2017). PUA contributes to urban food systems and constitutes a sheer means of survival for a wide range of the population in urban centres (Hardman & Larkham, 2014; Olsson et al., 2016). It contributes to raising the urban poor's income and improving their social lives (Nchanji & Bellwood-Howard, 2018). Zezza & Tasciotti (2010) demonstrate that 30–70% of urban inhabitants in sub-Saharan Africa (SSA) are involved in PUA (Pribadi et al., 2017). It is a source of full- or part-time employment not only for farmers but also for stakeholders involved along the value chain (Azunre et al., 2019). In urban and peri-urban landscapes, PUA contributes significantly to ecosystem services such as waste recycling, biodiversity preservation, microclimate regulation, air renewal, and ecotourism (Pham et al., 2023). PUA supports the socioeconomic and environmental sustainability of cities (Crush et al., 2011). The

implications of the multifunctional attributes of PUA are more overwhelming for developing countries compared to developed countries due to the prevailing food insecurity and poverty in urban and peri-urban populations (Zasada et al., 2011; Jampani et al., 2020; Spataru et al., 2020). PUA contributes to women's empowerment and gives them the opportunity to participate in decision-making processes related to agricultural production (Hando & Mitke, 2022; Rao et al., 2022). For example, women make up two-thirds of the urban farmer population in Yaoundé (Cameroon), Maputo (Mozambique), Nairobi (Kenya), and Kampala (Uganda) (Prain & Lee-Smith, 2010). For urban poor households, farming in urban areas, whichever the conditions are, is their single means of livelihood (Olivier, 2019). However, the multifunctionality of PUA is influenced by a range of factors, *i.e.*, land tenure, access to water and other resources, market opportunities, and the regulatory framework. Understanding these factors is important for the sustainability of PUA and its potential in metropolitan regions.

2.4 Peri-Urban Agriculture and the Sustainable Development Goals (SDGs) 2030

Peri-urban agriculture has a great potential for contributing to the achievement of different goals of the United Nations Sustainable Development Goals (SDGs) 2030 (Nicholls et al., 2020), including SDGs 1, 2, 3, 5, 8, 11, 12, 13, and 15. The contributions of PUA towards these SDGs are summarized in Table 2.2.

Table 2.1: PUA contribution to Sustainable Development Goals (SDGs) 2030

SDGs	Contributions	References
SDG 1: No Poverty	PUA helps in alleviating poverty by creating employment opportunities, improving food security, and generating income for communities	Karg et al. (2019); Foeken & Owuor (2008); Pribadi & Pauleit, 2016); Zezza & Tasciotti (2010)
SDG 2: zero hunger	PUA contribute to improve the access to fresh and nutritious food for urban and peri-urban populations, contributing to alleviate food insecurity. It has been reported in various studies that households with access to peri-urban agriculture exhibits higher dietary diversity and consumed more fruits and vegetables.	Ayerakwa (2017); Khumalo & Sibanda (2019); Zezza & Tasciotti (2010)
SDG 3: Good Health and Well-being	PUA contributes to improve good health and well-being conditions by providing access to fresh and healthy food. A diet rich in fruits and vegetables is associated with lower risk of cardiovascular diseases, blood pressure-related diseases, some cancers, and diabetes.	Newman et al. (2015); Butu & Rodino (2019); Clatworthy et al. (2013)
SDG 5: Gender Equality	PUA provides women with enhanced access to resources, income opportunities, and decision-making power. It has the potential to empower women in challenging traditional gender roles and promote their active participation in community's livelihood. Studies has reported that women who participate in PUA have exhibited better income and greater decision-making power in the households.	Robertson (2013); Rao et al. (2022); van den Bold et al. (2015)
SDG 8: decent work and economic growth	PUA creates job opportunities along the production chain from farm labourers, food transporters, farm products' vendors to actors in export market systems, representing an essential source of income for both local and international markets, thus contributing to decent work and economic growth. It is estimated that 266 million urban households are engage in one way or another in peri-urban farming activities	Angeles & Hill (2009); Hamilton et al. (2014); Foeken (2013)
SDG 11: sustainable cities and communities	PUA promotes local food systems, presence of green spaces and service in metropolitan regions, promote sustainable land use practices and contribute to reduce the carbon footprint of food production. Various studies demonstrated the great potential of PUA in reshaping cities in rapidly urbanizing regions	Azunre et al. (2019); La Rosa et al. (2018); Pribadi & Pauleit (2016); Chen et al. (2023)
SDG 12: consumption and production	PUA promotes sustainable food production; reduction of food waste, sustainable land use and biodiversity conservation	De Zeeuw et al. (2011); Nicholls et al. (2020); Butu & Rodino (2019)
SDG 13: climate action	PUA contributes to biodiversity conservation, soil conservation; water conservation and carbon sequestration	Wang et al. (2019); Lwasa et al. (2015); Mulya et al. (2023)

2.5 Characteristics of Peri-urban Agriculture and Market Orientation

PUA has become increasingly important in many developing countries in Asia and Africa as urbanisation and population growth continue to drive demand for food (Bai et al., 2017). PUA in developing countries is characterised by high heterogeneity and complexity due to cultural and socioeconomic factors, environmental differences, institutional frameworks, policies, and regulations in place. PUA resides mostly on marginal lands and often lacks legal status in developing countries (Bryld, 2003; Hamilton et al., 2014). Due to this complexity and heterogeneity, peri-urban farmlands exhibit a diversity of characteristics, which makes their comparison generally challenging. Ayambire et al. (2019) classify peri-urban farmlands into four categories based on their location: a) backyard gardening, b) building-integrated farming models, c) farming on marginal lands or interim use of idle city land, and d) emerging soil-free farming models and container farming/gardening. Farmland location can be influenced by factors such as socioeconomic, institutional, and geographical designations, which can influence access to land and water resources, benefits and costs, and the participation of farmers in decision-making at the local level (Binns et al., 2012). Farmland classification based on farming scale is generally challenging because it can be influenced by many factors, including geographical and cultural factors. Mougeot (2000) stressed that PUA in developing countries can be categorised into three types based on the scale of farming, small-scale subsistence farming, medium-scale commercial farming, and large-scale agribusiness.

Small-scale subsistence farming is characterised by small plots of land and low levels of productivity. The focus of this type of farming is primarily on producing food for household consumption rather than for commercial purposes (Omiti et al., 2009; Gallaher et al., 2015).

Medium-scale commercial farming involves larger plots of land and higher levels of productivity than small-scale subsistence farming. Farmers engage in this type of farming for commercial purposes and often sell their produce in nearby urban areas (Abdulkadir et al., 2012; Scoones et al., 2018).

Large-scale agribusiness involves large-scale farming operations that are often owned by multinational corporations (Willkomm et al., 2021). These farms use modern technologies and methods to produce high yields of crops and livestock for both domestic and international markets. However, a classification of urban and peri-urban agriculture by Willkomm et al. (2021) in Nakuru, a medium city in Kenya by exhibited four types, smallholder production, intensive small-scale open-field production, large-scale greenhouse production and large-scale greenhouse production. The ownership and control of land used for PUA vary widely across different regions and countries, while the scale of production is often determined by factors such as access to capital, technology, and market opportunities (Dossa et al., 2011).

The types of crops grown or animal husbandry in PUA also vary depending on the local environment and market demands, while the environmental impacts of PUA depend on the type of production system used (Abdulkadir et al., 2012). The form of PUA is a function of the type of activities considered, which generally includes include market gardening, livestock rearing, aquaculture, tree cropping, dairy farming, beekeeping and backyard gardening (Mougeot, 2000; Dossa et al., 2011). PUA appears more often in different combination of the forms of farming because of maximisation of income on a small plot (Alvarez et al., 2018; Musafiri et al., 2020). Although the definition of PUA include livestock, livestock activities are less common than cropping activities in PUA (Bellwood-Howard et al., 2015). However, there are cases in which livestock rearing

represent about one third of the farmers engaged in UA and PUA (Zezza & Tasciotti, 2010).

2.6 Dynamics of Peri-Urban Farming in Developing Countries

PUA in developing countries has undergone significant changes in recent years, driven by urbanization (Hussain & Hanisch, 2014; Pribadi & Pauleit, 2015; Follmann et al., 2021a; Follmann et al., 2021b; Willkomm et al., 2021). As cities grow and expand, peri-urban areas have become more densely populated and urban infrastructure has encroached on agricultural land. This has led to changes in land use patterns and farmers shifting from traditional crops to quick return crops such as fresh fruits and vegetables that are more profitable in small scale farming (Hussain & Hanisch, 2014; Willkomm et al., 2021).

Urbanization has led to loss of agricultural land and the fragmentation of remaining agricultural areas. As agricultural lands are being converted into urban areas, farmers face challenges related to land tenure insecurity, competition for resources (land use conflicts), limited access to production resources (water), water pollution, limited access to market, infrastructure and weak institutional framework (Follmann et al., 2021a). For example, the dynamics of peri-urban agriculture in Nakuru, Kenya showed that the spatiotemporal changes in the region were characterised by a combination of replacement and intensification processes (Willkomm et al., 2021). Replacement refers to the conversion of agricultural land to urban uses such as housing, commercial and industrial development, and transportation infrastructure, whereas intensification refers to increasing productivity of existing agricultural land by use of improved technologies, high yielding farming practices, and intensive use of input. In the face of these dynamics and challenges, farmers have developed resilience by adopting new farming practices,

such as using high-yielding crop varieties, investing in irrigation, applying more chemical fertilisers and pesticides or diversifying their income streams to include non-agricultural activities (Hussain & Hanisch, 2014; Pribadi & Pauleit, 2015; Follmann et al., 2021a; Willkomm et al., 2021). Follmann et al. (2021b) highlighted in peri-urban farming in Nakuru, Kenya, that there is a shift towards more market-oriented PUA with many farmers focusing on producing high-value crops such as fruits and vegetables for urban markets. Nevertheless, these changes have also brought challenges, increased competition, higher input costs, and environmental pollution and degradation (Hussain & Hanisch, 2014). The adaptive behaviour of peri-urban farmers is influenced by a range of factors such as access to information and resources, market dynamics, and government policies (Pribadi & Pauleit, 2015; Pribadi et al., 2017; Follmann et al., 2021b).

The underlying mechanisms shaping the dynamic of PUA in developing countries cut across a range of factors including land tenure systems, urban policies and regulations, market forces, and social and cultural norms. Previous studies analysing the dynamics of PUA in developing countries (Hussain & Hanisch, 2014; Pribadi & Pauleit, 2016; Jampani et al., 2020) concluded that policies aiming at promoting PUA should take into account the complex interactions between these factors and provide support for farmers to adapt to changing conditions. This support could include measures improving land tenure security, access to credit and markets, and promoting sustainable farming practices and efficient land use zoning (James & O'Neill, 2016; Gray et al., 2020).

2.7 Contamination and Health Risks in Peri-urban Agrosystems

Farming in urban and peri-urban areas is associated with various environmental and health concerns. These include among others the risk of contamination of farm products

with harmful pollutants such as heavy metals and trace elements, pesticides residues (organophosphates, carbamates, organochlorines), polycyclic aromatic hydrocarbons (PAHs), microbial pathogens (bacteria, viruses and fungi), air pollutants (particulate matter and nitrogen oxides) and Plastic pollutants. This study focuses only on heavy metals and trace elements and bacterial pathogens, which are the prominent contaminants in urban and peri-urban farming (Karanja et al., 2010; Abass et al., 2016).

2.7.1 Heavy Metals and Trace Elements Contamination in Peri-Urban Agriculture

Heavy metals and trace elements are ubiquitous in the environment and are toxic for humans, animals, and plants. They enter the food chain through the soil-plant-animal-human pathway, and thus posing a significant threat to food safety and human health. Heavy metals and trace elements contamination in peri-urban agriculture can originate from various sources, including industrial activities and municipal and industrial wastewater (Saha et al., 2017). Industrial activities, including mining, smelting, and manufacturing, are significant sources of heavy metals and trace elements contamination in peri-urban agriculture (de Vries et al., 2013). Industrial emissions and waste discharges can result in the deposition of heavy metals and trace elements in soil and water, which can then be absorbed by plants (Bradl, 2005; Mwesigye et al., 2016). Studies have shown that the accumulation of heavy metals and trace elements in crops grown in the vicinity of industrial areas is significantly higher than those grown in rural areas (Khan et al., 2021). Due to freshwater scarcity, wastewater is commonly used for irrigation in PUA, especially in developing countries. However, wastewater contains high levels of heavy metals and trace elements, which accumulate in soil and crops; thus, posing significant risk to food safety and human health (Karanja et al., 2010; Kinuthia et al., 2020). Studies have reported that crops grown with wastewater irrigation

have higher levels of heavy metals and trace elements than those grown with freshwater irrigation (Tomno et al., 2020; Kumar et al., 2022). The accumulation of heavy metals and trace elements in crops is exacerbated by overuse of agrochemicals (fertilizers and pesticides), leading to soil contamination, and leaching into water sources. Fertilizers containing phosphorous, can contain heavy metals such as Cd, Pb, and Zn, which accumulate in the soil and plant tissues (Naccarato et al., 2020) and some pesticides contain heavy metals such as copper and zinc (Zhang et al., 2019).

2.7.1.1 Distribution of Heavy Metals and Trace Elements in Peri-Urban Agrosystems

The distribution of heavy metals and trace elements in peri-urban agrosystems is influenced by various factors, including soil properties, crop types, and land use patterns. Soil properties, including pH, organic matter content, and cation exchange capacity affect the distribution and bioavailability of heavy metals and trace elements. Studies have shown that soils with low pH and high organic matter content tend to have higher levels of heavy metals and trace elements, as they can form complexes with organic matter, reducing their availability for plant uptake (Liu et al., 2018; Wierzbowska et al., 2018; Yan et al., 2020). However, soils with high cation exchange capacity adsorb heavy metals and trace elements and thus, reduce their mobility and bioavailability in soil solution (Liu et al., 2018).

Heavy metals and trace elements accumulation in plant tissues varies between plant species and varieties of a specific specie in some cases. Previous studies have demonstrated that leafy vegetable have higher propensity to heavy metals and trace elements accumulation compared to fruit vegetable and other crops (Hu et al., 2021). Among leafy vegetables, kale, spinach and lettuce, have demonstrated higher predilection in accumulating metals elements (Mutune et al., 2014; Zhou et al., 2016).

This is because leafy vegetables have large surface, which facilitates the uptake of heavy metals and trace elements from soil and water.

Land use patterns, including urbanization, industrialization and mining can significantly influence the distribution of heavy metals and trace elements in PUA (Chang et al., 2014; Mwesigye et al., 2016). These anthropogenic activities result in discharge of high quantity of heavy metals and trace elements in soil, air or water; thus, increasing their availability in soil and uptake by plants (Zhang et al., 2019; Zhu et al., 2019). Therefore, land use should be carefully monitored to minimize heavy metal and trace element contamination diffusion in agricultural lands.

2.7.1.2 Health Risks Related to Heavy Metals and Trace Elements Contamination

Heavy metals and trace elements have significant health impacts on humans, depending on the exposure level, duration, and route of exposure. Acute exposure to high levels of heavy metals and trace elements results in various health effects, including gastrointestinal distress, neurological symptoms, and respiratory problems (ATSDR, 2019). For example, acute exposure to lead causes abdominal pain, headache, and vomiting, while acute exposure to cadmium causes diarrhoea, fever, and abdominal pain (ATSDR, 2019). Chronic exposure to low levels of heavy metals and trace elements also results in various health effects, including developmental and cognitive disorders, cancer, and cardiovascular diseases (Szalontai et al., 2021). The chronic exposure to Pb can result in developmental delays and cognitive impairments in children, while chronic exposure to cadmium increases the risk of lung cancer and cardiovascular diseases (Kim et al., 2014). High concentrations of Zn and Cu interfere with redox reactions and cause oxidative stress (Hübner & Haase, 2021). The exposure of young children to Pb causes

mental retardation and delays in mental development (Hsueh et al., 2017). Li et al. (2019) and Zeng et al. (2021) noted that exposure to cadmium causes glomerula and metabolism alteration. Metals such as Hg and Pb are endocrine-disrupting chemicals responsible for metabolic dysfunction.

Humans' exposure to As, Cd, Hg, Cu, and Cr is associated with acute and chronic kidney diseases, brain and lungs damage, mental retardation and developmental delay (USEPA, 2009; Oyoo-Okoth et al., 2012; Hsueh et al., 2017; Lentini et al., 2017). Exposure to a high concentration of manganese (Mn) increases the incidence of lung-related illnesses such as bronchitis and cough (Szalontai et al., 2021). Chronic exposure to Hg, Cu, Cr and Cd is associated to alteration of reproduction functions (Bhardwaj et al., 2021). Accumulation of Cd, Pb, Cu, Hg and Cr in human organs has been correlated with liver damage and cancer (Mishra et al., 2019). Similarly, Pb, Cd, As and Hg ingestion in humans through food has been reported to cause cardiovascular-related diseases (Guo et al., 2022). The intake of Cr, Cu and Zn in humans is associated with gastrointestinal-related diseases, pancreas dysfunction and anaemia (Bilal et al., 2020). Severe immunological disorders have been linked to prolonged intake of As, Cd, Pb, Cu and Hg (Manwani et al., 2022). M. h. Wei et al. (2021) pointed out that the intake of Cd and Pb affects bones and exposure to soil materials rich in As and Cr induces skin-related diseases. The deleterious effect of Ni contamination on human health includes cancer in the respiratory system, allergy, dermatitis, and organs dysfunction (Seilkop & Oller, 2003). These acute effects are more likely to occur in individuals with high occupational exposure, such as miners and industrial workers (Kerin & Lin, 2010). In addition, chronic effects related to metals elements are more likely to occur in individuals who consume contaminated food and water over a prolonged period (Żukowska & Biziuk, 2008).

2.7.1.3 Risk Assessment of Heavy Metals and Trace Elements Contamination

Risk assessment is a crucial tool for evaluating the potential health risks associated with heavy metals and trace element contamination in peri-urban agriculture. Risk assessment involves four steps: hazard identification, exposure assessment, dose-response assessment, and risk characterisation (Barrio-Parra et al., 2019). Hazard identification involves identifying the potential health hazards associated with heavy metals and trace element contamination in peri-urban agriculture. This involves reviewing the available literature on the toxicity of different heavy metals and trace elements, as well as their levels in soil, water, and crops. Exposure assessment involves estimating the levels of exposure to heavy metals and trace elements in peri-urban agriculture (USEPA, 2022). This involves measuring the levels of heavy metals and trace elements in soil, water, and crops, as well as estimating the dietary intake of contaminated food. Dose-response assessment involves evaluating the relationship between exposure to heavy metals and trace elements and the risk of adverse health effects (Yang et al., 2021). This involves reviewing the available literature on the toxicology of different heavy metals and trace elements, as well as their dose-response relationships. Risk characterisation involves combining the results of hazard identification, exposure assessment, and dose-response assessment to estimate the overall risk associated with heavy metal and trace element contamination in peri-urban agriculture (Kamrin, 2014). This involves calculating the probability of adverse health effects occurring at different exposure levels, as well as identifying the most significant sources of risk.

Several mitigation strategies can be implemented to minimize heavy metal and trace element contamination in PUA, including soil management, water management, and crop management. Soil management strategies aim to reduce the levels of heavy metals

and trace elements available in soil by preventing their deposition and promoting their immobilization or removal. For example, soil amendments such as lime, phosphate, and organic matter can increase soil pH, reduce the availability of heavy metals, and promote plant growth (Karalić et al., 2013; Li et al., 2023). Phytoremediation involves use of plants or organisms to remove or immobilize heavy metals from soil, hence an effective soil management strategy. For example, algae, as photosynthetic organisms, have shown great potential for heavy metal bioremediation due to their unique properties (Ankit et al., 2022). Crop rotation and intercropping can contribute to reduce heavy metals and trace elements' accumulation in soil (Yang et al., 2017).

Water management strategies aim to minimize the levels of heavy metals and trace elements in irrigation water and prevent their runoff into nearby water bodies. This can be achieved by using alternative sources of water, such as rainwater harvesting, and treating irrigation water before use (Rossi, 2022). Conservation tillage and cover cropping can reduce soil erosion and prevent the deposition of heavy metals and trace elements in water bodies (Cooper et al., 2020). Crop management strategies that aim to minimize the uptake of heavy metals and trace elements by crops entail selecting appropriate crops or using non-edible crop with high metal elements uptake to reduce metal elements available in the soil (Wang et al., 2021).

2.7.1.4 Testing Methods for Heavy Metals and Trace Elements

Heavy metals and trace elements can accumulate in soils, water, and plant tissues including vegetables. Therefore, laboratory testing is essential for environmental monitoring and risk assessment. Testing for heavy metals and trace elements is usually conducted through chemical analysis of soil, water or plant tissue samples. The most common methods for heavy metal and trace element analysis in soil include atomic

absorption spectroscopy (AAS), inductively coupled plasma-optical emission spectroscopy (ICP-OES), and inductively coupled plasma-mass spectrometry (ICP-MS) (OMMU, 2020). Water testing for heavy metals and trace elements can be performed through various laboratory techniques such as AAS, ICP-OES, and ICP-MS. However, the sample preparation for water analysis is often more complex due to the low concentrations of these substances in water samples. Therefore, preconcentration methods such as solid-phase extraction (SPE) and cloud point extraction (CPE) are often employed to enhance the sensitivity of the analysis (Hall et al., 2022). Vegetable testing for heavy metals and trace elements is essential to ensure the safety of the food consumed. Methods used for heavy metal and trace element testing in vegetable include atomic absorption spectrometry (AAS), inductively coupled plasma-atomic emission spectrometry (ICP-AES), and inductively coupled plasma-mass spectrometry (ICP-MS) (Medvedev et al., 2018).

The AAS is used for the quantitative determination of metal elements in liquid or solid samples. It works based on the principle that free atoms in a sample absorb light at specific wavelengths, which is proportional to the concentration of the metal (García & Báez, 2012). AAS has relatively low sensitivity and selectivity compared to the other techniques, but it is simple, cost-effective, and can analyse several metals but not at simultaneously in one run. ICP-AES is used for the quantitative determination of metal elements in liquid or solid samples. It works based on the principle that the atoms in a sample emit light at specific wavelengths when excited by plasma. ICP-AES has higher sensitivity and selectivity compared to AAS, and it can analyse a wide range of metals simultaneously (Robin, 2016). However, it requires a more complex and expensive instrument compared to AAS, and it is prone to spectral interferences that can affect the accuracy of the analysis.

ICP-OES is used for the quantitative determination of metal and non-metal elements in liquid samples. It works based on the principle that the atoms or ions in a sample emit light at specific wavelengths when excited by plasma. ICP-OES has higher sensitivity and selectivity compared to AAS, and it can analyse a wide range of metals and non-metals simultaneously. It is also less prone to spectral interferences compared to ICP-AES (Proch & Niedzielski, 2022). However, it is still relatively expensive compared to AAS, and requires careful sample preparation to avoid matrix effects.

ICP-MS is used for the quantitative determination of metal and non-metal elements in liquid or solid samples. It works based on the principle that the ions in a sample are converted into charged ions and then separated based on their mass-to-charge ratio. ICP-MS has extremely high sensitivity and selectivity compared to AAS, ICP-AES, and ICP-OES and can detect and quantify trace elements in samples (Bressy et al., 2013; Yeung et al., 2017). It can also analyse a wide range of elements simultaneously, making it a powerful tool for environmental and biological applications. However, ICP-MS is the most expensive and complex of the four analytical techniques, and it requires careful monitoring and control of potential interferences such as isobaric interferences and polyatomic ion interferences.

2.7.2 Bacterial Pathogens Contamination in Peri-Urban Agriculture

Bacterial pathogen contamination in PUA refers to the presence of harmful bacteria in soil, water, vegetable, or edible part of crops (Alegbeleye et al., 2018). These bacteria cause various diseases and infections in humans and animals, and are transmitted through contaminated food, water, material, and soil. Most observed bacterial pathogens in peri-urban agrosystems include coliform bacteria *Escherichia coli*, *Shigella* spp., *Pseudomonas aeruginosa*, *Enterococcus faecalis*, *Vibrio cholerae* and

Salmonella spp. (Karanja et al., 2010; Abass et al., 2015). The risk of bacterial pathogen contamination in PUA is particularly high in developing countries, where access to clean water and proper sanitation services is still limited. For example, Abass et al. (2015) reported that bacteria such *E. coli* and *P. aeruginosa* were frequently detected in vegetables grown in urban and peri-urban areas in Ghana; in Tanzania, Kapeleka et al. (2020) found that *V. cholerae* was present in both irrigation water and lettuce samples collected from urban farms. Karanja et al. (2010) and Onyango et al. (2018) reported a strong correlation between serious health conditions and the presence of *E. coli* (up to $6.4 \times 10^5 \pm 2.1 \times 10^6$ CFU/100 mL), *S. typhi* (up to $1.6 \times 10^3 \pm 1.1 \times 10^3$), *P. aeruginosa* (up to $3.5 \times 10^3 \pm 1.8 \times 10^3$ CFU/100 mL), *Staphylococcus aureus* (up to 1.3×10^5 CFU/100 mL) and *V. cholerae* (up to $1.5 \times 10^3 \pm 1.7 \times 10^2$) in irrigation water in peri-urban farmlands in Nairobi (Kenya). Kiiru et al. (2012) noted 63% vegetable samples positive to faecal coliforms and 22% positive to *S. typhi* in Nairobi peri-urban areas. The authors pointed to the use of untreated sewage effluent for irrigation as the source of bacterial contamination.

2.7.2.1 Distribution of Bacterial Pathogens in Peri-urban Agro-Systems

The occurrence of bacterial contamination in PUA is influenced by several factors, including the use of contaminated irrigation water, soil, or fertilizer, improper handling of animal manure, disposal of human waste in or near agricultural sites, use of untreated or partially treated wastewater for irrigation, and lack of proper hygiene practices by farmers and consumers (Marti et al., 2017). Most peri-urban farmers rely on irrigation water from polluted sources, such as rivers and streams, which can contain high levels of pathogenic microorganisms (Abass et al., 2015). Also, bacterial pathogens originate from improper handling of animal manure. Mao et al. (2021) established that immature poultry manure is vector of both *Salmonella* spp. and *E. coli* in PUA.

Bacterial pathogens adherence to plant are either through irrigation or irrigation water splash on contaminated soil particle (Keraita et al., 2012). Bacterial pathogen contamination has been mostly reported for leafy vegetable and fruits produce in urban peri-urban areas compared to rural farming systems (Alegbeleye et al., 2018). For example, Abass et al. (2015), while investigating bacteriological contamination in vegetable from peri-urban farmlands in Kumasi Metropolitan Region (Ghana), reported up to 9.15×10^9 total coliform/100 mL, up to 4.15×10^7 faecal coliform and up to 3.2×10^7 *E. coli* bacteria in lettuce, onion and cabbage. In all these studies wastewater and contaminated urban hydrologic flows were the primary source of bacterial contamination. However, the distribution of bacterial pathogens in PUA vary depending on a range of factors, including climate, soil type, farming practices, and the prevalence of the specific bacterial organism in the region (Drechsel et al., 2006).

2.7.2.2 Health risk Related to Bacterial Pathogens Contamination

The adverse effects of bacterial pathogens on health range from personal distress, nausea, vomiting, abdominal pain, diarrhoea and fever to more severe illnesses such as typhoid fever, cholera, and hepatitis, which outbreaks can cause widespread deaths (Fung et al., 2018). For instance, a *cholera* outbreak caused by *V. cholerae* in western Kenya (near Lake Victoria) from January to April 2008 resulted to 790 cases and 53 fatalities (Shikanga et al., 2009). Between January 2009 and May 2010, another *cholera* outbreak in the country affected 56 districts, with 11,769 cases and 274 deaths (Mohamed et al., 2012). Moreover, *Salmonella* spp. contamination is one of the most common bacteriological contaminants in urban and peri-urban farmlands in Africa, responsible over half of the number of foodborne outbreak illnesses (Somorin et al., 2021). Salmonellosis is also one of the most prevalent and extensively spread foodborne

infections from urban stream irrigation, characterised by fever, diarrhoea, stomach discomfort, nausea, and vomiting. *Shigella* spp. infections affect millions of people in developing countries (Zulu & Nyila, 2018). The emergence of intrinsically resistant microbial strains against various antimicrobial treatments creates more complications in microbial contamination diseases' treatments (Bassetti et al., 2018). Therefore, preventive measures against microbial pathogens' spread to the food chain are crucial for public health risk monitoring (Luna-Guevara et al., 2019).

2.7.2.3 Risk Assessment for bacterial Pathogens Contamination in Peri-urban Agriculture

Risk assessment for bacterial contamination in urban and peri-urban agriculture in developing countries is crucial to ensure food safety and public health. It provides a systematic approach to evaluate the risks, prioritize interventions, and ensure food safety and public health. Risk assessment for bacterial pathogens contamination involves identifying and evaluating the hazards associated with bacterial contamination in agricultural systems, estimating the likelihood and severity of their occurrence, and developing strategies to manage or mitigate the risks (Ahmed et al., 2018). Several risk assessment frameworks have been developed for bacterial contamination in agricultural systems, such as the Codex Alimentarius Risk Analysis Framework (FAO/WHO, 2003) and the United States Environmental Protection Agency's (USEPA) Framework for Microbial Risk Assessment (USEPA, 2012). These frameworks provide a structured approach to identify and assess the risks associated with bacterial contamination in agricultural systems, and to prioritize interventions to reduce the risk of foodborne illness and other health impacts. Risk assessments provides useful information for policymakers, planners, farmers, and other stakeholders to make informed decisions

and implement appropriate measures to reduce the risk of bacterial contamination in agricultural systems.

2.7.2.4 Testing Methods for Bacterial Pathogens Contamination Screening

Bacterial pathogens are characterised using different methods, including morphological characterisation, use of selective specific media-based approaches and molecular techniques (Jenkins, 2016). Morphological characterisation involves the observation of physical characteristics of the pathogen, such as cell shape, size, and arrangement, as well as the presence of spores, capsules, or flagella (Manimegalai & Shanmugam, 2013). This approach is commonly used in the identification of bacteria and fungi. For example, Gram staining can be used to differentiate between Gram-positive and Gram-negative bacteria, while microscopy can be used to observe fungal hyphae and spores.

Selective specific media-based approaches involve the use of culture media that are designed to selectively promote the growth of a particular pathogen, while inhibiting the growth of other bacterial strains that could be present in the sample (Houf & Stephan, 2007). These media contain selective agents that inhibit the growth of certain bacteria, as well as nutrients and other factors that promote the growth of the targeted pathogen. For example, MacConkey agar is a selective specific medium commonly used for the isolation and differentiation of Gram-negative bacteria such as *E. coli*, *shigella* spp. and *Salmonella* spp. However, the use of specific selective media generally needs additional biochemical tests and microscopy analysis specific to the subsequent bacterium for confirmation of the isolate (Jenkins, 2016).

Molecular characterisation involves the analysis of nucleic acids (DNA or RNA) to identify and differentiate between different pathogens (Kumaraswamy et al., 2014).

This approach is based on the detection of specific DNA or RNA sequences that are unique to a particular pathogen. Molecular methods such as polymerase chain reaction (PCR), sequencing, and hybridization techniques can be used for pathogen identification and typing. Genome-based confirmatory test *i.e.*, polymerase chain reaction-based experiments, partial sequencing (16S rRNA) or whole genome sequencing, or some phenotypic identification kits/tests such as Analytical Profile Index, API and Vitek-2 system and etcetera are more useful in confirming the identity of bacterial isolates compared to the use of bacterium-specific selective media. For example, PCR can be used to detect the presence of genes specific to a particular pathogen, such as the Shiga toxin gene in *E. coli* O157:H7. Molecular methods are more efficient compared to specific-selective media, which is also more efficient compared to the use of morphological methods solely (Bakermans et al., 2014; Anderson, 2015; Flint et al., 2015). However, the cost associated with molecular characterisation techniques and the equipment required are the main limitation of implementation of molecular techniques in bacterial screening. Molecular techniques, such as whole-genome sequencing and PCR are costly to perform and require specialized laboratory facilities and instruments (Christensen et al., 2015). In practice all the three methods are integrated starting from morphological to molecular characterisation depending on the available resources and only presumptive isolate are taken to molecular characterisation.

2.8 Peri-urban Agriculture and Urban Planning

As the world population grows with about 67% of the global population projected to be living in urban centres by 2050, achieving food security in these areas will be challenging if substantial actions and planning measures are not taken (Grafton et al.,

2015). Peri-urban agriculture and urban management are crucial components of sustainable development, particularly in rapidly urbanizing regions of the world. As cities expand, the peri-urban areas that surround them become increasingly important for the provision of food, green space, and other ecosystem services. However, there are often conflicts between PUA and urban planning and management, as policymakers and planners struggle to balance the competing demands of urban development and agricultural land use (Hussain & Hanisch, 2014; Wadduwage, 2018).

The challenge of linking PUA with urban management is multifaceted and complex, requiring a comprehensive understanding of the social, economic, and environmental factors that affect these two domains. Several studies have identified key challenges in these areas, land use conflicts, environmental degradation, food safety concerns, and inadequate infrastructure (Bai et al., 2017). One of the primary challenges facing policymakers and planners is the issue of land use conflicts. As urban areas expand, the peri-urban areas are often converted to residential or commercial use, leading to the displacement of agriculture and loss of valuable agricultural land (Kinuthia et al., 2021). This can have a range of negative impacts, including reduced food security, loss of ecosystem services, and increased urban sprawl (Wadduwage et al., 2017).

Food safety is another important concern when linking peri-urban agriculture with urban management. Urban consumers often have high expectations for food safety and quality, and peri-urban agriculture can pose risks for foodborne illnesses due to food contamination (Wadduwage & Millington, 2019). To address these challenges, policymakers and planners need to develop informed strategies for ensuring food safety and quality, such as implementing quality standards, promoting good agricultural practices, and monitoring food production and distribution. Finally, inadequate infrastructure is a major challenge of peri-urban agriculture and urban management.

Peri-urban areas often lack basic infrastructure, such as roads, water supply, and sanitation facilities, which can influence the transport of products and the quality of irrigation water used (Wolff et al., 2021). To address this challenge, policymakers and planners need to invest in infrastructure development, such as building roads, improving efficient water supply systems, and providing sanitation facilities. By adopting a holistic and integrated approach, policymakers and planners can create policies and regulations that promote sustainable development and benefit both urban and rural communities. These include:

- Evidence-based planning:

The integration of PUA into urban planning requires evidence-based planning, which involves the collection and analysis of data on the location, extent, and potential for PUA. Previous studies (Faludi & Waterhout, 2006; Cullen & Adams, 2012) on the role of planning for PUA sustainability suggests that planners should use spatial data analysis to identify areas with the greatest potential for peri-urban agriculture, considering factors such as land availability, soil quality, and water availability.

- Land-use zoning

To promote PUA in metropolitan regions, planners must develop appropriate land-use zoning policies that recognize the multiple benefits of agriculture, such as food security, employment, and environmental sustainability. Planners can use a range of zoning tools, such as urban agriculture zones, green belts, and buffer zones, to support PUA (La Rosa et al., 2018).

- Infrastructure development:

The success of PUA in metropolitan regions requires the development of appropriate infrastructure, such as roads, water, and electricity, to support farming activities (Pribadi

& Pauleit, 2015). Planners must identify the appropriate infrastructure needs of peri-urban farmers and develop plans for providing these services.

- Collaboration with stakeholders

To promote peri-urban agriculture in metropolitan regions, planners must work closely with peri-urban farmers and other stakeholders to identify areas for peri-urban agriculture, develop appropriate land use policies, and provide the necessary infrastructure and services (Ahern, 2013).

2.9 Characterisation and Mapping of Peri-urban Agriculture

Peri-urban agriculture is a complex system influenced by urbanization, land availability, market demand, resource management, environmental impacts, socioeconomic factors, and governance. Different methods have been used in characterizing peri-urban agriculture, including remote sensing, manual mapping, multivariate statistical techniques, and expert opinion.

2.9.1 Manual Mapping of Peri-urban Agriculture

Manual mapping involves the use of geographic information systems (GIS) and ground-based surveys to collect and analyse data about the landscape. Manual mapping can provide detailed information about the location and extent of agricultural fields, crop types, and soil properties. Manual mapping allows for an expert and flexible context-specific approach. It enables the mapper to incorporate local knowledge and understand the nuances of the peri-urban landscape, including different types of crops, farming practices, and land uses (Fekete, 2022). This helps capture fine-grained details and provides a deeper understanding of the spatial patterns and dynamics of peri-urban

agriculture. It provides flexibility to adjust the mapping process based on specific requirements and local conditions. Mappers can incorporate additional information or modify the mapping approach to capture fine-grained details or address specific research objectives (Taylor & Lovell, 2012). Manual mapping can achieve a high spatial resolution in delineating peri-urban agriculture. Trained interpreters can analyse satellite imagery or other spatial data to identify and map small-scale agricultural activities, which may not be captured by automated techniques. Mappers can visually verify and validate the accuracy of mapped features, ensuring a higher level of data reliability compared to fully automated approaches.

Manual mapping also has some limitations (Fekete, 2022). Manual mapping is prone to subjective interpretations and potential biases introduced by individual mappers. Different interpreters may have varying levels of expertise and may perceive and classify features differently, leading to inconsistencies in the mapped results. Manual mapping can be time-consuming and labour and resource intensive, particularly for large study areas or when mapping at a fine spatial resolution. Due to the labour-intensive nature of manual mapping, its scalability is limited. It may not be feasible to manually map extensive peri-urban areas or conduct frequent mapping exercises over large regions, especially when timely and up-to-date information is required. Peri-urban agriculture is dynamic and complex, with changing land uses and agricultural practices. Manual mapping may struggle to capture these dynamic features accurately, as it typically provides a snapshot of the landscape at a specific point in time and may not capture temporal changes

2.9.2 Remote Sensing for Peri-urban Agriculture Mapping

Remote sensing technologies offer an impressive opportunity for mapping and characterizing peri-urban agriculture (Forkuor & Cofie, 2011). It allows to map and characterisation of large areas of land, making it easier to assess the extent and characteristics of peri-urban agriculture. Remote sensing provides a non-invasive method for monitoring and assessing peri-urban agriculture, which minimizes the need for costly and time-consuming fieldwork (Appeaning Addo, 2010). Forkuor & Cofie (2011) used remote sensing to estimate the extent and distribution of peri-urban agriculture in the Bangkok Metropolitan Region. The study showed that remote sensing can provide accurate information about different types of land use, including agricultural land, and identify peri-urban agriculture areas. Kamusoko et al. (2021) used Sentinel-2 satellite imagery to map and characterize peri-urban agriculture in the Harare metropolitan region, Zimbabwe. The study used spectral indices to classify different types of vegetation cover and land use and found that over 50% of the study area was used for agricultural purposes. Willkomm et al. (2019) used RapidEye satellite imageries to monitor changes in urban and peri-urban agriculture in Nakuru, a medium urban city in Kenya. Willkomm et al. (2021) used the same imagery to map different replacement and intensification processes of UPA in Nakuru, Kenya.

The use of remote sensing for mapping and characterising peri-urban agriculture has some limitations. Satellite imagery can be affected by cloud cover, atmospheric conditions, and sensor limitations, which can affect the accuracy of data (Li et al., 2022). Remote sensing technologies may have limited spectral resolution, which can make it difficult to distinguish between different types of crops and vegetation (Willkomm et al., 2019). The use of advanced remote sensing technologies can be costly, limiting their

use (White et al., 2016). Finally, remote sensing data may lack ground truth data, which can make it difficult to validate the accuracy of results (Stopher et al., 2015).

2.9.3 Multivariate Techniques for Peri-urban Agriculture Characterisation

Multivariate statistical techniques allow for comprehensive exploration of complex datasets associated with peri-urban agriculture. These methods can uncover hidden patterns, relationships, and trends within the data, enabling a deeper understanding of the agricultural system. Many multivariate techniques, such as principal component analysis (PCA) and factor analysis, can reduce the dimensionality of data while preserving the most important information (Dossa et al., 2011). This simplification facilitates data visualization and interpretation by representing complex datasets in a more concise manner. Multivariate techniques help identify the variables that have the most significant influence on peri-urban agriculture (Abdulkadir et al., 2012). By assessing the strength of relationships between variables, these methods enable researchers to prioritize and focus on the most critical factors affecting agricultural outcomes. Multivariate techniques integrate data from diverse sources, enabling a holistic analysis of the complex interplay between different variables and their impact on agricultural outcomes (Alvarez et al., 2018). They provide a robust framework for making statistical inferences about the relationships and associations between variables. Peri-urban agriculture is influenced by various factors, including socioeconomic, environmental, and demographic variables. Multivariate techniques allow for hypothesis testing, significance assessment, and the identification of statistically significant patterns and correlations.

The multivariate statistical techniques also have some limitations in characterising PUA. Multivariate statistical techniques often rely on assumptions about the underlying

data, such as normality or linearity. Deviations from these assumptions can affect the accuracy and reliability of the results. Additionally, these techniques may oversimplify complex relationships, potentially missing important nonlinear or interactive effects (Serra et al., 2018). The effectiveness of multivariate techniques depends on the quality and availability of data. Missing or incomplete data, measurement errors, and biases can impact the accuracy and interpretation of the results. Adequate data collection and pre-processing is essential for reliable analysis (Abdulkadir et al., 2012). Multivariate techniques can produce complex outputs that may be challenging to interpret without proper expertise. Understanding and communicating the results in a meaningful and actionable way requires statistical knowledge and domain expertise. While multivariate techniques can identify associations and relationships between variables, they may not establish causal relationships. Drawing causal inferences requires additional evidence and experimental design. Moreover, generalizing the findings beyond the specific study context may be limited, as peri-urban agriculture characteristics can vary across different regions and contexts (Zambon et al., 2018). Overfitting is a risk when using multivariate techniques, particularly when the number of variables is large compared to the sample size. Overfitting occurs when the model captures noise, outliers or random fluctuations in the data, leading to poor generalization performance when applied to new data (Faber & Rajkó, 2007).

2.9.4 Expert Opinion for Peri-urban Agriculture characterisation

Expert opinion involves the use of the knowledge and experience of experts to characterize peri-urban agriculture (Thapa & Murayama, 2008). Experts possess specialized knowledge and understanding of peri-urban agriculture. Their experienced expertise allows them to provide valuable insights, draw upon their experience, and

consider various aspects of the agricultural system that may not be captured by quantitative data alone (Žlender, 2021). Experts can provide information about the types of crops grown, the methods of cultivation, and the socioeconomic factors influencing PUA (Bozdağ et al., 2016). Expert opinion can provide a holistic perspective on PUA by considering multiple dimensions simultaneously, such as socioeconomic, environmental, and governance factors. This comprehensive view can offer a deeper understanding of the complexities and interdependencies within the peri-urban context. Experts can contextualize the characterisation of PUA based on the specific local conditions, including socio-cultural factors, institutional frameworks, and historical contexts. Their knowledge helps ensure a characterisation that aligns with the unique characteristics of the studied area (Alvares et al., 2018). They can provide qualitative insights that quantitative data may not capture. These insights can include nuanced observations, local practices, cultural dynamics, and tacit knowledge that contribute to a more comprehensive understanding of peri-urban agriculture. Expert opinion allows for flexibility and adaptability in the characterisation process (Gonçalves et al., 2017). As experts interact with the data and the context, they can adjust their perspectives, modify their analyses, and refine their interpretations based on emerging insights or additional information. Despite the in-depth knowledge, the use of expert opinion for PUA characterisation can have some shortcomings, which should be considered in the implementation of the process. The limitations include personal biases, professional backgrounds, or limited exposure to different perspectives (Ward, 2020). These biases can introduce subjectivity and limit the objectivity of the characterisation process. The use of expert opinions typically relies on a limited number of experts who may not fully represent the diversity of views and experiences within the field of peri-urban agriculture. This limited sample size may restrict the range of insights and perspectives

considered in the characterisation. Expert opinion can lack standardization, making it difficult to compare and integrate findings across different studies or contexts (Žlender, 2021). This lack of standardization may affect the reproducibility and generalizability of the characterisation results. Expert opinions may lack the systematic and rigorous validation process typically associated with quantitative data. Without extensive data validation, it can be challenging to assess the reliability and accuracy of the expert opinions (Ward, 2020).

Due to the complexity of peri-urban landscapes, characterizing PUA requires the use of a combination of different methods, including remote sensing, manual mapping, multivariate statistical techniques, and expert opinion. Each method has its strengths and limitations, and the choice of method depends on the specific research question and the availability of data as well as cost considerations. However, a combination of these methods provides a more comprehensive understanding of peri-urban agriculture and help develop strategies for sustainable peri-urban agriculture.

2.10 Agricultural Land Use Planning based on Analytic Hierarchy Process

The analytic hierarchy process (AHP) is a multi-criteria decision analysis (MCDA) tool that has been widely applied in PUA land use planning (Thapa & Murayama, 2008). The AHP is a widespread MCDA tool because it can be used to systematically evaluate complex decisions involving multiple criteria and stakeholders. The AHP has been implemented in various land suitability analysis (LSA) processes to respond to decision making process regarding the suitability of certain areas for agriculture or peri-urban agriculture (Thapa & Murayama, 2008; Akıncı et al., 2013), urban utilities (Chandio et al., 2011) suitability of industrial and transport infrastructures (Tseng et al., 2009),

contaminated sites remediation (Li et al., 2018) and urban and Environmental Planning at large (Mosadeghi et al., 2015).

One of the primary advantages of AHP is its ability to account for multiple criteria and stakeholders' preferences. AHP allows decision-makers to prioritize and evaluate different land use options based on multiple criteria, such as soil quality, water availability, climate, and socioeconomic and environmental factors. The AHP also allows stakeholders to express their preferences and priorities, which can improve the transparency and acceptability of the outcome of the decision-making process (Darko et al., 2019). Another advantage of the AHP is its ability to provide a structured and systematic approach to land suitability analysis. AHP allows decision-makers to break down complex problems into smaller, more manageable sub-problems, which can facilitate decision-making and reduce uncertainty. AHP also provides a framework for sensitivity analysis, which can help decision-makers to test the robustness of their decisions and identify critical factors that can affect the outcome (Bozdağ et al., 2016). Moreover, it can integrate different types of data and knowledge, such as remote sensing data, expert knowledge, and stakeholder preferences. AHP use remote sensing data to evaluate the spatial distribution of different criteria, such as soil quality and vegetation cover. AHP can integrate expert knowledge to evaluate the importance and weighing of different criteria and sub-criteria. Additionally, AHP can use stakeholder preferences to incorporate socioeconomic factors, such as land tenure and land use conflicts (Russo et al., 2014).

The AHP has been applied in different studies for land suitability evaluation. For instance, (Ali et al., 2020) applied AHP to prioritize the most suitable agricultural land use in peri-urban areas of Lahore, Pakistan. The study identified five criteria, including soil fertility, water availability, slope, accessibility, and land use compatibility. The

results showed that soil fertility and water availability were the most important criteria for peri-urban agricultural land use planning. Similarly, Thapa & Murayama (2008) applied AHP to evaluate the sustainability of peri-urban agriculture in Hanoi province, Vietnam. The study identified five criteria, including soil, land use, water resources, road network and market.

Some studies have criticized the accuracy of the AHP process. For example, (Nguyen et al., 2021) pointed out that the weighting of criteria and sub-criteria in AHP is subjective and can vary depending on the stakeholder's perspective. The author proposed the use of participatory approaches to overcome the subjectivity of AHP and ensure stakeholder engagement in peri-urban agricultural land use planning process. Kwong & Bai (2003) and Chan et al. (2008) argued that AHP could not adequately consider uncertainty sometimes with very complex decision cases. The authors suggested the use of participatory approaches, sensitivity analysis, and the use of alternative MCDA tools to ensure robust and transparent of the decision-making making process. Moreover, the exploration of the extensions the conventional AHP such as Fuzzy AHP Grey AHP, Interval AHP, Stochastic AHP, Group AHP, Analytic Network Process, also offer different capabilities and frameworks to address specific challenges of the decision-making process (Chan et al., 2008). However, the choice of AHP extension depends on the nature of the decision-problem, the availability of information, and the specific requirements of the decision-making context.

2.11 Research Gap

Urban settlements and industries have been actively mixing and interacting with agricultural lands in peri-urban areas in Kenya, with increasing contamination of vegetable deliver to urban dwellers. A range of studies have been conducted in Nairobi

metropolitan region to assess the impact of land use changes on agricultural lands. However, they have not focused on peri-urban agro-systems, from which fresh fruits and vegetables are supplied to the metropolitan population. The extent of the risks of heavy metals and bacterial pathogens contamination in peri-urban agro-systems is still unclear. Research studies focusing on land suitability evaluation for healthy and sustainable vegetable cultivation in peri-urban landscape, which is essential to inform rational planning and zoning of agricultural land, are still missing. Therefore, the study contributes to the understanding of the dynamics of peri-urban agrosystems, the extent of heavy metals, trace elements and bacterial contamination, and provides a land suitability model that will serve urban planners, decision makers and farmers in preserving peri-urban agrosystems and guarantee safe and healthy food for the metropolitan population.

CHAPTER THREE: METHODOLOGY

3.1 Introduction

This chapter presents the materials and methods used in the study. These includes description of the study area, research design and description of the procedures for data collection and analysis.

3.2 Study Area

The study was carried out in the peri-urban interface of Nairobi-Machakos counties in Kenya. The area covers part of four wards of Mavoko sub-county: Athi River, Kinanie, Muthwani and Mlolongo, Machakos county and Ruai ward of Kasarani sub-county in Nairobi County. The area lies on the Eastern side of Nairobi city between 1°14' 32" and 1°29'21" S latitude and between 36°57'59" and 37°07'30" E longitude (Fig.3.1). It is a plateau located in the central highland of Kenya, with elevation varying between 1440 and 1620 m above sea level.

The population was estimated in 2019 population census at 105,485 inhabitants in Ruai with a density of 1,051/sq.km and 322,499 inhabitants in Mavoko sub-county with a density of 386 inhabitants/sq.km (KNBS, 2019). Access to potable water and sanitation services are still challenging in the area. Only 51% of Nairobi county and 14% of Machakos county have sewer coverage (Machakos County Governement, 2020; Nairobi City County Governement, 2022). The area of focus of this study is not yet covered with sewerage systems and therefore, domestic sewage and industrial effluents are managed locally and often end up in open-drainage canals (Machakos County Governement, 2020).

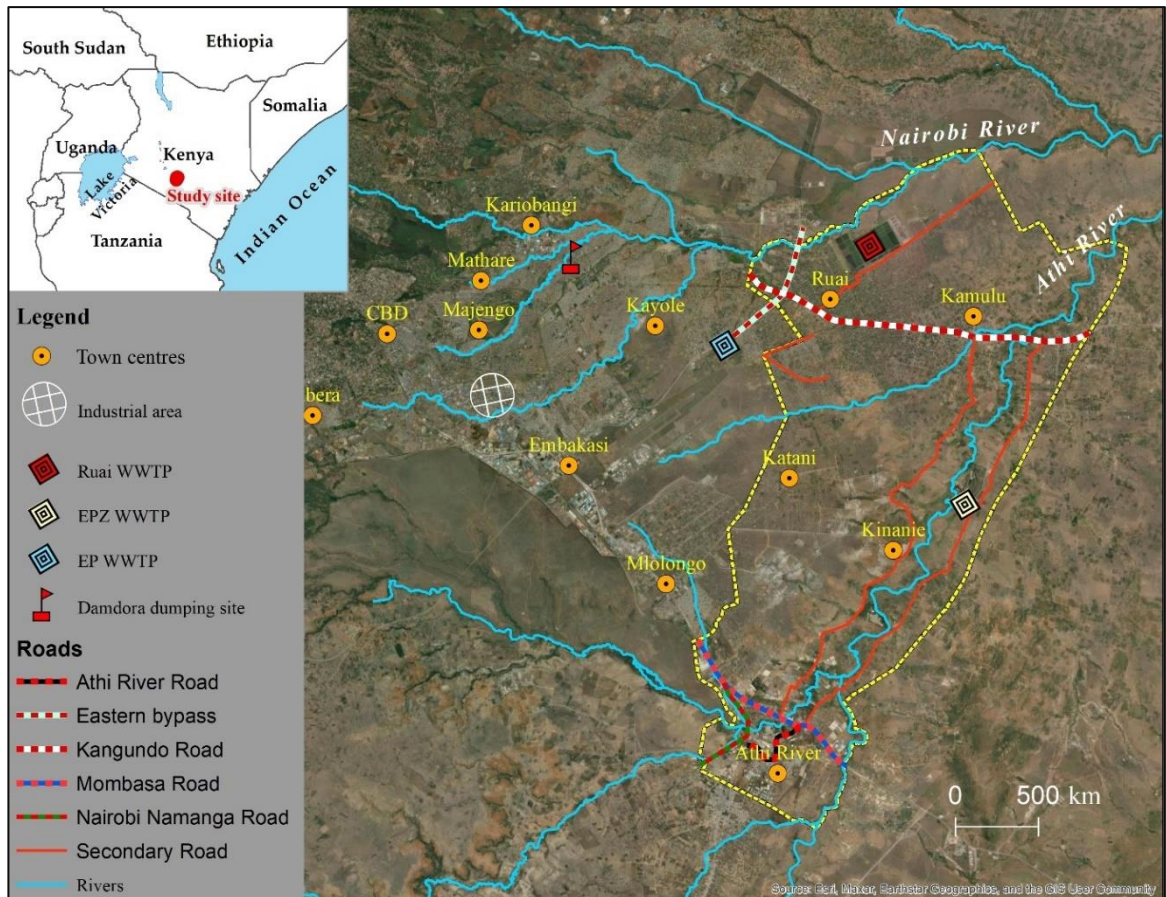
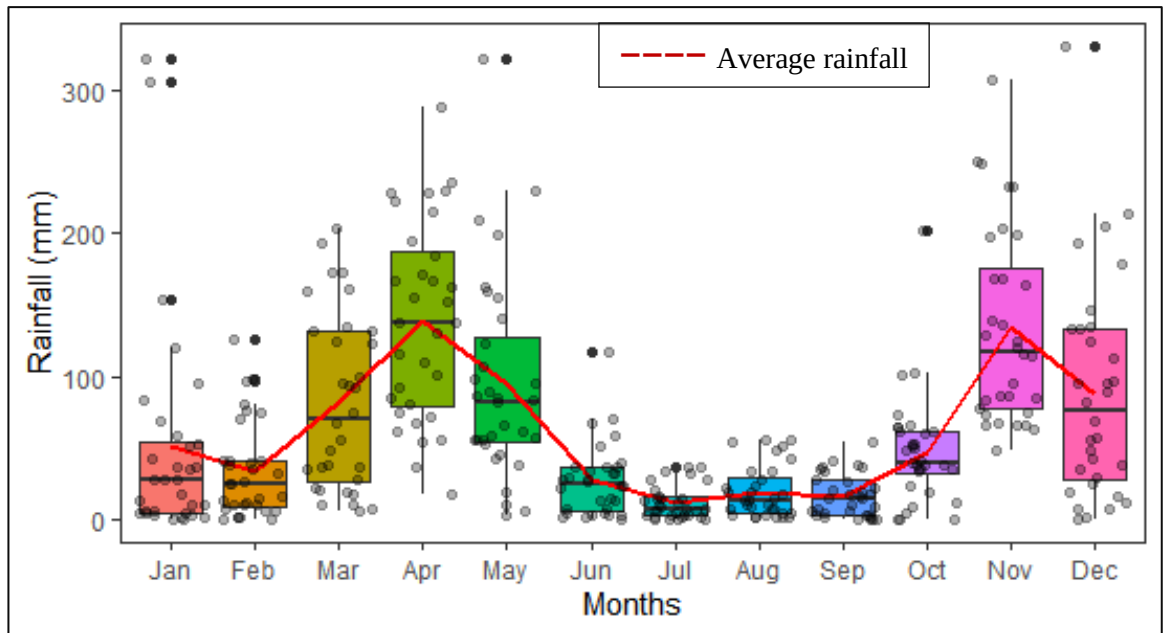


Figure 3.1: Map of the study area

The climate is a subtropical highland type with a bimodal rainfall pattern from mid-March to mid-May and October to November (Fig. 3.2). Meteorological data from the Kenya Meteorological Department over the last three decades (1990-2020) shows that the average annual rainfall is about 740 mm with high variability over the months and the years (322-1162 mm) with average temperature ranging between 18 °C and 28 °C. Due to poor spatiotemporal distribution of rain events and frequent extended drought spells, the cultivation of fresh fruits and vegetables depends significantly on irrigation even during rainy seasons (Mulwa et al., 2021).



Source: Kenya Meteorological Department, 2021

Figure 3.2: Average monthly rainfall 1990-2021

Considering the hydrological system, the area of study is part of Athi river basin, which is the fourth largest basin in Kenya. It covers an area of 69,930 sq.km with a total length of 390 km and flows from the Aberdare ranges and the Ngong highlands (Njuguna et al., 2017). The main tributary of Athi River basin is Nairobi River, which has two tributaries Ngong and Mathare Rivers. Nairobi River and its tributaries pass through the city, including the city's informal settlements of Kariobangi, Majengo, Korogocho, Dandora, Kibera, and Mathare as well as the industrial area (Fig. 3.1). The river flow through settlements, industrial area and public utilities, and receive loads of waste and effluent discharge from informal settlements, waste dumpsites, industrial complexes and wastewater treatment plant (WTPs), making the water flows polluted (Kithiia, 2007; Chowdhury & Maiti, 2016). The Dandora WTP, which is the biggest WWT in Kenya discharges its effluent into Nairobi River, is located in Ruai, Nairobi (Maina et al., 2020). The export processing zone (EPZ) WTP is located in Muthwani in Athi River town and discharges its effluent to Athi River (Musyoki et al., 2013a; Wafula et al.,

2020). Athi River flows towards the northeast of Nairobi city and meets the Nairobi River north-east.

The area of interest of this study encompasses eight soil types (Scott, 1985) presented in Fig. 3.3. these are (i) shallow-yellow to yellow red friable clay overlaying a laterite horizon shallow, (ii) stony soils with rock outcrops (Lithosols and Regosols), (iii) red friable clay with laterite horizon, (iv) dark greyish-brown mottled clays (Grey soil, Vlei soils), (v) ark greyish-brown calcareous clays (Rendzinic soils), (vi) dark grey-dark greyish-brown calcareous clays with light texture, (vii) black to dark-grey clays and (viii) alluvium. The predominant soils are deep and well-developed black to dark-grey clays and dark-greyish-brown calcareous soils, which roughly split the study area in two, south-east to north-west (Fig. 3.3).

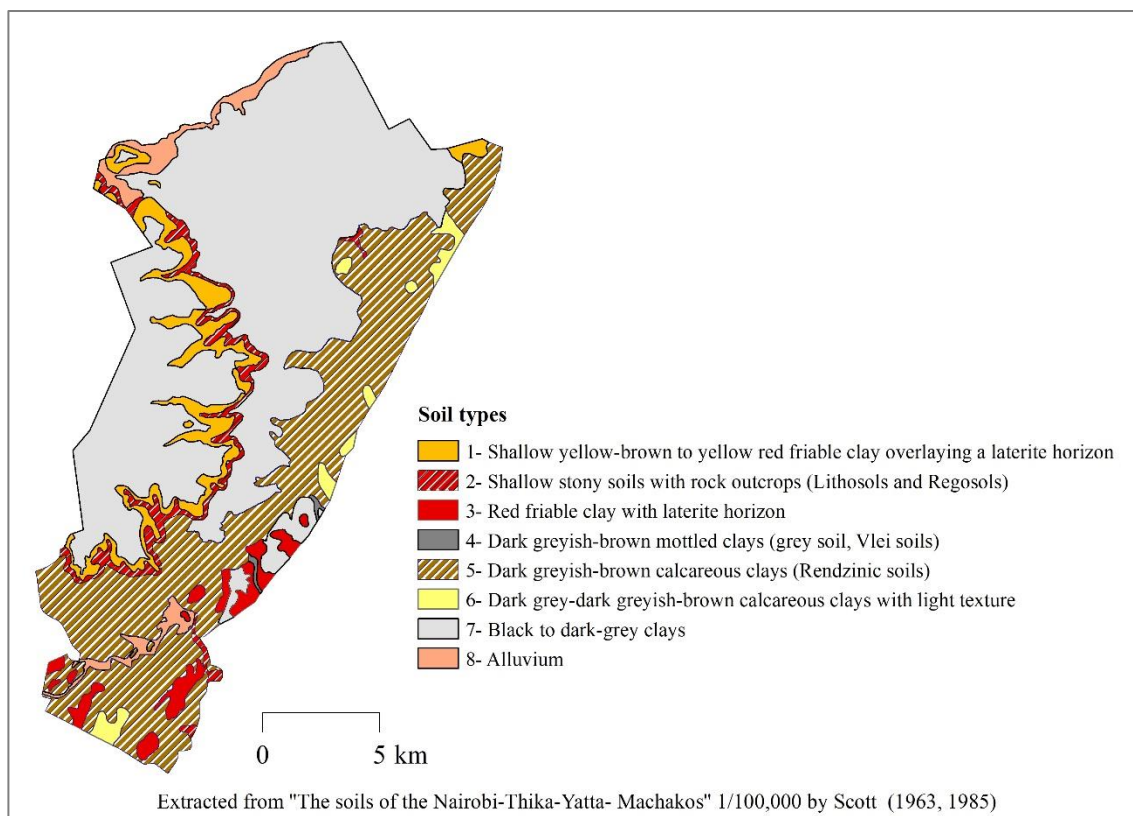


Figure 3.3: Soil types of Nairobi-Machakos counties interface

About 30% of Nairobi residents are involved in agricultural activities (Karanja et al., 2010). By cultivating vacant lands, rooftops, and small plots, farmers generate income, improve their livelihoods, and contribute to poverty reduction socioeconomic empowerment, particularly in marginalized communities (Gallaher et al., 2013). PUA contributes to sustainable land use practices and ecosystems services in Nairobi metropolitan region (Lwasa et al., 2014).

3.3 Study Design

The study used a descriptive correlational research design that allow to collect qualitative and quantitative data to describe the dynamics of PUA and contamination risks as well as model land use suitability for rational land use planning in the peri-urban interface of Nairobi-Machakos counties (Onwuegbuzie & Leech, 2006; Yaakob & Yunus, 2016; Ishtiaq, 2019). The descriptive correlational research design allows to explore the relationships between environmental and socioeconomic variables without manipulating them (Reinfried, 2006; Beauvais et al., 2014). This approach allows researchers to gain insights into how different environmental factors may be associated with one another. It is particularly useful when studying complex socioecological systems and natural environments where direct manipulation may not be feasible or ethical. Key characteristics of a descriptive correlational research design include (Iannarilli et al., 2019; Ishtiaq, 2019):

- **Observation:** The researcher does not manipulate any variables but rather observes them in their setting or as they occur naturally.
- **No control over variables:** Unlike experimental research designs, the researcher does not have control over the independent variables (factors believed to affect the outcome) or the participants' assignment to groups.

- **Measurement of variables:** Researchers measure the variables of interest in the study. These measurements can be obtained through surveys, questionnaires, observations, existing data, or other data collection methods.
- **Data Analysis:** Statistical analysis is used to determine the strength and direction of the relationship between the variables. Common statistical techniques used in descriptive correlational research include correlation coefficients (e.g., Pearson correlation) and regression analysis.
- **Descriptive findings:** The focus is on describing the relationship between variables, rather than making causal inferences. Researchers aim to identify patterns or associations in the data, not to establish cause-and-effect relationships.
- **External validity:** Descriptive correlational research design often has good external validity, meaning the findings can be generalised to a broader population because the data is collected in a naturalistic setting.

The descriptive correlational research design fits the research study as it enables to explain the relationships between different variables relevant for land suitability analysis in peri-urban landscapes (Seeram, 2019). Three approaches are combined in this study, in-person interviews and survey; laboratory testing of soil, irrigation water and vegetable samples collected and analysed from peri-urban farmland; and modelling by integrating remote sensing data and GIS to model land suitability for vegetable farming. The in-person interviews and survey allow to identify and classify different forms of peri-urban farming based on their socioeconomic, spatial arrangements and management characteristics as well as their underpinning factors. Laboratory testing of soil, irrigation water and vegetable tissue samples provides comprehensive evaluation of ecological and health risks related to heavy metals, trace elements and bacterial pathogens contamination in peri-urban agrosystems. Finally, the integrated AHP-GIS with the

analysis of remotely sensed data allows to model land suitability for vegetable farming in Nairobi-Machakos counties interface.

3.4 Peri-urban Farmland Characterisation

Peri-urban farmland characterisation in Nairobi-Machakos counties interface is based on two approaches, a spatial approach using Very-High Resolution Google Earth (VHR-GE) imagery and a socioeconomic approach based on peri-urban farming units' investigation.

3.4.1 Google Earth Imagery and Visual Interpretation

Google Earth (GE) imagery is one of the freely available virtual globe observation imageries collected from different satellites sources that give the opportunity to explore satellite and aerial imageries for various applications (Taylor & Lovell, 2012; Gorelick et al., 2017). GE provides very high resolution (VHR) imagery with up to 1 m spatial resolution. Despite the advances in automatic and semi-automatic land use classification technics namely object-based image analysis (OBIA), manual photointerpretation remains a method of choice for creating fine-scale land use/cover maps especially in the case of peri-urban landscapes due to the complexity in landscape (Jampani et al., 2020). GE imagery has higher spatial resolution compared to free satellite imageries like MODIS and LANDSAT series, making it a good option for small scale PUA land use characterisation (Taylor & Lovell, 2012). GE imagery has been increasingly used in scientific projects and in urban planning as an essential decision-making tool, especially in data scarce countries like Kenya (Hu et al., 2013; Malarvizhi et al., 2016; Pulighe et al., 2016; Li et al., 2020).

The applications of GE imagery include data collection, validation, visualisation, data integration, modelling, communication, dissemination, and decision support to support systems, in some cases, without any additional data. The accuracy of GE imagery for the city of Rome (Italy), concluded that the accuracy of GE imagery is satisfactory for land use land cover data analysis, validation and can generate relatively precise and accurate maps that can be used in urban planning and infrastructure management (Pulighe & Lupia, 2016). GE imagery is also used in most land use and land cover (LULC) analysis as a prominent source of ground truth data. GE imageries was successfully used in different studies (Taylor & Lovell, 2012; Pulighe & Lupia, 2016; Jampani et al., 2020) for explicit and detailed mapping of UPA in Rome (Italy), Chicago (USA) and Hyderabad (India).

This study used a multi-step and iterative visual interpretation of Very High-Resolution Google Earth (VHR-GE) imagery to map agricultural land use in Nairobi-Machakos counties interface. A global understanding of farmland structure and scale was acquired through a prospection of the study area and key informants' interviews (county Chief Officers Land and Physical planning and sub-county agricultural officers at Kasarani and Mavoko sub-counties). The mapping of PUA land use combines field investigation and ground truth data based on visual interpretation of GE imagery. Cloud free and high-resolution (1 m) GE imageries were acquired from Google Earth Pro <https://www.google.com/earth/> for the year 2021. Out of all the imageries available, the imagery of July 2021 was selected because of its overall good quality and because it was acquired during the period of ground truth data collection and farmland investigation (June-July 2021).

Visual interpretation of GE imagery helps identify and classify real world object owing to context, linkages to other objects, and complex variations in plant type or abundance (Lillesand et al., 2008). The visual interpretation was based on the appearance and context of the land use characteristics of the GE imagery. The resulting features for each land use type were cross checked to verify that all locations had been identified consistently throughout the study area once digitization was confirmed by ground truth data. The default grid in Google Earth pro 0.40 x 0.40 sq. km was used to facilitate the visual interpretation process. The agricultural land uses with relatively large land size were delineated using polygons, while those with very small land size were represented by place mark tools in Google Earth pro and saved as Keyhole Markup Language (KML) format and later exported into ArcGIS 10.8.2 to generate agricultural land use maps. PUA were classified as residential garden (RG), small-scale open field (SOF), small scale greenhouse (SGh), large-scale open field (LOF) and large-scale Greenhouse (LGh).

3.4.2 Peri-urban Farming Unit Survey

Prior to the beginning of the study, a research permit certificate from the National Commission for Science, Technology, and Innovation (NACOSTI) was obtained and clearance, and general information were gained from local administrative officials (counties commissioners and sub-counties agricultural officer officers). In each farming unit, the objectives of the study were explained and a verbal consent to participate in the survey requested from the farm manager, owner, household head or their representative. It was only upon favourable response that the questionnaire administration was conducted.

Farming units were investigated in the peri-urban interface of Nairobi-Machakos counties from farming unit survey from May to July 2021. A semi-structured questionnaire was administered to a total of 130 farming units randomly selected using a snowball sampling method across the peri-urban interface. The questionnaire was tested prior to the study on a sample of 28 farming units located in Juja along Thika River, a suburban area about 40 km north of Nairobi city, followed by appropriate modifications of the questionnaire. The questionnaire collected data on socioeconomic background of the farms, biophysical resources, farm management, and production constraints. The specification of the variables of interest for peri-urban farming system typification in Nairobi-Machakos interface are presented in Table 3.1. The selection of these variables was informed by previous studies in SSA (Dossa et al., 2011; Abdulkadir et al., 2012; Musafiri et al., 2020; Willkomm et al., 2021), field reconnaissance and preliminary information from key informants. Surveys were conducted on the farming units Monday to Saturday and participation in the survey was not compensated.

3.4.3 Survey Data Processing and Analysis

Descriptive statistics were used to account for socioeconomics variables, both quantitative and qualitative. The diversity of peri-urban farming systems was analysed using the Factor Analysis of Mixed Data (FAMD) followed by Hierarchical Cluster on Principal Components (HCPC) based on 18 quantitative and categorical variables (Table 3.1). The variable PUA type was derived from the farmland mapping using VHR-GE imagery (section 3.4.1) with five modalities RG, SOF, SGh, LOF and LGh. The variable PUA type was treated as a supplementary variable in the FAMD since it has no influence on the outcome of the typology construction but is computed to assess

any relationship between the farm types from the socioeconomic multivariate approach and the spatial approach using GE imagery.

Table 3.1: Variables used in farmland characterisation

Variables	Description	References
Education	Level of formal education of FU head (None, Primary, Secondary, University)	Dossa et al. (2011)
Farm owner profile	FU head profile (urban household, local company, international investor)	Willkomm et al. (2021)
Main profession	Principal profession of the FU head (Farming, Animal husbandry, Business, Formal employment, Informal employment, Casual labour)	Rehman et al. (2013)
Monthly income	Monthly income (US\$)	Dossa et al. (2011)
PUA contribution to income	Percentage of income from farming activities	Dossa et al. (2011)
Membership to farmers' organization	Is the FU member to any organisation (Yes / No)	Akplo et al. (2019)
Membership to out-grower scheme	Is the FU member of any out-grower scheme (Yes / No)	Justus & Yu (2014)
Total farmland size	Total land area (ha) of FU	Dossa et al. (2011)
Land tenure	Land tenure system (free hold, inherited, leased, purchased)	Dossa et al. (2011)
Irrigation water source	Borehole, open drainage channel, tap water, rainwater, river, sewage	Bhatia et al. (2015)
Presence of stream	Is the FU nearing a stream (Yes / No)	Akplo et al. (2019)
Irrigation system	Is the FU using an irrigation system (Yes / No)	Hide et al. (2001)
Leafy vegetable	Is the FU cultivating leafy vegetables (Yes / No)	Rehman et al. (2013)
Fruit vegetable	Is the FU cultivating fruit vegetables (Yes / No)	Rehman et al. (2013)
Cut flowers	Is the FU cultivating cut flowers Yes / No	Justus & Yu (2014)
Herbs	Is the FU cultivating herbs Yes / No	Justus & Yu (2014)
Staple crops	Is the FU cultivating staple crops Yes / No	Willkomm et al. (2021)
Livestock	What is the extent of livestock production in the FU? (high, low, medium, none)	Dossa et al. (2011)
Market orientation	Target market (export, open markets, supermarkets, subsistence farming)	Follmann et al. (2021b)
Access to agricultural extension	Is the FU accessing agricultural extension service (Yes / No)	Dossa et al. (2011)
PUA type	Type of agricultural enterprise (from visual interpretation of GE imagery RG, SOF, SGh, LOF, LGh)	Willkomm et al. (2021)
Farming regime	Year-round / seasonal farming	Dossa et al. (2011)
PUA profitability	Not profitable (0), marginally profitable (1), moderately profitable (2), above average profitable (3), highly profitable (4)	Vagneron (2007)

FU: Farming Unit; RG: modalities residential garden; SOF: small-scale open field; SGh: small scale greenhouse; LOF: large-scale open field; LGh: large-scale Greenhouse

The cluster analysis was performed on the principal components resulting from the FAMD to construct distinct groups of homogeneous elements that represent the farm types. The HCPC performs an agglomerative hierarchical analysis that starts with a

single pass through the dataset, during which the raw input data is compressed into a manageable set of sub-clusters. The second step used a hierarchical clustering method to progressively merge the sub-clusters into larger clusters. In this process, individual records serve as the starting clusters, which are subsequently merged into larger clusters. Although clustering under the FactoMineR package in R provides the optimal number of clusters, it also allows the researcher to choose the cut-off point. Considering the goal of optimizing both intra-cluster homogeneity and inter-cluster heterogeneity, the optimal cluster cut-off point was determined after striking the balance between the number of clusters and the amount of dissimilarity across clusters (Ornelas-Eusebio et al., 2020). The final clusters representing the different farm types, were examined for their inherent characteristics. The FAMD and HCPC were performed in R statistical software version R 4.2.1 (R Core Team, 2021), using the packages *ade4* (Thioulouse et al., 2018), *ggplot2* (Wickham, 2016), *FactomineR* (Husson et al., 2016) and *Factoextra* (Kassambara & Mundt, 2017).

3.4.4 Determinants of Peri-urban Agriculture in Nairobi-Machakos counties interface

The ordered Probit regression model was used to assess the socioeconomic determinants of PUA considering the variable PUA profitability as the dependent variable with five ordered outcomes. Farming units head or their representatives were asked to rank the profitability of PUA based on a Likert scale of five ordinal levels using four stone where, 0 not profitable, 1 marginally profitable, 2- moderately profitable, 3- above average profitable and 4- highly profitable (Vagneron, 2007; Hussain & Hanisch, 2014). These levels of PUA profitability were derived from ancillary studies (Dossa et al., 2011; Abdulkadir et al., 2012) and adapted to the context of peri-urban farming in

Nairobi outskirts during the pre-test of the questionnaire. The ordered Probit regression model uses a single regression equation in which inferences from marginal effects can only be made on the extreme outcomes (upper or lower ranking). The level of PUA profitability is referred to as Y^* , which is functionally related with its influencing factors (X), β is a parameter vector and ε follows a normal distribution with mean zero (Equation 1). PUA is less profitable when $y^* < 1$ while it is profitable when $y^* > 1$.

$$Y^* = X\beta + \varepsilon, \varepsilon \sim N(0, \sigma) \quad (\text{Equation 1})$$

$$Y^* = \begin{cases} 0, & \text{if } Y \leq \delta_0 \\ 1, & \text{if } \delta_0 < Y \leq \delta_1 \\ 2, & \text{if } \delta_1 < Y \leq \delta_2 \\ 3, & \text{if } \delta_2 < Y \leq \delta_3 \\ 4, & \text{if } \delta_3 < Y \leq \delta_4 \end{cases}$$

where $Y^* = 0; 1; 2; 3; 4$ represent the responses “not profitable”, “marginally profitable”, “moderately profitable”, “above average profitable” and “highly profitable” respectively, and $\delta_0, \delta_1, \delta_2, \delta_3$ and δ_4 are the critical thresholds. The probability of observing outcome i^{th} following the Probit model corresponds to Equation 2.

$$Pr(Y^* < x) = \Phi(x) = \int_0^x (1/2\pi) \exp(-x^2/2) dx \quad (\text{Equation 2})$$

3.5 Irrigation Water Suitability and Contamination in Peri-urban Agrosystems

3.5.1 Sampling and Preparation of Irrigation Water Samples

Prior to sampling, an exploration of the peri-urban interface was carried out to identify fresh fruits and vegetable farmlands bounded by Nairobi River and Athi River in the study area. After mapping the farmlands, a stratification of the study area based on

agricultural land location and potential contamination sources such as irrigation water sources *i.e.*, domestic sewage, urban wastewater, industrial areas, and the presence of settlement was conducted to subdivide the study area into distinct sampling stations. The subdivision considered farmland locations in the catchment: farmlands located around medium to high density residential and industrial areas, along roads, along rivers and before and after WTPs effluent discharge point (Table 3.2). This led to the subdivision of the area into 10 distinct sampling stations, S1 to S10 (Fig. 3.4). A detailed description of the sampling sites including the coordinates is provided in the appendices (Appendices 1). At each sampling station, water variables such electrical conductivity (EC), pH, total dissolved solid (TDS), and turbidity (Turb) were measured thrice in-situ using a handheld YSI Professional Plus (Hanna HI5521-02) Multiparameter Instrument (Ağca et al., 2014). Random sampling method was applied in each sampling station to collect irrigation water samples. Irrigation water sampling and in-situ data on irrigation water were conducted in the dry season of September and the wet season of November 2021.

For each season, three series of three composite irrigation water samples (one per decade) were collected in each site. Additionally, three tap water (T) and three borehole water (B) samples were added in each season to serve as control, making a total of 192 water samples. At each sampling station, the composite samples were obtained from eight to ten sampling points. Irrigation water samples were collected at 5 cm depth from water surface using 1.5 l clean-sterilized and corrosion-resistant plastic bottle and conserved in cool thermostatic box at 4°C from the sampling sites to the laboratory for physical, chemical, and bacterial pathogens analyses. These processes were carried out in the morning between 7 and 10 AM to avoid the interference of high temperature in the day. The temperature during the sampling period were 18-23° C in dry season and

16-20° C in wet season. At the laboratory, about 0.7 l of each sample was aseptically extracted for bacteriological analyses, 0.2 l of each water sample was filtered using 0.45 µm syringe filters for heavy metals and trace elements analysis and the remaining of the sample was used for physicochemical analyses of water quality parameters. Samples were stored at 4°C in a refrigerator awaiting further laboratory processing. Water samples preparation was performed at Spectralab Analytical Services Limited, in Nairobi.

Table 3.2: Characteristics of the sampling sites in Nairobi-Machakos counties interface

Sampling sites	Stations description	Irrigation water sources
S1	Residential-industrial mixed area, Pridelands,	Raw domestic sewage
S2	Athi River Town industrial area	Mixture of domestic sewage and river water (Athi River)
S3	High-density residential area, Athi River town	Mixture of domestic sewage and river water (Athi River)
S4	Before the EPZ wastewater treatment plant, Kinanie	Mixture of domestic sewage and river water (Athi River)
S5	After the EPZ wastewater treatment plant Kinanie	Mixture of domestic sewage, river water (Athi River) and WTP effluent 61,943 m ³ /day
S6	Muthwani-Kamulu Nairobi-Machakos borders	Mixture of domestic sewage, river (Athi River) and WTP effluent flowing from
S7	Kangundo Road, Nairobi	Open drainage canal flow, mixture of domestic sewage
S8	Stream, Katani-Utawala bridge	Mixture of domestic sewage and urban stream water
S9	Before the wastewater treatment plant discharge point, Ruai	Mixture of domestic sewage, river water (Nairobi River)
S10	Downstream after the wastewater treatment plant discharge point, Ruai	Mixture of domestic sewage, river water (Nairobi River) and WTP effluent 80,000 m ³ /day

WTP: Wastewater Treatment Plant; EPZ: Export Processing Zone

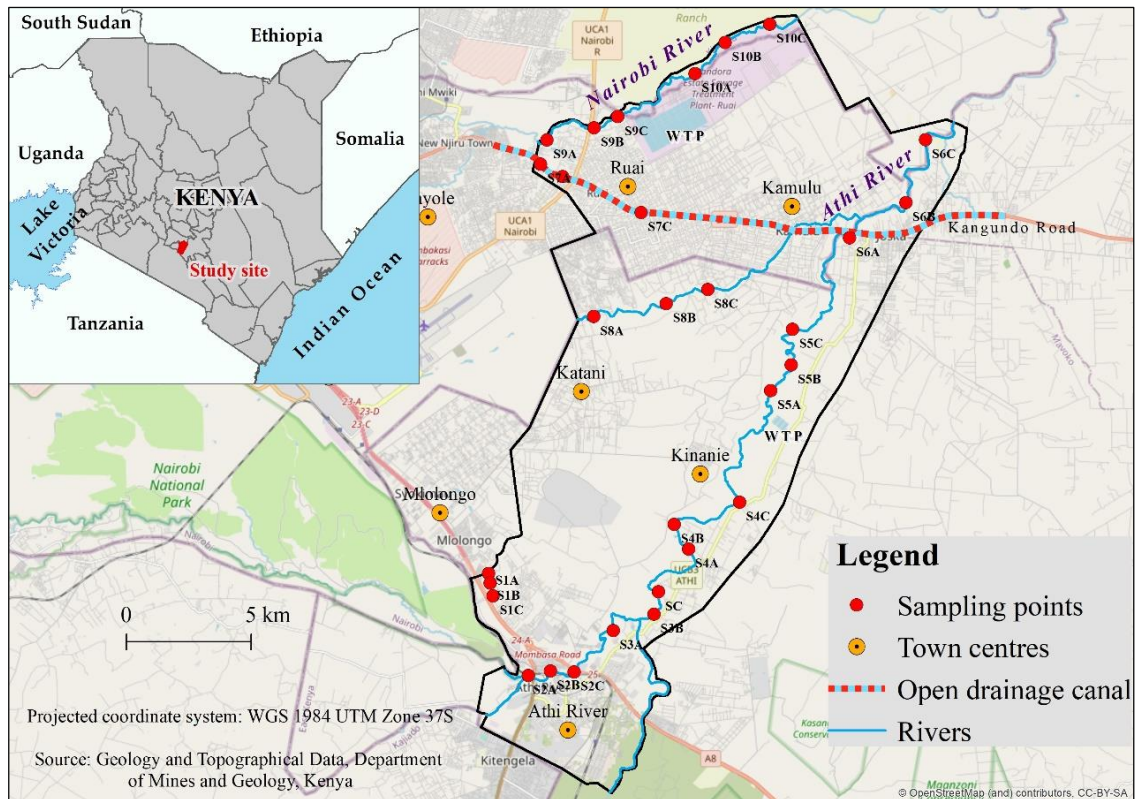


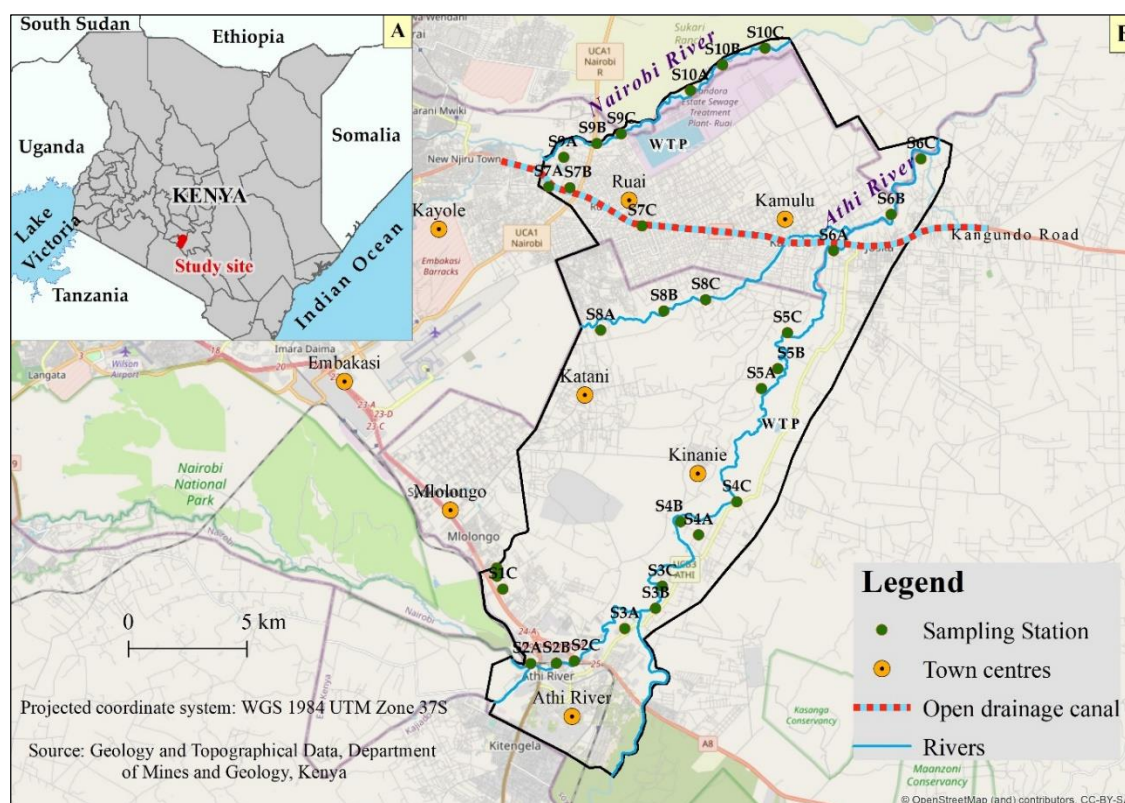
Figure 3.4: Irrigation water sampling stations

3.5.2 Sampling and Preparation of Soil Samples

Triplicate composite soil samples were collected in each sampling station during the dry season of September ($n = 3 \times 10 = 30$) and during the wet season of November ($n = 3 \times 10 = 30$) in 2021. A total of six composite soil samples (three per season) obtained at each sampling station from eight to ten random sampling points arranged in a zig-zag sampling pattern were collected using a stainless-steel soil auger from topsoil layer (0-20 cm depth). The samples were double packaged in sealed and clean polythene bag and transported to the laboratory for preparation. At the laboratory, the samples were air-dried for about four weeks, finely grounded and sieved to less than 2 mm and stored in plastic zip lock bags awaiting laboratory analyses. Soil samples preparation was performed at the AST Laboratory at Kenyatta University, Nairobi.

3.5.3 Sampling and Preparation of Vegetable Samples

To assess heavy metals and trace elements contamination in vegetable in Nairobi-Machakos counties interface, the leaves of kale (*Brassica oleracea* L.), which is one of the most consumed vegetables in Kenya (Njuguna et al., 2019), were collected in the ten sampling zones (Figure 3.5 & Table 3.2).



A: The Republic of Kenya in Eastern Africa; B: study site

Figure 3.5: Soil and vegetable sampling stations

A total of 60 composite samples of kale leaves were collected during the dry season of September ($n = 3 \times 10 = 30$) and the wet season of November ($n = 3 \times 10 = 30$) 2021. Each composite sample (approximately 1 kg) was collected from eight to ten random sampling points arranged in a zig-zag sampling pattern. The samples were double packaged in clean polythene bag and transported to the laboratory for processing. The leaves were carefully washed at tap water and rinsed with deionise water, oven-dry at 70°C till stable weight, crushed into fine powder and stored in double-plastic zip lock

bags awaiting laboratory analysis for heavy metals and trace elements. Kale samples preparation was performed at the AST Laboratory at Kenyatta University, Nairobi.

3.5.4 Physicochemical Analyses of Irrigation Water Samples

Irrigation water samples were analysed at Spectralab Analytical Services Limited in Nairobi, using the East-African Standard Method for Water Quality Analysis EAS 12 (NEMA-National Environmental Management Authority, 2017). Physicochemical parameters analysed in water samples included colour, total alkalinity (TA), total hardness (TH), chloride (Cl^-), fluoride (F^-), calcium (Ca^{2+}), magnesium (Mg^{2+}), sodium (Na^+), potassium (K^+), nitrate ($\text{NO}_3\text{-N}$), ammonia ($\text{NH}_3\text{-N}$), sulphate (SO_4^{2-}), phosphate (PO_4^-), bicarbonates (HCO_3^-) and carbonates (CO_3^{2-}). Water colour was measured by visual comparison of the sample with platinum-cobalt standards. One unit of colour/Hazen is produced by 1 mg platinum per litre in the form of chloroplatinate ion. Total hardness was determined by titration with ethylene diamine tetra-acetic acid (EDTA). Total Suspended Solid (TDS) was determined using weighed standard glass-fibre filter method. Total alkalinity was determined using the principle involving a reaction with hydrogen ions to pH 8.3 (phenolphthalein alkalinity) and then to pH 3.7 (methyl orange alkalinity). Chloride and fluoride were determined using argentometric method and SPADNS method respectively. Calcium and magnesium were analysed by EDTA titrimetric method and gravimetric method with magnesium pyrophosphate, respectively. Sodium and potassium were determined by flame emission photometric method using a flame photometer. Nitrate determination was carried out using chromotropic acid and the absorbance was read with a spectrophotometer at 410 nm. Sulphate was determined by the turbidimetric method, while orthophosphate was determined by ammonium molybdate and antimony potassium tartrate reaction in acid

medium. Bicarbonates and carbonates were deduced by calculation from pH and total alkalinity.

3.5.5 Bacteriological Analysis of Irrigation Water Samples

Bacteriological analyses were carried out at Spectralab Analytical Services Limited, in Nairobi. Bacteriological testing methods were performed as per the East African Standards (EAS 12: 2017) and the International Organization for Standardization ISO 11133:2014/Amd 1: 2020. BOD and COD were determined following the standards methods for water quality analysis described in ISO 5815-1:2003 and ISO 15705:2002. The log dilution method was applied to reduce the bacterial population to a level that would be easier to count when plated to an agar plate. For each microbial pathogen analysis, 1 mL of homogenized water sample was aseptically pipetted, transferred into 9 mL sterile distilled water, and thoroughly homogenized by vigorous agitation using a vortex. This dilution process was replicated until the desired dilution was attained. Specific selective enrichment culture media (15 mL) were used to isolate each microbial pathogen using 1 mL of the diluted sample. Violet Red Bile Agar, Eosin Methylene Blue Agar (EMB), MacConkey Agar, Cetrimide Agar, Slantez and Bartley medium (SBM), Rappaport-Vassiliadis medium with soya (RVS broth) and Thiosulfate-Citrate-Bile Salts-Sucrose (TCBS) Agar were used as culture media in isolating total coliforms, *E. coli*, *Shigella* spp., *P. aeruginosa*, *S. faecalis*, *S. typhi*, and *V. cholerae*, respectively. For *Shigella* spp., Xylose Lysine Deoxycholate Agar (XLD) and Salmonella Shigella (SS) Agar were used alongside MacConkey agar. The presumptive isolates were subjected to various internal microscopic and biochemical tests to confirm the isolated bacteria (Table 3.3). After incubation within the specific period for each microbiological pathogen, the typical colony forming units (CFU) were counted and the

numbers of confirmed colonies were first reported as the number of colonies per 1 mL and multiplied by 100 (Equation 3), where DF is the appropriate dilution factor:

Confirmed count (CFU/100mL)

$$= \frac{\text{Number of colonies} \times \text{DF}}{\text{Volume of sample (mL)}} \times 100 \quad (\text{Equation 3})$$

Table 3.3: Specific media and internal microscopic and biochemical tests performed on isolates

Bacterial pathogens	Isolation media	Microscopic and biochemical tests	References
Total coliform	Violet Red Bile Agar	-	Pangloli et al. (2006)
<i>Shigella</i> spp.	MacConkey agar, Xylose Lysine Deoxycholate Agar (XLD) and SS agar were used alongside	Gram staining, Shape, spore, motility, oxidase, catalase, urease, citrate	Jenkins (2016)
<i>Pseudomonas aeruginosa</i>	Cetrimide agar	Gram staining, shape, motility, capsule, spore, flagella, oxidase, catalase, citrate, urease, arginine dehydrolase, pigment, oxidative/fermentative, methyle red, indole, gas, and nitrate reduction	Alonso et al. (2020)
<i>Escherichia coli</i>	Eosin Methylene Blue Agar	Gram staining, shape, spore, flagella, motility, oxidase, catalase, urease, oxidative/fermentative, indole, gas, nitrate reduction, citrate	Goma et al. (2019)
<i>Enterococcus faecalis</i>	Slantez and Bartley medium (SBM)	Gram Staining, shape, motility, spore, oxidase, catalase, indole, citrate, urease, nitrate reduction, PYR, 6.5% NaCl, oxidative/fermentative, pigment, maltose fermentation.	Rehman et al. (2021)
<i>Salmonella Typhi</i>	Rappaport-Vassiliadis medium with soya (RVS broth)	-	Prabhakar et al. (2021)
<i>Vibrio cholerae</i>	Thiosulfate-Citrate-Bile Salts-Sucrose (TCBS) Agar	Gram staining, motility, shape, capsule, spore, flagella, oxidase, indole, catalase, citrate, urease, arginine dehydrolase, Hemolysis, methyle red, indole, gas and nitrate reduction	Lee et al. (2020)

PYR: Pyrrolidonyl aminopeptidase test

3.5.6 Physicochemical Properties of Peri-urban Agricultural Soil

Physicochemical analyses of soil samples were performed at the AST Laboratory at Kenyatta University, Nairobi. Air-dried and sieved to 2 mm soil samples were used for physicochemical analyses. Soil particle size was determined using the Bouyoucos hydrometer method and soil texture was determined on the soil textural triangle (Mwendwa, 2022). Soil pH and electrical conductivity (EC) were determined using the potentiometric method in a supernatant suspension distilled water-soil of 1:2.5 (Miller & Curtin, 2006; Hazelton & Murphy, 2016). Total phosphorus (Tot P) and total N were measured in a digest of soil sample with hydrogen peroxide + sulphuric acid + selenium and salicylic acid as described in Okalebo et al. (2002). Available phosphorus (av. P) was extracted using the Olsen P method, which is recommended for mildly acid, neutral and alkaline pH soils and read using a spectrophotometer calorimetrically at a wavelength of 880 nm (Olsen, 1954). Total soil organic carbon (TOC) was determined using a boiled potassium bichromate in acidic conditions read on a calorimetric spectrophotometer at a wavelength of 600 nm (Okalebo et al., 2002). Soil organic matter content was deduced considering the conversion coefficient 1.724 (Nelson & Sommers, 1996). Cation exchange capacity (CEC) and exchangeable bases Mg, Ca, K, and Na were extracted using ammonium acetate method (1N, NH₄OAc) at pH 7.0. An atomic absorption spectrophotometer (AAS) was used to determine exchangeable Ca and Mg in the extracts, while Na and K were determined using a flame photometer (Chapman, 1965). Cation exchange capacity (CEC) was estimated by titration of distilled ammonium that was displaced by sodium from NaCl solution. The percentage of base saturation (BS) was computed as the ratio of the sum of exchangeable cations (Ca, Mg, Na, and K) by the CEC of the soil multiply by 100 (Abure, 2022).

3.5.7 Heavy Metals and Trace Elements Analysis in Soil, Irrigation Water and Plant Tissues Samples

Heavy metals and trace elements analyses were performed in the school of Bioscience, Nottingham University, Sutton Bonington Campus in the United Kingdom. Twenty-eight elements including As, Cd, Co, Cr, Cu, Fe, Mn, Ni, Pb, V, and Zn, except Hg were analysed using the Inductively Coupled Plasma-Mass Spectrometry (ICP-MS) in soil, irrigation water and kale leave samples. The analysis of Hg in the samples was performed using a thermal decomposition amalgamation with an atomic absorption spectrophotometry (Phan et al., 2022). For multi-element analysis (ICP-MS), 2 g of finely ground material was used for soil and plant tissue, while 5 mL of filtered water was used for irrigation water samples testing. For Hg analysis, 1.5 mL was used for water samples, while 1.5 g was used for soil and plant tissue material.

The ICP-MS analytical technique allows simultaneous multi-element analyses with repeatable and accurate results in a short time compared to older analytical methods (Wilschefski & Baxter, 2019). Other advantages of the ICP-MS analytical approach include its low detection limit, extensive analytical range, high sample throughput, low sample volume and outstanding control of interfering elements. In the framework of this study, soil and plant tissue samples were digested in boiling aqua regia (trace element grade acid) using Milli-Q water (18.2 MΩ cm). Heavy metals and trace elements (except Hg) analyses were undertaken using two ICP-MS instruments: Thermo-Fisher iCAP-Q (single quadrupole) and iCAP-TQ (triple quadrupole). The equipment is provided with a 'flatapole collision cell' (typically charged with helium gas) upstream of the analytical quadrupole to reduce polyatomic interferences. The triple quadrupole instrument was routinely used to 'mass-shift' very low concentrations of selected elements away from interfering elements (e.g., Se) using an oxygen cell between the quadrupoles. Multiple internal standards were introduced to the sample

stream via a T-piece for instrument drift correction and typically include Sc ($50 \mu\text{g.L}^{-1}$), Ge ($20 \mu\text{g.L}^{-1}$), Rh ($10 \mu\text{g.L}^{-1}$), Re ($10 \mu\text{g.L}^{-1}$) and Ir ($5 \mu\text{g.L}^{-1}$) in a matrix of 2% HNO_3 ; a similar concentration of HCl is also acceptable. Direct spiking of internal standards into samples and a single-line delivery approach were also routinely used where preferred. Samples were introduced via an autosampler (Cetac ASX-520 with ASXpress™ rapid uptake module for the iCAP-Q) through a perfluoroalkoxy (PFA) microflow PFA-ST nebulizer (Thermo Fisher Scientific, Bremen, Germany). Sample processing was undertaken using "Qtegra™ software" (Thermo-Fisher Scientific). The analysis of Hg was performed using the US EPA method 7473 for Hg in solids and solutions with a DMA-80 Tri Cell (Direct Mercury Analysis). The concentration of Hg was determined in digested samples using a thermal decomposition amalgamation with two UV-enhanced photodiodes in an atomic absorption spectrophotometry. For all the analyses the elements were first reported as gravimetric concentrations in $\mu\text{g.l}^{-1}$ or mg.l^{-1} and converted later into mg.kg^{-1} or $\mu\text{g.kg}^{-1}$ dry weight (dw) for soil and plant tissue samples. For water sample the gravimetric concentrations were maintained for all elements.

3.5.8 Quality Control and Assurance

For heavy metals and trace elements, the samples were digested and analysed in replicate. The reagents used for sample digestions and laboratory tests were analytical reagents (AR) or trace analytical grade (TAG) reagents supplied by Fisher Scientific, United Kingdom. In each analytical run operational blanks were included to provide realistic limits of detection ($\text{LOD} = 3 \times \text{std. dev. of blanks}$) and limit of quantification of each element ($\text{LOQ} = 10 \times \text{std. dev. of blanks}$). The limits of detection (LOD) of heavy metals and trace elements in water, soil and kale leaves are presented in Table

3.4. Heavy metals and trace elements recoveries were assessed in each analytical run to provide realistic limits of detection and the limit of quantification of each element using the certified reference material NIST 1573a (tomato leaves) and BCR–142R (light sandy soil). The average recoveries for NIST 1573a were As (127%), Cd (103%), Co (92%), Cu (94%), Fe (86%), Mn (99), Ni (148%), Zn (100), while those of BCR–142R were Cd (96.64%); Ni (87.17%); Pb (91.23%) and Zn (96.39%).

Table 3.4: Limits of detection for heavy metals and trace elements analysis

Metal elements	Water (µg/l)	Soil (mg/kg)	Vegetable (mg/kg)
As	0.00481	0.005	0.002
Cd	0.00204	0.002	0.0007
Co	0.00044	0.001	-
Cr	0.00475	0.047	0.116
Cu	0.00502	0.032	0.083
Fe	0.01204	1.040	-
Hg	1.00E-06	3.00E-06 *	3.00E-06 *
Mn	0.01174	0.035	-
Ni	0.01502	0.048	0.092
Pb	0.00147	0.026	0.005
V	0.00171	0.048	-
Zn	0.07573	2.659	0.404

* Values in µg/kg

For bacterial pathogens, water quality and soil properties analyses, each analytical run was performed in triplicate. All reagents used were grade reagents and internal certified standard samples with known concentrations were used to assure the accuracy of the analytical processes. For bacterial pathogens analysis, biochemical test and microscopy were carried to confirm presumptive isolates from the selective media. Bacteriological analyses were carried out at Spectra Lab Analytical Services Ltd in Nairobi, Kenya.

3.5.9 Data Analysis

3.5.9.1 Water Quality and Irrigation Water Quality Indexing Approach

Physicochemical properties of irrigation water were examined with descriptive statistics (range, mean and standard deviation). Geochemical processes influencing water quality at the sampling sites were analysed using Gibbs Diagram. Water hydrochemistry software *Diagrammes* version 6.77 (Simler et al., 2022) was used for plotting Gibbs Diagrams. Water suitability for farm irrigation was assessed using irrigation water quality index (IWQI) and bacterial contamination index (BCI).

The IWQI index combines five principal water quality hazards in a single value that makes irrigation water suitability evaluation simple (Ayers & Westcot, 1985). The five hazard groups include salinity (G1), infiltration and permeability (G2), specific ion toxicity (G3), trace elements' toxicity (G4), and miscellaneous effects on sensitive crops (G5). The hazard groups are given a weight descending from 5 to 1, and the specific physicochemical properties related to each hazard group were rated according to their suitability for irrigation (Ayers & Westcot, 1985; Simsek & Gunduz, 2007). The IWQI was computed by aggregation (simple summation) of the value of the five hazard groups, G1, G2, G3, G4 and G 5.

Salinity hazard (G1) has the most prominent effect on crop productivity. Salts in water often originate from dissolved minerals in water or from high saline water table. In the case of salty soil, unless the soil is leached with low salt content water, soil salinization is an irreversible process that makes agricultural lands unusable. The extent of the salinity hazard was measured by interpreting the EC values. The permeability and infiltration hazard (G2) arises when elevated sodium ions reduce the pace of water reaching the soil's bottom layers (Table 3.5). A lower infiltration rate can affect crop accessibility to enough water. Insufficient crop water extraction from the soil reduces

yields and reduces agricultural productivity. Soil infiltration hazard was assessed using the combination of EC and SAR. Low salinity water with high SAR values affects water infiltration, while high salinity water with low SAR poses no such threat to water infiltration. The sodium adsorption ratio (SAR) measures the relative amounts of sodium to magnesium and calcium ions in water.

Table 3.5: Irrigation water quality index components

IWQ hazard	Formula	Weight (w)	IWQ Parameters	Classification Range	Score (r)	Suitability
Irrigation water quality	$IWQ = \sum_{i=1}^5 G_i$	-	G1, G2, G3, G4 and G5	≥ 37 30-37 22-30 < 22		Highly Moderately Doubtful Unsuitable
Salinity hazard	$G1 = w1r1$	5	Electrical conductivity (uS/cm)	EC < 700 $700 \leq EC \leq 3000$ EC > 3000	3 2 1	High Medium Low
Infiltration and permeability hazard	$G2 = w2r2$	4	Electrical conductivity (uS/cm) and Sodium Adsorption Ratio	See Table 3.6	3 2 1	High Medium Low
Specific ion toxicity	$G3 = w3 \sum_{i=1}^3 r_i$	3	Sodium Adsorption Ratio	SAR < 3 $3 \leq SAR \leq 9$ SAR > 9	3 2 1	High Medium Low
			Boron (mg/l)	B < 0.7 $0.7 \leq B \leq 3.0$ B > 3.0	3 2 1	High Medium Low
			Chloride (mg/L)	Cl ⁻ < 140 $140 \leq Cl^- \leq 350$ Cl ⁻ > 350	3 2 1	High Medium Low
Heavy metal and trace elements' toxicity*	$G4 = \frac{w}{N} \sum_{k=1}^N r_k$	2	As, Cd, Cr, Co, Cu, F, Hg, Fe, Pb, Mn, V and Zn	See Table 3.7	3 2 1	High Medium Low
Miscellaneous effects on sensitive crops	$G5 = \frac{w5}{3} \sum_{m=1}^3 r_m$	1	Nitrate (mg/L)	NO ₃ < 5 $5.0 \leq NO_3^- \leq 30$ NO ₃ > 30	3 2 1	High Medium Low
			Alkalinity (mg/L)	Alkalinity < 90 $90 \leq \text{alkalinity} \leq 500$ Alkalinity > 500	3 2 1	High Medium Low
			pH	$7.0 \leq pH \leq 8.0$ $6.5 \leq pH < 7.0$ and $8.0 < pH \leq 8.5$ pH < 6.5 or pH > 8.5	3 2 1	High Medium Low

* Trace elements' toxicity refers to the toxicity of heavy metal and trace elements

Table 3.6: Classification range for infiltration and permeability hazard

	SAR					Score	Suitability
	< 3	3–6	6–12	12–20	> 20		
EC	> 700	> 1,200	> 1,900	> 2,900	> 5,000	3	High
	700 –200	1,200–300	500–1,900	1,300–2,900	2,900–5,000	2	Medium
	< 200	< 300	< 500	< 1,300	< 2,900	1	Low

Table 3.7: Irrigation water suitability based on heavy metals and trace element

Factor	Range ($\mu\text{g.l}^{-1}$)	Rating	Suitability
Arsenic (As)	As < 100	3	High
	$100 \leq \text{As} \leq 2000$	2	Medium
	As > 2000	1	Low
Cadmium (Cd)	Cd < 10	3	High
	$10 \leq \text{Cd} \leq 50$	2	Medium
	Cd > 50	1	Low
Chromium (Cr)	Cr < 100	3	High
	$100 \leq \text{Cr} \leq 1000$	2	Medium
	Cr > 1000	1	Low
Cobalt (Co)	Co < 50	3	High
	$50 \leq \text{Co} \leq 5000$	2	Medium
	Co > 5000	1	Low
Copper (Cu)	Cu < 200	3	High
	$200 \leq \text{Cu} \leq 500$	2	Medium
	Cu > 500	1	Low
Fluoride (F)	F < 1000	3	High
	$1000 \leq \text{F} \leq 15000$	2	Medium
	F > 15000	1	Low
Mercury (Hg)	Hg < 0.5	3	High
	$0.5 \leq \text{Hg} \leq 1$	2	Medium
	Hg > 1	1	Low
Iron (Fe)	Fe < 5000	3	High
	$5000 \leq \text{Fe} \leq 20000$	2	Medium
	Fe > 20000	1	Low
Lead (Pb)	Pb < 5000	3	High
	$5000 \leq \text{Pb} \leq 10000$	2	Medium
	Pb > 10000	1	Low
Manganese (Mn)	Mn < 200	3	High
	$200 \leq \text{Mn} \leq 10000$	2	Medium
	Mn > 10000	1	Low
Nickel	Ni < 200	3	High
	$200 \leq \text{Ni} \leq 2000$	2	Medium
	Ni > 2000	1	Low
Vanadium (V)	V < 100	3	High
	$100 \leq \text{V} \leq 1000$	2	Medium
	V > 1000	1	Low
Zinc (Zn)	Zn < 2000	3	High
	$2000 \leq \text{Zn} \leq 10000$	2	Medium
	Zn > 10000	1	Low

The third hazard (G3) is related to specific ions toxicity. Some ions, including Na⁺, Cl⁻ and B are hazardous to plants when encountered in high concentrations. The G4 hazard is related to heavy metals and trace elements concentration in the irrigation water (Table 3.7). The thresholds for trace elements defined by (Ayers & Westcot, 1985; Crook, 1996) was used for irrigation water suitability. The last hazard, G5 is related to the influence of water pH, bicarbonate ion, and nitrate concentrations on crops.

The bacterial contamination Index (BCI) adapted from Boumaraf et al. (2022), is based on the load count of *E. coli* in irrigation water. The range irrigation water suitability classification is presented in Table 3.8.

Table 3.8: Bacterial contamination index

Range	Score	Suitability	References
E. Coli <100 cfu/mL	$4.6 \leq \text{BCI} \leq 5.0$	Very high	Boumaraf et al. (2022)
$100 < \text{E. Coli} \leq 500$ cfu/mL	$4.0 \leq \text{BCI} \leq 4.5$	High	
$500 < \text{E. Coli} \leq 2500$ cfu/mL	$3.0 \leq \text{BCI} < 3.9$	Moderate	
$2500 < \text{E. Coli} \leq 20000$ cfu/mL	$2.0 \leq \text{BCI} < 2.9$	Low	
E. Coli >20000 cfu/ml	$1.0 \leq \text{BCI} \leq 1.9$	Unsuitable	

3.5.9.2 Statistical Analysis of Irrigation Water Parameters

Measured and calculated parameters were screened for normality and homoscedasticity were necessary. Analysis of variance (ANOVA) was performed to check for eventual significance difference across the sites and t-test was used to assess the seasonal variability of physicochemical properties of irrigation variables. The bacterial pathogens load counts for the different sampling stations were compared to the permissible thresholds of water quality for unrestricted irrigation according to national and international standards (NEMA-National Environment Management Authority, 2006; World Health Organization, 2006) using descriptive statistics.

The normality test of Shapiro-Wilk performed on the parameters of bacterial pathogen contamination showed that the data did not follow a normal distribution despite the implementation of different data transformation algorithms. Therefore, non-parametric statistical methods were applied on the bacterial parameters. Kruskal-Wallis test was used to assess the variability of bacteriological variables between the sampling stations and Mann-Whitney test was used to assess seasonal variability. The confidence interval was 95% and the significance threshold was 5%. Pearson correlation matrix was used to assess eventual correlation between microbial parameters (Lv, 2019). All statistical analyses were performed in R statistical software version 4.1 (R Core Team, 2021). Pearson correlation was run using the packages *Hmisc* (Esser, 2012), *PerformanceAnalytics* (Peterson et al., 2018), *ggplot2* (Patil, 2021), and *corrplot* (T. Wei et al., 2021).

3.5.9.3 Statistical Analysis for Heavy Metals and Trace Elements Concentrations in Irrigation Water, Soil and Kale Samples

Heavy metals and trace elements concentrations in irrigation water, soil and kale as well as the parameter and ratios computed for the different sampling sites were screened for normal distribution using Shapiro-Wilk test and variance homogeneity was tested using Bartlett's test. Log or Box-Cox data transformations were applied where necessary to achieve normality and variance homogeneity conditions. One-way ANOVA was used to assess eventual significant differences in heavy metals and trace elements concentrations in irrigation water, soil and plant (kale leaves) across the sampling sites (S1-S10). Tukey's post hoc test was used to separate the means at 5% significance level threshold. The two independent sample t-test was used to assess seasonal variability.

The spatial distribution of heavy metals and trace elements was explored using geostatistical modelling and ordinal kriging in ArcMap 10.8.2. Ordinal kriging is one of the most employed interpolation techniques in environmental modelling (Van Huynh et al., 2022). It allows estimating a value of a specific parameter at an unsampled location based on the application of a geospatial algorithm on the results of sampled locations. For each element, the ordinal kriging was fitted based on variogram analysis. The most accurate model was selected by comparing the shape of the curve of the experimental variogram to the curve of the mathematical functions (Gia Pham et al., 2019). Heavy metals and trace elements concentrations in water and vegetable samples were illustrated in ArcMap 10.8.2 using the coordinates of the sampling sites and the corresponding concentrations of the element as input features.

Pearson correlation matrix was used to assess the correlation between the elements (Lv, 2019). Additionally, principal component analysis (PCA) followed by hierarchical clustering on principal component analysis (HCPC) was performed to establish the relationship between the heavy metals and trace elements and their potential sources (Gbedomon et al., 2020). Statistical analyses were performed in R statistical software version 4.1.2 (R Core Team, 2021). ANOVA was implemented in the *car* package, and Pearson correlation was run using the packages *Hmisc* (Esser, 2012), *PerformanceAnalytics* (Peterson et al., 2018), *ggstatsplot* (Patil, 2021) and *corrplot* (T. Wei et al., 2021). PCA and HCPC were performed with the packages *ade4* (Thioulouse et al., 2018), *FactomineR* (Husson et al., 2016), and *Factoextra* (Kassambara & Mundt, 2017)

3.5.9.4 Soil Pollution Indices

The total concentrations of heavy metals and trace elements and statistical interpretation approaches, give significant information about heavy metals and trace elements. However, there is limited understanding of the extent of the risk related to soil contamination (Nannoni et al., 2016). Therefore, different pollution indices have been elaborated and widely used for a comprehensive and most accurate evaluation of the extent of soil contamination. In this study, seven pollution indices, including geo-accumulation index (I_{geo}), enrichment factor (EF), single pollution index (PI) sum of contamination (PI_{sum}), Nemerow pollution index ($PI_{Nemerow}$), pollution load index (PLI) and potential ecological risk (RI) are used to assess the ecological toxicology related to heavy metals contamination in peri-urban farmlands in the interface. The heavy metals and trace elements concentrations of the upper continental crust by Wedepohl (1995) were used as background values.

a) Geoaccumulation Index (I_{geo})

The Geoaccumulation Index (I_{geo}) is an individual metal index that is use in assessing soil contamination level for a specific element in reference to its background value (Muller, 1969). I_{geo} was determined using Equation 4, where C_n is the concentration of individual element and GB the geochemical background of the given element. I_{geo} values are categorized into six soil quality classes (class 0-class 6) from unpolluted to extremely polluted (Table 3.9).

$$I_{geo} = \log_2 \left[\frac{C_n}{1.5GB} \right] \quad (Equation 4)$$

Table 3.9: Soil classification according to I_{geo} values

classes	Values of I_{geo}	Soil quality
0	$I_{geo} \leq 0$	Unpolluted
1	$0 < I_{geo} \leq 1$	Unpolluted to moderately polluted
2	$1 < I_{geo} \leq 2$	Moderately polluted
3	$2 < I_{geo} \leq 3$	Moderately to highly polluted
4	$3 < I_{geo} \leq 4$	Highly polluted
5	$4 < I_{geo} \leq 5$	Highly to extremely high polluted
6	$5 < I_{geo} \leq 6$	Extremely polluted

b) Single Pollution Index (PI) and sum of contamination (PI_{sum})

PI_{sum} provides an overall estimation of metals and trace elements' contamination by combining in a single value the contamination related to all analysed metals and trace elements (X. Gong et al., 2018). Equation 5 gives the formula for PI_{sum} computation:

$$PI_{sum} = \sum_{i=1}^n PI_i \quad (Equation 5)$$

where n is the total number metals and trace elements determined and PI is the single element contamination index calculated using the expression given in Equation 6. PI is classified into different soil pollution classes ranging from absence of pollution to very strong pollution (Table 3.10).

$$PI = \frac{Cn}{GB} \quad (Equation 6)$$

Table 3.10: Contamination classes of Single Pollution Index (PI)

Classes	1	2	3	4	5
Value of PI	$PI < 1$	$1 < PI < 2$	$2 < PI < 3$	$3 < PI < 5$	$PI > 5$
Soil pollution	Absent	Low	Moderate	Strong	Very strong

c) Enrichment Factor (EF)

The Enrichment Factor (EF) is a single element index that allows to determine the contribution of anthropogenic activities to heavy and traces elements concentration in soil. The determination of EF is based on a low variability occurrence metal usually Fe, Al, Ca, Ti, Sc or Mn which serve a reference metal (Kowalska et al., 2018). In this study iron (Fe) was use as reference element for EF computation (Mwesigye et al., 2016). EF was computed using Equation 7, where Cn is the concentration of the individual heavy metal and GB the geochemical background of the given element. EF values between 0.5 and 1.5 indicate utterly natural sources for heavy metals whereas values above 1.5 indicate anthropogenic enrichment.

$$EF = \frac{\left[\frac{Cn}{Fe}\right]_{sample}}{\left[\frac{GB}{Fe}\right]_{Background}} \quad (Equation 7)$$

d) Nemerow Pollution Index (PI_{Nemerow})

PI_{Nemerow}, is used to assess the overall metals and traces elements based on all analysed elements. PI_{Nemerow} allow to assess soil quality regarding metals and traces elements contamination, into five of soil quality classes: clean (≤ 0.7), warning limit (0.7-1), slight pollution (1-2), moderate pollution (2-3) and heavy pollution (≥ 3). It is computed using Equation 8, where avePI is the mean single pollution index for a given metals or elements and P_{max} the maximum single pollution index observed for the same element and n is the total number of metals and trances element analysed.

$$PI_{Nemerow} = \sqrt{(AvePI^2 + PI_{max}^2)/2} \quad Equation 8$$

e) Pollution Load Index (PLI)

The PLI is used to assess the overall extent of metals and trace elements contamination in soil. The PLI is widely used compared to other pollution indices for it gives a simple and comparative soil quality conditions related to heavy metals contamination using all analysed elements (Li et al., 2017; Kowalska et al., 2018; Orlando et al., 2020). PLI is computed as the nth root of the product of single pollution index (PI) of all the metals analysed (Equation 9). Soil quality is classified as polluted when PLI exceeds 1.0.

$$PLI = \sqrt[n]{PI_1 \times PI_2 \times PI_3 \times \dots \times PI_n} \quad \text{Equation 9}$$

3.5.9.5 Bioaccumulation Factors of Heavy Metals and Trace Elements

Soil-plant and water-plant bioaccumulation factors (BAF_s and BAF_w) were used to assess the phytoaccumulation of heavy metals and trace elements to plant tissue through soil and irrigation water. These ratios express the accumulating capability of the metal elements in plant (Zhou et al., 2016). In this study, BAF_s and BAF_w were estimated only for the edible portion of kale leaves (Cui et al., 2004; Chang et al., 2014). The BAF_s and BAF_w were computed as the ratio of the concentration of a given heavy metal or trace element in kale leaves (C_p in mg/kg dry weight) on its concentration from the subsequent soil (C_s in mg/kg) or irrigation water (C_w in µg/l) (Equation 10). The soil-plant transfer factor is considered as significant when the ratio is above 0.5 (Ogunkunle et al., 2016).

$$BAF_{s/w} = \frac{C_p}{C_{s/w}} \quad \text{(Equation 10)}$$

3.5.9.6 Daily Intake of Heavy Metals and Trace Elements from Vegetable consumption

Heavy metals and trace element ingestion through daily consumption of kale was determined using the daily intake (DI in mg/kg/day) formula in Equation 11, expressed as the daily rate of heavy metals and trace element ingested daily per body weight unit (Kumar et al., 2022). The DI was estimated for adult (above 18 years old) and children assumed to have less or equal to 18 years old.

$$DI = \frac{C_K \times IR \times Cf}{BW} \quad (\text{Equation 11})$$

Where C_K (mg/kg dry weight) is the concentration of metal elements in kale leaves; IR (g/person/day) is the daily ingestion rate of kale, 150 g for adult and 100 g for children between 7-18 years old; Cf is the conversion factor dry to wet weight; BW is the average body weight, 29.6 kg for children (7-18 years old) and 65.5 kg for adult (beyond 18 years old) were derived from previous study by Mwesigye et al. (2016).

3.6 Ecological and Health Risk Assessment

3.6.1 Potential Ecological Risk of Heavy Metals and Trace Elements Contamination in Soil

The ecological risk related to heavy metals and trace elements contamination in the farmland was assessed using Hakanson ecological risk index (RI). RI was used to evaluate the extent of the threat related to heavy metal and trace element contamination to human health, ecosystem and environmental sustainability (Hakanson, 1980). To compute RI, each metal's single pollution index (PI) is multiplied by its toxicity response coefficient, giving the single metal ecological risk, which is then summed into a single value (Equations 12 and 13). The toxicity response coefficient for RI defined

by Hakanson (1980) include As (10), Cd (30), Cr (2), Cu (5), Hg (40), Ni (5), Pb (5) and Zn (1). The ecological risk is estimated only for these elements.

$$E_r^i = T_r^i \times PI \quad \text{Equation 12}$$

$$RI = \sum_{i=1}^n E_r^i \quad \text{Equation 13}$$

Where n , E_r^i and T_r^i represent the number of heavy metals and trace elements, the single index of the ecological risk, and the toxicity response coefficient. Soil quality classification based on E_r^i and RI values is presented in Table 3.11.

Table 3.11: Hakanson potential ecological risk levels

Risk level	Low	Medium	Strong	Very strong	Extremely strong
E_r^i	$40 < E_r^i$	$40 \leq E_r^i < 80$	$80 \leq E_r^i < 160$	$160 \leq E_r^i < 320$	$E_r^i > 320$
RI	$RI < 150$	$150 \leq RI < 300$	$300 \leq RI < 600$	$RI \geq 600$	-

3.6.2 Health Risk Assessment

In this study, the carcinogenic risk (CR and TCR) and non-carcinogenic risk (HQ and HI) related to heavy metals and trace elements contamination was assessed according to the USEPA methods for heavy metals and trace elements health risk screening (USEPA, 2011a). Two principal exposure substrate paths were considered for metals element diffusion: daily consumption of food stuff and intake from soil materials. The intake of heavy metals and trace elements from food stuff is generally related to consumption of contaminated food, while the intake from soil can occur through three exposure pathways: ingestion, inhalation, and dermal contact of soil particles (Zararsiz & Öztürk, 2020; USEPA, 2022). The health risks related to heavy metals and traces elements contamination were estimated using the chronic daily intake from the different exposure routes.

3.6.2.1 Chronic Daily Intake

The Chronic daily intake of heavy metals and trace elements from kale consumption (CDI_K) was estimated using Equation 14 (Shams et al., 2022).

$$CDI_K = \frac{C_k \times IR \times Cf \times F_{exp} \times T_{exp}}{BW \times AT} \quad (Equation14)$$

where C_k (in mg/kg) is the concentration of a given heavy metal or trace element in kale leaves (dry weight), IR (in kg of fresh weight), daily intake represents the quantity of kale consumed daily, the daily quantity of kale consumed is adapted from a previous study in Thika municipality, a suburban town in the outskirts of Nairobi, Kenya (Njuguna et al., 2019), the daily intake of fresh kale of 100 g and 150 g are respectively used for children between 7-18 years old and adult (above 18 years old); Cf (no unit) is the conversion factor dry-fresh weight of kale derived from fresh weight and dry weights, which is deducted for each kale sample during sample preparation and processing; F_{exp} (days/year) is the annual frequency of exposure, 365 days/year; T_{exp} (years) represents the duration of exposure, 66.7 years, the life expectancy in Kenya; BW (kg/person) represents the average body weight, the BW of 29.6 kg for children (7-18 years old) and 65.5 kg for adult (beyond 18 years old) were derived from previous study by Mwesigye et al. (2016); and AT (days) is the average exposure time equivalent to life expectancy in Kenya, $AT = 66.7 \times 365$ days for adults and $AT = 18 \times 365$ days for children for non-cancerogenic risk and $AT = 66.7 \times 365$ days for cancerogenic risk.

The chronic daily intake of heavy metals and trace elements from soil via dust ingestion (CDI_{ing}), inhalation (CDI_{inh}), and dermal exposure (CDI_{dermal}) are estimated using Equation 15-17 (Gul et al., 2022). The specifications of the different parameters of these equations are displayed in Table 3.12.

$$CDI_{ing} = \frac{C_s \times R_{ing} \times F_{exp} \times T_{exp}}{BW \times T_{avg}} \times 10^{-6} \quad (Equation 15)$$

$$CDI_{inh} = \frac{C_s \times R_{inh} \times F_{exp} \times T_{exp}}{PEF \times BW \times T_{avg}} \quad (Equation 16)$$

$$CDI_{dermal} = \frac{C_s \times SAF \times A_{skin} \times DAF \times F_{exp} \times T_{exp}}{BW \times T_{avg}} \times 10^{-6} \quad (Equation 17)$$

Table 3.12: Parameters used for the estimation of human health risk assessment

Parameters	Description	Unit	Value	References
CDI_{ing}	chronic daily intake by dust ingestion	$\mu\text{g g}^{-1} \text{ day}^{-1}$	-	-
CDI_{inh}	chronic daily intake by dust inhalation	$\mu\text{g g}^{-1} \text{ day}^{-1}$		
CDI_{dermal}	chronic daily intake by dermal dust contact	$\mu\text{g g}^{-1} \text{ day}^{-1}$	-	-
C_s	Metal elements concentration in the soil	$\mu\text{g g}^{-1}$	-	-
R_{ing}	Soil ingestion factor	$\text{mg day}^{-1} \text{ dust}$	Children: 60 Adults: 30	(USEPA, 2011) (USEPA, 2011)
R_{inh}	Soil inhalation factor	$\text{m}^3 \text{ day}^{-1}$	Children: 7.6 Adults: 20	van den Berg (1994) van den Berg (1994)
F_{exp}	Frequency of exposure	days year^{-1}	180	N. Zheng et al. (2010)
T_{exp}	Duration of exposure	years	Children: 6 Adults: 24	USEPA (2011) USEPA (2011)
A_{skin}	Skin surface area	cm^2	Children: 2800 Adults: 5700	USEPA (2011) USEPA (2011)
SAF	Skin adherence factor	$\text{mg (cm}^2)^{-1} \text{ h}^{-1}$	Children: 0.07 Adults: 0.7	USEPA (2011) USEPA (2011)
DAF	Dermal adsorption factor	no unit	0.001	Kurt-Karakus (2012)
PEF	particulate emission factor from dust to air	$\text{m}^3 \text{ kg}^{-1}$	1.36×10^9	(USEPA, 2011a)
BW	Average body weight	kg	Children: 29.6 Adults: 66.7	Mwesigye et al. (2016)
T_{avg}	average duration	days	non-carcinogens: $T_{avg}=T_{exp}*365$ carcinogens: $T_{avg}=70 \times 365$	Kamunda et al. (2016) Kamunda et al. (2016)

3.6.2.2 Hazard Quotient

The hazard quotient (HQ) also known as the non-cancerogenic risk of heavy metals and trace elements from soil exposure and kale consumption in Nairobi-Machakos was estimated using equation 18. The hazard quotient (HQ) for a single element considering a specific exposure route is the ratio of its chronic daily intake (CDI) with the corresponding reference dose (RfD) Equation 18. The reference dose for the different heavy metals and trace elements is displayed in Table 3.12.

$$HQ = \frac{CDI}{RfD} \quad (Equation\ 18)$$

Where RfD is the reference dose, a numerical estimate of the daily exposure to the human population, including sensitive subgroups, that is unlikely to induce lifetime health impacts. The RfD values of the metals elements of interest in this study are as per USEPA (2011): As (4×10^{-4} mg/kg-d), Cd (1×10^{-3} mg/kg-d), Cr (5×10^{-3} mg/kg-d), Cu (3.70×10^{-2} mg/kg-d), Hg (2×10^{-1} mg/kg-d), Ni (2.0×10^{-2} mg/kg-day), Pb (3.5×10^{-3} mg/kg-d), Zn (3×10^{-1} mg/kg-d).

3.6.2.3 Hazard Index

The hazard index (HI), which represent the overall non-cancerogenic risk of multiple heavy metals and trace elements was determined on the assumption of dose additivity (Yang et al., 2020; USEPA, 2022). The HI was computed as the sum of the hazard quotient (HQ) of all the metals elements analysed including As, Cd, Cr, Cu, Hg, Ni, Pb and Zn (Equation 19).

$$HI = \sum_{j=1}^n HQ_j \quad (Equation\ 19)$$

where n is the total number of metals elements analysed. A value of HQ and HI less than 1 indicate a low non-cancerogenic risk, while a value equal or above 1 imply significant non-cancerogenic risks (USEPA, 2011b).

3.6.2.4 Carcinogenic Risk

The carcinogenic risk calculated over a lifetime represent the likelihood of cancer if an individual is exposed to any harmful chemical having cancer-causing potential. The carcinogenic risk was estimated for human carcinogens and probable carcinogens including AS, Cd, Cr and Pb. The carcinogenic risk is acceptable when CR value is less than 1×10^{-4} (USEPA, 2011a). The carcinogenic risk (CR) and total carcinogenic risk (TCR) were computed using Equation 20-21.

$$CR = CDI \times CSF \quad (\text{Equation 20})$$

$$TCR = \sum_{i=1}^n CR_i \quad (\text{Equation 21})$$

Where CSF represents the cancer slope factor, which is specific to each carcinogen (Table 3.13).

Table 3.13: Reference dose and cancer slope factor for non-cancerogenic and cancerogenic risks assessment

Heavy metals	Ingestion RfD	Inhalation RfD	Dermal RfD	Ingestion CSF	Inhalation CSF	Dermal CSF	References
AS	3.0 E-4	3.0 E-4	3.0 E-4	1.5	15	1.5	[1-3]
Cd	1.0 E-3	5.7 E-5	1.0 E-3	-	6.3	-	[1-3]
Cr	1.5 E+0	3.0 E-5	3.0 E-3	0.5	41	-	[1-3]
Cu	4.0 E-2	4.5 E-2	4.0 E-2	-	-	-	[1-3]
Hg	3.0 E-4	8.6 E-5	3.0 E-4	-	-	-	[1-3]
Ni	2.0 E-2	2.5 E-2	2.0 E-2	-	-	-	[1-3]
Pb	3.5 E-3	3.5 E-3	5.3 E-4	8.5 E-3	4.2 E-2	-	[1-3]
Zn	3.0 E-1	3.5 E-1	3.0 E-1	-	-	-	[1-3]

[1]: USEPA (2011a) ; [2]: USEPA (1991); [3]: Kamunda et al. (2016);
RfD: reference doze, CSF: cancer slope factor, -: no data

3.7 AHP-GIS Land Suitability Modelling for Vegetable Farming

3.7.1 Land Use Land Cover Classification

3.7.1.1 Geospatial Data

Cloud free and high-resolution satellite imagery of Planet-Scope from March 08, 2022 (PS-2022), during dry season, that was acquired free of charge through the Education and Research Program of Planet Labs, was used for land use and land cover classification. PS is a constellation of approximately 130 satellites, providing entire land surface imagery of the Earth every day. PS sensors are in heliosynchronous orbits (sun-synchronous orbits) *i.e.*, they are synchronised to always be in the same position relative to the sun, providing imagery of the same spot at the same local time (Planet Labs, 2022). The PS imagery used in this study is from the Dove-R (PS2.SD), the second-generation PS satellite that operated from March 2019 to April 2022. Each PS2.SD imagery has a radiometric resolution of 12 bit, a daily temporal resolution with four multispectral bands including blue (B: 464 – 517 nm), green (G: 547 - 585 nm), red (R: 650 - 682 nm) and NIR (NIR: 846 - 888 nm). PS2.SD covers 24 x 16 sq.km area with a ground sampling distance (spatial resolution) between 3.0 and 4.1 m depending on orbit altitude (450 - 580 km).

The imagery was acquired as level 3A product (ortho tile product) indicating that the image was already orthorectified using ground control points (GCPs) and fine-scale digital elevation models (DEMs) to a positional accuracy of < 10 m RMSE, distributed at 16 bits, projected to UTM 37 S WGS 1984 in GeoTIFF image format and resampled to 3.125 m (Raab et al., 2018; Planet Labs, 2022). Although, PS imageries belong to the group of very high resolution (VHR) imageries that provide more detail on land use and land cover processes compared to lower resolution imageries such as Landsat image series, the acquired PS imagery was limited to four spectral bands (G-B-R-NIR). It does

not provide other spectral bands such as short-wave infrared (SWIR) band, medium wave infrared (MWIR), long wave infrared (LWIR), thermal infrared (TI) band or panchromatic bands, which can be very important for specific geospatial analyses or computation of certain spectral indices. This is limiting in terms of the potential applications and analyses that can be performed using PS. Despite this limitation of PS imagery, it has been extensively used in various value-added analytical imagery processing and monitoring of environmental and ecological phenomena (Adam, 2014; Francini et al., 2020; Acharki, 2022; Cui et al., 2022; Gašparović et al., 2023).

3.7.1.2 Image Pre-processing

The pre-processing step of satellite imagery allow to correct or minimize image distortions which may be related to imaging systems, eventual sensor artifacts, atmospheric interference or observing conditions to appropriately distinguish land surface objects based on reflectivity. The area of interest of this study covered nine scenes in the PS-2022 imagery. These scenes were mosaicked using the create mosaic dataset tool in ERDAS IMAGINE 2022. The layer stack tool was used to combine the bands of the imagery into a single image. The imagery was displayed in false colour composite NIR-R-G in ArcGIS Pro 3.0 (Fig. 3.6).

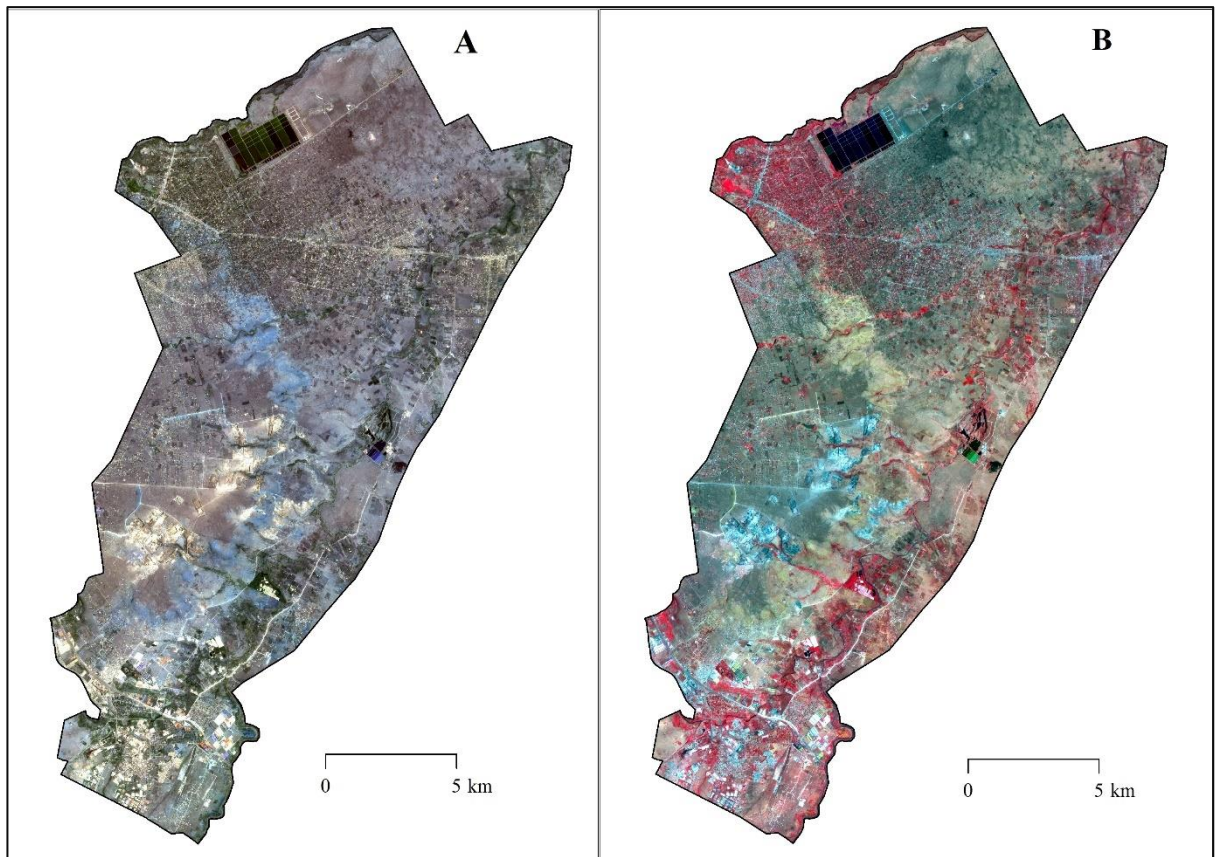


Figure 3.6: Satellite imagery PS-2022, A: true colour R-G-B; B: false colour NIR-R-G

3.7.1.3 Image Processing

Urban and peri-urban landscape are generally characterised by complex geographical structure, which results generally in high heterogeneous spectral signatures due to diverse miniature land use and land cover distribution (Willkomm et al., 2021). Conventional pixel-based techniques for land use land cover analysis have been typically efficient for extracting relatively broad LULC classes based on the spectral information of each pixel. These techniques used either a pixel-based supervised or unsupervised classification or some combination of the two approaches (Weih & Riggan, 2010; Wu et al., 2023). Although this approach has contributed to significant understanding of geospatial patterns of environmental processes, their accuracy substantially depends on pixel spectral information and the scale of observation

(Robertson & King, 2011). This limitation is worsened in urban and peri-urban landscapes due to their highly heterogeneous spectral responses (Small, 2005). Consequently, classes displaying high heterogeneous spectral response may be classified as different classes resulting in elevated misclassification and low accuracy. The principal limitation of this classification approach resides in the fact that the classification does not consider the neighbouring pixels, which may contribute to improving the accurate of LULC classification (Yang et al., 2015). In addition, the seasonal variability in land cover due to phenological appearance can have a significant impact on land use and land cover characteristics and therefore can influence the outcome of LULC analysis (Willkomm et al., 2020).

With the advance in remote sensing, the accessibility to better earth observation equipment providing very high spatial, radiometric, and temporal resolution imagery, traditional/conventional pixel based LULC classification has become more challenging. In this study, we opted to combine different remote sensing and GIS methods to develop and evaluate a decision tree classification approach for land use land cover classification of Nairobi-Machakos counties peri-urban interface using PS-2022 imagery. The use of decision tree in LULC classification has gained more notoriety in the last decade as it provides the opportunity to combining different methods, techniques and algorithms to achieve better accuracy in LULC classification (Sharma et al., 2013; Teffera et al., 2018; Willkomm et al., 2019). Different artificial bands thresholding, image segmentation and a supervised classification using the support vector machine (SVM) machine learning algorithm were iteratively combined for land use land cover features extraction (Fig.3.7).

Table 3.14: Specifications of LULC classes as distinguished by means of PlanetScope satellite imagery

LULC classes	Description
Sealed areas	Areas that have been covered with impermeable materials as a consequence of urban growth, building of infrastructure, or a change in soil surface structure, resulting in impermeability and serious impairment or prevention of biological soil processes
Greenhouse	Farming in a greenhouse is a one-of-a-kind farming approach that consists of cultivating horticultural crops inside of a structure that is covered and is often constructed out of a material that is transparent or partially transparent. The major purpose of greenhouses is to provide perfect growing conditions for plants and to shelter those plants from unfavourable weather conditions and pests.
Vegetation cover	Green to dark green vegetation made of cultivated crop, trees, herbaceous vegetation, woody vegetation and shrubs subdivided into three classes according vegetation greenness intensity: thick-medium-low vegetation cover
Water bodies	Surface water including streams, rivers, water ponds, flooded plain or open drainage canals
Quarry	Relatively large and deep open pit mine in which dimension stone, rock, construction aggregate, riprap, sand, gravel, or slate is excavated from the ground
Bare ground and sparse vegetation	Land devoid of vegetation or with very little vegetation cover

Knowledge of the study area from review of pre-existing LULC maps (Mundia & Aniya, 2005; Katyambo & Ngigi, 2017; Oyugi et al., 2017), the field reconnaissance survey and observation of very high resolution Google Earth imageries combined with repeated preliminary automated multiclass unsupervised classification using the Iterative Self-Organizing ISO-Data classifier (Teffera et al., 2018) allowed to decide on six LULC classes, which appeared the most relevant considering the characteristics of the peri-urban interface and the potential of the remotely sensed data. The six LULC classes included (a) sealed area, (b) greenhouse, (c) vegetation, (d) water body, (e) bare ground and sparse vegetation, and (f) quarry.

In a previous study conducted in Nakuru county, Kenya by (Willkomm et al., 2019), the authors used the Feature Analyst 5.2 (Textron Systems, Providence), an assisted feature extraction software package, and were able to accurately distinguish separate

LULC classes including greenhouse, tree cover, hedges and natural vegetation and agricultural patches. Due to the cost implication related to the accessibility of this software package, and the high confusion in the spectral signatures between natural vegetation, tree cover and agricultural land in the imagery, these classes were classified under vegetation cover in a pixel-based approach. The LULC class of vegetation was further subdivided into three classes based on the intensity of greenness of the vegetation. These include low vegetation cover, medium vegetation cover and thick vegetation cover. The spectral separability of these LULC features were tested on five representative subset images each covering approximately 5 x 5 sq. km area. The specifications of the LULC classes are presented in Table 3.14.

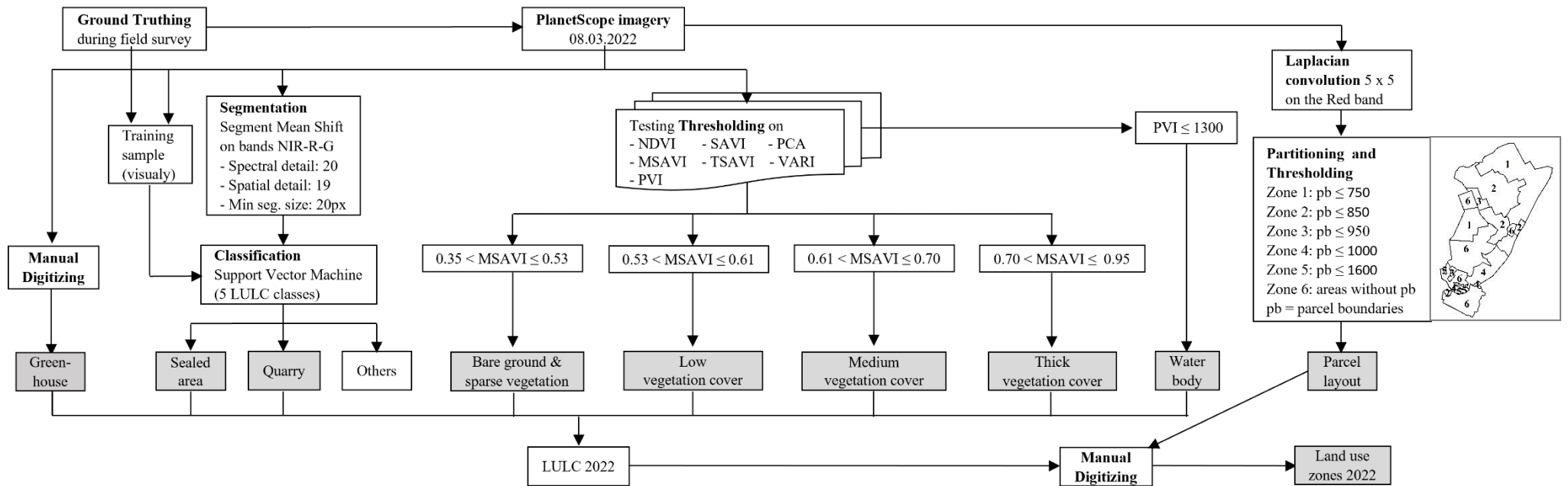


Figure 3.7: Decision tree for LULC analysis workflow on VHR satellite imagery of PlanetScope 2022

3.7.1.4 Testing of Artificial Bands for LULC Features Separability

LULC features extraction was first explored using an unsupervised classification with decreasing LULC classes from 10 classes to two classes using the ISODATA algorithm (Taufik et al., 2019). The result of the iterative process showed that unsupervised classification was efficient for classifying in two wide classes only: pervious and impervious area. Different vegetation and soils indices were explored for LULC features extraction. The screening of different artificial bands was the first step of LULC classification, based on the spectral bands of PS-2022, which are limited to four bands, including R-G-B-NIR. The artificial bands explored for LULC features extraction were based on the spectral bands available and included the Normalized Difference Vegetation Index (NDVI), the Soil-Adjusted Vegetation Index (SAVI), the Transformed Soil-Adjusted Vegetation Index (TSAVI), the Modified Soil Adjusted Vegetation Index (MSAVI), the Perpendicular Vegetation Index (PVI), the Visible Atmospherically Resistant Index (VARI), and Principal Components Analysis for three components. The artificial bands were computed using the indices wizard and the multivariate toolset in ArcGIS Pro version 3.0. The specifications of each artificial band and its computation parameters are displayed in Table 3.14. Based on cautious and thorough exploration of the range of values covered by each spectral index or component, the artificial bands were examined to determine the best ones for specific LULC features. A graduated colour scheme lighter to darker or red to dark green was used to facilitate visual interpretation of LULC features (Tefferet et al., 2018).

The thoughtful thresholding process performed on the NDVI and TSAVI exhibited good distinction for thick vegetation but were less efficient in discriminating low vegetation cover from bare ground and sparse vegetation (Fig.3.8 and 3.9). The SAVI showed an improvement over NDVI and TSAVI but still exhibited some confusion between bare ground and sparse vegetation and low vegetation cover at some locations (Fig. 3.8). The VARI was promising

only for recognizing bright rooftop buildings (Fig. 3.9). This spectral index could not be used because the roofs in the area have a wide range of colours with different saturation intensity with colours such as light blue to dark blue, light red or brown to dark red or brown and light grey to dark grey.

The PCA allows to transform the data in the input bands from a multivariate attribute space to a new multivariate attribute space by compressing the data and eliminating redundancy (Uddin et al., 2021). The outcome of the PCA, considering the combination of first three components (PC1-3) resulted in a mixture of bright red to dark-red representation of most of the built-up and quarry areas (Fig. 3.10-3.11). However, a significant portion of the built-up area exhibited a similar spectral characteristic with bare ground, creating a confusion between these two LULC classes. The exploration of LULC features considering separately each of the three principal components PC1, PC2 and PC3 was neither convincing due to substantial confusion between LULC classes (Fig. 3.10-3.11). Thus, PCA was not promising for LULC classes' delineation. Nevertheless, the first dimension PC1 and PC2 were later examined for parcel layout.

The thresholding of MSAVI exhibited a better demarcation of all the land use classes with the lowest values recorded on sealed and quarry areas, and a better scaling of vegetation cover from bare ground and sparse vegetation, low vegetation cover, medium vegetation cover to thick vegetation cover (Fig. 3.12). The MSAVI was thus used for the extraction of the three vegetation classes and the class of bare ground and sparse vegetation (for the thresholds see Fig. 3.7). The PVI values enabled to easily distinguish water bodies: rivers, water ponds close to large farmland and WTPs with $PV \leq 1300$ (Fig. 3.12). A summary of the evaluation considering all the artificial bands is presented in Table 3.15.

The iterative experiment process with the different spectral indices revealed that a satisfactory extraction of LULC classes including bare ground and sparse vegetation and thick-medium-low vegetation cover was achieved via MSAVI thresholding, while a satisfactory extraction of water bodies was achieved based on PVI (Fig 3.12).

Table 3.15: Summary of artificial bands screened for thresholding in the decision tree-based land use and land cover classification

Artificial bands	Formula	Description (why deemed useful?)	Opportunities for LULC features extraction	Limitations
Unsupervised classification	ISOdata, 10 classes, 95%, iterations Karthik & Shivakumar (2021)	ISODATA is an unsupervised classification method that uses mean values for each class to uniformly partition data space and remaining pixels are clustered using minimum distance	Efficient for classifying in two wide classes only: pervious and impervious	Mismatches and misclassification of target LULC classes
NDVI	$NDVI = \frac{NIR-R}{NIR+R}$ Rouse et al. (1974)	Measure the difference between the reflectance in visible (R) and near-infrared (NIR) part of the spectrum	Good distinction of thick vegetation	Failure in discriminating dry vegetation, low green vegetation, and farmland
SAVI	$SAVI = \frac{NIR-R}{NIR+R+L} (1+L)$ with L = 0.5 Huete (1988)	Attempts to minimize the influence of soil brightness on vegetation cover evaluation using a constant L as soil brightness correction factor	Improved distinction over NDVI, detailed representation of different vegetation intensity	Confusion between dry vegetation/ shrub and farmland
TSAVI	$TSAVI = \frac{S(NIR - S * R - A)}{R + B(NIR - A) + X(1+S^2)}$ With S = 0.33; A = 0.5 and X = 1.5) Baret & Guyot (1991)	Attempt to minimize soil brightness considering that the soil line has a slope (S), and soil line intercept (A). X is soil brightness adjustment factor	-	Poor differentiation of different vegetation cover Less effective compared to SAVI and NDVI
MSAVI	$MSAVI = \frac{2NIR + 1 - \sqrt{(2NIR + 1)^2 - 8(NIR - R)}}{2}$ Qi et al. (1994)	MSAVI is designed to reduce the impact of unvegetated land on the SAVI.	More subtle and detailed representation of different intensity of vegetation, better differentiation of vegetation compared to SAVI	-
PVI	$PVI = \frac{NIR - S * R - b}{\sqrt{1+S^2}}$ (here: S = 0.3 and b = 0.5) Jackson (1983)	PVI measures vegetation intensity by considering soil emissivity (one deficiency of NDVI) but is highly sensitive to atmospheric variation thus can be used only for atmospherically corrected imagery	Good demarcation of water bodies by low brightness (PVI < 1300)	High influence of soil background, high spectral heterogeneity and confusion between different LULC
VARI	$VARI = \frac{G - R}{G + R - B}$ Gitelson et al. (2002)	Statistically quantifies vegetation fraction by using just the visible portion of the electromagnetic spectrum	Promising for bright buildings identification	Not efficient for other LULC classes
PCA	Dharani & Sreenivasulu (2021)	PCA transforms multiband imagery into new bands that compress data redundancy and noise. It organizes vital information into linear dimension "principal components"	PC1 (71.7%) and PC2 (25.9%) better demarcation of parcel boundaries	Similar spectral characteristic with bare ground, creating a confusion between these two LULC classes
Laplacian convolution 5x5 on R band	Rajesh et al. (2020)	Laplacian filters are used for edge detection. The Laplacian of an image highlights area with intensive changes by measuring the second derivatives of the image	Better demarcation of edges and promising for parcel boundaries extraction	Laplacian filter proved difficult to turn image in a binary result (boundaries vs. background) unless by considering different subdivided portion of imagery

R: Red, G: Green, B: Blue, NIR: Near Infrared



PS-2022 satellite imagery, True colour R-G-B, standard deviation 2, Gamma 1-1-1



PS-2022 satellite imagery, False colour Nir-R-G, standard deviation 2, Gamma 1-1-1



Figure 3.8: Subset of PS-2022 true colour R-G-B; PS-2022 false colour NIR-R-G and artificial band SAVI

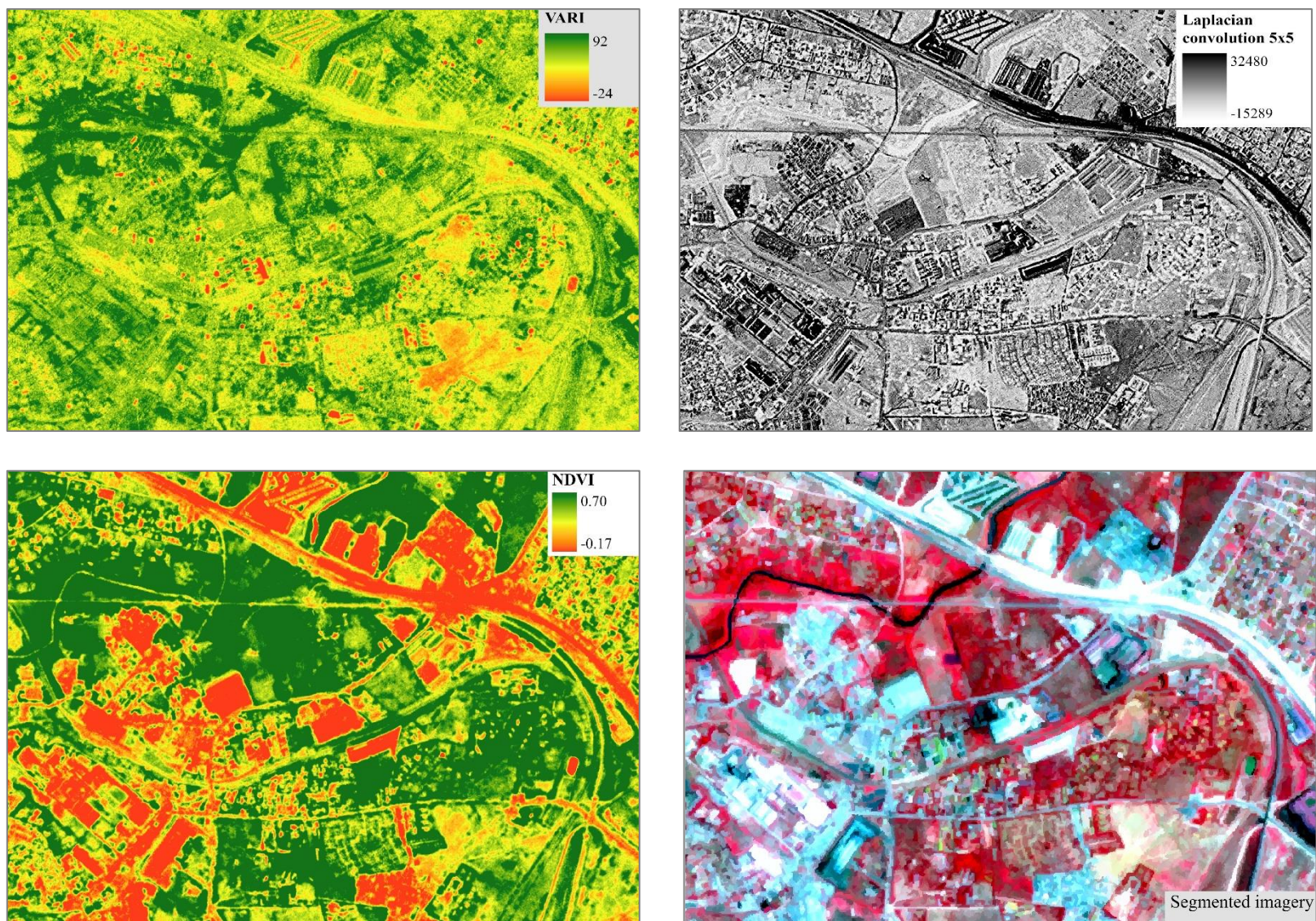


Figure 3.9: Subset of artificial bands VARI, NDVI, Laplacian convolution 5 x 5 on R band and PS-2022 true colour

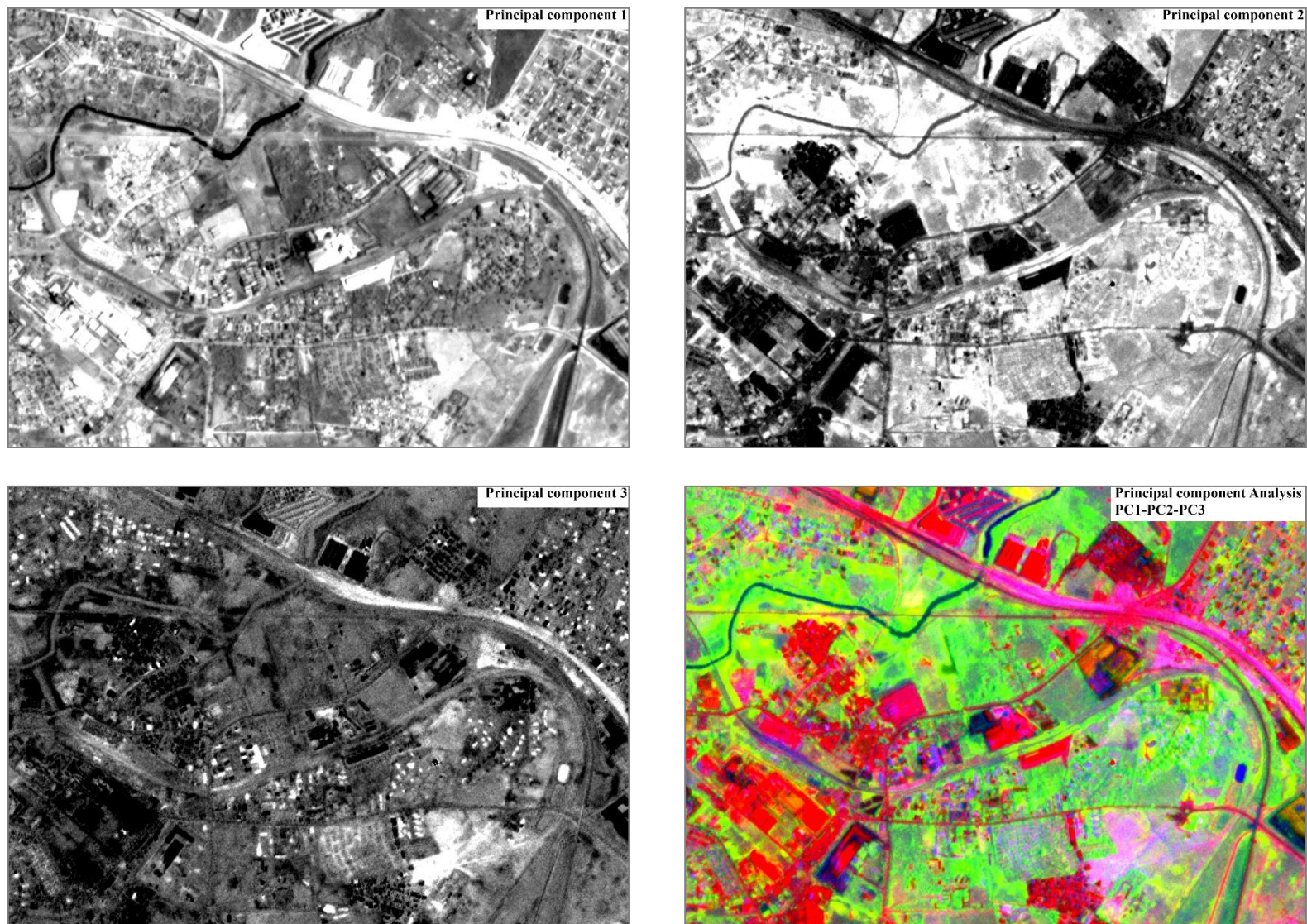


Figure 3.10: Subset of artificial bands PCA based combination PC 1-PC2-PC3, PC1, PC2 and PC3

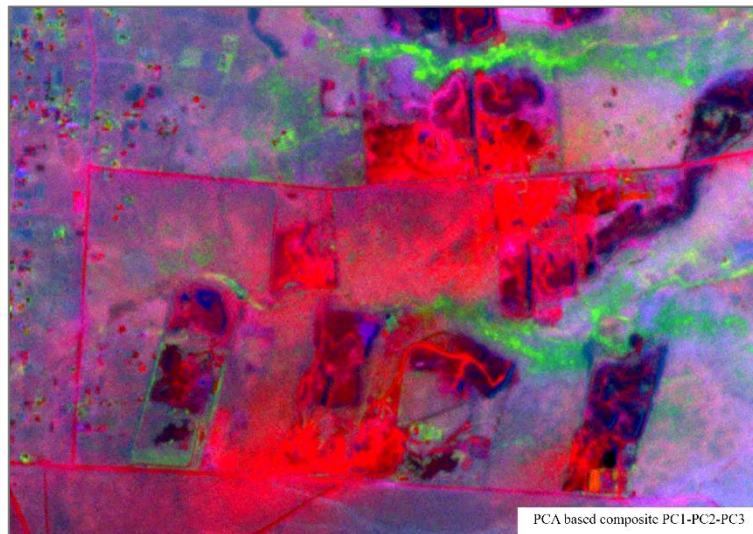
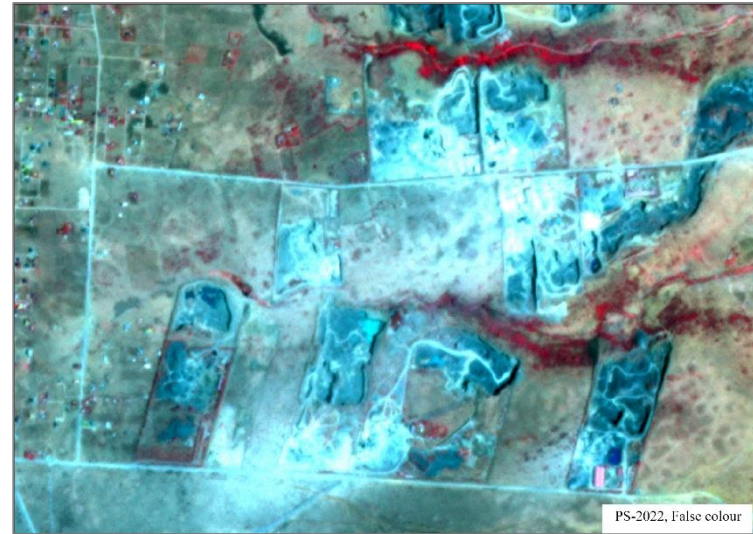


Figure 3.11: Subset of quarry area PS-2022 true colour, PS false colour, PCA based composite PC1-PC2-PC3 and PC1

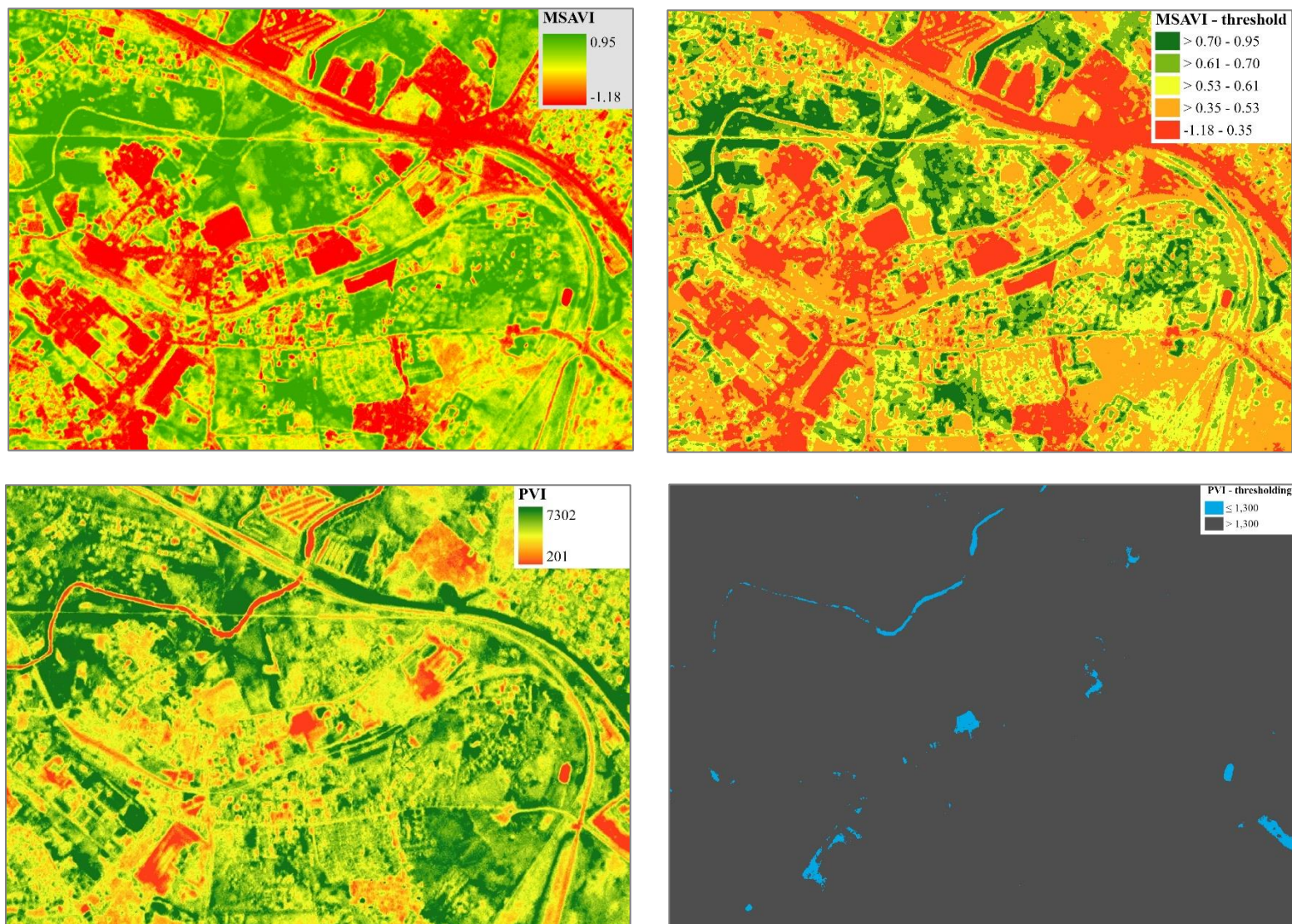


Figure 3.12: Subset of artificial bands MSAVI and PVI

3.7.1.5 Gaining Information on Parcel/Farmland Layout

Due to the extensive distribution of relatively small LULC units in urban and peri-urban landscapes and different cultivation methods and different farm types, different production regime (irrigated/rain fed, year-round/seasonal production and different crops), an accurate extraction of agricultural land solely based on the spectral information of the pixels with the PS-2022 imagery was not possible. In addition, the image segments resulting from the mean shift segmentation in ArcGIS Pro 3.0 exhibited tiny and shapeless segments due to very small LULC features, which was not promising in agricultural land demarcation. Various image filtering tools in ArcGIS Pro were tested on the principal components (PC1 and PC2), and on each of the four bands NIR, R, G and B for assessing their potential for parcel layout extraction (Tefferu et al., 2018). A series of trial and error showed that the Laplacian convolution 5 x 5, which is a filter used for edge detection, exhibited the best representation of parcel layout (parcel boundaries) when performed on the on the R bands. It was therefore used to determine different spatial arrangements of farmland patches existing in the peri-urban interface of Nairobi-Machakos (Fig. 3.8).

Although the Laplacian filter showed a visually convincing outcome, it proved difficult to further turn the image in a binary result *i.e.*, boundaries vs. background. Reasons are that some areas exhibited the intensive spectral response expected for hedges throughout the parcel. These areas include areas with thick vegetation cover (natural vegetation and farmland at intensive green phenological stage) and some rooftop. Therefore, the filtered image was explored for suitable thresholds based on small subdivisions which could be analysed using the same binary thresholds boundaries vs. background (Fig. 3.13). This process resulted in six thresholding zones (see Fig 3.7, Fig. 3.13), which were separately explored for better binary result. Thresholding was

successful on the zones 1-5, while the Zone 6 was excluded due extreme background noise effect, which made the thresholding impossible.

After the iterative thresholding, satisfactory subsets were reclassified as binary result, the parcel layout were extracted and merged in one geospatial dataset Fig. 3.13.

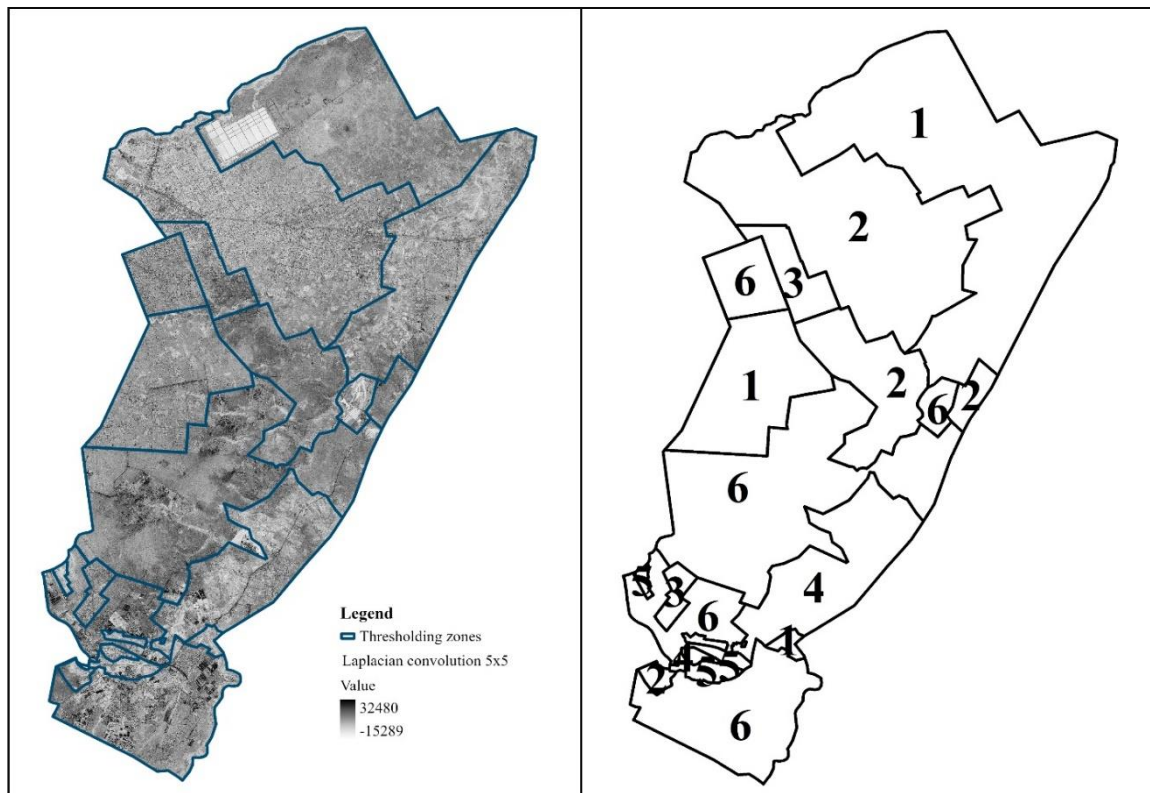


Figure 3.13: Laplacian filter partitioning and thresholding

3.7.1.6 Segmentation and Support Vector Machine classification

Image segmentation and the Support Vector Machine (SVM) classification algorithm were used to extract the LULC classes sealed area and quarry. Image segmentation was implemented using the segment mean shift function in ArcGIS Pro 3.0. The segment mean shift allows to control the amount of spatial and spectral smoothing in helping derive features of interest. As image segmentation under ArcGIS Pro 3.0 using the segment mean shift requires exclusively a three bands imagery, the Extract band

function was used to specify the optimum band combination NIR-R-G. The stretch band function was then used to enhance the display for better visualization of land use features on the new three bands imagery resulting from band extraction.

Prior to image segmentation a series of testing on five representative subsets of the imagery was performed to determine the adequate segmentation parameters for the best extraction of LULC classes. The settings of the level of spectral details, spatial details and the minimum segment size for image segmentation process determine the delineation between the pixel groups representative of object in the imagery (Michel et al., 2015). The final specifications of the settings of the mean shift segmentation applied is presented in Fig. 3.7. Although, only two LULC classes, sealed area and quarry, were retrieved from this step of LULC classification, the SVM classifier algorithm was trained considering five LULC classes including also vegetation, agricultural land and water bodies, to prevent misclassification between the desired LULC classes and the other classes (Fig. 3.7). The outcome of these three LULC (vegetation, agricultural land and water bodies) was not used in the final LULC classification (Fig. 3.7) because of minor quality compared to the extraction from MSAVI. This is attributable to the shapes very tiny of the segments which resulted in low accuracy.

For each LULC classes, between 300 and 400 training samples were collected by selecting segments. Training samples were collected based on the visible and clearly recognisable surface features in the false colour stretched NIR-R-G image composite. During this process VHR Google Earth imagery and part of ground truth data were used alongside for feature recognition. The LULC greenhouse was manually digitised and mask out from sealed area (Fig. 3.7).

3.7.1.7 Image Classification and Accuracy Assessment

As all the pixels per raster dataset resulting from the different methods applied for LULC analysis had a value either targeted or not, a comprehensive prioritization procedure based on the quality of the various output was used for combining the LULC classes. The LULC classes extracted from the different image processing methods were combined in a single raster as illustrated in Fig. 3.11. This process was conducted using the Conditional toolset and the Map Algebra toolset in ArcGIS Pro. The higher a pixel in the vertical LULC classes hierarchy is placed, the more of other pixel values at the same pixel position are overwritten (Willkomm et al., 2019). Therefore, LULC features were arranged in the order of classification quality achieved: greenhouse, water body, sealed area, low vegetation cover, medium vegetation cover, thick vegetation cover, quarry and bare aground (Fig. 3.14).

LULC classification algorithms operate with a likelihood of making certain errors, therefore it is essential to carry out accuracy evaluation based on reference data. The confusion matrices comparing the LULC classification outcome and reference data. For each LULC class, stratified and randomly distributed reference pixels were used for accuracy assessment. For each LULC class except sealed area 30 pixels points were used, while 60 random pixels were used for sealed area because it combines different urban development, infrastructure, and impervious land. For each random point the classified pixel was compared to its reference LULC obtained from a visual assessment of the corresponding pixel in the PS-2022 imagery, sometimes checked with VHR Google Earth imagery of January 2022. The outcome of this process resulted in the confusion matrix, which was used to compute the four accuracy measures usually used in LULC analysis: producer's accuracy, user's accuracy, overall accuracy, and Kappa coefficient.

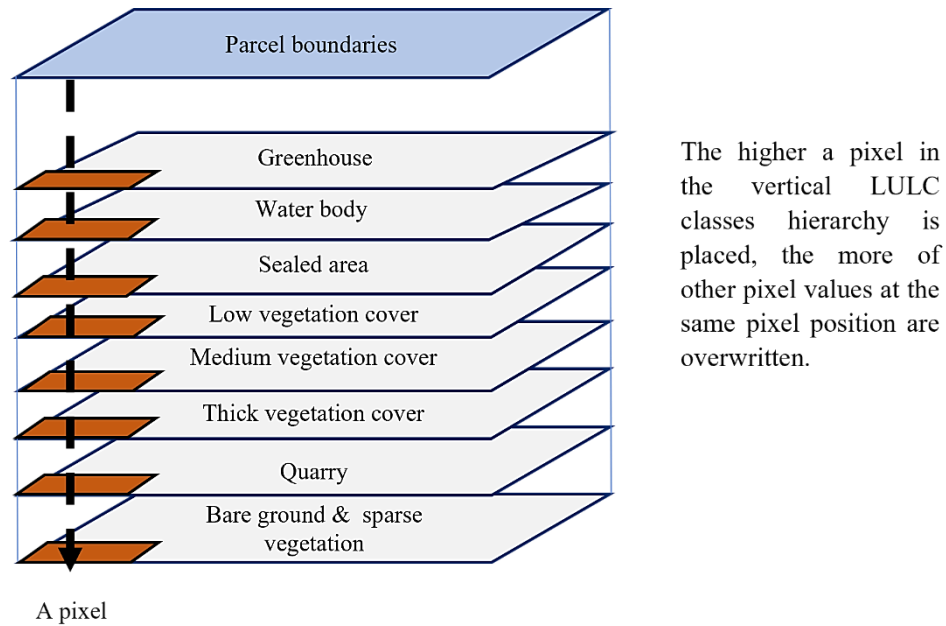


Figure 3.14: Overlaying LULC features within a raster dataset

3.7.2 Geospatial Dataset and Analytic Hierarchy Process (AHP)

3.7.2.1 Geospatial Dataset

The geospatial dataset used for land use suitability modelling includes the result of LULC classification process as described in section 3.7.1, a USGS 1 arc-second Digital Elevation Model (DEM) with 30 m spatial resolution, the soil map Nairobi-Machakos area 1:100,000 by Scott (1985) and the master plan 2030 of Mavoko Subcounty. The DEM tiles were freely downloaded as raster data from <https://earthexplorer.usgs.gov/>, while the soil type map and the planning maps, all in pdf format, were acquired respectively from the national soil survey archive of the Directorate of Oversea Survey (DOS) and the Physical Planning department of Machakos County. The two datasets were georeferenced to UTM 37 S WGS 1984 and digitized to create vector layers in ArcGIS Pro. Additional geospatial datasets include road network, freely downloaded from OpenStreetMap <https://www.openstreetmap.org/> and river network extracted from geology and topographical data, department of Mines and Geology Kenya, 1991. Both

datasets were projected to the coordinate system UTM 37 S WGS 1984, screened for accuracy and corrected based on the PS 2022 imagery.

3.7.2.2 Land Use Suitability Analysis and Analytic Hierarchy Process

In the context of increasing pressure on land resources due to population growth coupled with urbanization pressure (Güneralp et al., 2017) and alarming environmental pollution (Kinuthia et al., 2020) the optimization of land use is crucial for sustainable and safe agricultural production especially in peri-urban areas, where land resources advocated for farming are shrinking (Pribadi & Pauleit, 2015; Kinuthia et al., 2021). One of the primeval steps in this path is the efficient zoning of agricultural land considering both transient and permanent agricultural land (Halloran & Magid, 2013). Here, the understanding of land suitability across the peri-urban interface is necessary for informing efficient land use zoning for agricultural purposes (Akıncı et al., 2013).

Land suitability analysis is a land evaluation method with the purpose to identify the major limiting factors for particular purpose (Taghizadeh-Mehrjardi et al., 2020), which is vegetable farming in the case of this study. Land suitability analysis is a complex and multidimensional decision-making process which integrates various factors and criteria including environmental, social, biophysical, and economic conditions (Thapa & Murayama, 2008). It allows to integrate different scenarios and variables to provide an aggregation of the various facets of the decision problem into a single objective function (Spataru et al., 2020). Over recent decades, the combination of multiple criteria decision analysis (MCDA) technique and GIS has advanced the land suitability analysis with location specific output in form of maps that can inform locally and regionally (Koschke et al., 2012). Analytical Hierarchy Process (AHP) is one of the most used multi-criteria decision-making approaches widely used in combination with GIS methods for spatially

explicit agricultural land suitability evaluation (Akpoti et al., 2019). In the AHP approach, the initial step involves utilizing a hierarchical structure that illustrates the criteria, sub-criteria, and decision alternatives (as shown in Fig. 3.15). At the pinnacle of this structure resides the objective or purpose of the decision-making problem, which is land suitability for vegetable farming in the case of this study.

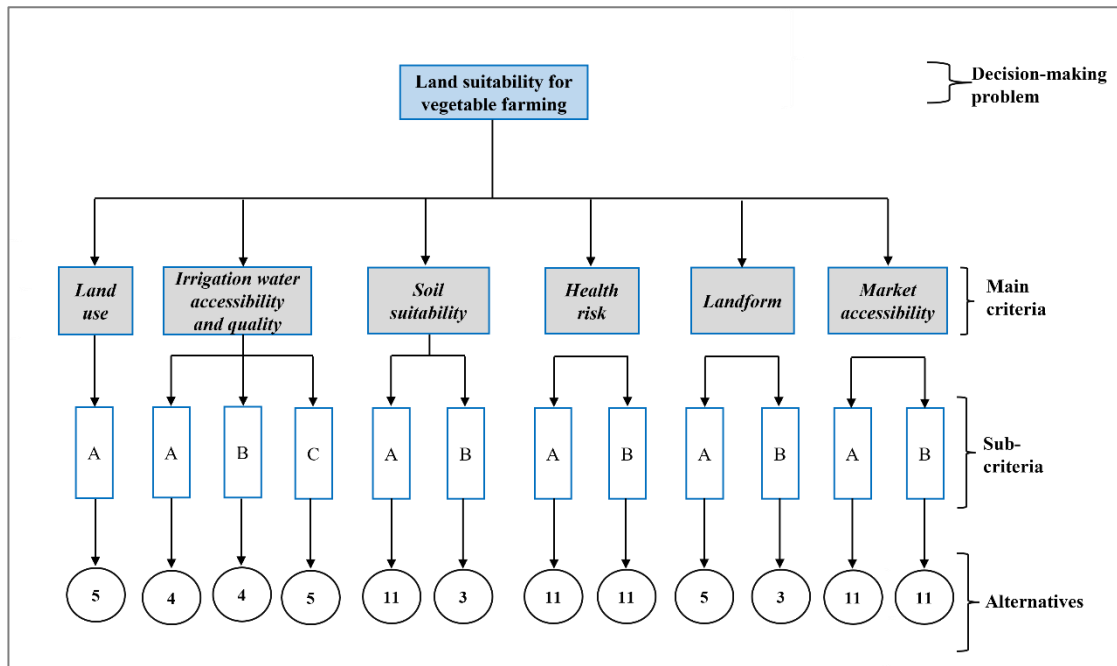


Figure 3.15: AHP hierarchy for modelling of land use suitability for vegetable farming

By prioritizing and ranking options according to how well they meet a set of criteria and sub-criteria, the AHP approach streamlines the decision-making process (Saaty, 2001). At the end of the process, all the considerations for the specific decision-problem are translated into a single value, which simplifies the decision-making process.

The process begins by the identification of situation-specific assessment criteria, including aims and qualities. The chosen criteria for assessment should accurately reflect the decision-making process and provide value to the result. Each criterion for assessment has its own geospatial dataset in which each location is assigned a

"suitability degree" according to the subsequent criterion/sub-criteria (Bozdağ et al., 2016). These "suitability degrees" are then weighted in accordance with the significance of their individual contributions to the overarching goal. The main goal of the AHP configuration in this study being land suitability for vegetable farming was placed at the top of the hierarchy structure and the relevant sub-criteria and alternative scenarios follow accordingly (Fig. 3.15). A combination of the analytical hierarchy process (AHP) and GIS was used to elaborate a land use suitability map for sustainable and safe vegetable farming in Nairobi-Machakos interface. This process allowed to integrate different dataset such as remote sensing data, edaphic and environmental parameters, ancillary data and experts and local stakeholders' opinions.

3.7.3 Land Suitability Criteria and Hierarchy Depiction

Six main criteria including land use zones, irrigation water accessibility and quality, soil suitability, landform, health risk and market accessibility were considered relevant for land suitability analysis for vegetable farming based on pertinent literature (Thapa & Murayama, 2008; Zolekar & Bhagat, 2015), key informant opinions and environmental conditions specific to the peri-urban landscape of Nairobi-Machakos interface (Wolff et al., 2021; Žlender, 2021). In the following first the various sub-criteria with their classes are explained per main criteria, which leads to different numbers of alternatives, before the subsequent section 3.7.4 then sheds light on how the informants' opinions were considered.

3.7.3.1 Land Use

Land use and land cover characteristics appeared in the literature as one of the most important factors affecting agricultural production (Hussain & Hanisch, 2014; Pribadi

& Pauleit, 2015). In this study, a land use zone map was prepared for the current situation (2022) and a future scenario (2030), the latter based on a county master plan. For land use suitability analysis, the result of LULC analysis was further reorganised into land use zones, which were used as input in the AHP-GIS land suitability modelling process. The land use zone classes of interest were adapted from master plan 2030 (County Government Machakos, 2020) and the results of LULC analysis of from PS-2022.

For purpose of comparability of the land zone in the current situation and the 2030 scenario, the principal land use zones classes considered were classes worked out from the planning map 2030 but which could be at the same time inferred from the remote sensing analysis result. Therefore, land use zone classes were informed by the planning map 2030. The land use zones for 2022 were manually digitized at a scale of 1: 50,000 based on the PS image analysis result, following a thorough and iterative evaluation of the LULC analysis results, field survey and additional information acquired from key informants including county commissioner, chief officer physical planning and agricultural officers at the time. The land use zones for 2030 were manually digitized at a scale of 1: 50,000 based on the planning map 2030. During this iterative process, areas having a certain advancement in the change of land use in the 2022-time step, *i.e.*, being current situation in settlement compared to what the planning map states for 2030 were adjusted accordingly. For example, if an area which is planned to be a low-density residential area in the 2030 planning map is shown already as a medium density residential area in the RS analysis result for 2020, then the land use zone for the year 2030 was adjusted from low to medium residential area. These adjustments prevented from any contradiction between the two land use zone datasets. Land use has one sub-

criteria criterion, land use zones with five suitability classes (alternatives) (Fig. 3.15, Table 3.16).

3.7.3.2 Irrigation Water Accessibility and Quality

Fresh fruit and vegetable production depends substantially on irrigation because of rainfall irregularity and unexpected dry spells even during wet season (Chandrasiri et al., 2020). Three sub-criteria were considered for irrigation water accessibility and quality: irrigation water accessibility, irrigation water quality index (IWQI) and bacterial contamination index (BCI). Irrigation water accessibility was evaluated in term of proximity to relatively permanent irrigation water sources. The nearer the water source is, the higher the potential for vegetable farming. The IWQI and BCI were derived from the results of irrigation water quality evaluation explained in section 3.5.4. IWQI and BCI were analysed based on sub-catchment area, which were targeted in the purposeful sampling *i.e.*, assuming to have distinct water quality characteristics. Irrigation water accessibility was classify using four intervals of distance (in km), IWQI have four suitability classes, while the BCI have five suitability classes (Fig. 3.15, Table 3.16).

3.7.3.3 Soil Suitability

Soil resources represent a valuable component of the environment, as they form the basis of ecosystem functions, support food production, water supply and host biogeochemical cycles indispensable for life (Zhu et al., 2017; Ahogle et al., 2022). Soil suitability was evaluated considering soil types and heavy metals and trace elements contamination in soil. Soil types were extracted from the 1:100,000 soil map by (Scott,

1985). The soil types were classified into three groups: stony soil, laterite soil and other soil and which represented the degree of suitability (Table 3.16-3.17). Heavy metals and trace elements contamination in soil is derived from the Pollution Load Index (PLI) explained in section 3.5.9.4 (Equation 9). The PLI being an index with continuous values indicates the level of soil contamination: the higher the value is, the lower the suitability for vegetable farming (Fig. 3.15, Table 3.16-3.17).

3.7.3.4 Health Risk

The prevalence of health risk related to PUA has gained more emphasis with the trends of urbanisation and industrialisation along with increasing environmental contamination (Rai et al., 2019). Health risk in the land suitability analysis process was computed as the cumulative of the non-carcinogenic risk HI (Hazard Index) and the Total Carcinogenic Risk (TCR), calculated based on the daily exposure to heavy metals and trace elements via ingestion, inhalation, and dermal contact, described in section 3.6.2 (Equation 19 and 21). The HI and TCR are indices with continuous values, the higher their values are, the higher the risk and, therefore, the lower the potential for vegetable farming (Fig. 3.15, Table 3.16-3.17).

3.7.3.5 Landform

Landform is described as a natural or anthropogenic land feature making up a given terrain, whose arrangement in the landscape is known as topography. Landforms can influence water and nutrients mobility and accumulation, and therefore can have substantial impact on agricultural production (De Gryze et al., 2008; Liao et al., 2019). In the framework of this study, landform was captured through slope and elevation

having an impact on soil suitability for vegetable farming. Elevation can affect agricultural land suitability because it influences temperature changes and thus plant cover variations. The characteristics of geomorphology are intimately connected to the process of soil formation and the degree of the slope is the principal factor that determines erosion control (Koulouri & Giourga, 2007). The slope was structured in five suitability classes, while land elevation was classified in three ranges (Mwendwa, 2022). The slope and elevation maps were extracted from the DEM in 30 m resolution. The higher the elevation and the slope, the lower the potential for agricultural production (Fig. 3.15, Table 3.16-3.17).

3.7.3.6 Market Accessibility

Market accessibility is a crucial parameter for vegetable production in peri-urban areas because of the high perishability of fresh vegetables, the lack of refrigeration equipment for vegetable conservation in developing countries and the long distance transportation from rural area, which induce additional production costs and can eventually lead to quality depreciation and losses for farmers (Okop et al., 2019). Adequate market accessibility allows farmers to access market information easily and secure the marketability of their products (Thapa & Murayama, 2008).

Although fresh fruit and vegetable markets include international and local marketing systems, the analysis of market accessibility in this study focused on local market only because it appears the predominant marketing system with supply of above 90% of the overall quantity of fresh fruit and vegetable produced (Krishnan, 2018). For the local market, farmers can take their production to local air-open markets, retailer shop or supermarkets in medium and high-density residential areas.

Table 3.16: Criteria and sub-criteria used for land use suitability evaluation

Main criteria	Sub-criteria	Alternatives	Suitability classes
Land use	Land use zones	Agricultural	100
		Bare ground/ Reserve area	75
		Low density residential	30
		Medium density residential	16
		High density residential/ Light industrial	7
		Quarry/WTP/Medium-Heavy industrial	0
Water quality	Irrigation water accessibility (distance in km)	≤ 0.5 km	100
		> 0.5-1 km	75
		> 1-2 km	50
		> 2 km	25
	IWQI	> 37	100
		30-37	75
		22-30	50
		< 22	25
	BCI	5	100
		4	80
		3	60
		2	40
		1	20
Soil suitability	PLI	PLI values	See Table 3.17
	Soil types	Others soil	100
		Laterite soil	50
		Stony soil	25
Health risk	HI	HI values	See Table 3.17
	TCR	TCR values	See Table 3.17
Landform	Slope	< 2%	100
		> 2-5%	80
		> 5-8%	60
		> 8-16%	40
		> 16%	20
	Elevation	1449-1510 m	100
		> 1510-1560 m	80
		> 1560-1610 m	60
Market proximity	Market proximity	Distance (km)	See Table 3.17
	Road proximity	Distance (km)	See Table 3.17
	Residential area proximity	Distance (km)	See Table 3.17

WTP: wastewater treatment; IWQI: Irrigation Water Quality Index; BCI: Bacterial Contamination Index; PLI: Pollution Load Index; HI: Hazard index; TCR: Total Carcinogenic Risk

Market accessibility can be influenced by the distance from the farm to the market, road accessibility and the closeness of the farm to medium- and high-density residential areas, which has many retailer shops and supermarkets selling fresh vegetables. Therefore, market accessibility was analysed following three dimensions: market proximity to farm, which is the distance from the farm to the nearest market; road

proximity, which is the distance from the farm to the nearest main road and secondary road, and the distance from the farm to medium and high-density residential areas. Proximity analysis was based on direct distance (bird's eye view) in km and for the three dimensions considered, the lower the distance the higher the potential for vegetable farming (Thapa & Murayama, 2008). Proximity analysis was implemented in ArcGIS Pro using the *Multiple Ring Buffer* tool with a uniform buffer distance of 200 m. All the farmland in the same buffer were given the same proximity suitability score (Table 3.16-3.17).

For market proximity, the primary of air-open market in and around the study area were identified during the key informant interview, farming unit survey and confirmed during ground truth data collection (see section 3.4). In the Geographic Information System (GIS), each market was represented by a point feature. Road proximity analysis was based on both main roads and secondary roads in the study area, represented using the line feature in GIS. The buffering was carried out separately for main roads and secondary roads first and combine later following some rules. A buffer zone of 2 km was used to delineate farmland that could have direct access to the main road, such that for the farmland locate in this 2 km buffer road proximity was based only on their direct distance to the main road. In contrast, for the farmland located out of the 2 km buffer zone, the road proximity was computed as the sum of their distances to main and secondary road. The proximity to medium- and high-density residential areas was based on the results of land use zoning for 2022 and 2030 which is describe in section 3.7.3.1. Medium- and high-density residential areas were extracted as polygon feature and used as input for in the multiple ring buffering. The overall result for market accessibility was computed as the weighted sum of the outcome of the three proximity analyses for

each pixel position, but still as distance. Finally, the distances were translated in suitability score base the scale in table 3.17.

Table 3.17: Suitability classification based on indices, health risks and market accessibility

Suitability score	Pollution Load Index	Total Hazard Index	Total Carcinogenic Risk	Market accessibility (distance in km)
100	0 – 0.1	0 – 0.1	$0 - 10^{-5}$	0 – 1
90	0.1 – 0.2	0.1 – 0.2	$10^{-5} - 2 \times 10^{-5}$	1 – 2
80	0.2 – 0.3	0.2 – 0.3	$2 \times 10^{-5} - 3 \times 10^{-5}$	2 – 3
70	0.3 – 0.4	0.3 – 0.4	$3 \times 10^{-5} - 4 \times 10^{-5}$	3 – 4
60	0.4 – 0.5	0.4 – 0.5	$4 \times 10^{-5} - 5 \times 10^{-5}$	4 – 5
50	0.5 – 0.6	0.5 – 0.6	$5 \times 10^{-5} - 6 \times 10^{-5}$	5 – 6
40	0.6 – 0.7	0.6 – 0.7	$6 \times 10^{-5} - 7 \times 10^{-5}$	6 – 7
30	0.7 – 0.8	0.7 – 0.8	$7 \times 10^{-5} - 8 \times 10^{-5}$	7 – 8
20	0.8 – 0.9	0.8 – 0.9	$8 \times 10^{-5} - 9 \times 10^{-5}$	8 – 9
10	0.9 – 1.0	0.9 – 1.0	$9 \times 10^{-5} - 10^{-4}$	9 – 10
1	> 1	> 1	$> 10^{-4}$	> 10

3.7.4 Pairwise Comparison of Pairs of Criteria and Sub-criteria

The pairwise comparison of the AHP was used to determine the weights of land suitability criteria and sub-criteria. The nine-point priority measurement scale (Table 3.18) of the AHP procedure (Saaty, 2001) was used to establish the pairwise comparison matrix based on the opinion of twelve experts all conversant with the area including analytical chemists (2), medical doctors (3), public health officers (2), soil scientists (2) and environmental scientists (3). It allows an independent evaluation of each factor's contribution to land suitability analysis (Rezaei-Moghaddam & Karami, 2008). The experts' opinions in form of scores for each pair of criteria and sub-criteria were averaged and used to set the ranking of each criterion and sub-criterion influencing vegetable farming in Nairobi-Machakos peri-urban interface. The questionnaire used for this process is presented in the Appendix 2 and the nine-point ranking scale for the pairwise comparison is described in Table 3.18.

Table 3.18: Comparison scale in AHP

Intensity of importance	Definition	Explanation
1	Equal importance of i and j	Two activities contribute equally to the objective
3	Weak importance of i over j	Experience and judgment slightly favour one activity over another
5	Strong importance of i over j	Experience and judgment strongly favour one activity over another
7	Demonstrated importance of i over j	An activity is strongly favoured, and its dominance is demonstrated in practice
9	Absolute importance of i over j	The evidence favouring one activity over another is of the highest possible order of affirmation
2,4,6,8	Intermediate values the two adjacent judgments	When compromise is needed
Reciprocals of above nonzero	If activity i has one of the above nonzero numbers assigned to it when compared with activity j , then j has the reciprocal value when compared with i	-

Source: Saaty (1980)

The eigenvector method developed by Saaty (2014) was used to determine the weight of each criteria and sub-criteria. For each individual pairwise comparison matrix, the consistency ratio (CR) was determined to assess the constancy of the weighing process. The CR was calculated by dividing the Consistency Index CI (Equation 25) for a set of judgments by the Random Index (RI) for the corresponding random matrix (Equation 24). The maximum eigenvalue ($\lambda_{\max}$) in a matrix is always equal or bigger than the number of rows and columns (n). The pair comparison matrix is expressed in the form of $A = [a_{ij}]_n$.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & \cdots & a_{2n} \\ \vdots & \vdots & \cdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \cdots & \vdots \\ a_{n1} & a_{n2} & \cdots & \cdots & a_{nn} \end{bmatrix}$$

Where for all i and j , $a_{ii} = 1$, $a_{ij} = 1/a_{ji}$ and $i, j = 1, 2, 3, \dots, n$.

Once all pairwise comparison matrices were created, the weights vector, represented as $w = [w_1, w_2, w_3 \dots w_n]$, was determined using the eigenvector method. The eigenvector was normalized using Equation 22, followed by computation of the weights through Equation 23. Finally, the elements of the normalized eigenvector were rated with respect to the alternatives, while being weighted in relation to the criteria or sub-criteria (Saaty, 1980).

$$a_{ij} = \frac{a_{ij}}{\sum_{j=1}^n a_{ij}} \quad (\text{Equation 22})$$

$$w_{ij} = \frac{a_{ij}}{\sum_{j=1}^n a_{ij}} \quad (\text{Equation 23})$$

$$CR = \frac{CI}{RI} \quad (\text{Equation 24})$$

where RI is the random index, the average of the resulting consistency index depending on the pairwise comparison matrix (Ying et al., 2007). The value of RI according to the number (n) of elements in the pairwise comparison is presented in Table 3.19. Saaty (1980, 1984) suggest that if CR exceeds 0.1, the set of judgments is inconsistent and not reliable. Thus, the ranking has to be adjusted. In contrast, if the CR is less or equal to 0.10, it means that the pairwise comparison matrix has an acceptable consistency.

Table 3.19: Random Index

<i>n</i>	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
<i>RI</i>	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.58

Source: Saaty (1980)

CI quantifies the consistency of the pairwise comparison and was computed using Equation 26:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (\text{Equation 25})$$

Where n is the number of elements being compared in the matrix, $\lambda_{\max}$ is the largest or principal eigenvalue of the matrix.

3.7.5 *Weighted Sum in Geographic Information System*

The alternatives of each criterion were normalised and scaled to five suitability classes (Akıncı et al., 2013; Bozdağ et al., 2016). For each criterion, the local ratings were combined by the weights of sub-criteria and aggregated to get a global ratings of the subsequent criteria (Equation 26) (Bhushan & Rai, 2004). The overall land suitability map was achieved by overlaying the raster layers of the six main criteria of land suitability for vegetable farming according to their specific weight using the weighted sum overlay toolset in ArcGIS Pro (Memarbashi et al., 2017). The results for land suitability for vegetable farming in Nairobi-Machakos interface were organised in five suitability classes including unsuitable (0-20), marginally suitable (20-40), moderately suitable (40-60), suitable (60-80) and highly suitable (80-100). The results are presented for the year 2022 as the current situation and the year 2030 as a scenario for the future. For each time step the results are presented for dry season and wet season because of the seasonal variation in water quality and health risks.

$$LS = \sum_{i=1}^n W_i S_i \quad (\text{Equation 26})$$

where LS is land suitability for sustainable and safe vegetable farming; W_i is the weight of the land suitability criteria; S_i is the score of criteria i ; and n is the number of land suitability classes.

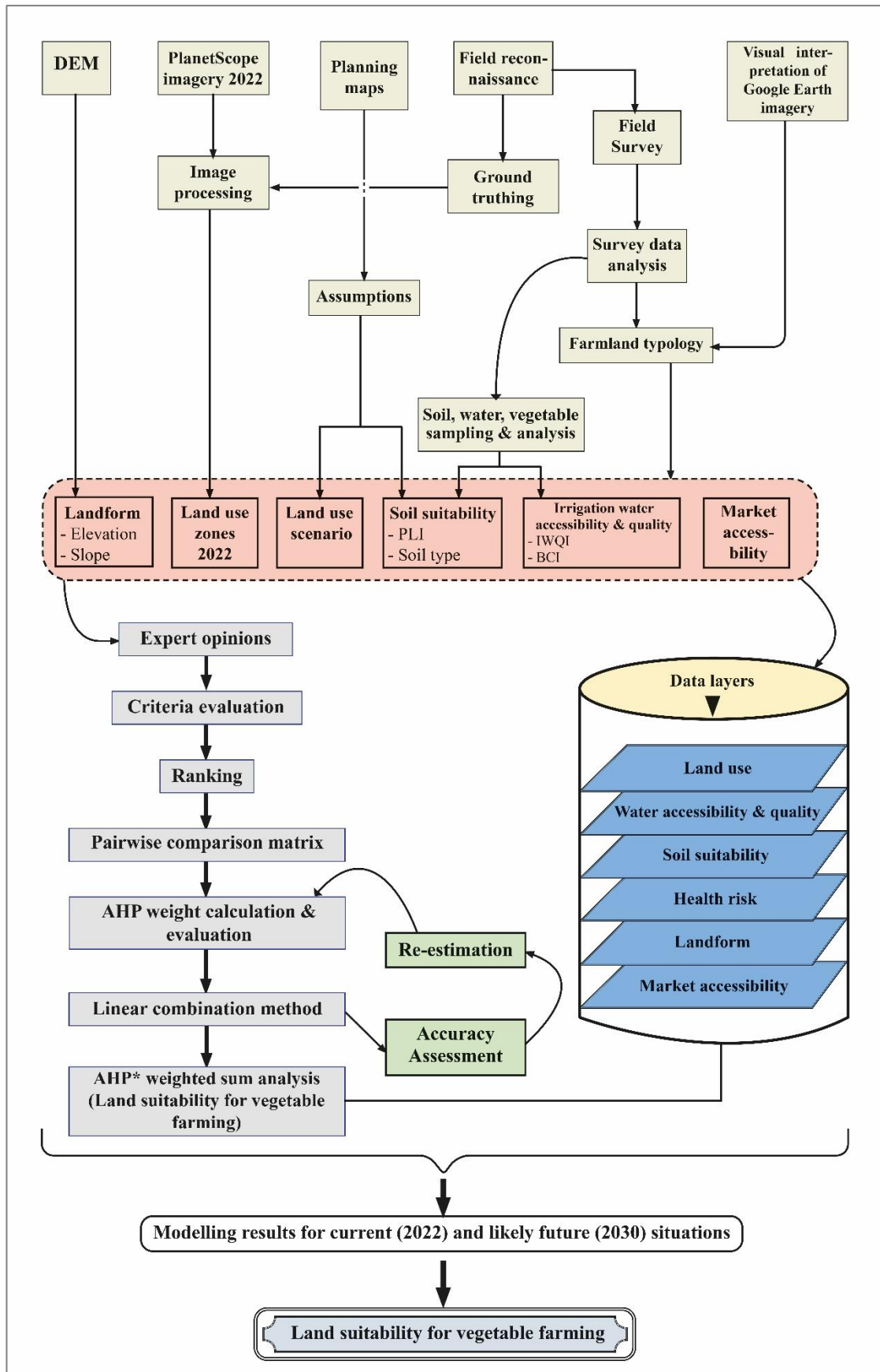


Figure 3.16: Flowchart of AHP-GIS land suitability analysis for vegetable farming

CHAPTER FOUR: RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter presents and discusses the research findings based on the methodology espoused in Chapter 3. The section is structured according to the specific objectives of the study, which are:

1. To explore the diversity of peri-urban agrosystems and their determinants in Nairobi-Machakos counties interface.
2. To assess irrigation water suitability and the contamination of peri-urban agrosystems in Nairobi-Machakos counties interface.
3. To determine the ecological and health risks of peri-urban agrosystems contamination in Nairobi-Machakos counties interface.
4. To model land suitability for vegetable farming in Nairobi-Machakos counties interface.

4.2 Characterisation of Peri-urban Farmland in Nairobi-Machakos Counties Interface

4.2.1 Socioeconomic Characteristics of Peri-urban Farming Units

The characteristics of peri-urban farming units surveyed in the framework of this study are presented in Table 4.1. The farming units are mostly men-led (95.4%), with at least a high school education (92.5%). The ages of farming unit heads range between 22 and 76 years with an average of 44 years, with 87.7% aged between 25-60 years. Three categories of actors operate peri-urban agricultural units in Nairobi-Machakos counties interfaces: urban households (90%), local companies (6.9%) and international investors (3.1%). About 64% of the farmers derive their monthly income exclusively from farming. The main off-farm activities include animal husbandry, business, and formal

employment. The monthly income ranges from US\$30 to US\$5,000 (US\$1= KES120 at the time of the survey) with an average of US\$200. About 20% and 18% of the farming units have a monthly income of less than US\$100 and above US\$500, respectively. However, local and multinational horticultural firms engaged in large-scale and high value horticultural crop production (herbs, cut flowers and fruits) for export market reach thousands of US\$ in revenue monthly.

Cultivated agricultural commodities include fresh fruits (36.9%), leafy vegetables (87.7%), herbs (9.2%), cut flowers (3.1%), and staple crops (31.5%) that are essentially maize and beans. Farmland sizes vary between 0.005 and 60.7 Ha with 31% of the farms having formal land ownership rights, while the remaining have access to land through verbal lease contracts³ with landowners (33.1%) or by squatting on public land, open spaces, and vacant urban plots (26.9%). Farming units' experiences in PUA range from 1 year to 36 years with an average of 10 years. About 13% of the farming unit access agricultural extension service. Most of the farming units are not member of any farmers' organisation. However, farming units involved in horticultural export are members of organisation such as out-growers' schemes which support them in the exportation process. About 71.5% of the farms are located along urban stream and irrigation water sources include urban rivers (67%), borehole (21.5%), open drainage canal flow (2.3%), tap water (2.3%), harvested rainwater (2.3%), and sewage flow (4.6%). Irrigation water is also used for refreshing vegetables after harvesting. About 23% of the farm hold low to high livestock while the majority (76.2%) has no livestock. PUA production is mainly directed to open market with export market and supermarket representing only 6.9% and 8.5%, respectively.

Table 4.1: Characteristics of farming units in Nairobi-Machakos counties interface

Socioeconomic variables	Modalities	Frequency	Percentage
Gender	Female	6	4.62
	Male	124	95.38
Age	< 25	6	4.62
	25 - 60	114	87.69
	> 60	10	7.69
Education level	None	2	6.92
	Primary	34	1.54
	Diploma	9	26.15
	Secondary	65	50
	University	20	15.39
FU head profile	Urban household	117	90
	Local Company	9	6.9
	International investor	4	3.1
Main source of income	Animal husbandry	2	1.5
	Business	14	10.8
	Employed	31	23.9
	Farming	83	63.9
Monthly income (US\$)	< 100 \$	25	19.2
	100-200 \$	47	36.2
	200-500 \$	35	26.9
	> 500 \$	23	17.7
Total farmland size	Minimum	Mean	Maximum
	0.005	3.35	60.70
Land tenure	Free hold	35	26.92
	Inherited	12	9.23
	Leased	43	33.07
	<i>Purchased</i>	<i>40</i>	<i>30.78</i>
Irrigation water source	Borehole	28	21.54
	Open drainage canal	3	2.31
	Piped water	3	2.31
	Rainwater	3	2.31
	River water	87	66.92
	Sewage	6	4.61
Market	Export	9	6.9
	Open markets	108	83.2
	Subsistence farming	2	1.6
	Supermarkets	11	8.5
Livestock	High	8	6.2
	Medium	7	5.4
	Low	16	12.3
	None	99	76.2
PUA profitability	Not profitable	0	0
	Marginally profitable	7	5.4
	Moderately profitable	86	66.1
	Above average profitable	33	25.4
	Highly profitable	4	3.1
PUA type	Residential garden (RG)	30	23.08
	Small-scale greenhouse (SGh)	5	3.85
	Small-scale open field (SOF)	48	36.92
	Large-scale open field (LOF)	37	28.46
	Large-scale greenhouse (LGh)	10	7.69

All the farms use chemical pesticides for pest and diseases management and combined mineral fertilizers and organic manure for soil fertility management, although mineral

fertiliser remains the predominant mode of soil fertility management. The use of urban hydrological flows: urban rivers, sewage combined sometimes with WTP effluent and industrial effluent is considered by the farmers as an additional source of nutrients in soil fertility management. The level of PUA profitability for the farming units are ranked marginally profitable (5.4%), moderately profitable (66.1%), above average profitable (25.4%) and highly profitable (3.1%).

4.2.2 Agricultural Land Use Typology Based on Google Earth Imagery

Five principal forms of peri-urban agricultural land use types were distinguished from the visual interpretation of VHR-GE imagery (Table 4.2). These include residential garden (RG), small-scale open field farms (SOF), small-scale greenhouse farms (SGh), large-scale open field farms (LOF) and large-scale greenhouse farms (LGh).

The RG are small plots with sizes of 0.005-0.3 Ha located in the vicinity of residential areas (Fig. 4.1 & Table 4.2). These farms are located on vacant plots next to houses or complexes of buildings, and surrounded by fences, hedges, or walls. These farms are managed by urban households of different socioeconomic backgrounds, who generally live close to the garden and derive part of their daily food and some occasional contribution to their monthly income from the small garden. The production is focused on fresh fruits and vegetables, sometimes combined with small-scale poultry production and farming can be seasonal or year-round. These farms are managed by households engaged in on-site farming with low to medium input and intensification. The primary sources of irrigation water are borehole, tap, harvested rainwater and water flowing in open drainage canal along road.

The SOF are characterised by aggregation of small farmland size (< 1 Ha) located closer to built-up areas (< 1.5 km) and generally along urban streams or urban sewage flows (Fig. 4.1). This farmland type is managed by urban households and the production is extensive to semi-intensive. Cultivated crops include leafy vegetables, fruit vegetables, and staple crops (maize and beans). Production relies primarily on river water or sewage flow for farm irrigation. Cultivation is generally year-round, and the production is market-oriented but can be seasonal or year-round depending on the river's water regime (water availability).

The SGh are intensive farming unit with greenhouse sizes between 0.5-1 Ha cultivating horticultural crops, generally located close to build-up areas (1-2 km). These farmlands are in low and medium density residential areas, but not necessarily close to urban streams. The farms are managed by local companies or urban households with medium to high technicality including automated irrigation equipment and small water ponds. Cultivated crops are essentially herbs and fruit vegetables. Production depends entirely on irrigation and the main irrigation water sources are borehole and stabilised or treated river water.

The LGh are characterised by permanent and intensive market-oriented large greenhouse farming of up to 60 Ha land size, generally located along urban rivers (Table 4.2). These farmlands have a typical structure of a company with employed staff, well established agricultural crop value chains and are owned by multinationals or local companies. The production is conducted in greenhouse conditions with high input, integrated irrigation systems and extensive water storage facilities and technologies. The farms are equipped with large water ponds for water storage and treatment which can be seen close to the farm on GE imagery. Cultivated crops in the greenhouses

include cut flowers, vegetables, and herbs. The production depends fully on irrigation, with irrigation water sources being from borehole or stabilised or treated river water.

Table 4.2: Agricultural land use from visual interpretation

Land use classes	Description	
Residential garden	Small plots of land (0.005-0.44 ha) located in the vicinity of residential area, with single or numerous farming plots that is typically inaccessible and surrounded by fences, hedges, walls, or wire mesh fences.	 100 m
Small scale open field	Small to medium size plots (< 1 ha area) located generally in the immediate neighbourhood of residential area	 300 m
Small scale greenhouse	Small size and whitish structure of greenhouse clusters (less than 1 ha area) located at a certain distance (< 3 km) to residential area	 50 m
Large scale open field	Large continuous and isolated open farmland area characterised by patches above 1.5 ha size and monocropping systems	 1.2 km
Large scale greenhouse	Large patches greenhouse (above 1 ha area) permanently installed and geographically clustered	 1.5 km

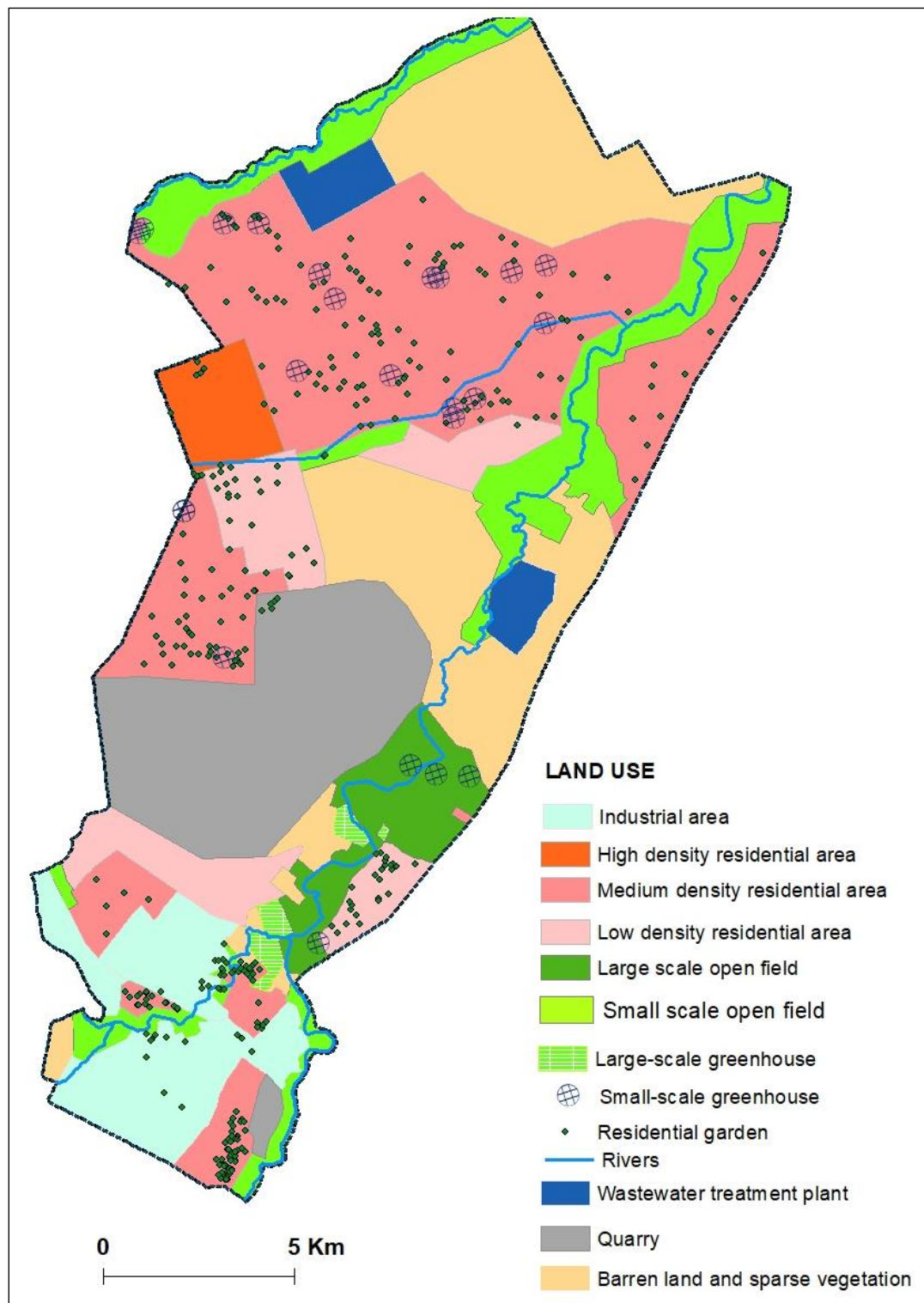


Figure 4.1: Farmland typology based on VHR GE imagery for Nairobi-Machakos interface

The LOF are characterised by large continuous farmlands located 3-7 km from built-up areas with farmland land sizes ranging between 1.5-10 Ha of continuous agricultural

patches located along rivers with relatively low subdivisions. As the distance from residential areas increase, the farmland patches become larger. These farms are managed by urban households, and in a few cases by local companies, as a principal source of income. The farms are characterised by open cultivation of fresh vegetable and staple crops like maize and beans with various level of intensification. Farming is carried out year-round and relies typically on urban hydrological flows notably urban rivers and sewage flows.

4.2.3 Typology Based on Multivariate Analysis of Socioeconomic Characteristics

The segregation of the farmlands in distinct groups based on their socioeconomic attributes using the Factorial Analysis of Mixed Data (FAMD) reveals that the first five dimensions have a cumulative eigenvalue equal or higher than 1 (Table 4.3) and explain about 42% of the variation in the dataset ($p < 0.05$). These five dimensions are used for Hierarchical Clustering on Principal Components (HCPC).

Table 4.3: Principal components loading and their significance for HCPC analysis

FAMD components	Eigen values	% of variance	Cumulative % of variance	r	P-value
Dim.1	6.44	16.52	16.52	0.868	< 0.001***
Dim.2	3.16	8.09	24.62	0.751	< 0.001***
Dim.3	2.57	6.59	31.20	0.453	< 0.001***
Dim.4	2.17	5.56	36.76	0.183	< 0.001***
Dim.5	1.94	4.97	41.74	0.070	0.027*

*Significant at $\alpha = 0.05$, ***significant at $\alpha = 0.001$

The correlation test from the HCPC shows that only the first two components have a correlation coefficient r greater than 0.50. Therefore, the first two principal components (Dim 1 and Dim 2) describe best the correlations between the different variables. These two principal components are used to explore farmland diversity. Out of the 18 variables

included in the HCPC, 15 variables are relevant and significant (Khi 2: p-value < 0.001) for describing the characteristics of the different farmland types (Table 4.4).

Table 4.4: Significant variables for farm type segregation

Variables	df	p.value
Farm head profile	6	9.41E-44***
PUA type	12	1.57E-30***
Cut flowers	3	5.41E-28***
Leafy vegetable	3	8.10E-17***
Herbs	3	1.74E-16***
Membership out-grower scheme	3	3.13E-14***
Irrigation Water sources	15	3.51E-14***
Irrigation system	3	2.32E-11***
Presence stream	3	2.44E-11***
Land tenure	9	4.25E-10***
Monthly income	24	4.73E-09***
Membership farmers organisation	3	8.99E-06***
Market orientation	9	1.49E-05***
Staple crop	3	4.64E-05***
Livestock	9	5.63E-03**

significant at $\alpha = 0.01$, *significant at $\alpha = 0.001$

The dendrogram from the HCPC analysis illustrates the identification of four peri-urban farm types (Fig. 4.2), each reflecting specific features related to farmers' socioeconomic characteristics, resource allocation, farm management, and farming orientation. Farm type 1 assembles 69% of the farming units and represents the major farmland type. The second cluster (farm type 2) holds 23%, while the third and the fourth represent 5% and 3%, respectively (Table 4.5).

4.2.3.1 Farm Type 1

Farm type 1 accounts for 69.2% of the respondents and is the predominant form of peri-urban farming systems across the peri-urban interface of Nairobi-Machakos Counties. These farms are located along urban stream (river) of which water is used for crop irrigation. They are owned by urban households and led in management by the head of the household. Land tenure system are free holding and leasing (90%), making the

farming activities susceptible to the land owner resolution or public infrastructure development policies. The farm don't belong to any farmers' association and cultivation is carried out year round with plot sizes varying from 0.05-6.1 Ha with an average of 1.3 Ha.

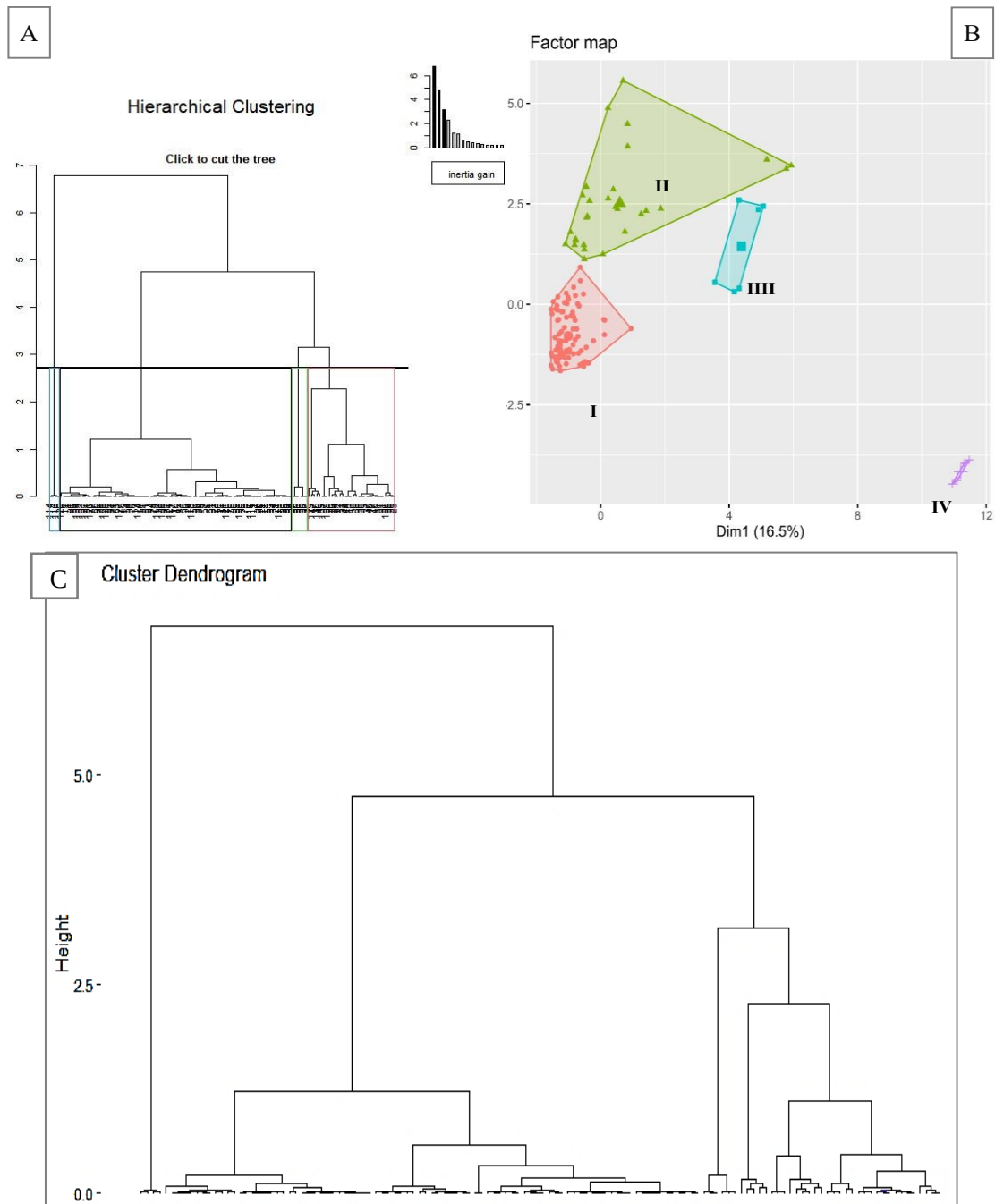


Figure 4.2: Cluster-gram of farmland types A (nested cluster) B (factor map) C (cluster dendrogram)

The cultivated crops are leafy vegetables and fruit vegetables. Farm type 1 is devoid of livestock production (81%) and farm products are mainly intended for local open market. The monthly income is generally less than US\$200 but reaches close to US\$500 for few households having large land size (18.6%). The numbers of year of experience in peri-urban farming in this group is about 10 years and greatly depends on the professional background of the household head and his age ($F=8.542$, $p < 0.001$). Farmland type 1 include part of the farms pre-classified as SOF (51%), LOF (11%) and RG (38%) from the VHR-GE imagery interpretation.

4.2.3.2 Farm Type 2

Farm type 2 accounts for 23% of the respondents and is located in the vicinity of residential areas, in some cases along busy traffic highways and generally away from rivers or streams. It is characterised by small plots of land scattered in medium to densely populated areas that vary from 0.005-0.8 Ha with an average of 0.3 ha. The farms are either home gardens or vacant plot located in residential areas on plots awaiting construction and are managed by urban households usually living close to the farm. Land tenure system in this cluster is purchased (80%), leased (16.7%) and freehold (3.3%). However, the pressure of land speculation and subdivision is evident in this farmland type. Borehole water, tap water and open drainage channel flows are the primary sources of crop irrigation. Cultivation is carried out year-round or seasonally on open field or in small greenhouses. Farmers in this group hold small to medium scale livestock production (poultry or sheep). Crop products are supplied to local open markets and street shops neighbouring the farm. The majority of these farms have a monthly income of less than US\$200. Cultivated crops are leafy vegetables (90 %), sweet corn (70%) and fruit vegetables (40%). Most of the farm in this group

(65%) are classified as residential garden (RG) from the VHR-GE imagery interpretation.

4.2.3.3 Farm Type 3

Farm type 3 is an intensive greenhouse production of herbs for export market and local supermarkets. The farmland are characterised by greenhouse farming on plot size ranging from 1.2 to 4.0 Ha and managed by local companies or urban professionals. These farms use intensive production means including irrigation systems and intensive input. Farming is conducted year-round and occasionally combined with low livestock production. Irrigation is a pre-requisite in this farmland type and borehole and river water are the primary source of farm irrigation depending on the position of the farm to the river. River water is treated or stabilised in water pond before use. Land tenure systems is purchased or leased and the monthly income is above US\$500. This farm type encompasses LGh (50%) and SGh (50%) from the VHR-GE imagery interpretation.

4.2.3.4 Farm Type 4

Farmland type 4 is a more intensified form of farm type 3. These farms are characterised by greenhouse cultivation of high-value horticultural crops including cut flowers, fruit vegetable and herbs for export market. The farm owners in this group are international investors and the farms have a well structured and strong management scheme with modern production means and technologies including irrigation systems, intensive input and hundreds of trained contractual staff. In this category, the farmlands are large, generally about 20-60.7 Ha with an average of 42.6 Ha. These farms are located downstream near rivers with large scale clustered greenhouse farming. The main source for

Table 4.5: Socioeconomic characteristic of peri-urban farmland types

Variables	Modalities	Type 1 (%)	Type 2 (%)	Type 3 (%)	Type 4 (%)	All (%)
Age	< 25	6.67	0	0	0	87.7
	25 - 60	90	76.7	100	100	4.6
	> 60	3.3	23.3	0	0	7.7
Farm owner profile	Urban household	98.9	93.3	0	0	90
	Local Company	1.1	6.7	100	0	6.9
	Multinational	0	0	0	100	3.1
Monthly income (US\$)	< 100 \$	29.2	66.7	0	0	19.2
	100-200 \$	52.2	20	0	0	36.2
	200-500 \$	18.6	13.3	0	0	23.1
	> 500 \$	0	0	100	100	21.5
Membership to farmers' organization	Yes	1.1	30	100	100	92.3
Membership to out-grower scheme	No	98.8	90	66.7	100	93.9
Access to agricultural extension	Yes	12.3	36.7	66.67	100	42.3
Total farmland size (ha)	Minimum	0.05	0.005	1.2	20	0.01
	Mean	1.3	0.8	2.6	42.6	3.4
	Maximum	6.1	2.0	4.1	60.7	60.7
Land tenure	Free hold	37.8	3.3	0	0	26.9
	Inherited	10	0	0	0	9.2
	Leased	42.2	16.7	50	0	33.1
	Purchased	10	80	50	100	30.8
Presence stream	Yes	87.8	23.3	50	100	71.5
Irrigation water source	Borehole	3.3	73.3	50	50	21.5
	Open drainage canal	2.2	3.3	0	0	2.3
	Piped water	0	10	0	0	2.3
	Rainwater	1.1	6.7	0	0	2.3
	River water	86.7	6.7	50	100	66.9
	Sewage	6.7	0	0	0	4.6
Irrigation system	Yes	1.1	23.3	100	100	11.5
Leafy vegetable	Yes	96.7	90	0	0	87.7
Fruit vegetable	Yes	38.9	43.3	0	0	36.9
Cut flowers	Yes	0	0	0	100	3.1
Herbs	Yes	0	13.3	100	100	9.2
Staple crops	Yes	74.4	70	0	0	67.7
Livestock	High	2.2	20	0	0	6.2
	Medium	4.5	10	0	50	13.9
	Low	12.2	63	50	0	73.1
	None	81.1	6.7	50	50	6.9
Market	Export	3.3	6.7	33.3	50	6.9
	Open markets	90	83.3	33.3	0	83.1
	Subsistence farming	1.1	3.3	0	0	1.6
	Supermarkets	5.6	6.7	33.3	50	8.5
PUA type	RG	11.1	66.7	0	0	23.1
	SGh	0	6.7	50	0	3.9
	SOF	51.1	6.7	0	0	36.9
	LOF	37.8	10	0	0	28.5
	LGh	0	10	50	100	7.69

irrigation water is river water that is generally treated or stabilised in large water ponds installed next to the greenhouse and borehole water. The production is commercial

based with very large monthly sales. This group is categorized as LGh (100%) from the GE imagery classification.

4.2.4 Determinants of Peri-Urban Agriculture in Nairobi-Machakos Interface

The screening of the determinant factors of PUA in Nairobi-Machakos interface using a Probit regression model is presented in Table 4.6 and 4.7. The probability of the null hypothesis test comparing the null model and the model including the covariates (Chi-Sq (df=13) = 63.277, $p < 0.001$) shows that the Probit model is globally significant.

Table 4.6: Accuracy parameters of the Ordinal Probit Model

Fitting null model Versus Probit model			
Criterion	Intercept model		Intercept and Covariates model
AIC	307.81		270.531
-2 Log L	301.81		238.531
Residual DF	127		114
Testing Global Null Hypothesis: BETA = 0			
Test	Chi-Square (G2)	DF	Pr > Chi-Square
Likelihood Ratio (LR)	63.277	13	< 0.001
	McFadden	r2ML	r2CU
Pseudo-r2	0.21	0.39	0.43

The model indicates that the variables PUA type, presence of stream, land tenure system and irrigation water sources influence farmers perception on the PUA profitability, while socioeconomic characteristics such as level of education age, gender, monthly income are not significant. Peri-urban farming in the interface of Nairobi-Machakos counties is less likely profitable ($p < 0.05$) for farmers operating in LOF, RG, SGh and SOF compared to the reference LGh. Farmlands near streams/rivers are most likely profitable than the one away from streams/rivers. Land tenure is a determinant factor of farming especially in the peri-urban areas. Farming unit having land tenure system different from freehold perceived that they are less likely profitable.

Peri-urban agriculture is more likely profitable for farming units using rainwater and open drainage canal flows compared to other irrigation water sources. The predicted probabilities of the level of profitability show that farmers perception about the profitability of peri-urban farming varied significantly from marginally profitable to moderately profitable (1|2) at $p < 0.001$ and moderately profitable to above average profitable (2|3) at $p < 0.001$. However, there is no significant difference between above average profitability and high profitability (3|4).

Table 4.7: Specifications of the determinants of profitability

Predictors	Modalities	Coefficient	Std.Error	t-value	P-value ($p> t $)
PUA type	LGh	Reference			
	LOF	-2.921	0.887	-3.291	0.001**
	RG	-5.065	0.887	-5.707	< 0.001***
	SGh	-2.468	1.145	-2.155	0.0311*
	SOF	-4.765	0.952	-5.003	< 0.001***
Irrigation water source	Borehole	Reference			
	Open drainage channel	0.831	1.504	0.552	0.5 ns
	Piped water	-1.945	1.634	-1.19	0.23ns
	Harvested rainwater	2.083	1.156	1.801	0.071*
	River water	-1.153	0.943	-1.222	0.221ns
	Sewage	-1.767	1.114	-1.586	0.112ns
Presence stream	No	Reference			
	Yes	1.830	0.788	2.321	0.020*
Land tenure	Free hold	Reference			
	Inherited	-1.790	0.748	-2.392	0.016*
	Leased	-0.884	0.501	-1.763	0.077*
	Purchased	-1.096	0.6221	-1.761	0.078*
Predicted probabilities	1 2	-6.694	1.099	-6.089	< 0.001***
PUA profitability	2 3	-3.247	0.984	-3.298	< 0.001***
	3 4	-0.672	0.903	-0.744	0.456ns

*, **, ***: significant at α equal to 0.1, 0.01 and 0.001, respectively; ns: not significant; PUA profitability 1: marginally profitable, 2: moderately profitable, 3: average profitability, 4: high profitability

4.2.5 Bottleneck of Peri-urban Agriculture in Nairobi-Machakos Interface

The main bottlenecks hindering peri-urban farming from surveyed farming units in Nairobi-Machakos counties interface are presented in Fig. 4.3. These factors are water pollution (76.2%), water scarcity (70%), high cost of input (66.9%), unpredictable climatic patterns (59%), and unsecured land tenure system (40.8%). Other limiting

factors include lack of credit, crop devastation by livestock/wildlife, incidences of pest and diseases and farm exposure to industrial dust. The frequency of citation of the bottlenecks is dependent of farmland location ($\chi^2 = 39.66$, $p < 0.001$) and farm types ($\chi^2 = 36.47$, $p < 0.001$). Water pollution, water scarcity, unsecured land tenure system, lack of credit and agricultural extension services and crop destruction by livestock were mostly reported by farmers having their farm along the river (Farm type 1 and 2). The farm type 3 and 4 listed the challenges concerning the export market, which sometimes result in rejection of batches of their products. Farming units located in the industrial area of Athi River highlighted the presence of industrial dust which negatively affect the quality of their farm produce. The other bottlenecks including high cost of inputs, climate variability and incidences of pests and diseases, cut across the farms and are not specific to farm types.

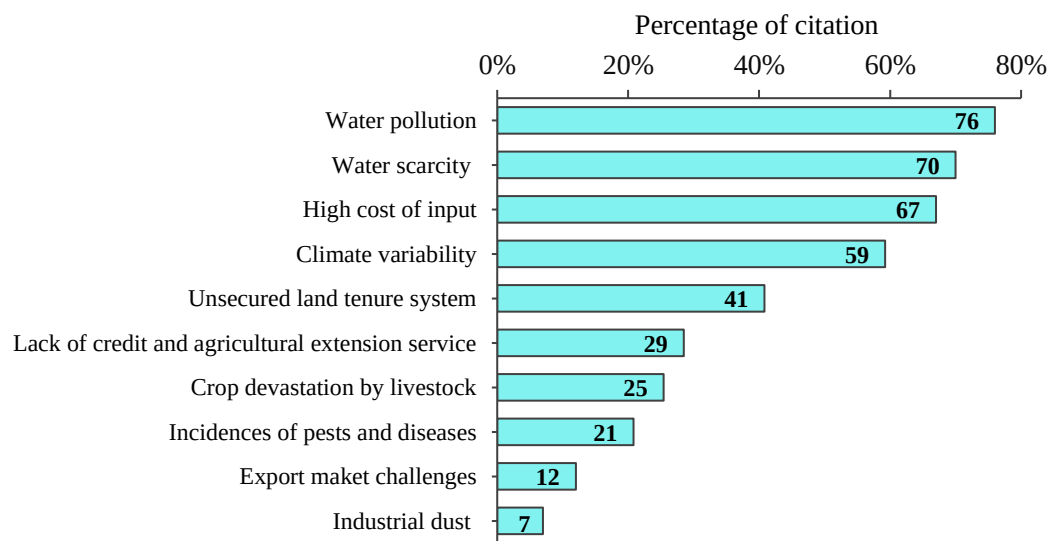


Figure 4.3: Bottleneck of peri-urban agriculture in Nairobi-Machakos interface

4.2.6 Discussion

The visual interpretation of VHR-GE imagery exhibits five farm types, while the multivariate analysis based on socioeconomic variables produces four farm types.

Although, the two classifications seem different, they share some similitudes. The farm type 1 encompasses SOF and LOF mostly. The farm type 4 (cluster 4) is exclusively made of LGh, which are large scale intensive and export market-oriented greenhouse farming. The farm type 3 is a combination of LGh and SGh, which are all greenhouse farming system but share features related to type of actors and market orientation. The farm type 2 is predominated by of RG, while the farm type 1 is predominated by SOF and LOF. The two classifications are useful for decision making. The typology from the visual interpretation of VHR-GE imagery gives a spatial perspective of peri-urban farmland arrangement in the peri-urban interface, which can inform urban planning and land use zoning. The typology derived from the multivariate analysis provide more insight regarding socioeconomic variables, including type of actors and production resources endowment, which are relevant for developing specific intervention measures targeting specific group of farmers. These measures include extensions services and regulatory compliance for food safety and market (Ayambire et al., 2019).

The small farmland sizes that are observed in residential areas show that the size of the farmland increase as the distance from residential area increases. This is consistent with previous studies (Snep et al., 2006; Li et al., 2017b; Willkomm et al., 2021), which demonstrated that there is less fragmentation as the distance from urban centres grow and consequently farmlands become larger. Although livestock keeping represents a great potential for nutrient cycling in vegetable production in PUA studies (Dossa et al., 2011; Abdulkadir et al., 2012), farmland typology in Nairobi-Machakos counties interface shows that it is not an important component of the peri-urban farm types. Only farm type 2 (mostly farm located in residential areas) depicts presence of small-scale livestock production. This can be attributed to the fact that the study area is part of the immediate neighbourhood of Nairobi, while extensive livestock keeping generally

reside not close to urban areas because of availability of less grazing land and extensive and busy transport network around urban centres (Graefe et al., 2008).

The main factors underpinning PUA in Nairobi-Machakos interface are the type of peri-urban agriculture (RG, SOF, LOF, SGh and LGh), irrigation water sources, the presence of stream nearby the farm, and land tenure system. Most of the farmers squats on public open spaces, road reserve or lease contract with landowners or first land squatters. Consequently, farmers are prevented from investing in high-tech equipment, which could improve the scope of their production, due to the constant fear that their ongoing production may be suspended. The land tenure system is cited as a major challenge of PUA in developing countries (Adam, 2014) because vacant plots used for farming in the peri-urban interface are land awaiting public or private development, as demonstrated by Kinuthia et al. (2022).

Socioeconomic factors such as level of formal education, age of the farming unit head, and monthly income of the farming unit are not relevant determinants of peri-urban farming in Nairobi-Machakos counties interface. This is consistent with Prain & Lee-Smith (2010) and Dossa et al. (2011) who pointed out that farming activities in metropolitan regions are multi-actors with substantially diversified socioeconomic backgrounds. Peri-urban farmland in Nairobi-Machakos interface is predominantly market oriented with various market destination: local open market, supermarket, and export market. The biggest production in the peri-urban interface originates from farm type 1 (69%) and farm type 2 (23%). Urban household farming units (farm type 1 and 2) are the principal supplier of fresh fruits and vegetables to the metropolitan regions. They play a major role in maintaining food security and ecosystem services in the metropolitan region. This imply that PUA in the outskirt of Nairobi have a substantial

importance for food security for metropolitan population, and therefore, contamination during production process could have considerable public health risks.

Water pollution and water accessibility are the most cited bottlenecks of peri-urban farming in Nairobi-Machakos interface. Most of the farmlands, especially farm type 1 and part of 2 rely on sewage flow or river water that is a mixture of storm water, industrial effluent, and urban wastewater for irrigation. Urban streams in Athi River basin are reported to be highly polluted (Kithiia, 2012), which pose significant health issues. Despite farmers acknowledging that urban surface water flows are polluted, over 71% of the farms rely on these water sources. Thus, understanding the extent of contamination in these farming systems is crucial for policy, decision-making, and the efficient zoning of farming at the peri-urban interface. In the next section, we present a more detailed investigation of the farmlands to assess the risks of contamination.

4.3 Irrigation water suitability and Peri-Urban Agrosystems Contamination in Nairobi-Machakos Counties Interface

4.3.1 Irrigation Water Quality, Contamination and Suitability

4.3.1.1 Spatio-Seasonal Variations in Physicochemical Parameters of Irrigation Water

The physicochemical characteristics of irrigation water inform on water chemistry, water suitability and pollution risks. The physicochemical characteristics of irrigation water across the sampling stations are presented in Table 4.8-4.11. The colour of irrigation water is used as water quality indicator to apprise on the accumulation of suspended and dissolved materials in water. Water colour intensities in the samples are from less than 5 to 90 TCU (Table 4.8 & 4.9). The intensities of water colour are slightly higher in wet season compared to dry season. All irrigation water in wet season shows colour intensities above the recommended threshold of 50 TCU, while in dry season, it

is 60% of the samples from sites S1, S4, S5, S6, S7 and S10 that exhibit above the threshold.

Water turbidity (Turb) is used as an indicator of water quality that measures the relative opacity and cloudiness of water (USGS, 2018). Higher turbidity can affect soil hydraulic and physical properties such as infiltration rate, hydraulic conductivity, and porosity. Turbidity values in irrigation water samples show a significant variability across the sites (S1-S10) ranging from 14.71 to 575.70 NTU in dry season and from 43.16 to 625.38 in wet season (Table 4.8-4.9). The highest values of turbidity are recorded at the sites S7 (575.70 NTU), followed by S4 (421.46 NTU), S1 (316.11 NTU) and S5 (190.44 NTU). Tap water and borehole water show the lowest turbidity values (0.34 to 3.37 NTU). The values of turbidity in irrigation water are significantly different across the sampling stations. Turbidity values are higher in wet season compared to dry season, owing to surface runoff and waste washed off during rainfall dragging substantial amount of particles in the streams. For all the sampling sites water turbidity were above the recommended limit of 5 NTU for water reuse (NEMA, 2006).

Total suspended solid (TSS) measures the amount of solids in water that can be trapped by a filter (Ismail et al, 2019). TSS in the water samples range between < 4 and 36.36 mg/L in dry season and < 4 and 201 mg/L in wet seasons (Table 4.8-4.9). Tap water and borehole water have the lowest value for TSS. TSS values are high in wet season compared to dry season. Irrigation water with above 30 mg/L TSS is considered unsuitable for irrigation. The high variability of TSS values observed across the sites, is attributable to anthropogenic activities along the streams. TSS values are higher in wet season compared to dry season, due to high surface runoff and high leaching during season.

Table 4.8: Observable properties of irrigation during dry season

Parameters	Sampling sites												p-value	Permissible limits
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	T	B		
Colour (TCU)	60±4.33e	5±0f	5±0f	70±4.33c	80±4.33b	65±4.33d	90±4.33a	5±0f	5±0f	61.67±2.5de	< 5	< 5	<.001	< 50 ^A
Turb (NTU)	316.11	70.60 ±	23.98 ±	421.46 ±	190.44 ±	48.76 ±	575.70 ±	14.71 ±	19.93 ±	42.98 ±	0.34 ±	3.25 ±	<.001	< 2 ^B
	±24.56c	6.15ef	1.85gh	3.21b	5.29d	1.67ef	44.2a	1.02hi	0.98ghi	1.67fg	0.03i	0.09hi		
TSS (mg.L ⁻¹)	31.76 ±	24.68 ±	16.85 ±	29.77 ±	36.36 ±	14.65 ±	28.01 ±	22.16 ±	16.95 ±	14.96 ±	< 4	< 4	<.001	< 30 ^A
	3.15b	0.04d	0.45f	0.42bc	1.80a	2.02f	1.49c	1.32e	1.13f	2.17f				

A: Ayers & Westcot (1985); B: USEPA (2012)

Table 4.9: Observable properties of irrigation during wet season

Parameters	Sampling sites												p-value	Permissible limits
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	T	B		
Colour (TCU)	85±4.33a	70±4.33	80±4.33	65±4.33f	70±4.33	90±4.33a	73.33±6.	66.67±6.	91.67±6.	76.67±2.	< 5	< 5	<.001	≤ 50 ^A
Turb (NTU)	b	def	bc		def		61cdf	61ef	61a	5cd				
	43.16 ±	625.38 ±	59.59 ±	283.11 ±	157.12 ±	246 ±	249.33 ±	75.74 ±	147.79 ±	94.85 ±	0.34 ±	3.37 ±	<.001	≤ 2 ^B
TSS (mg/l)	0.59h	24.57a	0.58g	6.79b	3.21d	4.90c	2.29c	2.925f	3.83d	3.2e	0.03j	0.02i		
	11.91 ±	128.67 ±	21.22 ±	24.49 ±	16.9 ±	104 ±	35.17 ±	201 ±	39.81 ±	19.99 ±	< 4	< 4	<.001	≤ 30 ^A
	0.68i	3.28b	0.99fg	1.51f	0.40h	2.55c	1.45e	6.02a	2.01d	1.30gh				

A: Ayers & Westcot (1985); B: USEPA (2012)

Electrical conductivity (EC) and total dissolved solid (TDS) indicate salt enrichment in water, which is very important for irrigation water quality. TDS range from 10 to 8066.1 mg/L and from 13 to 4623 mg/L in dry and wet seasons, respectively (Table 4.8 & 4.9). The samples with a TDS above 2000 mg/L are not suitable for irrigation (Davis & De Wiest, 1966; Ayers & Westcot, 1985). The values of TDS observed indicate that the samples from the sites S1, S2, S5 and S7 during dry season are unsuitable for irrigation, while those from the sites S2 and S7 in wet season are also unsuitable for irrigation. TDS values observed in wet season samples are lower compared to those of dry season samples, because of high dilution of the concentration of dissolved material in water due to voluminous water flow during rainy season.

The values of EC range from 18 to 3270 $\mu\text{S}/\text{cm}$ in dry season and 333 and 7882.2 $\mu\text{S}/\text{cm}$ in wet season. The highest EC values are observed at the sites S3, S7 and S1 (3270.5; 3229 and $\mu\text{S}/\text{cm}$) for dry season and at the sites S2, S7 and S1 (3231.7, 7882.2 and 7435.2 $\mu\text{S}/\text{cm}$) for wet season. The lowest EC values are recorded with tap water and borehole water. The EC of 75% of the samples are above the permissible limit of 700 $\mu\text{S}/\text{cm}$, indicating high salt enrichment and high solute dissolution in irrigation water. Total hardness (TH) and total alkalinity (TA) are important parameters of water quality for irrigation. TH measures the amount of dissolved magnesium, calcium, sulphates, bicarbonates and carbonates in water, while TA measures carbonate, bicarbonate and hydroxide ions in water (USGS, 2018). The use of hard water to irrigate crops does not constitute a threat to human health but it does have a detrimental influence on the irrigation delivery systems (pipe, tap and water supplying canals), soil quality and ultimately affects plant physiology (Liu et al., 2015). The values of TH in the samples vary from 4.33 mg/L (T) to 345.69 mg/L (S5) for dry season and from 4.35 to 270.91 mg/L (S2) in wet season. Irrigation water from the sites S1, S2, S3 and S7 (40% of the

samples) are classified as hard to very hard water (> 120 mg/L) in wet season, while all the samples from dry season are classified as hard to very hard (USGS, 2018).

Alkalinity is a critical water quality indicator that is used to assess the capability of resisting to acidic changes in pH or neutralizing acids in water. High alkalinity in irrigation water can have a corrosive effect on plant roots and stems (Ali et al., 2019). Total alkalinity (TA) values range from 4.4 to 1092 mg/L and from 10.8 to 1540.7 mg/L in dry and wet seasons, respectively. The highest TA values are observed at S5 (1108.9 mg/L) during dry season and at S2 (1540.7 mg/L) during wet season. The samples of the sites S1, S3, S5 and S7 (40%) in dry season and S1 and S2 (20%) in wet season have TA above the maximum permissible threshold of 500 mg/L and thus are classified as unsuitable for irrigation. The values of TA and TH observed are higher in dry season compared to wet season. This is attributable to high dilution in water caused by large volumes of water flow during wet season and high evaporation during dry season which leading to accumulation of limestone minerals in water column.

Chlorides (Cl^-) can be extensively disseminated in natural water from rock weathering, sedimentary rocks and soil, but also from anthropogenic activities such as wastewater, industrial effluent, urban waste and agricultural inputs. The concentrations of Cl^- in the samples range between 1.79 (T) and 3724.6 mg/L (S2) for dry season and between 1.81 (T) and 1661.6 mg/L (S7) for wet season, with significant variation across the sampling sites. The concentrations of Cl^- observed in dry season are higher compared to those of wet season. The concentrations of Cl^- across the sites indicate that the samples from the sites S5 and S7 in dry season (20%) and S7 in wet season (10%) have above the permissible limit of 1063.5 mg/L of Cl^- in irrigation water. The highest Cl^- concentrations are recorded at the farm located closed to residential areas and after WTP

effluent discharge point (S5 and S7), indicating that water flow along these sampling stations receive substantial loads of Cl^- from anthropogenic activities.

Fluoride (F^-) diffusion in water arises naturally from rock and soil materials. Fluoride is toxic for plants and can accumulate in plant leaves. Higher accumulation of F^- hinders plant photosynthesis. The concentrations of F^- in the samples varied between 0.11 (T) and 2.40 mg/L (S5) for dry season and between 0.11 (S5) and 2.85 mg/L (S8) for wet season. About 83.3% of the samples show above the permissible limits of 1 mg/L F^- in irrigation water (Ayers & Westcot, 1985). F^- concentrations are higher in wet season compared to dry season.

Nutrients' content in irrigation water is vital in water quality assessment (Simsek & Gunduz, 2007). The concentrations of Nitrate ($\text{NO}_3\text{-N}$) in irrigation water samples range from 0.02 (T) to 15.36 mg/L (S5) and from 0.02 (T) to 11.26 mg/L (S6) for dry and wet season samples, respectively. The values indicate that about 91.7% of the samples are within the permissible limit of 10 mg/L $\text{NO}_3\text{-N}$ for irrigation water (Ayers & Westcot, 1985). The concentration of ammonia ($\text{NH}_3\text{-N}$) ranged between 0.05 and 15.57 mg/L and 91.7% of the samples are within the admissible range of 5 mg/L $\text{NH}_3\text{-N}$ for irrigation water. The concentrations of $\text{NO}_3\text{-N}$ and $\text{NH}_3\text{-N}$ are high at the sites S5 and S7.

Calcium (Ca^{2+}) and magnesium (Mg^{2+}) originate from rock weathering and wide use of artificial materials rich in these elements (Washbourne et al., 2012). The concentration of Ca^{2+} in irrigation water vary from 0.86 (T) to 65.56 mg/L (S3) and 0.84 (T) and 89.74 mg/L (S3) for dry and wet seasons, respectively indicating that all the samples are within the permissible limit of 400 mg.L^{-1} for irrigation (Ayers & Westcot, 1985). The concentrations of Mg^{2+} in the samples range from 0.53 (T) to 49.49 mg/L (S5) and from 0.54 (T) to 27.88 mg/L in dry and wet seasons, respectively. All the samples are within

the permissible range of Mg^{2+} concentration in irrigation water (0-60 mg/L). The concentration of Ca^{2+} and Mg^{2+} observed in dry season are higher than those of wet season. This is attributable to high dilution of dissolve materials in water flows during wet season.

Potassium (K^+) concentration in the samples range from 0.50 (T) to 432.92 mg/L (S5) and from 0.50 (T) to 125 mg/L (S2) in dry and wet seasons, respectively. Most of the samples (95.83%) have above permissible concentration of K^+ (2 mg/L) in irrigation water. K^+ concentrations are higher in dry season compared top wet season. Sulphate (SO_4^-) concentrations in the samples range from 2.26 (T) to 2188.9 mg/L (S5) and from 9.31 to 882.5 mg/L (S2) for dry and wet seasons, respectively. All the samples except S5 in dry season and S2 in wet season are within the permissible range of 960 mg/L for SO_4^- in irrigation water. Phosphate (PO_4^{3-}) is essential for irrigation water quality. A high concentration of PO_4^{3-} in water can contribute to eutrophication. The concentrations of PO_4^{3-} in the samples varied from 0.01 (T) to 1.77 mg/L (S7) and from 0.48 (T) to 2.47 mg/L (S2). Most of the samples (91.67%) showed phosphate concentrations within the permissible range for irrigation of 0-2 mg/L (Ayers & Westcot, 1985).

High levels of sodium (Na^+) in irrigation water affect soil aggregate structure of fine- and medium-textured soils resulting in high toxicity for plant. High Na^+ concentrations in irrigation water can result in calcium and potassium deficit and affect crop nutrition (Wakeel, 2013). The concentrations of Na^+ in the samples varied between 1.63 (T) and 2,234 mg/L (S5) and between 1.63 (T) and 1,225.4 mg/L (S7) for dry and wet seasons, respectively. The concentrations of Na^+ in 17% of the samples are above the permissible threshold of 920 mg/L of Na^+ in irrigation water (Ayers & Westcot, 1985). The

concentrations of Na^+ appear globally lower in wet season in wet season compared to dry season due to dilution effect of large volume of water in rainy season.

Bicarbonate ions (HCO_3^-) are one of the major components affecting the quality of irrigation water. The presence of bicarbonate ions can have both positive and negative effects on plants and the overall irrigation process. They contribute to water alkalinity, salinity, clogging in irrigation systems and can affect the availability of certain nutrients to plants (De Pascale et al., 2013). The concentrations of HCO_3^- in the samples range from 4.36 (T) to 1,091.3 mg/L and from 4.36 (T) to 1,539.7 mg/L (S2) for dry and wet season, respectively. About 75% of the sample fell within the permissible limit of HCO_3^- in irrigation water of 610 mg/L (Ayers & Westcot, 1985). Irrigation water samples from the sampling stations S1, S3 and S5 in dry season and the sampling stations S1 and S2 in wet season are unsuitable. Carbonate (CO_3^{2-}) concentrations in the samples fluctuated between 0 and 203.04 mg/L and between 0 and 128 mg/L during dry and wet season, respectively. All the samples except S5 (dry season) are within the permissible limit of 3 mg/L for carbonate content in irrigation water. The high concentrations of CO_3^{2-} at the site S5 in dry season is attributable to the discharge of wastewater effluent from the EPZ WTP and low clogging related to low water flow during to dry season.

The evaluation of seasonal variability in physicochemical properties of irrigation water (Fig. 4.4) shows that most physicochemical parameters were significantly higher in dry season compared to wet season. However, the opposite situation was observed for irrigation water parameters such as colour, TSS, PO_4^- , $\text{NO}_3\text{-N}$ and Turb. This is attributable to higher flow and runoff during wet season compared to dry season.

Table 4.10: Chemical properties of irrigation during dry season

Parameters	Sampling sites												p-value	Permissible limits**
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	T	B		
pH	8.17 ± 0.81b	7.96 ± 0.00fg	8.86 ± 0.09a	7.43 ± 0.01de	9.12 ± 0.00a	7.02 ± 0.21fg	6.89 ± 0.00g	7.62 ± 0.06cd	7.15 ± 0.03efg	7.00 ± 0.00fg	7.37 ± 0.03d	8.06 ± 0.01b	<.001	6.5-8.5
TDS	2153.5 ± 30.70b	1119.2 ± 4.23d	2189.9 ± 2.61b	1771.7 ± 2.65c	8066.1 ± 115.5a	1724.8 ± 3.82c	2154.2 ± 16.4b	669.44 ± 10.19f	634.89 ± 19.09f	732.78 ± 5.07e	10 ± 0.43h	212.89 ± 2.62g	<.001	< 2000 ^A
EC	3229.4 ± 7.33b	1730.3 ± 5.93f	3270.5 ± 3.96a	2622.7 ± 50.1d	2671.7 ± 13.1c	2586.8 ± 12.3e	3231.7 ± 7.84b	1033.1 ± 5.42h	976.56 ± 8.60i	1128.8 ± 8.61g	18 ± 1.11k	317.67 ± 11.53j	<.001	< 3000 ^A
TA	1092 ± 7.1b	330.39 ± 12.56f	708.41 ± 2.61c	246.4 ± 0.00h	1108.9 ± 3.06a	334.52 ± 1.91f	536.9 ± 3.93d	308.73 ± 1.89g	338.88 ± 14.14f	435.88 ± e	4.4 ± 0.18j	127.61 ± 1.44i	<.001	≤ 500
TH	192.22 ± 2.83f	212.04 ± 5.31e	240.07 ± 2.78d	290.78 ± 2.49c	345.69 ± 3.4a	240.93 ± 2.75d	336.97 ± 2.68b	134.46 ± 3.09h	153.63 ± 1.79g	134.43 ± 2.89h	4.33 ± 0.07j	23.52 ± 1.17i	<.001	≤ 120
Cl ⁻	228.06 ± 4.71f	218.72 ± 6.80g	416.15 ± 1.18 e	613.11 ± 1.06 c	3724.6c ± 10.50 a	446.59 ± 2.51 b	2413.7 + 8.78 b	110.29 ± 0.99h	66.53 ± 1.83 j	76.26 ± 4.63 i	1.79 ± 0.15 l	13.33 ± 0.69k	<.001	≤ 1063.5
F ⁻	1.93 ± 0.06c	1.29 ± 0.07e	1.74 ± 0.06d	2.15 ± 0.01b	2.40 ± 0.29a	2.23 ± 0.11ab	2.37 ± 0.09a	0.86 ± 0.08g	0.64 ± 0.09h	0.23 ± 0.03 i	0.11 ± 0.00i	1.07 ± 0.03f	<.001	≤ 15
Ca ²⁺	38.52 ± 2.23e	49.92 ± 1.34 d	65.56 ± 0.58a	61.44 ± 0.38b	57.62 ± 2.72c	57.64 ± 1.39c	61.56 ± 1.48b	26.89 ± 1.47g	18.70 ± 1.29h	32.34 ± 2.43 f	0.86 ± 0.00j	4.70 ± 0.81i	<.001	≤ 400
Mg ²⁺	23.80 ± 4.52d	21.05 ± 0.95de	18.78 ± 0.64ef	32.68 ± 0.00c	49.49 ± 0.79a	23.36 ± 2.16d	43.92 ± 3.25b	16.36 ± 0.91f	30.77 ± 1.79c	13.25 ± 0.87g	0.53 ± 0.01 h	2.82 ± 0.24h	<.001	≤ 60
Na ⁺	524.20 ± 5.47d	278.21 ± 1.9g	567.89 ± 4.43c	485.67 ± 1e	2234 ± 3.35a	422.83 ± 8.84f	1663 ± 4.11b	153.88 ± 3.5i	124.86 ± 5.21j	165.10 ± 2.2h	1.63 ± 0.09l	47.33 ± 3.53k	<.001	≤ 920
K ⁺	50.19 ± 1.24c	21.40 ± 0.77ef	37.46 ± 0.64d	28.71 ± 2.29de	432.92 ± 20.89a	37.43 ± 0.17d	76.44 ± 1.56b	16.54 ± 1.23f	27.23 ± 0.91e	31.27 ± 0.97de	0.50 ± 0.02	3.75 ± 0.28g	<.001	≤ 2
NO ₃ -N	0.43 ± 0.02fg	0.76 ± 0.43ef	1.11 ± 0.06de	1.28 ± 0.03d	15.36 ± 0.95a	0.36 ± 0.03fg	3.07 ± 0.21b	1.22 ± 0.15de	2.26 ± 0.28c	1.53 ± 0.15d	0.02 ± 0.00	0.02 ± 0.00	<.001	≤ 10
NO ₂ -N	0.01a	0.001b	0.01a	0.01a	0.001b	0.001b	0.001b	0.001b	0.001b	0.001b	< 0.001	< 0.001	<.001	≤ 5
NH ₃ -N	0.31±0.03	0.05±0.0	0.05±0.0	1.07±0.03	1.13±0.08	0.05±0.0	2.99±0.09	2.65±0.08	3.43±0.18	3.39±0.56	0.05±0	0.05±0	<.001	≤ 5
SO ₄ ²⁻	194.83 ± 6.8e	243.95 ± 9.52d	366.69 ± 3.18b	303.69 ± 3.04	2188.3 ± 20.6a	308.7 ± 2.29c	194.62 ± 3.02	86.51 ± 0.70	72.97 ± 1.14g	46.63 ± 1.75h	2.26 ± 0.04i	9.31 ± 0.04i	<.001	≤ 960
PO ₄ ³⁻	1.21 ± 0.18c	0.69 ± 0.03f	1.11 ± 0.10cd	0.99 ± 0.10de	1.75 ± 0.08a	0.79 ± 0.01f	1.77 ± 0.24a	1.42 ± 0.08b	0.85 ± 0.01ef	0.70 ± 0.15f	0.01 ± 0.00h	0.49 ± 0.01g	<.001	≤ 2
HCO ₃ ⁻	1091.3 ± 3.32a	330.02 ± 13.66f	708.83 ± 8.91c	246.12 ± 1.27h	827.88 ± 2.75b	334.55 ± 2.36f	536.97 ± 3.21d	308.36 ± 2.43g	338.85 ± 7.16f	435.26 ± 7.39e	4.36 ± 0.03j	126.19 ± 1.23i	<.001	≤ 610
CO ₃ ²⁻	0b	0b	0b	0b	203.04 ± 3.69a	0 b	0b	0b	0b	0b	0.02 ± 0.00b	1.36 ± 0.09b	<.001	≤ 3

****Ayers & Westcot (1985);** All parameters except pH and EC are expressed in mg/l, TDS: total dissolved solids, EC (µS/cm): electrical conductivity TH: total hardness, Cl⁻: chloride, F⁻: fluoride, Ca²⁺: calcium, Mg²⁺: magnesium, Na⁺: sodium, K⁺: potassium, NO₃-N: nitrate, NO₂-N: nitrite, NH₃-N: ammonia, SO₄²⁻: sulphate, PO₄³⁻: orthophosphate, HCO₃⁻: bicarbonate, CO₃²⁻: carbonate

Table 4.11: Chemical properties of irrigation during wet season

Parameters	Sampling sites												p-value	Permissible limits**
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	T	B		
pH	6.83 ± 0.04de	6.76 ± 0.12ef	6.73 ± 0.08f	6.93 ± 0.12cd	7.90 ± 0.046b	6.98 ± 0.021c	6.58 ± 0.069g	6.97 ± 0.014c	6.59 ± 0.032g	6.90 ± 0.004cd	7.37 ± 0.034bc	8.06 ± 0.010a	<.001	6.5-8.5
TDS (µS/cm)	1589.4 ± 32.6c	4623 ± 504a	927.07 ± 6.55d	405.22 ± 11.52ef	353.67 ± 6.08ef	439.44 ± 2.01ef	3687.3 ± 11b	461.67 ± 5.22e	506.67 ± 7.81e	508.33 ± 6.5e	10 ± 0.43g	215 ± 2.69f	<.001	≤ 2000 ^A
EC (µS/cm)	3215.9 ± 22.6c	7882.2 ± 171.6a	1782 ± 8.15d	620.11 ± 3.44h	681.22 ± 2.22h	843.56 ± 6.44g	7435.2 ± 13.3b	885 ± 34.8fg	976.44 ± 10.55e	965 ± 5.68ef	18 ± 1.11k	333 ± 2.12j	<.001	≤ 3000 ^A
TA	740.28 ± 2.15b	1540.7 ± 23a	317.31 ± 3.99d	176.11 ± 1.69gh	171.62 ± 3.07h	184.82 ± 1.52g	404.8 ± 3.35c	268.43 ± 4.23e	233.34 ± 5.38f	325.57 ± 7d	4.4 ± 0.18j	127.6 ± 1.27j	<.001	≤ 500
TH	169.11 ± 5.54d	270.91 ± 3.61a	240.75 ± 2.92b	88.19 ± 2.28g	90.753 ± 1.088g	87.62 ± 1.35g	208.54 ± 1.34c	91.85 ± 3.91fg	95.77 ± 3.32f	100.8 ± 1.86e	4.35 ± 0.07i	23.52 ± 0.32h	<.001	≤ 120
Cl ⁻	179.66 ± 5.63d	587.77 ± 18.38b	237.68 ± 2.25c	50.357 ± 1.37g	58.96 ± 1.54g	87.769 ± 2.40e	1661.6 ± 3.14a	78.63 ± 1.12ef	71.59 ± 6.55f	76.96 ± 4.65f	1.79 ± 0.15 i	13.5 ± 1.127h	<.001	≤ 1063.5
F ⁻	1.43 ± 0.02d	1.69 ± 0.01c	1.53 ± 0.44cd	0.82 ± 0.03f	0.5 ± 0.004g	1.178 ± 0.04e	1.17 ± 0.01e	2.85 ± 0.10a	2.12 ± 0.23b	2.13 ± 0.13b	0.11 ± 0.007f	1.07 ± 0.03e	<.001	≤ 15
Ca ²⁺	51.65 ± 1.88c	62.88 ± 6.9b	89.74 ± 9.79a	25.18 ± 0.37d	26.78 ± 0.79d	25.11 ± 0.87d	58.53 ± 0.96b	28.94 ± 2.61d	30.00 ± 0.06d	26.75 ± 2.65d	0.83 ± 0.001f	4.70 ± 0.64e	<.001	≤ 400
Mg ²⁺	9.36 ± 0.50c	27.88 ± 0.79a	6.30 ± 0.91e	6.42 ± 0.5e	6.10 ± 0.82e	6.1 ± 0.14e	15.22 ± 0.79b	5.08 ± 0.20f	5.09 ± 0.01f	8.45 ± 0.65d	0.54 ± 0.01 h	2.86 ± 0.10g	<.001	≤ 60
Na ⁺	388.22 ± 1.92c	1206 ± 4.99b	243.78 ± 6.14d	77.27 ± 4.78gh	81.53 ± 0.346g	121.04 ± 2.08f	1225.4 ± 5.55a	126.69 ± 2.55f	125.9 ± 3.17f	162.8 ± 8.26e	1.63 ± 0.09 j	47.51 ± 0.71i	<.001	≤ 920
K ⁺	31.47 ± 0.92c	125.9 ± 4.31a	18.94 ± 0.28d	10.50 ± 0.41f	9.7 ± 0.18	13.90 ± 0.53e	36.71 ± 0.83b	10.81 ± 1.08f	17.71 ± 0.21d	18.93 ± 1.69d	0.50 ± 0.02 h	3.80 ± 0.11g	<.001	≤ 2
NO ₃ ⁻ N	5.88 ± 0.26c	4.63 ± 1.02d	6.07 ± 0.62c	4.41 ± 0.31de	0.93 ± 0.02f	11.26 ± 0.03a	10.98 ± 0.12a	4.43 ± 0.10d	9.85 ± 1.03b	3.63 ± 0.59e	0.02 ± 0.00h	0.02 ± 0.0g	<.001	≤ 10 ^A
NO ₂ -N	0.08 ± 0.01d	0.08 ± 0.03e	0.07 ± 0.01e	0.48 ± 0.13c	0.58 ± 0.0b	0.42 ± 0.02c	0.19 ± 0.02d	1.1 ± 0.05a	0.18 ± 0.03d	0.17 ± 0.01d	0.003 ± 0.0f	0.001 ± 0f	<.001	≤ 5
NH ₃ -N	0.80 ± 0.06d	15.57 ± 0.50a	0.06 ± 0.01e	0.05 ± 0.0e	0.05 ± 0.0e	0.05 ± 0.0e	1.94 ± 0.05b	0.74 ± 0.06d	0.88 ± 0.02c	1.11 ± 0.10c	< 0.05	< 0.05	<.001	≤ 5
SO ₄ ²⁻	166.83 ± 0.209c	882.5 ± 91.6a	221.15 ± 92b	44.38 ± 2.16ef	53.87 ± 4.6	76.61 ± 2.92de	67.11 ± 1.35de	43.17 ± 1.80ef	88.28 ± 8.9	78.9 ± 3.06	2.26 ± 0.04g	9.31 ± 0.20f	<.001	≤ 960
PO ₄ ³⁻	1.43 ± 0.07c	2.47 ± 0.008a	1.96 ± 0.48b	1.71 ± 0.18b	1.02 ± 0.06d	1.23 ± 0.01cd	2.4813 ± 0.08a	1.92 ± 0.05b	2.44 ± 0.24a	2.47 ± 0.08a	0.01 ± 0.00f	0.48 ± 0.01e	<.001	≤ 2
HCO ₃ ⁻	739.22 ± 14.03b	1539.7 ± 16.4a	317.94 ± 1.47d	171.49 ± 5.12h	170.43 ± 2.21h	184.65 ± 3.24g	404.88 ± 1.66c	268.45 ± 4.82e	233.24 ± 4.42f	326.82 ± 8.68d	4.36 ± 0.03k	126.18 ± 1.39j	<.001	≤ 610
CO ₃ ²⁻	0	0	0	0.18 ± 0.04b	1.28 ± 0.11a	0.17 ± 0.01d	0	0	0	0	0.02 ± 0.00c	1.36 ± 0.10a	<.001	≤ 3

**Ayers & Westcot (1985); All parameters except pH and EC are expressed in mg/l, TDS: total dissolved solids, EC (µS/cm): electrical conductivity TH: total hardness, Cl⁻: chloride, F⁻: fluoride, Ca²⁺: calcium, Mg²⁺: magnesium, Na⁺: sodium, K⁺: potassium, NO₃-N: nitrate, NO₂-N: nitrite, NH₃-N: ammonia, SO₄²⁻: sulphate, PO₄³⁻: orthophosphate, HCO₃⁻: bicarbonate, CO₃²⁻: carbonate,

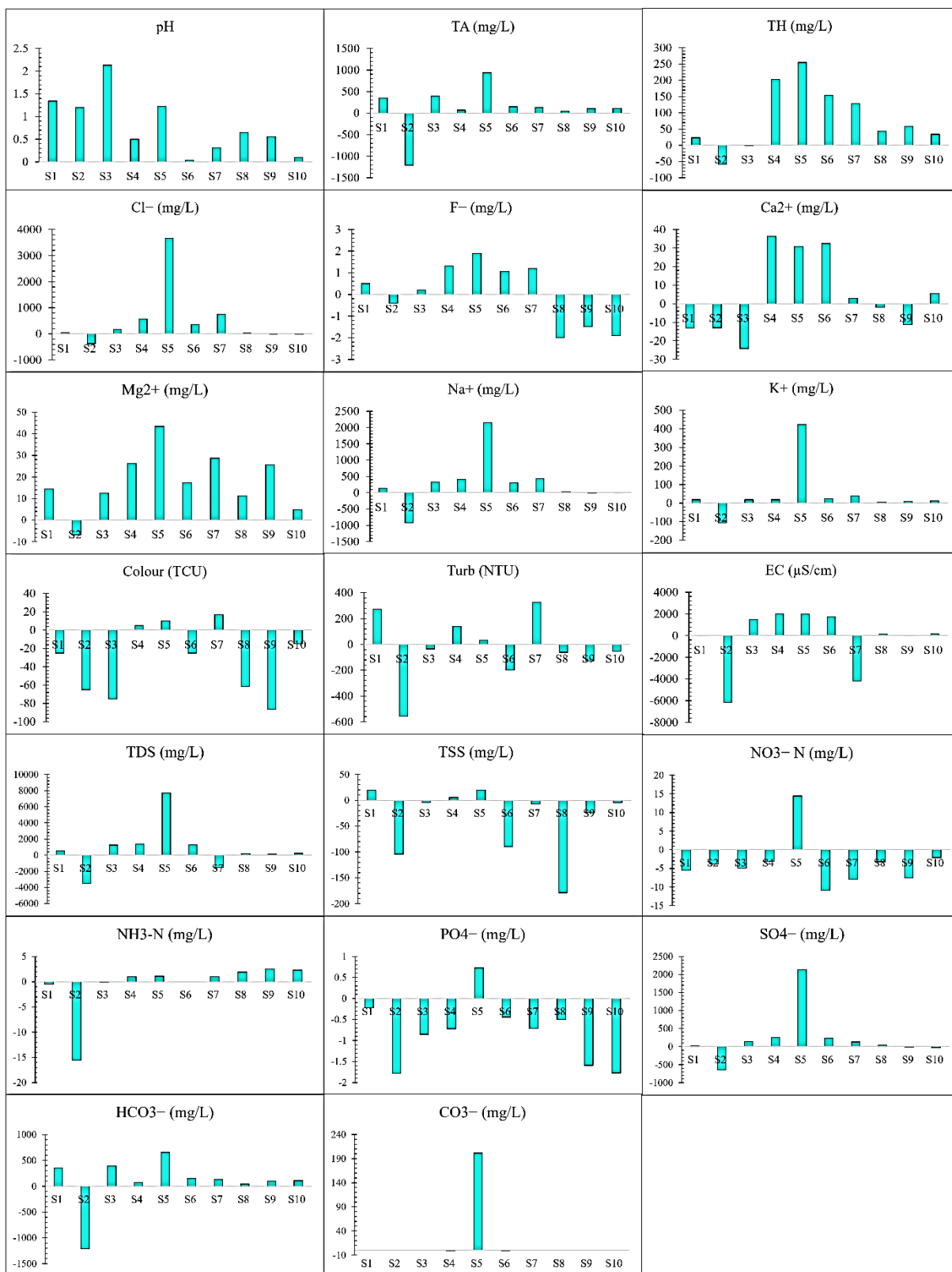


Figure 4.4: Seasonal variation in physicochemical properties of irrigation water

4.3.1.2 Mechanisms Controlling Irrigation Water Chemistry

The mechanisms controlling irrigation water chemistry is analysed using Gibbs Diagram. The diagram consists of two plots of TDS vs $\text{Na}^+ / (\text{Na}^+ + \text{Ca}^{2+})$ and TDS vs $\text{Cl}^- / (\text{Cl}^- + \text{HCO}_3^-)$. Gibbs diagram allows simple representation of large amount of data and indicates which of the three mechanisms including precipitation dominance, rock weathering/water-rock interaction and evaporation dominance is responsible of the prevailing water chemistry (Gibbs, 1970).

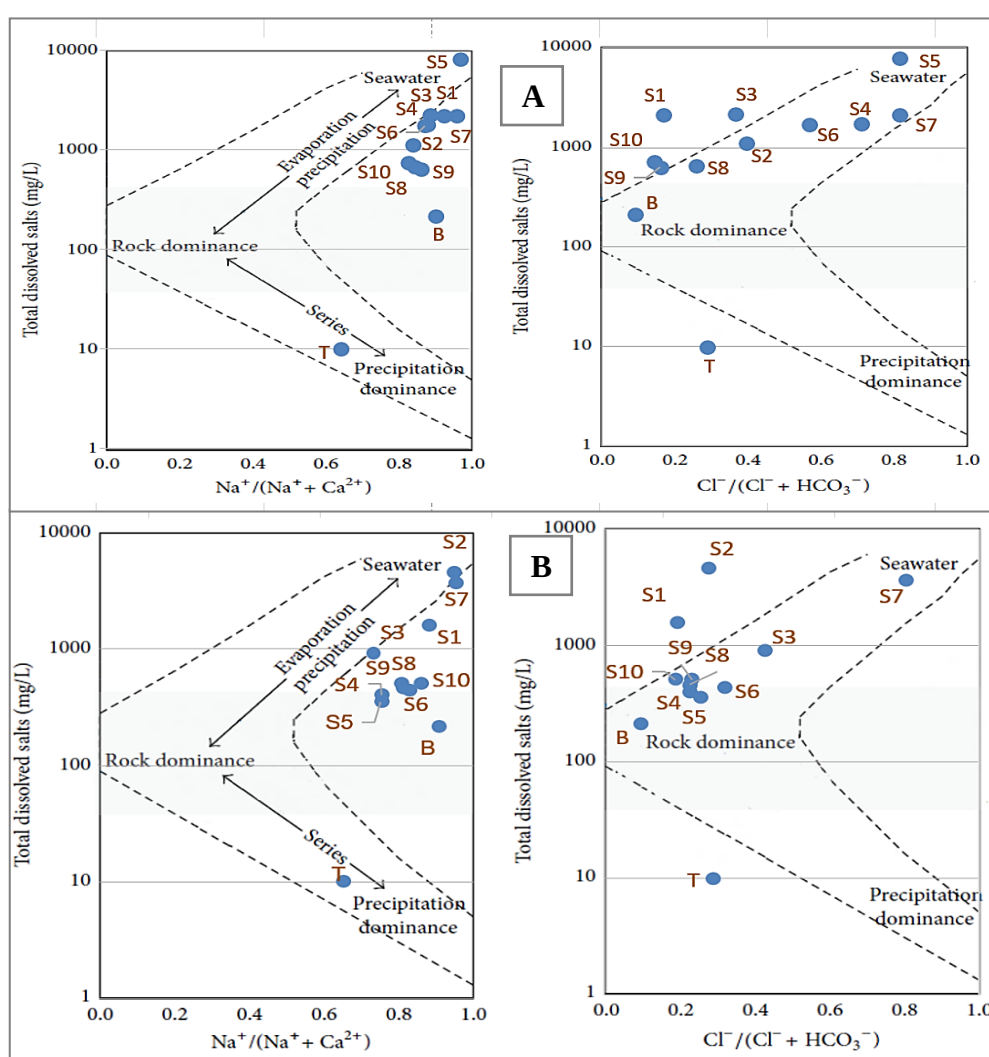


Figure 4.5: Gibbs Diagram A: dry season, B: wet season

The chemical configurations of irrigation water samples plotted on the Gibbs diagram (Fig. 4.5) show that the samples from S1 to S10 are close to the boomerang tip on the upper right side, in the evaporation dominance zone for the two seasons. As result, the process governing water chemistry in the peri-urban interface is evaporation dominance, indicating a dominant influence of anthropogenic activities on water chemistry (Marandi & Shand, 2018; Geetha & Dharmendira, 2021). However, a slight trend in the rock dominance zone is observed for S4, S5, S6, S8 and S10 in wet season compared to dry season. This could be explained by the increase in freshwater from storm water in wet season. T and B belong respectively to precipitation and rock dominance zones indicating abundant fresh water with low dissolve salt. The diagram indicates that T and B have a typical characteristic of fresh groundwater, while the water recharging source for all the other samples (S1-S10) is influenced by anthropogenic activities and surface drainage, including residential and industrial wastewater, erosion and leaching from urban settlements.

4.3.1.3 Heavy Metals and Trace Elements' Concentrations in Irrigation Water

The concentrations of heavy metals and trace elements in irrigation water samples for dry and wet seasons are presented in Table 4.12-4.13. The elements Mn, Fe, Zn and Pb are the predominant metals elements in irrigation water regardless of the seasons and the sampling stations. The concentrations of As in irrigation water range from 0.65 and 16.95 µg/l and the highest concentrations are recorded at the sites S1, S3, S4 and S5: 5.74, 6.37, 5.01 and 16.39 µg/l, respectively. The concentrations of As in irrigation water are within the permissible limit of 100 µg/l for unrestricted irrigation (Simsek & Gunduz, 2007). The concentrations of cadmium (Cd) in irrigation water range between 0.002-0.24 µg/L and the average highest concentration is recorded at site S5 (0.17

µg/L). The concentrations of Cd in irrigation water are within the permissible threshold of 10 µg/L (Simsek & Gunduz, 2007). Cobalt (Co) concentrations in irrigation water vary between 0.24-13.95 µg/L and the highest concentrations is recorded at the sites S5 (12.42 µg/L). The concentrations of Co in irrigation water are within the permissible range of 50 µg/L for unrestricted irrigation (Simsek & Gunduz, 2007).

Chromium (Cr) concentrations range between 0.93 and 104.58 µg/L and the highest concentrations are recorded at S5 (84.96-104.58 µg/L). About 1.7% of the samples in dry season and 2.3% of the samples in wet season exhibit Cr concentrations above the permissible range of 100 µg/L (Simsek & Gunduz, 2007). The concentrations of Cu in irrigation water range from 0.32-17.24 µg/L, with the highest concentrations recorded at S4 (9.92 µg/L and S6 (9.79 µg/L). The concentrations of Cu in irrigation water are within the admissible threshold of 100 µg/L (Simsek & Gunduz, 2007). The concentrations of Fe in irrigation water vary between 1.0-1426 µg/L and the highest concentrations are recorded at S5 (up to 1426 µg/L) and S7 (up to 1221 µg/L). Fe concentrations in irrigation water are within the admissible limit in irrigation water of 5000 µg/L.

The concentrations of Hg in irrigation water range from 0.0-0.53 µg/L and the highest concentrations are recorded at S1 (0.43 µg/L) and S2 (0.15 µg/L). The concentrations of Hg in irrigation water exceed the admissible threshold of 0.5 in 1.7% of the samples and 3.3% of the samples exhibit Hg concentrations close to the admissible threshold (Simsek & Gunduz, 2007). The concentrations of Mn in irrigation water vary between 24 and 6,337 µg/L with the highest concentrations recorded at the sites S4 (5,491 µg/L), S7 (5,547 µg/L and S8 (3,257 µg/L). Above permissible threshold concentrations of Mn for irrigation water of 200 µg/L are recorded in 95% of the samples. The concentrations of Ni in irrigation water range between 0.79-62.02 µg/L with the highest average

concentration recorded at S5 (60.79 µg/L). The concentrations of Ni in irrigation water are below the permissible limit of 200 µg/L for irrigation water (Simsek & Gunduz, 2007).

The concentrations of Pb in irrigation water are in the range of 0.05-23.58 µg/L and the highest concentrations are recorded at the sites S1 (13.15 µg/L), S9 (13.8 µg/L) and S10 (12.45 µg/l). The concentrations of V and Zn in irrigation water are in the range of 1.47-65.79 µg/l and 0.93-132.30 µg/l, respectively. The highest concentrations were observed at the site S5 (61.92 µg/l) for V and at the sites S3 (121.39 µg/l), S4 (70.10 µg/l), S5 (71.16 µg/l) and S7 (73.62 µg/l) for Zn. The concentrations of Pb, V and Zn are below their permissible limits of 5000, 100 and 2000 µg/l in irrigation water, respectively (Simsek & Gunduz, 2007).

The evaluation of the seasonal variability in heavy metals and trace elements concentrations in irrigation water using the two-sample t-test is presented in Fig. 4.6. The concentrations of all heavy metals and trace elements in irrigation water are significantly higher ($p < 0.05$) in dry season compared to wet season, except for Cd, Co, Cu, and Pb, which exhibit the opposite situation at some sites.

Table 4.12: Heavy metals and trace elements concentrations in irrigation water in dry season

Sites		As (ppb)	Cd (ppb)	Co (ppb)	Cr (ppb)	Cu (ppb)	Fe (ppb)	Hg (ppb)	Mn (ppb)	Ni (ppb)	Pb (ppb)	V (ppb)	Zn (ppb)
S1	Mean ± SD	5.74±0.47b	0.07±0.0c	1.16±0.16de	4.30±0.19d	5.0 ±1.64bc	541±15c	0.43±0.03a	1962±463c	5.80±0.80de	13.15±1.25ab	5.69±0.11de	64.47±1.49bc
S2	Mean ± SD	1.41±0.12e	0.04±0.01d	0.52±0.11e	3.21±0.80d	2.47±2.16c	80±16f	0.15±0.01b	1191±611cde	2.99±0.14e	1.9769±0.0d	6.50±0.08d	44.76±16.76c
S3	Mean ± SD	6.37±0.60b	0.12±0.01b	3.99±1.34b	14.62±9.16bc	6.62±1.98abc	276±46d	0d	1551±894cd	15.74±7.98b	7.84±3.65abc	22.01±0.0b	121.39±10.91a
S4	Mean ± SD	5.01±1.90bc	0.07±0.01c	1.29±0.21de	7.18±1.0cd	9.92±7.31a	230±18de	0.02c	5491±846a	7.73±1.78de	4.808±1.32d	6.25±0.36d	70.10±21.30bc
S5	Mean ± SD	16.39±0.56a	0.16±0.01a	12.42± 1.53a	94.77±9.81a	2.87±0.31bc	1426±21a	0d	694±12de	60.79±1.23a	7.12±1.74abc	61.92±3.87a	71.16±14.28b
S6	Mean ± SD	4.72±2.33bc	0.07±0.02c	2.91±1.58bc	16.07±7.20b	9.79±1.16a	140±16ef	0d	353±167e	15.35±5.89bc	5.942.29bcd	14.76±4.74c	52.60±20.90bc
S7	Mean ± SD	3.47±0.06cd	0.06±0.01cd	3.42±0.02bc	4.89±0.72d	5.87±2.5abc	1221±205a	0d	5547±84a	9.86±0.13cd	4.94±0.07cd	3.57±0.39def	73.62±4.05b
S8	Mean ± SD	2.510±0.10de	0.07±0.01c	2.23±0.09cd	8.04±4.20bcd	5.10±1.64bc	286±33d	0d	3257±758b	7.45±3.07de	5.57±0.39cd	4.90±0.18def	65.07±4.38bc
S9	Mean ± SD	1.79±0.25de	0.07±0.03c	1.23±0.15de	9.62±3.21bcd	7.52±0.41ab	751±75b	0d	1771±718c	4.94±1.30de	13.8±9.79a	2.89±0.49ef	65.70±24.10bc
S10	Mean ± SD	1.29±0.05e	0.06±0.01cd	0.88±0.06de	3.97±0.65d	3.82±0.27bc	748±8b	0d	1454±11.3cd	3.24±0.21e	12.45±8.61abc	2.18±0.03f	50.97±16.05bc
p-value		< .001***	< .001***	< .001***	< .001***	< .001***	< .001***	< .001***	< .001***	< .001***	< .001***	< .001***	< .001***
Threshold values		100 ^{A, B}	10 ^{A, B}	50 ^{A, B}	100 ^{A, B}	200 ^{A, B}	5000 ^{A, B}	0.5 ^{A, B}	200 ^{A, B}	200 ^{A, B}	5000 ^{A, B}	100 ^{A, B}	2000 ^{A, B}

*A:(Simsek & Gunduz, 2007), B: (Ayers & Westcot, 1985), *** Significant at the threshold of = 0.001*

Table 4.13: Heavy metals and trace elements concentrations in irrigation water in wet season

Sites		As (ppb)	Cd (ppb)	Co (ppb)	Cr (ppb)	Cu (ppb)	Fe (ppb)	Hg (ppb)	Mn (ppb)	Ni (ppb)	Pb (ppb)	V (ppb)	Zn (ppb)
S1	Mean±SD	2.96±1.31a	0.04±0.01bc	1.61±0.57a	13.44±2.07a	5.57±1.50bcd	304±32b	0.02±0.01a	1400±809c	11.17±2.51a	4.30±1.54a	3.84±1.27d	20.59±5.56abc
S2	Mean±SD	1.86±0.65b	0.15±0.09a	1.33±0.785a	7.10±1.62b	5.23±2.20bcd	225±66bc	0b	505±475d	7.12±2.56b	8.95±3.83a	4.30±0.99d	15±2.32bcd
S3	Mean±SD	1.84±0.03bc	0.04±0.01bc	0.66±0.05bc	5.31±0.48bcd	7.62±1.40b	163±34cd	0b	366±265d	6.087±0.4bc	3.81±1.35a	5.23±0.11c	23.28±6.07ab
S4	Mean±SD	0.94±0.01de	0.03±0.0bc	0.37±0.01c	5.96±0.42bc	7.57±2.78b	112±10d	0b	32±1d	5.45±0.08bcd	3.50±1.48a	6.99±0.04b	12.37±1.53bcd
S5	Mean±SD	1.20±0.02bcd	0.05±0.01bc	0.44±0.02c	6.31±1.27bc	5.25±1.53bcd	95±1d	0b	27±4d	5.81±0.39bc	6.81±0.31a	8.71±0.28a	13.27±1.08bcd
S6	Mean±SD	1.38±0.06bcd	0.06±0.0b	0.53±0.04c	6.85±0.14b	11.83±1.53a	168.0±62cd	0b	40±12d	5.96±0.06bc	6.47±4.01a	9.03±0.02a	29.6±17.30a
S7	Mean±SD	0.72±0.07e	0.01±0.01c	0.33±0.08c	3.28±2.35d	1.66±0.89e	87±86d	0b	2191±730b	2.24±1.45e	2.47±2.41a	1.67±0.20e	3.91±2.98d
S8	Mean±SD	1.71±0.16bcd	0.02±0.0bc	1.11±0.26ab	4.47±0.34cd	3.62±0.81cde	248±152bc	0b	3722±359a	4.61±0.11cd	10.42±7.10a	3.87±0.02d	27.31±5.98a
S9	Mean±SD	1.06±0.09cde	0.02±0.0bc	0.67±0.02bc	5.66±0.02bc	2.730.53de	487±48a	0b	1553±69bc	4.11±0.48cde	4.87±1.27a	2.35±0.33e	12.42±2bcd
S10	Mean±SD	0.94 ±0.07de	0.01±0.0bc	0.57±0.04bc	5.10±0.67bcd	6.60±2.99bc	304±18b	0b	1289.5±41c	3.41±0.26de	5.82±0.15a	2.35±0.22e	10.33±2.85cd
p-value		0.002**	0.001***	< .001***	< .001***	< .001***	< .001***	< .001***	< .001***	< .001***	0.1 ns	< .001***	< .001***
Threshold values		100 ^{A, B}	10 ^{A, B}	50 ^{A, B}	100 ^{A, B}	200 ^{A, B}	5000 ^{A, B}	0.5 ^{A, B}	200 ^{A, B}	200 ^{A, B}	5000 ^{A, B}	100 ^{A, B}	2000 ^{A, B}

A:(Simsek & Gunduz, 2007) , B: (Ayers & Westcot, 1985), *** Significant at the threshold of = 0.001

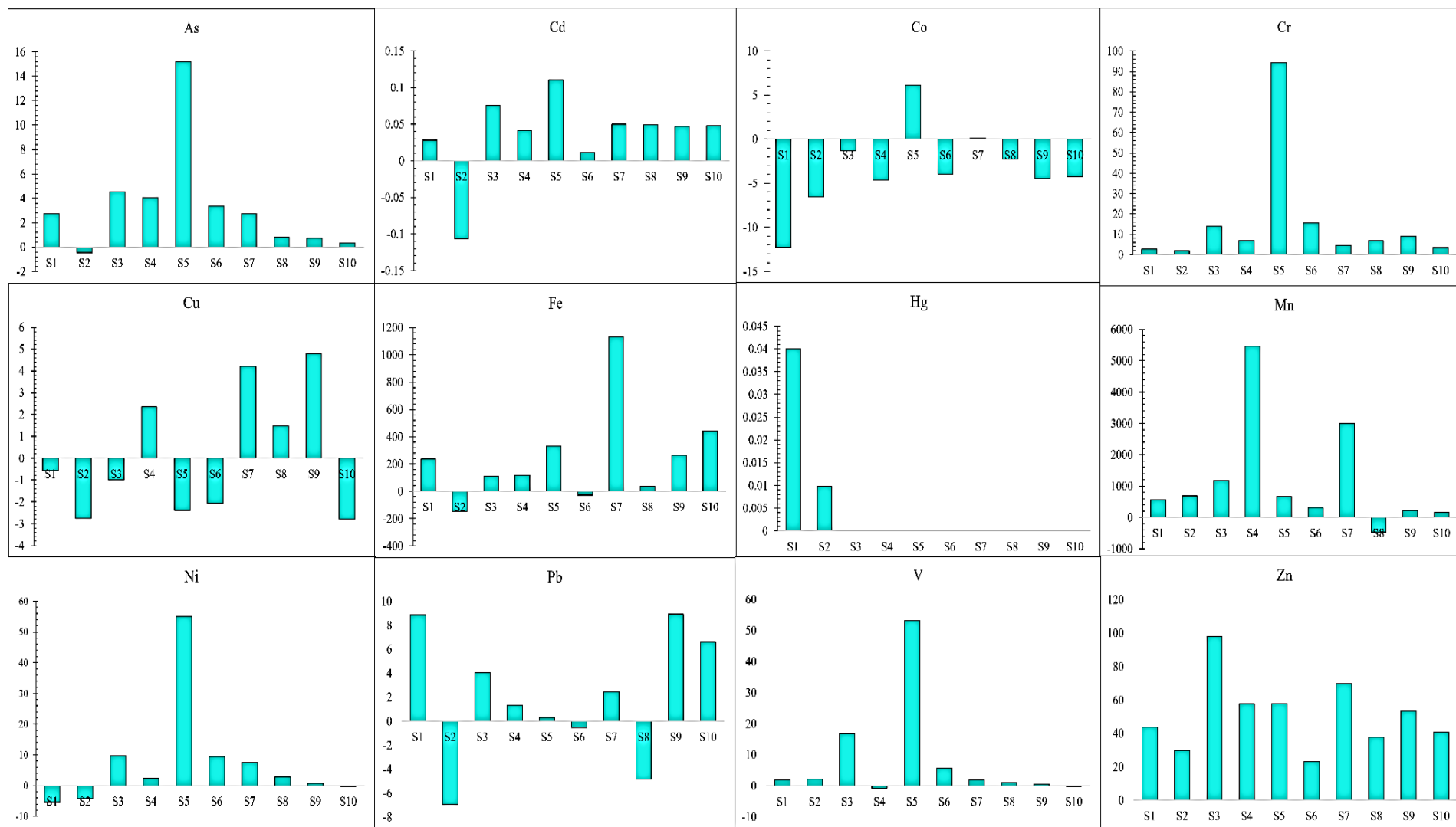


Figure 4.6: Seasonal variation of heavy metals and trace elements in irrigation water

4.3.1.4 Pearson Correlation and Cluster Analysis of Physicochemical Parameters in Irrigation Water

Pearson correlation is used to analyse the relationships between heavy metals and trace elements and physicochemical properties of irrigation water (Fig. 4.7). The analysis of Pearson correlation matrix reveals that there is strong positive correlation between As, Cd, Co, Cr, Ni, V, TDS, Cl, Na, TH, Mg, CO₃, K, SO₄ and pH; between Hg, TDS, EC, TA and HCO₃, between Zn and pH and between Cd, TA and HCO₃. Strong negative correlation is observed between Zn and the individual elements PO₄, TSS, pH and irrigation water colour. These correlations further explored using cluster analysis, organises the physicochemical properties of irrigation water into four distinct clusters based on their associations (Fig. 4.8): (i) Pb, Hg, HCO₃, TA, EC, NH₃-N, Fe, T and Mn; (ii) Cu ; (iii) Ni, Cr, V, Co, As, SO₄, K, CO₃, Cd, Mg, TH, Na, Cl, TDS, Zn, Ca and F and (iv) NO₃-N, colour, PO₄ an TSS.

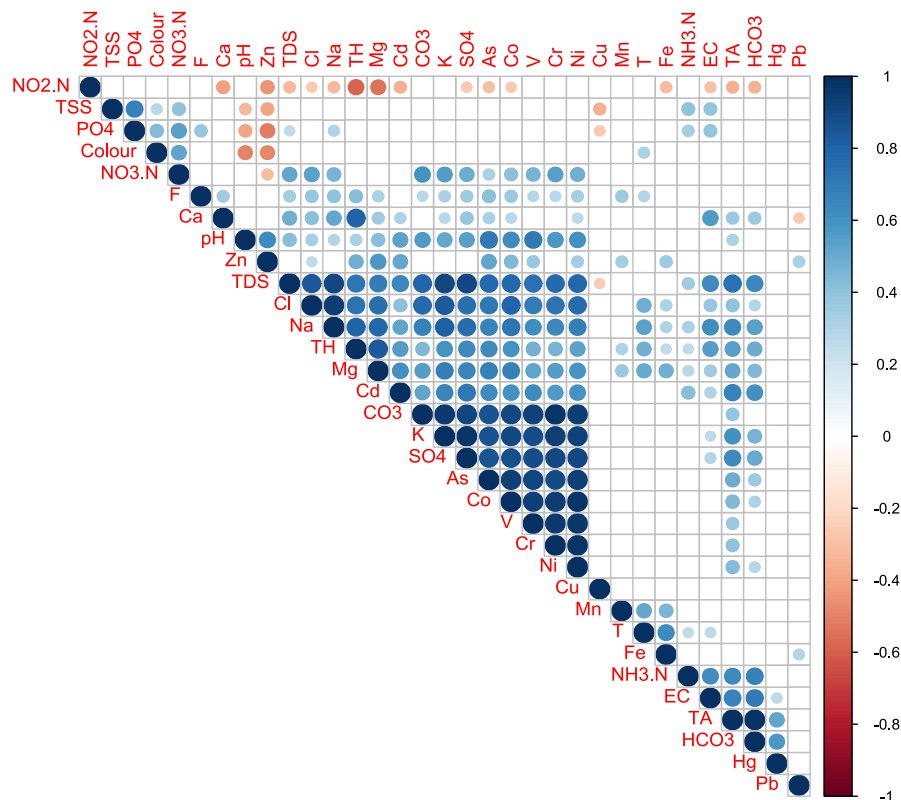


Figure 4.7: Pearson correlation matrix of physicochemical properties in irrigation water

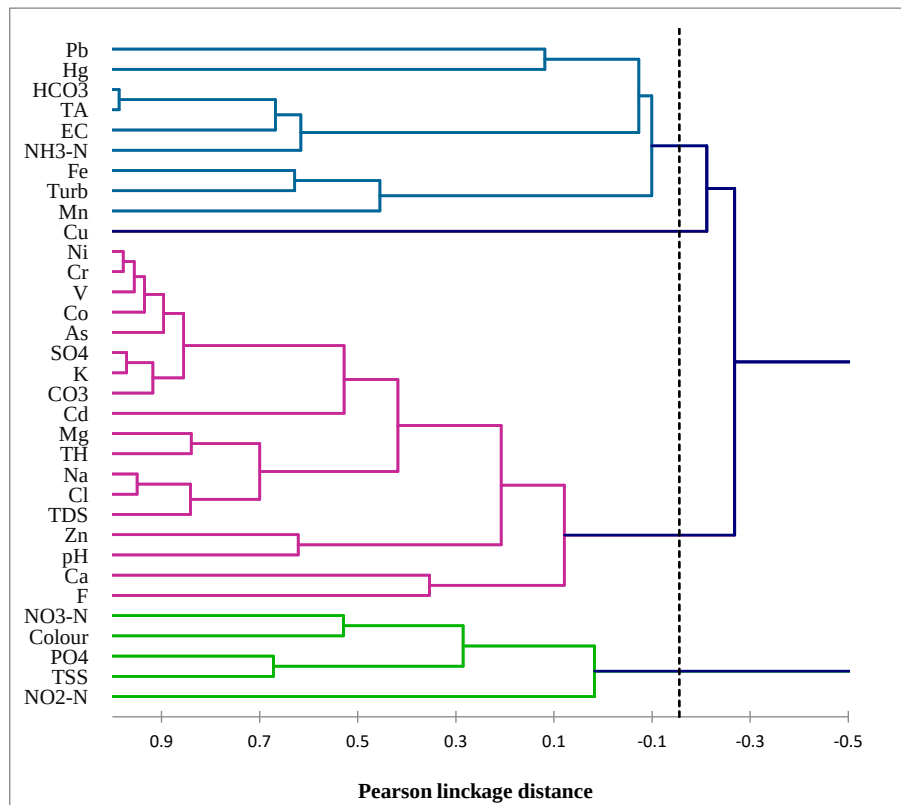


Figure 4.8: Pearson correlation matrix of physicochemical properties in irrigation

4.3.1.5 Bacterial Pathogens in Irrigation Water

The bacterial properties of irrigation water are evaluated and compared to the permissible threshold set by the World Health Organisation (WHO) for safe use of wastewater in agriculture and the one set by Kenya's National Environment Management Authority (NEMA) in dry (Table 4.14) and wet seasons (Table 4.15). Bacterial pathogens tested include total coliforms, *Escherichia coli*, *Shigella* spp., *Pseudomonas aeruginosa*, *Enterococcus faecalis*, *Vibrio cholerae*, and *Salmonella typhi*. *Salmonella typhi* is not detected in all the samples, but *V. cholerae* tested positive in the samples from station (S2) in wet season with an average count of 1.6×10^5 CFU/100 mL. The bacterial pathogens *E. coli*, *Shigella* spp., *P. aeruginosa* and *E. faecalis* are positive in the samples from most of the sampling stations. The bacteriological quality of irrigation water varies significantly between the tested pathogenic bacteria ($p <$

0.001) and the sampling stations ($p < 0.001$). The prevalence of total coliform in irrigation water is 100% in all the stations, with load count ranging between 7.2×10^4 and 2.4×10^6 CFU/100 mL in dry season and 9.3×10^4 and 1.8×10^6 CFU/100 mL in wet season. The lowest CFU mean are recorded at the station S4 with 7.2×10^4 CFU/100 mL in dry season and station S5 with 9.3×10^4 CFU/100 mL in wet season. The highest load counts of total coliform are observed at the stations S7 (2.40×10^6 CFU/100 mL) and S9 (1.40×10^6 CFU/100 mL) in dry season and S1 (1.5×10^7 CFU/100 mL) and S10 (1.3×10^6 CFU/100 mL) in wet season.

E. coli is the most abundant bacterial pathogen in all the sampling stations for the two seasons, with 100% prevalence and average load count ranging from 3.3×10^4 and 1.6×10^6 CFU/100 mL in dry season and from 4.1×10^4 and 1.5×10^7 CFU/100 mL in wet season. The highest load counts of *E. coli* are recorded at stations S7 (1.6×10^6 CFU/100 mL) in dry season and S1 (1.1×10^7 CFU/100 mL) in wet season. The CFUs of *E. coli* in irrigation water in all the stations are above the permissible threshold of 10^3 CFU/100 mL set by the World Health Organization (WHO, 2006) and the zero/100 mL threshold set by the Kenya's National Environment Management Authority (NEMA, 2006) for safe use of wastewater in agriculture. *Shigella* spp. is detected in all the samples in dry season and detected in 60% of the sample in wet season, with average CFU count ranging from 3.2×10^4 to 1.6×10^7 CFU/100 mL. The highest load counts are recorded at the station S7 (1.6×10^7 CFU/100 mL) in dry season and S1 (1.5×10^7 CFU/100 mL) in wet season. In wet season *Shigella* spp. is negative for the stations S2, S5, S8 and S10. The average count of *Shigella* spp. exceed the maximum permissible limit of zero CFU/100 mL recommended by WHO (2006) and USEPA (2009) in all dry season samples and 60% of wet season samples.

P. aeruginosa is positive in 50% of the samples in dry season and 60% in wet season, with average counts ranging of 3.1×10^3 - 1.6×10^6 and 2.2×10^4 - 5.8×10^4 , respectively; thus exceeding the permissible threshold of zero CFU/100 mL by WHO (2006) and USEPA (2009). *P. aeruginosa* is not detected at the sampling stations S4, S5, S6 and S9 in dry season and S3, S4, S5 and S8 in wet season. *E. faecalis* is detected in all samples in dry season, with average count ranging from 3.3×10^3 - 9.2×10^4 CFU/100 mL, but is detected in 50% of the samples in wet season, with average CFUs varying between 1.1×10^5 and 1.8×10^5 CFU/100 mL; exceeding the permissible threshold of zero/100 mL by WHO (2006) and USEPA (2009). *E. faecalis* is negative at the stations S3, S4, S5, S6 and S8 in wet season.

The Biological Oxygen Need (BOD) of irrigation water samples range from 37.9 to 47.4 mg/L in dry season and 35.2 to 45.3 mg/L in wet season. The highest values of BOD (> 40 mg/L) are recorded in the stations S2, S3, S4, S7, S8, S9 and S10 in dry season and S1, S2, S3, S4, S7, S8, S9 and S10 in wet season. There is no established threshold value for BOD and COD in the Kenya's standards (NEMA, 2006) and the WHO guidelines for safe use of wastewater in agriculture (WHO, 2006). However, the values of BOD recorded in all the stations are above the maximum permissible threshold of 10 mg/L set by USEPA (2009) and the European Union guidelines of 10-20 mg/L (Paranychianakis et al., 2015). The values of COD in irrigation water vary between 365 and 3,872 mg/L in dry season and 712 and 3,851 mg/L in wet season. The highest values are recorded at the stations S5 (3,698 mg/L) and S7 (3,681 mg/L) in dry season and S7 (3,851 mg/L) in wet season. The COD values were above the standards of 150 mg/l set by USEPA (2009) for unrestricted irrigation water across the sites.

Table 4.14: Bacterial contamination in irrigation water for dry season

Stations		Microbial pathogen load (10 ⁴ CFU/100 mL)							Water quality indicators			
		<i>Total coliform</i>	<i>E. coli</i>	<i>Shigella spp.</i>	<i>P. aeruginosa</i>	<i>E. faecalis</i>	<i>V. cholerae</i>	<i>S. typhi</i>	BOD (mg/l)	COD (mg/l)	BOD/COD	pH
S1	Median	13	7.1	15	ND	8.1	ND	ND	37.9	733	0.05	8.17
	Range	13-14	7.0-7.6	15-16	-	8.1-8.2	-	-	35.1-39.7	733-742	0.04-0.05	7.15-9.01
S2	Median	140	56	7.9	4.1	0.5	ND	ND	42.5	369	0.12	7.96
	Range	140-150	55-59	7.7-8.1	4.1-4.2	0.5-0.6	-	-	40.1-44.0	365-374	0.11-0.12	7.96-7.97
S3	Median	16	13	6.4	160	6.4	ND	ND	44.9	1846	0.02	8.86
	Range	15-16	12-13	6.4-6.5	150-160	6.3-6.5	-	-	44.8-45.0	1844-1850	0.01-0.02	8.75-8.97
S4	Median	7.2	3.3	8.2	ND	0.4	ND	ND	41.9	369	0.11	7.43
	Range	7.2-7.3	3.3-3.4	8.2-8.3	-	0.4-0.5	-	-	41.6-42.2	359-379	0.11-0.12	7.41-7.46
S5	Median	110	13	6.2	ND	1.3	ND	ND	37.9	3698	0.01	9.12
	Range	110-120	12-14	6.1-6.5	-	1.2-1.3	-	-	36.4-39.4	3529-3872	0.01-0.01	9.09-9.17
S6	Median	8.6	5.8	1.3	ND	0.3	ND	ND	38.3	1109	0.03	7.02
	Range	8.6-8.7	5.8-5.9	1.3-1.4	-	0.3-0.4	-	-	36.8-40.4	1098-1121	0.03-0.04	7.01-7.04
S7	Median	190	160	1600	3.2	14	ND	ND	41.7	3681	0.01	6.89
	Range	190-200	160-1700	1300-1700	3.2-3.3	13-14	-	-	41.0-43.0	3661-3703	0.01-0.01	6.89-6.9
S8	Median	17	12	7.1	0.3	31	ND	ND	47.5	1846	0.03	7.62
	Range	17-18	11-12	7.1-7.2	0.29-0.32	29-32	-	-	45.2-49.4	1842-1852	0.02-0.03	7.52-7.7
S9	Median	240	18	130	ND	13	ND	ND	47.4	365-	0.13	7.15
	Range	240-250	18-19	120-130	-	12-13	-	-	46.3-48.2	362-368	0.13-0.13	7.10-7.19
S10	Median	130	10	130	5.2	9.2	ND	ND	40.9	370	0.11	7.00
	Range	120-130	9.7-11	120-130	5.2-5.3	9.1-9.2	-	-	38.2-44.3	363-377	0.10-0.12	7.0-7.01
T	Median	ND	ND	ND	ND	ND	ND	ND	-	-	-	7.37
	Range	-	-	-	-	-	-	-	-	-	-	7.36-7.37
B	Median	ND	ND	ND	ND	ND	ND	ND	-	-	-	8.06
	Range	-	-	-	-	-	-	-	-	-	-	8.04-8.08
P-value		< .001	< .001		< .001	< .001	< .001	< .001	< .001	< .001		< .001
Permissible ranges		1 ^A 0.1 ^B	0.1 ^A 0 ^{B,C}	Nil	Nil	Nil	Nil	Nil	10 ^B 10-20 ^D	150 ^B		6.5-8.5 ^A

ND: Not Detected; ^AWHO (2006); ^BUSEPA (2009); ^CNEMA (2006); ^DParanychanakis et al. (2015)

Table 4.15: Bacterial contamination in irrigation water for wet season

Stations		Microbial pathogen load (10 ⁴ CFU/100 mL)							Water quality indicators			
		Total coliform	<i>E. coli</i>	<i>Shigella spp.</i>	<i>P. aeruginosa</i>	<i>E. faecalis</i>	<i>V. cholerae</i>	<i>S. typhi</i>	BOD	COD	BOD/COD	pH
S1	Median	1500	1100	1500	5.8	11	ND	ND	40.3	1346	0.03	6.83
	Range	1400-16000	120-1200	110-16000	5.7-5.9	10-12	-	-	39.1-41.3	1319-1372	0.02-0.03	6.78-6.89
S2	Median	230	75	ND	7.7	13	16	ND	45.3	1108	0.04	6.76
	Range	220-240	62-92	-	6.8-8.8	12-18	14-6.4	-	45.0-46.0	1091-1125	0.03-0.04	6.68-6.93
S3	Median	120	100	83	ND	ND	ND	ND	43.2	1489	0.03	6.73
	Range	110-120	100-110	83-92	-	-	-	-	40.2-45.2	1421-1557	0.02-0.03	6.63-6.83
S4	Median	130	120	3.2	ND	ND	ND	ND	45.3	1847	0.02	6.93
	Range	130-140	120-130	3.1-3.4	-	-	-	-	44.1-46.2	1833-1862	0.02-0.03	6.76-7.08
S5	Median	9.3	4.1	ND	ND	ND	ND	ND	35.2	885	0.04	7.9
	Range	8.6-10	4.1-4.2	-	-	-	-	-	34.1-36.3	858-909	0.04-0.04	7.86-7.96
S6	Median	110	11	100	4.0	ND	ND	ND	38.0	1810	0.02	6.98
	Range	110-120	110-120	90-120	3.8-4.2	-	-	-	37.8-38.2	1807-1816	0.01-0.02	6.96-7.02
S7	Median	170	120	110	5.6	18	ND	ND	42.6	3851	0.01	6.58
	Range	170-180	120-130	110-120	5.5-5.8	17-18	-	-	39.9-45.2	3700-3898	0.01-0.01	6.5-6.66
S8	Median	120	43	ND	ND	ND	ND	ND	46.1	2284	0.02	6.97
	Range	110-120	42-45	-	-	-	-	-	44.2-48.0	2173-2392	0.01-0.02	6.96-7.0
S9	Median	180	140	5.5	2.2	15	ND	ND	43.4	712	0.06	6.59
	Range	170-190	140-150	5.3-5.7	2.2-2.3	15-16	-	-	41.2-46.4	697-739	0.05-0.06	6.56-6.64
S10	Median	130	150	ND	4.9	1.4	ND	ND	40.9	739	0.06	6.9
	Range	130-1400	100-1200	-	4.8-4.9	14-15	-	-	39.0-43.4	734-747	0.05-0.06	6.90-6.92
T	Median	320	ND	ND	ND	ND	ND	ND	-	ND	ND	8.15
	Range	ND	-	-	-	-	-	-	-	-	-	8.13-8.17
B	Median	ND	ND	ND	ND	ND	ND	ND	-	-	-	8.06
	Range	-	-	-	-	-	-	-	-	-	-	8.05-8.08
P-value		< .001	< .001		< .001	< .001	< .001	ND	< .001	< .001		< .001
Permissible ranges		1 ^A	0.1 ^A	Nil ^{A, B}	Nil ^{A, B}	Nil ^{A, B}	Nil ^{A, B}	Nil ^{A, B}	10 ^B	1000 ^A		6.5-8.5 ^A
		0.1 ^B	Nil ^{B, C}						10-20 ^D	150 ^B		

ND: Not Detected; AWHO (2006); BUSEPA (2009); C NEMA (2006); D Paranychianakis et al. (2015)

The results of the Mann-Whitney test used for assessing the seasonal variability of bacterial pathogens in irrigation water are presented in Fig. 4.10. The bacterial pathogens count varies significantly between dry and wet season ($p < 0.001$). The average CFU counts of total coliforms and *E. coli* are high in wet season in all stations except S5, S6 and S9. The loads of *Shigella* spp. in irrigation water are higher in dry season than in wet season for most of the stations except S1, S3 and S6. Similarly, the load count of *P. aeruginosa* CFU are higher in wet season compared to dry season, except in stations S3, S8 and S10. The CFU of *E. faecalis* are higher in wet season compared to dry season at the stations S1, S2, S7, S9 and S10, representing 50% of the samples, whereas *V. cholerae* is detected only during wet season.

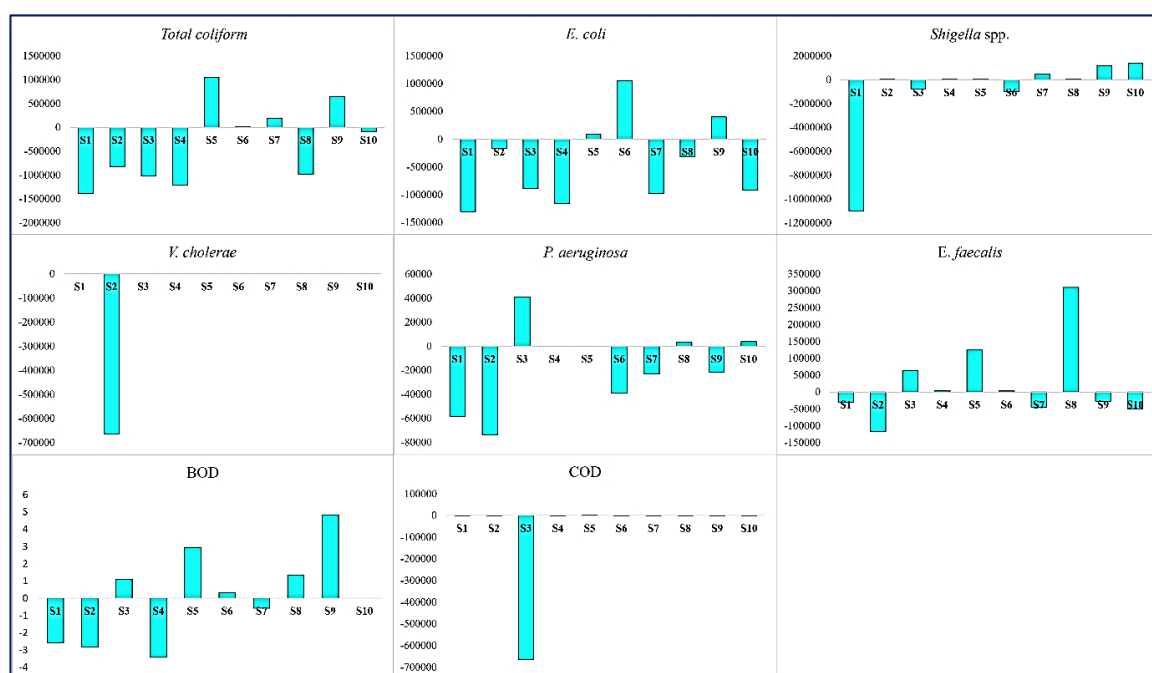


Figure 4.9: Seasonal variation of microbial pathogen load count in irrigation water

Figure 4.10 shows the results of Pearson correlation analysis performed on the bacterial properties of irrigation water in dry and wet seasons. The pH shows a strong negative correlation with the microbiological pathogens in the water samples. Higher pH values

are deleterious for the pathogens isolated from irrigation water. In dry season, strong positive correlations ($r > 0.80$) are observed between total coliform and *E. coli*, total coliform and *Shigella spp.*, *E. coli* and *Shigella spp.*, *E. coli* and BOD, and total coliform and BOD. In contrast, strong positive correlations ($r > 0.80$) are observed between total coliform and *P. aeruginosa*, total coliform and *E. faecalis*, total coliform and BOD, total coliform and COD, *E. coli* and *Shigella spp.*, *P. aeruginosa* and *E. faecalis*, and BOD and COD in wet season.

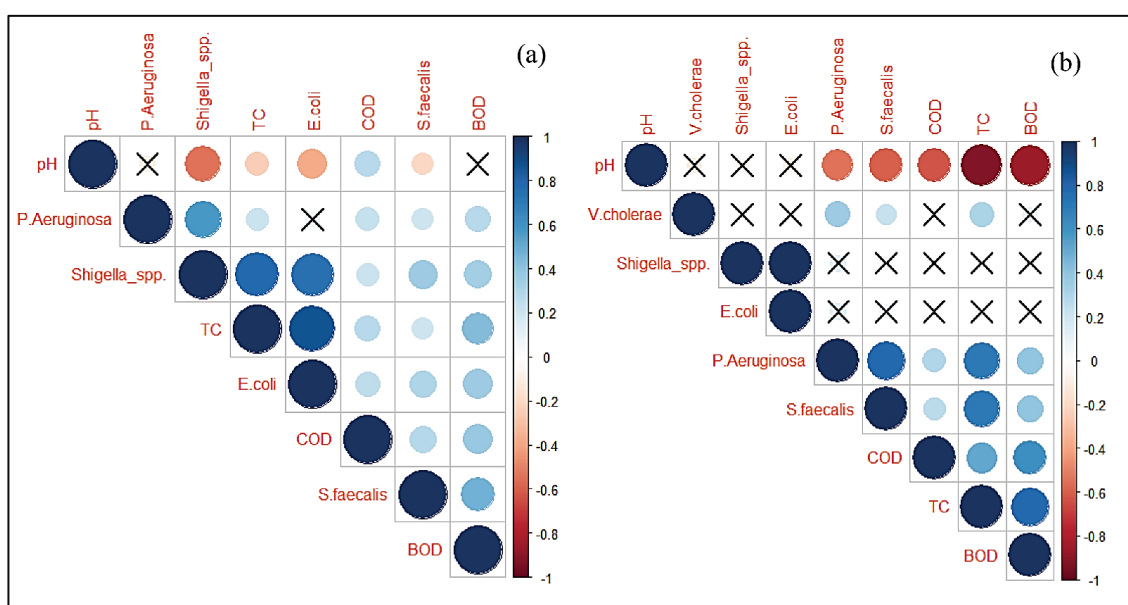


Figure 4.10: Pearson correlation matrix of bacterial pathogens in irrigation water
(a) dry season, (b): wet season

4.3.1.6 Irrigation Water Quality Indices

Water quality is assessed using irrigation water quality index (IWQI) and bacterial contamination index (BCI). The IWQI is based on five hazard groups including salinity hazard (G1), infiltration and permeability problems (G2), specific ion toxicity (G3), trace elements toxicity (G4) and miscellaneous effects to sensitive crops, while the BCI is based on *E. coli* load count in irrigation water.

a) Irrigation Water Quality Index

Salinity hazard (G1) is evaluated based on electrical conductivity (EC) values across the sampling sites and the seasons (wet and dry season). The sites S1, S3 and S7 during dry season and S1, S2 and S7 during wet season have high $EC > 3000 \mu\text{S/cm}$ and therefore recorded the lowest suitability regarding the salinity hazard $G1 = 5$ (Table 3.5). Infiltration hazard (G2) is based on interpretation of EC and SAR values (Table 3.6). The highest scores of G2 are reported at the sites S1, S2 and S3. The values of G2 are higher in wet season compared to dry season. Specific ions toxicity (G3) is based on SAR (Sodium adsorption ratio), chloride and boron concentrations in the water samples (Table 3.5). The values of G3 range from 5 to 8 in dry season and wet season. The sites S1, S3, S4, S5, S6 and S7 in dry season and S1, S2 and S7 in wet season have the lowest scores ($5 \leq G3 \leq 6$). The highest scores of G3 are recorded at S2, S8, S9, S10, B and T for dry season samples and S4, S5, S6, S8, S9, S10, B and T for wet season. The values of G3 are higher in wet season compared to dry season. Trace element toxicity hazard (G4) is based on 13 elements including As, Cd, Cr, Co, Cu, F, Hg, Fe, Pb, Mn, V and Zn. The scores of G4 range between 5.52 and 6.0 and the sites S2, S3 and S5 have the lowest score. The values of G4 are higher in wet season compared to dry season. The miscellaneous effect (G5) is based on pH, nitrate and bicarbonate concentrations of irrigation water and its scores range from 1.67 to 3.0 with the lowest values observed at the sites S1, S3 and S5.

The values of IWQI are 25.81-39.33 in dry season samples and 29.81-39.33 in wet season. In dry season, the samples from S3, S5 and S7 are classified as marginally suitable and the sites S1, S2, S4, S6, S8, S9 and S10 are classified as moderately suitable for irrigation (Table 4.16). Wet season samples are classified as marginally suitable (S2 and S7), moderately suitable (S1, S3, S6, S8, S9 and S10) and highly suitable (S4 and

S5). Regardless of the sampling sites the values of IWQI are higher in wet season compared to dry season. The samples from T and B are classified as highly suitable.

Table 4.16: Irrigation Water Quality Index

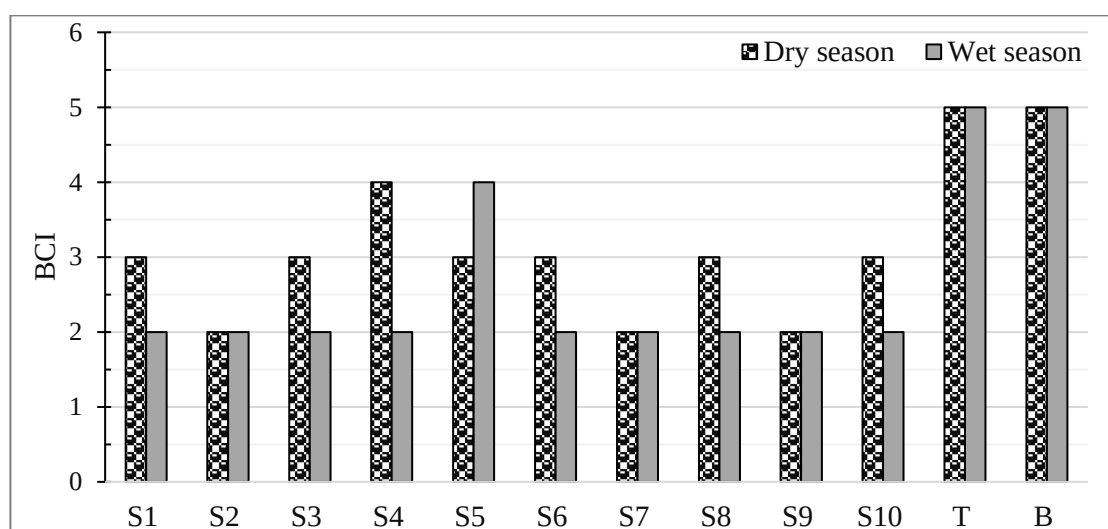
Sites	Season	G1	G2	G3	G4	G5	IWQI
S1	Dry season	5.0	12.0	6.0	5.71	2.0	30.71
	Wet season	5.0	12.0	6.0	5.81	1.67	30.48
S2	Dry season	10.0	8.0	7.0	5.62	2.67	33.29
	Wet season	5.0	12.0	5.0	5.81	2.00	29.81
S3	Dry season	5.0	12.0	5.0	5.52	1.67	29.19
	Wet season	10.0	8.0	7.0	5.81	2.00	32.81
S4	Dry season	10.0	8.0	5.0	5.81	2.67	31.48
	Wet season	15.0	8.0	8.0	5.81	2.33	39.12
S5	Dry season	10.0	4.0	5.0	5.62	1.67	26.29
	Wet season	15.0	8.0	8.0	5.81	2.67	39.48
S6	Dry season	10.0	8.0	5.0	5.62	2.67	31.29
	Wet season	10.0	8.0	8.0	5.81	2.00	33.81
S7	Dry season	5.0	8.0	5.0	5.82	2	25.81
	Wet season	5.0	12.0	5.0	5.81	2.00	29.81
S8	Dry season	10.0	8.0	8.0	5.90	2.67	34.57
	Wet season	10.0	8.0	8.0	5.90	2.33	34.24
S9	Dry season	10.0	8.0	8.0	5.90	2.67	34.57
	Wet season	10.0	8.0	8.0	5.90	2.00	33.9
S10	Dry season	10.0	8.0	8.0	5.90	2.67	34.57
	Wet season	10.0	8.0	8.0	5.90	2.33	34.24
T	Dry season	15.0	4.0	9.0	6.0	3	37.00
	Wet season	15.0	4.0	9.0	6.0	3.00	37
B	Dry season	15.0	8.0	8.0	6.0	2.33	39.33
	Wet season	15.0	8.0	8.0	6.0	2.33	39.33

Note: T: tap water; B: borehole water; IWQI ≥ 37 highly suitable; $30 \leq IWQI < 37$ moderately suitable; $22 \leq IWQI < 30$ doubtful; $IWQI < 22$ unsuitable (Simsek & Gunduz, 2007; Elsayed et al., 2020); $4.6 \leq BCI \leq 5.0$ Null bacterial contamination; $4.0 \leq BCI \leq 4.5$ Low bacterial contamination; $3.0 \leq BCI \leq 3.9$ Moderate bacterial contamination; $2.0 \leq BCI \leq 2.9$ Strong bacterial contamination; $1.0 \leq BCI < 1.9$ Very strong bacterial contamination (Boumaraf et al., 2022)

The values of IWQI indicate deterioration of irrigation water quality across the sites associated with pollution from anthropogenic activities. The sites S1 (drainage of sewage and wastewater from the industrial area in Nairobi), S2 (affected by flows from densely populated), S5 (effluent from EPZ WTP) and S7 (affected by urban drainage along Kangundo road) have the lowest IWQI. The irrigation water of these sites influenced by water flows from urban sewage, WTPs effluent and industrial waste.

b) Bacterial Contamination Index

The bacterial contamination index (BCI) based on *E. coli* load in irrigation water samples is presented in Fig. 4.11. The values of BCI vary between null contamination and strong contamination for dry season and null to very strong contamination in wet season. Null contamination is observed only for T and B samples. The values of BCI are classified as strong to very strong for the sites S2, S7 and S9 in dry season and S1, S2, S3, S4, S6, S7, S8, S9 and S10 in wet season. The load of bacterial contamination across the sites are higher in wet season compared to dry season. This is attributable to the wash off of substantially contaminated sites during the rainy season, which is drained to surface water.



Note: $4.6 \leq BCI \leq 5.0$: Null, $4.0 \leq BCI \leq 4.5$: Low, $3.0 \leq BCI < 3.9$: Moderate, $2.0 \leq BCI < 2.9$: Strong, $1.0 \leq BCI \leq 1.9$: Very strong (Boumaraf et al., 2022)

Figure 4.11: Bacterial Contamination Index

4.3.2 Soil Properties and Contamination

4.3.2.1 Physicochemical Properties of Agricultural Soils

The particle size (Table 4.17) shows that the soils are sandy loam (S1-S5 and S7) to sandy clay loam (S6, S8-S10) with sand contents ranging between 60.7 and 80%, silt

content 10.3-15% and clay contents 10.7-28%. Soil textural properties are significantly different between the sites due to significant variations in sand and clay contents ($p < 0.01$). Highest proportions of clay are associated with low sand proportions (S6, S8, S9 and S10). The proportion of coarse element varied significantly across the farmland with the highest proportions being recorded at the sites S1, S5, S7 and S8. These soil texture properties are reported to be substantially influenced by soil parental material, which are predominated by vertic gley soil and vertisol (Mangale et al., 2016). However, the evolution of these soil in the urban and peri-urban areas can be substantially influenced by anthropogenic activities especially in urban and peri-urban landscape (Pickett & Cadenasso, 2009; Tresch et al., 2018).

Table 4.17: Particle size and soil texture

Sites	Coarse element (%)	Sand (%)	Silt (%)	Clay (%)	Soil texture
S1	31.6±2.7ab	70±6ab	15.33±5.9a	14.7±2.1	Sandy loam
S2	27.7±3.3abc	71±7.2ab	14.67±9.1a	14.3±2.1	Sandy loam
S3	11.9±3.8d	73.6±7ab	12.33±1.5a	14±5.2	Sandy loam
S4	17.5±8.2cd	74±6.1ab	11±1.7a	15±4.4	Sandy loam
S5	31.8±3.8ab	76±3.6ab	8±1.7a	16±2.7	Sandy loam
S6	25.7±4.9bc	64.67±1.5ab	12.7±2.1a	22.7±2.5	Sandy clay loam
S7	39.5±3.8a	80±5.3a	9.33±5.1a	10.7±1.5	Sandy loam
S8	38.9±5.5ab	70±3.5ab	6±3.5a	24.0±7.0	Sandy clay loam
S9	26.2±4.8abc	60.67±8.1b	11.33±5.5a	28.0±2.7	Sandy clay loam
S10	28.6±3.9abc	67.83±3.2ab	10.33±3.0a	21.8±1.4	Sandy clay loam
F	9.8	3.3	1.2	7.3	-
p-value	< .001	0.012	0.3	< .001	

Means that do not share a letter are significantly different at $\alpha = 0.05$.

The chemical properties of agricultural soils are presented in Table 4.18-4.19. Soil pH has a substantial effect on plant growth as it influences nutrients and contaminants bioavailability. Soil pHs across the sites are neutral to moderately alkaline (7.23-7.80) in dry season and slightly acid to neutral (6.4-7.2) in wet season. Soil electrical conductivity (EC) ranges between 5.28-11.60 dS.m⁻¹ in dry season and 4.61 to 10.87 in wet season. The values of EC for both seasons are above 4 dS.m⁻¹, which is the

threshold from which soils are moderately saline and crop growth and yield can be impacted (Richards, 1954). Regardless of the sites, soil pH values are low in wet season compared to dry season, while EC values are in contrast higher in dry season and lower in wet season. This could be attributed to various physicochemical processes occurring in soil solution along with water flux dry-wet season. These include soil solution dilution by rainwater during wet season (Musyoki et al., 2013b), high salinity in soil occurring from natural parent material (Gorji et al., 2015) and wastewater irrigation, which is intensive in dry season (Muyen et al., 2011).

Nitrogen (N) concentrations in soil range between 0.31 and 0.44% in dry season and 0.13 and 0.31% in wet season (Table 4.18-4.19). The N contents in soil during dry season are above the threshold of N deficiency in agricultural soil of 0.25% and the sites S1, S2, S3, S4, S7 and S10 have the highest N contents. In wet season, 90% of the soils are N deficient (S2-S10). There is a significant difference in N contents across the sites for the two seasons. The concentrations of total phosphorus (tot. P) vary from 0.49-0.78% in dry season and 0.48-0.92% in wet season. In contrast, available phosphorus (av. P) ranges between 7.66-35.20 ppm in dry season and 11.34-33.53 ppm in wet season. Regardless of the season, the concentrations of av. P in soil for all the sites except S8 (33.53-35.20 ppm) are less than the deficiency threshold of 30 ppm (Mangale et al., 2016). For all the sites total P concentrations are high but only a small proportion of it is available in soil solution for plant nutrition, thus the soils are P-deficient for crop production. Total soil organic carbon (TOC) content in the soils range between 2.0 and 3.17% in dry season and 2.20 and 5.03% in wet season (Table 4.18-4.19). The sites have adequate TOC content in soil in all the sites have above the deficiency threshold for agricultural soils soil of 1.33% (Mangale et al., 2016). Soil organic matter content variation show the same trend as TOC with values ranging from 3.66 to 5.48% in dry

season and 3.80 8.67% in wet season. The ratio C/N is a key indicator of soil biological activity, which informs on the degree of evolution of soil organic matter, and the potential of nitrogen supply (mineralisation). The ratio C/N varies between 4.48-6.39 indicating rapid mineralization of soil organic carbon during dry season, while the variation between 7.44-29.19 during wet season indicates reduced biological activity and slow decomposition of soil organic carbon (SOM). The seasonal differences in C/N ratio could be attributed to N reduction and fine colloids erosion, which may occur during heavy rain event (He et al., 2019).

The concentrations of exchangeable Na in the soils are in the range of 0.81-4.37 cmol/kg in dry season and 1.11-5.43 cmol/kg in wet season. About 40% of dry season sample (S1, S2, S6 and S7) and 90% of the sample in wet season exhibited exchangeable Na values above 2 cmol.kg⁻¹, which is the threshold above which exchangeable Na become toxic for crops (Delgado & Gómez, 2016; Mangale et al., 2016). The soils have satisfactory exchangeable K (> 0.24 cmol/kg) and Ca (> 1 cmol/kg), with average ranging between 1.79 and 4.13 cmol/kg and 16.35 and 63.31 cmol/kg, respectively in dry season for K, and 0.85 and 2.67 cmol/kg and 10 and 37.78 cmol.kg, respectively in wet season for Ca. However, the concentration of exchangeable K and Ca are considerably low in wet season compared to dry season. This is attributable their loss via runoff streaming during rainy season (Bah et al., 2014). The concentrations of exchangeable Mg in the soils are above the deficiency threshold of 1 cmol/kg (Mangale et al., 2016), with 2.9 to 4.05 cmol/kg in dry season and 3.86 to 5.2 cmol/kg in wet season. The soils have high exchangeable cations and sum of bases with higher values in dry season compared to wet season. The cation exchangeable capacity (CEC) values ranged from 31.37 to 76.63 cmol.kg⁻¹ and from 41.77 to 72.5 cmol.kg⁻¹ for dry and wet season respectively, which are highly suitable for crop production.

Table 4.18: Chemical properties of soil for dry season samples

Soil properties	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	F	Critical level
pH	7.58±0.2a	7.57±0.1a	7.80±0.4a	7.42±0.2a	7.34±0.9a	7.55±0.2a	7.32±0.14a	7.52±0.3a	7.29±0.6a	7.23±0.5a	0.5ns	≤ 5.5 ¹
EC (dS.m ⁻¹)	8.42±0.8abc	6.8±1.4 c	5.28±0.5c	10.9±1.6ab	6.32±2.3c	5.54±0.4c	7.23±0.6c	6.18±1.7c	7.57±1.1abc	11.6±2.2a	7.0***	> 4
N (%)	0.42±0.0a	0.43±0.0a	0.44±0.0a	0.41±0.0ab	0.37±0.0ab	0.35±0.0ab	0.43±0.0a	0.38±0.1ab	0.31±0.1b	0.441±0.0a	4.9**	< 0.25 ¹
Tot. P (%)	0.66±0.1a	0.63±0.03a	0.78±0.1a	0.61±0.0a	0.56±0.2a	0.56±0.1a	0.85±0.1a	0.59±0.3a	0.49±0.1a	0.73±0.2a	1.8ns	-
Av. P (ppm)	19.24±3.1cd	7.66±0.4f	12.75±2.1ef	8.06±1.7f	17.17±2.4de	9.21±1.1f	24.14±2.1bc	35.20±1.0a	12.81±2.3def	27.02±3.9b	49.6***	< 30 ¹
C (%)	2.54±0.1b	2.16±0.0bc	2.41±0.1bc	2.34±0.3bc	2.28±0.2bc	2.21±0.0bc	3.17±0.4a	2.28±0.0c	2.12±0.1bc	2.0±0.0c	12.1***	< 1.33 ¹
SOM (%)	4.38±0.2b	3.40±0.1bc	3.72±0.0bc	4.16±0.2bc	4.06±0.5bc	3.86±0.3bc	5.48±0.0a	4.49±0.6bc	3.93±0.1bc	3.66±0.1c	12.4***	-
C/N	6.00±0.2abc	5.02±0.1bc	5.45±0.6abc	5.66±0.5abc	6.17±0.6abc	6.39±0.4abc	7.33±1.0a	6.18±1.2abc	6.91±1.2ab	4.48±0.1c	4.45***	-
Na (cmol.kg ⁻¹)	4.37±0.6a	2.36±0.1cd	1.80±0.2de	1.59±0.1de	0.81±0.2e	3.07±0.2bc	3.49±0.7ab	1.11±0.2e	1.37±0.1de	1.55±0.2de	32.8***	> 2 ¹
K (cmol.kg ⁻¹)	3.97±0.2ab	2.44±0.2abc	3.89±0.7ab	3.48±0.8abc	1.79±0.4c	2.27±0.2bc	2.78±0.9abc	4.13±0.5a	3.01±0.7abc	3.09±0.8abc	5.1**	< 0.24 ¹
Ca (cmol.kg ⁻¹)	30.24±2.5bcd	63.31±5.0a	28.8±4.6bcd	39.33±4.1b	20.24±3.1	37.35±3.9b	29.95±3.4bcd	32.58±5.9bc	22.87±1.9cde	16.95±1.9e	34.7***	< 2 ¹
Mg (cmol.kg ⁻¹)	2.90±0.7a	4.05±0.5a	3.21±0.8a	3.07±0.2a	2.79±0.4a	3.34±0.4a	3.16±0.6a	3.29±0.1a	3.82±0.1a	3.37±0.8a	1.6ns	< 1 ¹
SB (cmol.kg ⁻¹)	41.49±3.3bc	72.17±4.5a	37.69±5.0bc	47.47±3.6b	25.63±2.5d	46.04±4.1b	39.38±5.4bc	41.11±5.3bc	31.08±1.3cd	24.96±3.2d	33.9***	< 6
CEC (cmol.kg ⁻¹)	64.32±4.9ab	76.63±2.6a	49.52±12.8bc	43.84±5.4bc	42.92±11.8bc	60.98±2.8ab	31.37.3c	63.8±13.4ab	45.9±5.1bc	57.4±7.8ab	7.7***	< 6 ²
Saturation (%)	64.62±5.1bc	94.34±8.3abc	78.07±14.0bc	109.9±20.5ab	63.4±20.5bc	75.59±7.2bc	132.5±4a	65.23±5.7bc	68.48±9.8bc	44.01±8.4c	6.1***	< 40 ³

Means that do not share a letter are significantly different at $\alpha = 0.05$. ns non-significant at 5%; * p value significant at 5%; **p value significant at 1%; ***p value significant at 0.1%; ¹Mangale, N. *et al.* Manual for Integrated Soil Fertility Management in Kenya. (2016); ²Estefan *et al.* (2013); ³Hazelton & Murphy (2016)

Table 4.19: Chemical properties of soil for wet season samples

Soil properties	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	F	Critical level
pH	7.20±0.1a	7.13±0.15a	7.2±0.0a	6.90±0.2ab	6.80±0ab	6.87±0.3ab	6.80±0.4ab	7.13±0.06a	6.4±0.1b	6.60±0.1b	6.7***	≤ 5.5 ¹
EC (dS.m ⁻¹)	6.65±0.4bc	8.73±1.2ab	4.85±0.1cd	5.70±1.4c	4.84±1.1cd	4.61±1.1cd	5.99±0.4c	5.34±0.5c	6.48±0.2bc	10.87±1.2a	20.1***	> 4
N (%)	0.31±0.1a	0.18±0.0ab	0.21±0.01ab	0.21±0.1ab	0.17±0.0ab	0.20±0.0ab	0.17±0.0b	0.13±0.0b	0.21±0.0ab	0.22±0.0ab	2.8*	< 0.25 ¹
Tot. P (%)	0.60±0.0bc	0.48±0.0c	0.60±0.2bc	0.58±0.1bc	0.55±0.1bc	0.73±0.0ab	0.92±0.1a	0.64±0.0bc	0.64±0.1bc	0.59±0.1bc	6.6***	-
Av. P (ppm)	20.95±1.8bc	14.09±1.2de	18.25±2.1cd	17.98±2.9cd	17.95±3.2cd	11.34±1.0e	24.84±0.1b	33.53±0.3a	13.67±1.5de	31.78±2.4a	45.6***	< 30 ¹
C (%)	2.20±0.3b	2.86±0.9b	2.54±0.2b	2.32±0.1b	2.23±0.3b	2.49±0.2b	5.03±0.3a	3.13±0.9b	3.45±0.5b	2.32±0.1b	10.9***	< 1.33 ¹
SOM (%)	3.8±0.6b	4.93±1.5b	4.39±0.3b	4.0±0.2b	3.84±0.5b	4.30±0.3b	8.67±0.5a	5.40±1.5b	5.95±0.8b	4.01±0.1b	10.9***	-
C/N	7.44±1.6c	16.05±3.1b	12.13±1.7bc	12.06±3.9bc	12.98±0.62bc	12.30±0.9bc	29.91±2.1a	23.80±5.3a	16.28±1.0b	10.99±1.7bc	19.8***	-
Na (cmol.kg ⁻¹)	4.48±0.23ab	4.27±0.7ab	2.11±0.1cd	2.60±0.3bcd	2.12±0.2cd	3.87±1.6abc	2.06±1.1cd	2.15±0.1cd	1.11±0.0a	5.43±0.1a	12.7***	> 2 ¹
K (cmol.kg ⁻¹)	2±0.1bc	0.85±0.0g	2.19±0.2b	1.54±0.2de	1.41±0.2def	1.58±0.0de	1.36±0.2ef	2.67±0.1a	1.11±0.2fg	1.74±0.1cd	59.9***	< 0.24 ¹
Ca (cmol.kg ⁻¹)	21.37±3.8b	37.78±0.7a	10.0±2.9e	21.12±1.3b	14.43±0.6de	12.33±0.6de	20.23±2.2bc	16.60±0.2bcd	12.95±0.3de	15.43±0.9cd	59.0***	< 2 ¹
Mg (cmol.kg ⁻¹)	4.1±0.1bc	5.20±0.3a	4.64±0.5ab	5.06±0.5a	3.98±0.1ab	3.86±0.1c	3.96±0.0bc	4.1±0.0bc	4.19±0.0bc	4.09±0.0bc	11.8***	< 1 ¹
SB (cmol.kg ⁻¹)	31.95±3.7b	48.10±0.4a	18.95±3.6f	30.32±0.9bc	21.95±0.7def	21.64±1.1ef	27.60±3.2bcd	25.52±0.1cde	19.37±0.5f	26.69±0.8bcd	54.6***	< 6
CEC (cmol.kg ⁻¹)	48.32±2.9ab	72.75±12.0a	50.38±5.1ab	46.79±1.4b	41.77±0.3ab	44.73±5.3b	61.60±19.3ab	54.04±4.5ab	61.61±0.9ab	62.23±10.9ab	4.0**	< 6 ²
Saturation (%)	66.58±11.6a	67.43±12.0a	38.35±11.1c	64.87±3.9ab	52.56±1.9abc	48.64±3.5abc	46.53±8.1abc	47.45±4.1abc	31.44±0.5c	43.90±8.8bc	7.5***	< 40 ³

Means that do not share a letter are significantly different at $\alpha = 0.05$. ns non-significant at 5%; * p value significant at 5%; **p value significant at 1%; ***p value significant at 0.1%; ¹Mangale, N. et al. Manual for Integrated Soil Fertility Management in Kenya. (2016); ²Estefan et al. (2013); ³Hazelton & Murphy (2016)

Base saturation ranges from 44.01 to 132.5% for dry season and 31.44 to 67.43% in wet season. Base saturation in the soil is substantially influenced by exchangeable Ca, which is a characteristic of the parent material of the soil. Base saturations are low in wet season compared to dry, due to dilution and loss through runoff (He et al., 2019). Base saturations are satisfactory for all the sites in dry season. In contrast, the base saturations of the sites S3 and S10 (20%) are below the minimum of 40% recommended for crop production in wet season (Hazelton & Murphy, 2016).

4.3.2.2 Heavy Metals and Trace Elements Contamination in Agricultural Soils

The average (mean $\pm$ standard deviation) and range of heavy metals and trace elements concentrations in soil across the different sites are presented in Table 4.20. The concentrations of all the heavy metals and trace elements except Pb exhibit significantly higher variation across the sites ($p < 0.05$). Arsenic (As) concentrations range between 1.6-5.3 mg/kg and the sites S1, S7, S8, S9 and S10 have the highest As concentrations at 4.8, 4.6, 4.7, 4.5, and 5.3 mg/kg, respectively. Although only 1.7% of the samples (one out of six at S10) show above the permissible concentration of As for agricultural soil, 43.3% of the samples have concentrations very close to the threshold value of 5 mg/kg (MEF, 2007). The average concentration of As in the soil per site appear in the descending order $S8 > S1 > S9 > S7 > S10 > S5 > S3 > S6 > S2 > S4$.

Cadmium (Cd) concentrations in soil vary between 0.1 and 0.4 mg/kg, and the sites S1, S5, S7, S9 and S10 recorded the highest Cd concentrations (0.4 mg/kg). Above permissible threshold concentrations of Cd for agricultural soil of 0.3 mg/kg (MEF, 2007) are observed for 13.3% of the samples from the sites S1, S5, S7, and S10. Additionally, 55% of the samples have a concentration close to the threshold concentration ($0.2 \leq Cd < 0.3$). Cobalt (Co) concentrations in the soil range from 5.3-

17.7 mg/kg, with the sites S2, S5, and S8 recording the highest concentrations, 11.8, 13.5, and 17.7 mg/kg, respectively.

The concentrations of Co in soil for the different sites are within the recommended range (≤ 20 mg/kg) for agricultural use (MEF, 2007; He et al., 2015). Chromium (Cr) concentrations in the soil vary between 6.5-29.9 mg/kg and are below the threshold concentration for agricultural soil of 100 mg/kg (URT, 2007). The highest Cr concentrations in soil are recorded at S2, S5 and S10 with 29.9, 26.8, and 19.5 mg/kg, respectively. The sites appear according to Cr content in the descending order, $S2 > S5 > S10 > S3 > S1 > S8 > S7 > S6 > S4 > S9$. Copper (Cu) concentrations in soil range from 6.5-23.1 mg/kg and the highest concentrations are recorded at S2 (19.4 mg/kg), S5 (23.1 mg/kg), and S10 (16.7 mg/kg). The Cu contents in soils are lower than the permissible limit of 100 mg/kg for agricultural soil (URT, 2007; Chiroma, 2008). The concentrations of Cu in the sampling sites are in the decreasing order $S5 > S2 > S10 > S7 > S3 > S4 > S1 > S8 > S6 > S9$.

Iron (Fe) concentrations in soil vary between 17844 and 38250 mg/kg, which are within the permissible range of 50000 mg/kg Fe for agricultural soil. The highest Fe contents in soil are recorded at S1 (35679 mg/kg), S9 (36093 mg/kg) and S10 (38250 mg/kg). The concentrations of mercury (Hg) in soil range from 6.8 to 82.7 $\mu\text{g/kg}$, with the highest concentrations in soil recorded at S1 (38.5 $\mu\text{g/kg}$), S9 (36.4 $\mu\text{g/kg}$) and S10 (82.7 $\mu\text{g/kg}$). The concentrations of Hg across the sites are within the permissible limit of 500 $\mu\text{g/kg}$ for agricultural soil (MEF, 2007). The concentrations of Hg in soil in the sites appear in the order $S10 > S1 > S9 > S7 > S8 > S3 > S2 > S6 > S4 > S5$. Manganese (Mn) contents in soil range between 1262-7693 mg/kg, with the sites S7 and S8 recording the highest concentrations.

Mn contents above the permissible range of 2000 mg/kg for agricultural soil are recorded at the sites S1, S2, S3, S5, S6, S7, S8, S9 and S10 with 80% of the samples. Considering the concentration of Mn in soil, the sites are in the order $S8 > S7 > S1 > S9 > S5 > S10 > S3 > S6 > S2 > S4$. Nickel (Ni) concentrations in the soil vary between 6.4-21.1 mg/kg. In all the sites, Ni concentrations are within the permissible range of 35 mg/kg for agricultural soil (Riccardo & Gabriella, 2008). The sites S1, S2, S5, S8, and S10 have the highest concentrations of Ni, 14.0-21.1 mg/kg.

Lead (Pb) concentrations in the soil range between 5.8-62.6 mg/kg, with the highest concentration at the sites S5 (62.6 mg/kg) and S10 (51.9 mg/kg). Pb concentrations are within the permissible limit of 60 mg/kg for agricultural soil (MEF, 2007) for all the sites except S5, with 1.7% of the samples. The sites are in the decreasing order $S5 > S8 > S7 > S1 > S10 > S9 > S2 > S6 > S3 > S4$. Vanadium (V) concentrations in soil samples range between 13.0-40.0 mg/kg. The highest V concentrations in soil are recorded at S2 and the sites ranking in the decreasing order are $S2 > S9 > S10 > S5 > S8 > S3 > S4 > S1 > S6 > S7$. Vanadium concentrations in the soil from all the sites are within the limit range of 50 mg/kg for agricultural soil.

Zinc (Zn) concentrations in the soil vary between 41.3-249.4 mg/kg. The sites S1, S5 and S10 exhibit above permissible Zn limit (150 mg/kg) for agricultural soil (URT, 2007), which represents 11.7% of the samples. Additionally, 13.3% of the samples show concentrations very close to the threshold value. The sites are ranked according to Zn concentrations in soil in the decreasing order $S1 > S10 > S7 > S5 > S9 > S5 > S6 > S2 > S8 > S3 > S4$.

The spatial distribution of the twelve elements (Fig. 4.12) illustrates the distinct zones of lower or higher concentrations across the farms. Although the spatial distributions of the different heavy metals and trace elements are not uniform across the catchment, the

patterns of their spatial distributions exhibited some similarities and dissimilarities. Three similar distribution patterns are observed with slight variation between the hotspot sites for the different heavy metals and trace elements: (i) Co and Mn, (ii) Cu and Cr and (iii) As, Cd, Fe, Hg, Pb and Zn. For As, the leading hotspot sites are S1, S7, S8, S9 and S10; for Cd and Zn it is S1, S5, S7, S9 and S10; for Co and Mn it is S8; for Cr and Cu it is S2, S5 and S10; for Fe it is S1, S8, S9 and S10; for Pb it is S1, S5, S7, S8, S9 and S10, while for Hg it is S1, S9 and S10. The elements Ni and V exhibit singular spatial distribution compared to other elements with the sites S1, S2, S5, S8 and S10 being the hotspots for Ni and the sites S2, S9 and S10 showing being the hotspot for V.

Table 4.20: Heavy metals and trace elements concentrations in soil in Nairobi city catchment

Sites		As (ppm)	Cd (ppm)	Co (ppm)	Cr (ppm)	Cu (ppm)	Fe (ppm)	Hg (ppb)	Mn (ppm)	Ni (ppm)	Pb (ppm)	V (ppm)	Zn (ppm)
S1	Mean $\pm$ SD	4.4 $\pm$ 0.3 ^a	0.3 $\pm$ 0.1 ^b	7.0 $\pm$ 1.0 ^{cd}	12.7 $\pm$ 0.9 ^b	9.4 $\pm$ 2.9 ^{bc}	30846 $\pm$ 3230 ^{abc}	33.5 $\pm$ 4.4 ^{ab}	2815 $\pm$ 296 ^c	12.3 $\pm$ 0.3 ^{abc}	22.4 $\pm$ 5.0 ^a	20.4 $\pm$ 0.8 ^{cd}	148 $\pm$ 16.3 ^a
	Range	4.0-4.8	0.2-0.4	5.7-8.3	11.5-13.9	7.1-14.2	26880-35679	28.5-38.5	2342.9-3094	12.0-12.7	17.8-30.6	19.5-21.3	129.2-176.8
S2	Mean $\pm$ SD	3.2 $\pm$ 0.2 ^{cd}	0.2 $\pm$ 0.1 ^{bcd}	10.2 $\pm$ 1.3 ^{bc}	20.8 $\pm$ 6.8 ^a	13.9 $\pm$ 3.5 ^a	28619 $\pm$ 2254 ^{abc}	11.4 $\pm$ 2.5 ^{cd}	2016 $\pm$ 511 ^{cd}	15.7 $\pm$ 3.6 ^a	16.7 $\pm$ 1.8 ^a	32.3 $\pm$ 4.7 ^a	102 $\pm$ 11.2 ^{ab}
	Range	2.7-3.3	0.1-0.3	8.2-11.8	12.3-29.9	9.6-19.4	25469-31323	8.6-14.2	1262-2587	11.4-21.1	14.7-19.2	26.6-40.0	88.2-122.3
S3	Mean $\pm$ SD	3.2 $\pm$ 0.9 ^{cd}	0.2 $\pm$ 0.1 ^{bcd}	7.6 $\pm$ 0.8 ^{cd}	13.0 $\pm$ 2.1 ^b	10.6 $\pm$ 3.1 ^{abc}	24930 $\pm$ 5141 ^{cd}	11.9 $\pm$ 1.8 ^{cd}	2176 $\pm$ 428 ^{cd}	11.8 $\pm$ 2.3 ^{abc}	14.5 $\pm$ 2.3 ^a	21 $\pm$ 0.5 ^{cd}	98.0 $\pm$ 22.4 ^{ab}
	Range	2.6-4.7	0.1-0.3	6.7-8.4	10.0-16.4	7.6-15.9	18946-33383	9.9-14.0	1685-2846	8.8-15.8	12.2-18.3	20.4-21.9	66.9-131.3
S4	Mean $\pm$ SD	2.2 $\pm$ 0.4 ^d	0.1 $\pm$ 0.1 ^d	7.8 $\pm$ 1.8 ^{bcd}	11.6 $\pm$ 3.5 ^b	9.7 $\pm$ 2.8 ^{bc}	20196 $\pm$ 4679 ^d	7.0 $\pm$ 2.5 ^d	1559 $\pm$ 274 ^d	10.7 $\pm$ 3.1 ^{bc}	9.6 $\pm$ 2.4 ^a	20.5 $\pm$ 4.1 ^{cd}	72.4 $\pm$ 18.4 ^b
	Range	1.6 – 2.8	0.1-0.2	6.7-10.9	6.5-16.0	5.7-14.3	12641-26841	4.2-9.7	1305-2034	6.4-14.4	5.8-13.4	15.4-27.4	41.3-93.1
S5	Mean $\pm$ SD	3.2 $\pm$ 0.9 ^{bc}	0.2 $\pm$ 0.1 ^{bc}	10.9 $\pm$ 1.9 ^b	15 $\pm$ 6.3 ^{ab}	14.1 $\pm$ 5.4 ^a	25760 $\pm$ 5403 ^{bcd}	6.9 $\pm$ 0.1 ^d	2445 $\pm$ 439 ^{cd}	12.2 $\pm$ 3 ^{abc}	21.5 $\pm$ 20.2 ^a	24.6 $\pm$ 5.6 ^{bcd}	112.0 $\pm$ 69.3 ^{ab}
	Range	2.5-4.8	0.1-0.4	8.1-13.5	10.2-26.8	8.5-23.1	19999-33205	6.8-6.9	2027-3109	9.3-17.7	11.2-62.6	17.3-33.3	70.3-249.4
S6	Mean $\pm$ SD	3.2 $\pm$ 0.3 ^{cd}	0.2 $\pm$ 0.1 ^{bcd}	7.9 $\pm$ 3.3 ^{bcd}	12.3 $\pm$ 1.8 ^b	9.1 $\pm$ 1.7 ^{bc}	25863 $\pm$ 2202 ^{abcd}	10.9 $\pm$ 0.7 ^{cd}	2146 $\pm$ 362 ^{cd}	11.3 $\pm$ 2.5 ^{8bc}	15.2 $\pm$ 3.3 ^a	20.2 $\pm$ 4.7 ^{cd}	104.0 $\pm$ 16.7 ^{ab}
	Range	2.7-3.7	0.2-0.3	5.3-13.1	10.6-14.3	6.9-11.5	23440-29794	10.0-11.7	1544-2533	8.2-13.9	10.9-20.8	15.7-27.2	85.3-129.6
S7	Mean $\pm$ SD	4.1 $\pm$ 0.4 ^{abc}	0.3 $\pm$ 0.1 ^a	7.3 $\pm$ 1.1 ^{cd}	11.7 $\pm$ 1.1 ^b	11.0 $\pm$ 2.7 ^{abc}	27851 $\pm$ 5684 ^{abcd}	18.4 $\pm$ 3.6 ^{bcd}	3988 $\pm$ 1371 ^b	8.3 $\pm$ 0.8 ^c	23.5 $\pm$ 5.5 ^a	17.2 $\pm$ 2.5 ^d	132.0 $\pm$ 11.4 ^a
	Range	3.5-4.6	0.2-0.4	5.9-8.8	10.4-13.6	8.3-15.5	17844-32798	14.5-22.4	2555-6147	6.9-9.3	16.9-32.3	13.0-19.3	116.8-149.5
S8	Mean $\pm$ SD	4.5 $\pm$ 0.2 ^a	0.2 $\pm$ 0.1 ^{cd}	16.1 $\pm$ 0.9 ^a	11.7 $\pm$ 1.4 ^b	9.1 $\pm$ 3.0 ^{bc}	29333 $\pm$ 2079 ^{abc}	16.9 $\pm$ 0.1 ^{bcd}	6933 $\pm$ 740 ^a	14.0 $\pm$ 1.7 ^{ab}	24 $\pm$ 2.1 ^a	21.6 $\pm$ 2.5 ^{bcd}	101.0 $\pm$ 8.6 ^{ab}
	Range	4.2-4.7	0.1-0.2	15.5-17.7	10.3-14.1	5.9-13.6	27164-32560	16.79-17.0	5758-7693	12.1-16.2	21.8-26.9	18.8-24.8	91.5-113.0
S9	Mean $\pm$ SD	4.2 $\pm$ 0.2 ^{ab}	0.2 $\pm$ 0.1 ^{bc}	6.3 $\pm$ 0.4 ^d	11.5 $\pm$ 0.9 ^b	8.7 $\pm$ 1.5 ^c	33372 $\pm$ 1748 ^{ab}	28.0 $\pm$ 7.5 ^{bc}	2559 $\pm$ 57 ^{cd}	9.0 $\pm$ 0.6 ^c	22.1 $\pm$ 8.2 ^a	30.1 $\pm$ 3.9 ^{ab}	124.0 $\pm$ 5.9 ^{ab}
	Range	3.9-4.5	0.2-0.3	5.8-7.0	10.7-13.1	5.9-10.0	31253-36093	19.7-36.4	2493-2639	8.7-10.0	11.9-36.8	24.3-35.4	114.0-130.1
S10	Mean $\pm$ SD	3.9 $\pm$ 0.8 ^{abc}	0.3 $\pm$ 0.1 ^b	8.5 $\pm$ 2.5 ^{bcd}	15.6 $\pm$ 2.5 ^{ab}	12.3 $\pm$ 2.2 ^{ab}	33658 $\pm$ 5661 ^a	48.3 $\pm$ 30.7 ^a	2423 $\pm$ 522 ^{cd}	12.4 $\pm$ 2.0 ^{abc}	22.2 $\pm$ 14.6 ^a	28.7 $\pm$ 9.2 ^{abc}	142 $\pm$ 35.5 ^a
	Range	3.1-5.3	0.22-0.4	6.3-13.4	11.7-19.5	10.9-16.7	22867-38250	13.9-82.7	1978-3231	9.0-19.3	14.0-51.9	17.4-39.8	78.9-188.9
p-value		< .001***	< .001***	< .001***	< .001***	0.015**	< .001***	< .001***	< .001***	< .001***	0.089 ns	< .001***	< .001***
Threshold values		5 ¹	0.3 ⁶	20 ^{1,4}	100 ^{1,2,5}	100 ^{1,2,3,5}	50000 ³	500 ¹	2000 ³	35 ⁴	60 ¹	50 ²	150 ⁵

Note: For each column the means that do not share the same alphabetic letter are not significantly different Tukey's HSD test $p < 0.05$; SD = standard deviation ¹MEF (2007); ²Kloke et al. (1984); ³Chiroma et al. (2014); ⁴Scalenghe & Fasciani (2008); ⁵URT (2007); ⁶He et al. (2015), ns: non-significant; *: significant at $\alpha = 0.05$; **: significant at $\alpha = 0.01$; ***: significant at $\alpha = 0.001$

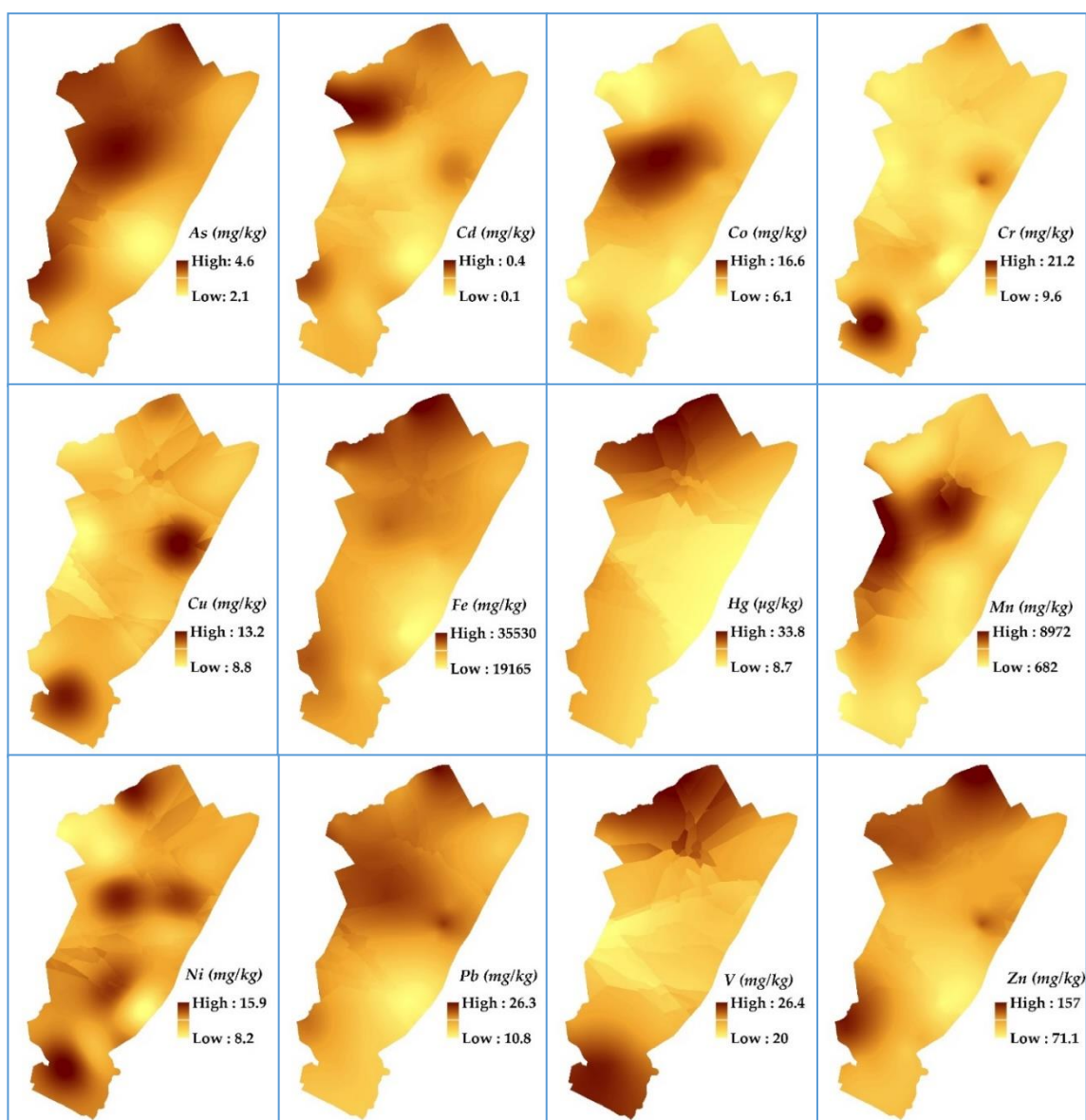


Figure 4.12: Spatial distribution of heavy metals and trace elements in agricultural soils across Nairobi city catchment

4.3.2.3 Soil Pollution Indices

a) Geo-accumulation Index

The average geo-accumulation Index (*I_{geo}*) of heavy metals and trace elements in the soils for each site is presented in Table 4.21. The *I_{geo}* for the twelve heavy metals and trace elements across the sites depict extensive variability ranging from 3.13 to 3.68. The *I_{geo}* values for As range from 0.46 to 0.54 and the sampling sites S1, S2, S3, S5,

S6, S7, S8, S9 and S10 are classified as unpolluted to moderately polluted, whereas S4 is classified as unpolluted. The *Igeo* for Cd vary between 0.38 and 1.05 with the sampling sites S1, S2, S3, S5, S6, S7, S9 and S10 classified as unpolluted to moderately polluted, whereas S4 and S8 are classified as unpolluted. The *Igeo* for Co, Cr, Cu, Fe, Hg, Ni, Pb, V and Zn for all the sites are classified as unpolluted ($0 \leq Igeo$). The *Igeo* of Mn range between 0.96-3.13 indicating that the soils are unpolluted to highly polluted in Mn, with the sites S7 and S8 classified as moderately to highly polluted, S1, S2, S3, S5, S6, S9 and S10 as moderately polluted and S4 as unpolluted to moderately polluted.

Table 4.21: Geo-accumulation Index (*Igeo*)

HMTE	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
As	0.54	0.07	0.04	-0.46	0.06	0.07	0.45	0.57	0.48	0.36
Cd	0.86	0.36	0.28	-0.38	0.43	0.30	1.05	-0.05	0.53	0.69
Co	-1.33	-0.78	-1.21	-1.18	-0.69	-1.24	-1.27	-0.11	-1.48	-1.07
Cr	-2.05	-1.40	-2.03	-2.25	-1.89	-2.11	-2.16	-2.17	-2.20	-1.77
Cu	-1.25	-0.67	-1.07	-1.20	-0.69	-1.26	-1.00	-1.31	-1.33	-0.82
Fe	-0.59	-0.70	-0.92	-1.23	-0.87	-0.85	-0.76	-0.66	-0.48	-0.48
Hg	-1.56	-2.91	-2.83	-3.68	-3.61	-2.95	-2.21	-2.32	-1.63	-1.14
Mn	1.83	1.31	1.44	0.96	1.61	1.42	2.27	3.13	1.69	1.59
Ni	-1.19	-0.86	-1.26	-1.44	-1.23	-1.34	-1.75	-1.00	-1.63	-0.98
Pb	-0.22	-0.61	-0.83	-1.45	-0.58	-0.77	-0.15	-0.09	-0.48	-0.38
V	-1.96	-1.31	-1.92	-1.98	-1.72	-2.01	-2.22	-1.89	-1.41	-1.54
Zn	-1.50	-1.04	-1.63	-1.66	-1.42	-1.73	-1.76	-1.50	-1.07	-1.27

HMTE: Heavy metals and trace elements

b) Single pollution index and sum of contamination

The single pollution index (*PI*) and the sum of contamination (PI_{sum}) computed for the different agricultural zones (Equation 5 and 6) are presented in Table 4.22. Considering all the elements, *PI* values range from 0.12 (Hg at S4) to 13.16 (Mn at S8) and the elements Cr, Cu, Ni, Hg, and V have the lowest values of *PI*, which are all less than 1 ($PI < 1$), indicating absence of soil pollution by these elements in all the sites. The *PI* values for Fe in the soils indicate absent pollution (75%) to low pollution (25%). The *PI* values for As reveal that the soils have low pollution (66.7%: S2, S3, S4, S5, S6 and

S10) to moderate pollution (33.3%: S1, S7, S8 and S9) in As. The PI values for Cd range from 1.45 to 2.75 and the sites S1, S7, S9 and S10 are classified as moderately polluted, while S2, S3, S4, S6 and S8 have low pollution. The values of PI for Co indicate absence of pollution for all the sites except for S8, which exhibits low pollution in Co. The PI values for Pb indicate that the soils have absent pollution (S2, S3, S4 and S6) to low pollution (S1, S5, S7, S8, S9, and S10). The PI values for Zn indicate low pollution (S2, S3, S4, S6, and S8) to moderate pollution (S1, S5, S7, S9 and S10).

The overall soil pollution using sum of contamination (PI_{sum}) for the sites varies between 11.36 and 24.96 (Table 4.22). The most polluted site is S8 and the least polluted is S4. The total pollution (PI_{sum}) in soil considering the sites appear in the decreasing order $S8 > S7 > S1 > S10 > S9 > S5 > S2 > S3 > S6 > S4$.

Table 4.22: Single Pollution Index (PI) and Sum of contamination (PI_{sum})

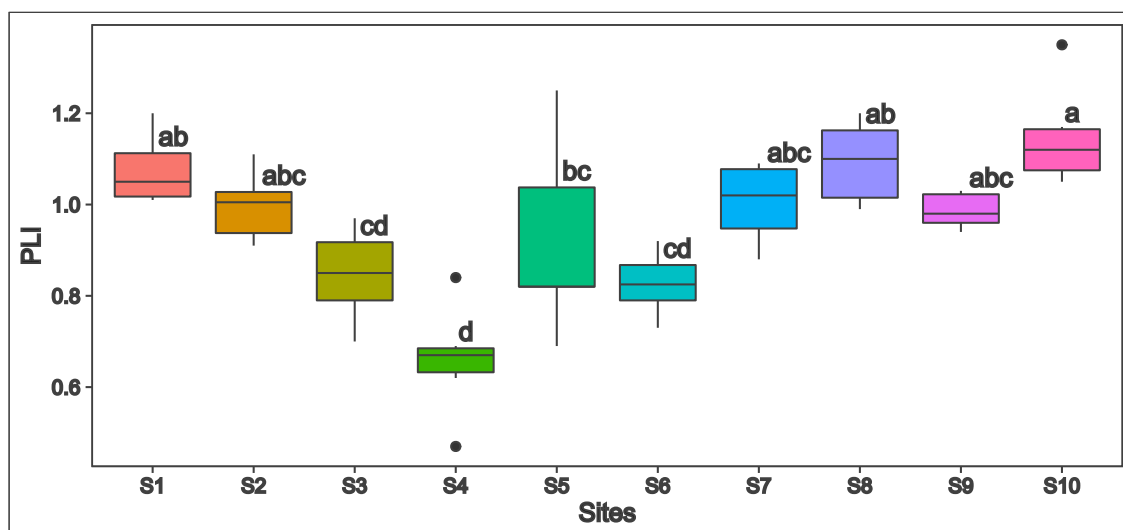
HMTE	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
As	2.19	1.57	1.59	1.11	1.61	1.58	2.05	2.22	2.09	1.95
Cd	2.75	1.95	1.88	1.19	2.14	1.86	3.21	1.45	2.18	2.44
Co	0.60	0.88	0.65	0.67	0.94	0.68	0.63	1.39	0.54	0.74
Cr	0.36	0.60	0.37	0.33	0.43	0.35	0.34	0.34	0.33	0.44
Cu	0.66	0.97	0.74	0.68	0.98	0.64	0.77	0.64	0.61	0.86
Fe	1.00	0.93	0.81	0.65	0.83	0.84	0.90	0.95	1.08	1.09
Hg	0.60	0.20	0.21	0.12	0.12	0.19	0.33	0.30	0.50	0.86
Mn	5.34	3.83	4.13	2.96	4.64	4.07	7.57	13.16	4.86	4.60
Ni	0.66	0.85	0.64	0.57	0.66	0.61	0.45	0.75	0.49	0.79
Pb	1.32	0.98	0.85	0.57	1.26	0.90	1.38	1.41	1.17	1.31
V	0.38	0.61	0.40	0.39	0.46	0.38	0.32	0.41	0.57	0.54
Zn	2.85	1.97	1.88	1.39	2.16	1.99	2.54	1.94	2.39	2.74
PI_{sum}	18.71	15.33	14.15	10.63	16.24	14.09	20.49	24.96	16.80	18.35

HMTE: Heavy Metals and Trace Elements

c) Pollution Load Index

The Pollution Load Index (PLI) computed based on the twelve heavy metals and trace elements (Equation 9) indicates a significant variation of the levels of heavy metals and trace elements pollution across the sites ($p < 0.001$), with values ranging from 0.67 to 1.35 (Fig. 4.13). The values of PLI are in the decreasing order $S10 > S8 > S1 > S7 > S2$

$> S9 > S5 > S3 > S6 > S4$. The average *PLI* of the sites S1, S7, S8 and S10 are above the pollution threshold of 1 ($PLI > 1$) and are classified as polluted. Besides, for the sites S2, S5 and S9, 50%, 33.3% and 50% of the samples are classified as contaminated, respectively.



Box plots that are not sharing the same letter(s) are significantly different at $\alpha = 0.001$

Figure 4.13: Box plot showing the Pollution Load Index (*PLI*) of agricultural soils

d) Nemerow Pollution Index

The Nemerow pollution index ($PI_{Nemerow}$) range between 2.80 and 10.43, indicating that the sites are moderately polluted to highly polluted (Fig. 4 14). S4 having the lowest value of $PI_{Nemerow}$ is classified as moderately polluted, while all the other sites are heavily polluted ($PI_{Nemerow} \geq 3$). The sites are ranged in the decreasing level of pollution as $S8 > S7 > S10 > S1 > S5 > S3 > S9 > S2 > S6 > S4$.

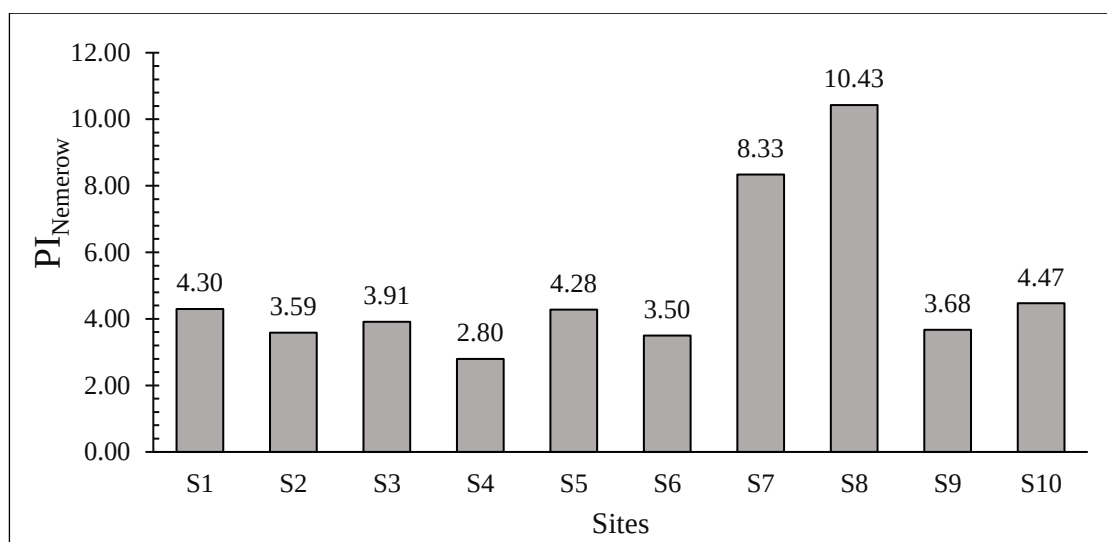


Figure 4.14: Nemerow Pollution Index of agricultural soils

4.3.2.4 Heavy Metals and Trace Element Sources Apportionment in Agricultural Soils

a) Enrichment Factor of Heavy metals and trace elements in soil

The Enrichment Factor (Equation 7) of the heavy metals and trace elements in peri-urban agricultural soils is displayed in Table 4.23. The *EF* values for Ni (0.4-1.1), Cr (0.3-0.8), and V (0.3-0.8) are lower than 1.5, indicating that they are of lithogenic or natural sources. The *EF* values exceed 1.5 in all the sites for the elements As (1.7-2.2), Cd (1.5-3.6), Mn (4.2-14), and Zn (2.1-3.9), which indicate that these metal elements originate from anthropogenic sources. The *EF* values for Co (0.4-1.6), Cu (0.4-1.9), Hg (0.1-2.0), and Pb (0.6-3.4) range from less than 1.5 at some sites: Co (S1-S7 and S9); Cu (S1-S4 and S6-S10), Hg (S1-S9) and Pb (S2-S6), to exceeding 1.5 at other sites Co (S8 and S10), Cu (S5), Hg (S10), and Pb (S1 and S7-S10). This indicate that these metals elements have both anthropogenic and natural or lithogenic sources, depending on the sites. For example, the *EF* values for Co at the sites S8 and S10, Cu at S5 and Hg at S10 indicate enrichment from anthropogenic activities. The *EF* values for Pb are higher at S1 (0.9-1.9), S5 (0.9-3.4), S7 (1.2-2.1), S8 (1.5-1.6), S9 (0.6-2.1), and S10

(0.7-2.9) indicating that Pb concentrations in the soil at these sites are of anthropogenic origin.

Table 4.23: Enrichment Factor of heavy metals and trace elements in soil

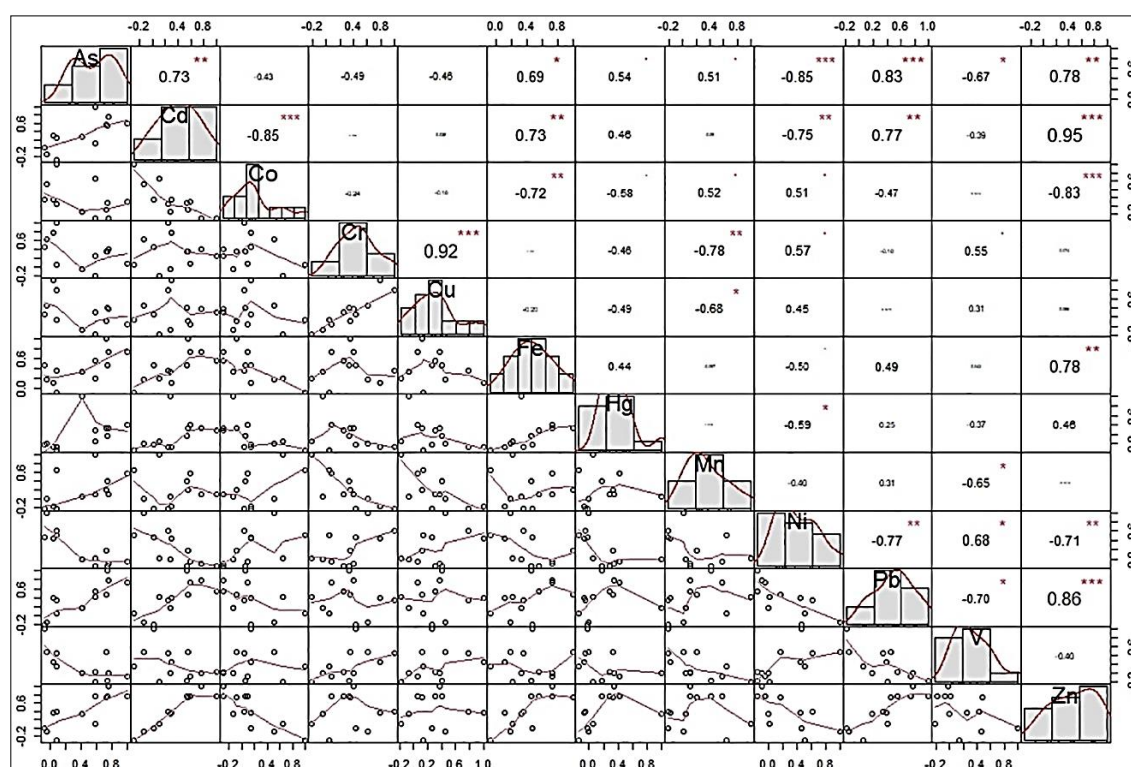
HMTE		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
As	Mean	2.2	1.7	2.0	1.7	1.9	1.9	2.3	2.4	2.0	1.9
	Range	1.8-2.5	1.4-2.0	1.7-2.2	1.6-2	1.7-2.2	1.8-2	2.0-3.0	2.2-2.4	1.8-2.2	1.4-2.5
Cd	Mean	2.8	2.1	2.3	1.8	2.5	2.2	3.6	1.5	2.0	2.3
	Range	1.9-3.5	1.6-2.3	1.8-2.6	1.6-2.0	2.0-3.0	2-2.7	2.7-4.4	1.5-1.7	1.7-2.2	1.9-3.1
Co	Mean	0.6	1.0	0.8	1.1	1.2	0.8	0.7	1.5	0.5	0.7
	Range	0.4-0.8	0.7-1.2	0.5-1.1	0.8-1.5	0.7-1.4	0.5-1.4	0.5-1.1	1.3-1.6	0.4-0.6	0.5-1.6
Cr	Mean	0.4	0.6	0.5	0.5	0.5	0.4	0.4	0.4	0.3	0.4
	Range	0.3-0.4	0.4-0.8	0.3-0.6	0.4-0.6	0.4-0.7	0.3-0.5	0.3-0.5	0.3-0.4	0.3-0.4	0.4-0.5
Cu	Mean	0.7	1.0	1.0	1.0	1.2	0.8	1.0	0.7	0.6	0.8
	Range	0.4-1.0	0.8-1.3	0.5-1.4	1.0-1.2	0.9-1.9	0.5-1.0	0.5-1.5	0.5-0.9	0.4-0.7	0.6-1.1
Hg	Mean	0.6	0.2	0.3	0.2	0.2	0.2	0.4	0.3	0.5	0.9
	Range	0.5-0.8	0.2-0.3	0.2-0.3	0.1-0.4	0.1-0.2	0.2-0.3	0.2-0.6	0.3-0.4	0.3-0.6	0.2-2.0
Mn	Mean	5.4	4.2	5.2	4.7	5.6	4.9	8.5	14.0	4.5	4.5
	Range	3.9-6.5	2.4-6.0	4.3-7.4	3.4-6.1	4.9-6.4	3.9-5.7	5.9-12.8	10.4-16.6	4.3-4.8	3.2-7.5
Ni	Mean	0.7	0.9	0.8	0.9	0.8	0.7	0.5	0.8	0.5	0.7
	Range	0.6-0.7	0.8-1.1	0.6-1.1	0.7-1.0	0.5-0.9	0.5-0.9	0.4-0.8	0.7-0.9	0.4-0.5	0.5-1.0
Pb	Mean	1.4	1.1	1.1	0.9	1.4	1.1	1.6	1.5	1.1	1.2
	Range	0.9-1.9	0.9-1.4	1.0-1.2	0.8-0.9	0.9-3.4	0.9-1.4	1.2-2.1	1.5-1.6	0.6-2.1	0.7-2.9
V	Mean	0.4	0.7	0.5	0.6	0.6	0.5	0.4	0.4	0.5	0.5
	Range	0.3-0.4	0.6-0.8	0.4-0.6	0.6-0.7	0.3-0.7	0.3-0.6	0.3-0.4	0.4-0.5	0.5-0.6	0.3-0.7
Zn	Mean	2.9	2.1	2.3	2.1	2.5	2.4	2.9	2.0	2.2	2.5
	Range	2.5-3.5	1.9-2.3	2.1-2.4	2.0-2.3	2.0-4.5	2.0-2.6	2.4-3.9	2.0-2.1	2.0-2.4	2.1-3.4

HMTE: Heavy Metals and Trace Elements

b) Correlation between heavy metals and trace elements in soil

The correlation matrix between heavy metals and trace elements in soil (Fig. 4.15) shows significant relationships between the different elements, informing about their potential sources. At 0.001 statistical significance level, strong and positive correlation is observed between As and Pb ($r = 0.83$), Cd and Zn ($r = 0.95$), Cr and Cu ($r = 0.92$), and Pb and Zn ($r = 0.86$). In contrast, there is strong negative correlation between As and Ni ($r = -0.85$), Cd and Co ($r = -0.85$), and Co and Zn ($r = -0.83$). At the 0.01 statistical significance level, strong and positive correlation is observed between As and Cd ($r = 0.73$), As and Zn ($r = 0.78$), Cd and Fe ($r = 0.73$), Cd and Pb ($r = 0.77$), and Fe and Zn

($r = 0.78$); whereas strong negative correlation is observed between Cd and Ni ($r = -0.75$), Co and Fe ($r = -0.72$), Cr and Mn ($r = -0.78$), Ni and Pb ($r = -0.77$), and Ni and Zn ($r = -0.71$). At 0.05 statistical significance level, strong and positive correlation is observed between As and Fe ($r = 0.69$), and Ni and V ($r = 0.68$) and strong negative correlation is observed between As and V ($r = -0.67$), Cu and Mn ($r = -0.68$), Hg and Ni ($r = -0.59$), Mn and V ($r = -0.65$), and Pb and V ($r = -0.70$). The strongest correlations ($r \geq 0.85$) are recorded between Cd and Co, Cd and Zn, Cr and Cu, and Pb and Zn.



* non-significant correlation with a p -value close to 0.05; * significant at $\alpha = 0.05$; ** significant at $\alpha = 0.01$; *** significant at $\alpha = 0.001$; small front size correlation coefficients (r) stand for non-significant correlations

Figure 4.15: Pearson correlation matrix of heavy metals and trace elements in agricultural soils

c) Multivariate analysis on heavy metals and trace elements

Principal component analysis (PCA) performed on heavy metals and trace elements concentrations in soil reveals that the first three principal components explain 75% of

the total variance and adequately describes the interrelations between the elements (Fig. 4.16 A). The first principal component (PC1) represents 36% of the total variance and exhibit high loading factor for As, Cd, Fe, Hg, Pb and Zn. The second principal component accounts for 22% of the total variance with high loading scores for Cr, Cu, Ni, and V, while the third principal component accounts for 17% and loads the highest score for Co and Mn (see Appendix 9).

The results of hierarchical cluster analysis on principal components (HCPC) performed on PCA results assemble the twelve heavy metals and trace elements into three distinct groups (Fig. 4.16 B). The conjoint interpretation of the results of EF, PCA and HCPC indicates that the elements Cr, Cu, Ni, and V contents originate from natural sources. In contrast, Pb, Hg, As, Zn, Fe, Cd, Mn, and Co have significant inputs from anthropogenic sources.

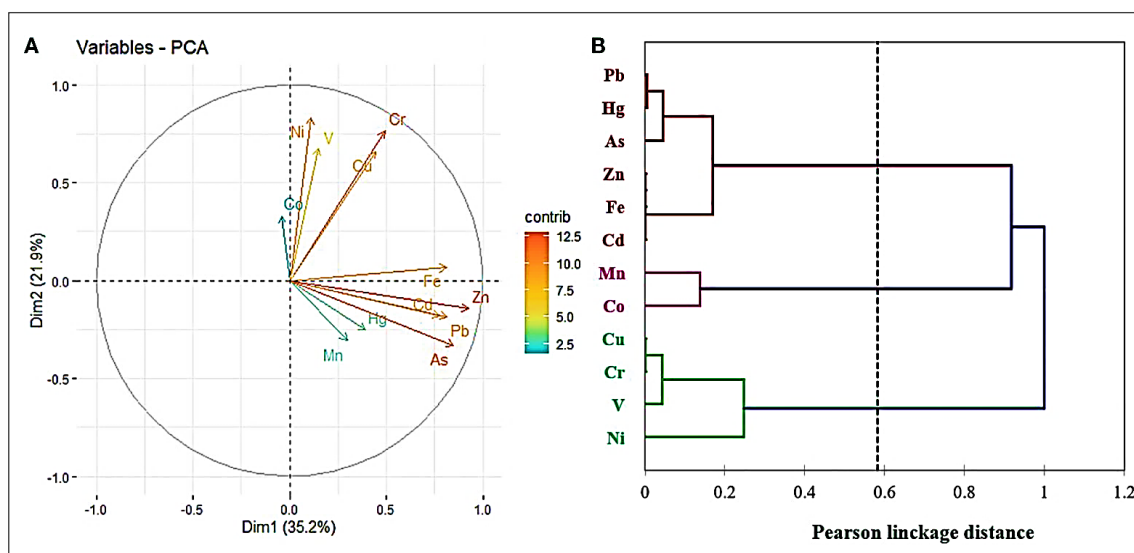


Figure 4.16: Heavy metals and trace elements association - (A) PCA and (B) clustergram

4.3.3 Heavy Metals and Trace Elements Concentrations in Kale Leaves

4.3.3.1 Heavy Metals and Trace Elements in Kale Leaves in Dry Season

The concentrations of heavy metals and trace elements in kale leaves for dry season is presented in Table 4.24. Arsenic (As) concentrations in the leaves range from 0.05 to 0.20 mg/kg. The highest concentrations of As in kale leaves are recorded at the sites S1, S2, S5, S7 and S10 and the lowest are recorded at the sites S4 (0.05-0.07 mg/kg) and S9 (0.06-0.07 mg/kg). Above the maximum allowable concentrations (MAC) of As of 0.10 mg/kg in vegetable (FAO/WHO, 2019) are recorded in 36.7% of the samples originating from the sites S1 (3.3%), S2 (10%), S5 (10%), S7 (10%) and S10 (3.3%). The concentrations of As in kale vary significantly across the sites ($p < 0.001$) and the sites considering As concentration in kale are in the decreasing order $S10 > S2 > S5 > S1 > S7 > S8 > S3 > S6 > S9 > S4$.

Cadmium (Cd) concentrations in kale range between 0.07 and 0.24 mg/kg. The highest Cd concentrations in kale are recorded at the sites S2 (0.16-0.21 mg/kg), S3 (0.12-0.17 mg/kg), S9 (0.23-0.24 mg/kg) and S10 (0.16-0.20 mg/kg), while the lowest are observed at S8 (0.07-0.09 mg/kg). All the samples (100%) exhibit Cd concentrations above the MAC of 0.05 mg/kg for vegetable (FAO/WHO, 2019). In addition, Cd concentrations in kale leave vary significantly across the sites ($p < 0.001$) and the sites are arranged in the decreasing order of Cd concentrations as $S9 > S10 > S2 > S3 > S7 > S5 > S1 > S6 > S4 > S8$.

Table 4.24: Concentrations of heavy metals and trace elements in kale leaves in dry season

Sites		AS (mg/kg)	Cd (mg/kg)	Cr (mg/kg)	Cu (mg/kg)	Hg (µg/kg)	Ni (mg/kg)	Pb (mg/kg)	Zn (mg/kg)
S1	Mean ± SD	0.10±0.02bcd	0.13±0.02bcd	0.37±0.04bcd	6.73±1.58c	19.67±0.39b	0.50±0.06a	0.60±0.14c	32.58±1.40bcd
	Range	0.07-0.12	0.12-0.15	0.33-0.41	5.15-8.31	19.28-20.05	0.45-0.56	0.46-0.74	31.18-33.98
S2	Mean ± SD	0.13±0.03ab	0.18±0.03bc	0.74±0.25a	6.94±1.79c	11.55±0.16de	0.60±0.09a	3.60±0.71a	42.40±0.94abc
	Range	0.10-0.16	0.16-0.21	0.48-0.99	5.88-9.01	11.39-11.7	0.51-0.69	3.12-4.41	41.46-43.33
S3	Mean ± SD	0.08±0.00cd	0.15±0.02bc	0.45±0.06bcd	6.94±1.02c	16.92±2.0bc	0.49±0.02a	0.43±0.13c	29.00±1.07d
	range	0.07-0.08	0.12-0.17	0.38-0.51	6.12-8.08	14.93-18.92	0.47-0.51	0.30-0.56	27.93-30.07
S4	Mean ± SD	0.06±0.01d	0.13±0.00bcd	0.21±0.01d	2.17±0.06d	16.57±0.40bc	0.67±0.05a	0.10±0.00c	25.22±0.15d
	Range	0.05-0.07	0.13-0.13	0.20-0.23	2.11-2.22	16.18-16.97	0.63-0.72	0.09-0.10	25.07-25.37
S5	Mean ± SD	0.12±0.01bc	0.13±0.02bcd	0.18±0.02d	2.11±0.12d	10.56±0.461e	0.38±0.01a	0.07±0.00c	27.93±3.02d
	Range	0.11-0.13	0.12-0.15	0.15-0.20	2.0-2.23	10.11-11.03	0.37-0.39	0.06-0.07	24.91-30.95
S6	Mean ± SD	0.07±0.02cd	0.13±0.01bcd	0.27±0.03cd	3.27±0.32d	8.32±0.55e	0.94±0.12a	0.35±0.44c	34.81±2.61bcd
	Range	0.05-0.09	0.12-0.14	0.25-0.30	2.94-3.59	7.79-8.88	0.84-1.07	0.10-0.86	32.20-37.42
S7	Mean ± SD	0.09±0.01bcd	0.13±0.03cd	0.54±0.11abc	3.23±0.81d	14.78±0.34cd	1.05±0.82a	0.51±0.03c	47.70±10.15a
	Range	0.07-0.10	0.10-0.16	0.44-0.65	2.42-4.04	14.45-15.17	0.23-1.87	0.48-0.54	37.55-57.86
S8	Mean ± SD	0.08±0.01cd	0.08±0.01d	0.40±0.03bcd	10.18±1.11b	9.58±0.37e	0.34±0.04a	0.51±0.36c	31.48±3.44cd
	Range	0.07-0.08	0.07-0.09	0.37-0.43	9.07-11.29	9.21-9.95	0.30-0.38	0.15-0.87	28.04-34.91
S9	Mean ± SD	0.06±0.00d	0.24±0.00a	0.19±0.05d	2.31±0.21a	9.26±0.24e	0.39±0.06a	0.09±0.01c	45.00±5.28ab
	Range	0.06-0.07	0.23-0.24	0.14-0.23	2.11-2.52	9.03-9.51	0.479-0.64	0.08-0.11	39.71-50.28
S10	Mean ± SD	0.18±0.02a	0.18±0.02b	0.57±0.11ab	23.28±0.74a	47.57±2.89a	0.56±0.08a	1.74±0.30b	44.60±5.66ab
	Range	0.15-0.20	0.16-0.20	0.50-0.69	22.60-24.08	44.69-50.47	0.33-0.45	1.54-2.09	38.95-50.26
F (p-value)		14.65 (< .001)	15.95 (< .001)	10.55 (< .001)	132.52 (< .001)	297.64 (< .001)	2.35 (0.054)	37.92 (< .001)	10.21 (< .001)
MAC		0.1*	0.05*	2.3*	5**	10 (µg/kg)**	10*	0.1*	5**

SD = standard deviation; MAC = Maximum allowable concentration; * FAO/WHO (2019); ** KEBS (2016); Means that are not sharing the same letter(s) are significantly different at $\alpha = 0.05$.

Chromium (Cr) concentrations in kale leaves vary between 0.14 and 0.99 mg/kg, with the highest concentrations recorded at the sites S2 (0.48-0.99 mg/kg), S7 (0.44-0.65 mg/kg), S10 (0.50-0.69 mg/kg). The concentrations of Cr in all the sites are below the MAC of 2.3 mg/kg Cr in vegetables (FAO/WHO, 2019). The concentrations of Cr show significant differences across the sites ($p < 0.001$) and the sites are in the decreasing order $S2 > S10 > S7 > S3 > S8 > S1 > S6 > S4 > S9 > S5$.

Copper (Cu) concentrations in kale range from 2 to 24.08 mg/kg with the highest concentrations recorded at S10 (22.60-24.08 mg/kg) and the lowest at S4 (2.11-2.22 mg/kg) and S5 (2.0-2.23 mg/kg). Copper concentrations above the MAC of Cu in vegetable of 5 mg/kg (KEBS, 2016) are recorded in 50% of the samples originating from the sites S1, S2, S3, S8 and S10. The sites show a significant variation in Cu concentrations in kale leaves ($p < 0.001$) with the decreasing order $S10 > S8 > S2 > S3 > S1 > S6 > S7 > S4 > S5 > S9$.

Mercury (Hg) concentrations in kale leaves vary between 7.79 and 50.47 mg/kg. The highest concentrations are recorded at S1 (19.28-20.05 mg/kg) and S10 (44.69-50.47 mg/kg), while the lowest are recorded at S6 (7.79-8.88 mg/kg). The concentrations of Hg in kale leaves exceed the MAC of 10 μ g/kg for vegetable (KEBS, 2016) in 70% of the samples, originating from the sites S1 (10%), S2 (10%), S3 (10%), S4 (10%), S5 (10%), S6 (10%) and S7 (10%). Significant differences are observed in Hg concentrations in kale leaves across the sites ($p < 0.001$), and the sites are in the decreasing order $S10 > S1 > S3 > S4 > S7 > S2 > S5 > S8 > S9 > S6$.

Nickel (Ni) concentrations in kale leaves range between 0.23 and 1.87 mg/kg, with the highest concentrations recorded at S7 (0.23-1.87 mg/kg). The concentrations of Ni in kales leaves from all the sites are below the MAC of 10 mg/kg for vegetable (FAO/WHO, 2019) and there is no significant differences in Ni concentration in kale

leaves across the sites ($p = 0.054$). Lead (Pb) concentrations in kale leaves range from 0.07-4.41 mg/kg. The highest Pb concentrations in kale leaves are observed at the sites S2 (3.12-4.41 mg/kg) and S10 (1.54-2.09 mg/kg). About 83.3% of the samples (all the sites except S5) exhibit above MAC of Pb in vegetable of 0.1 mg/kg (FAO/WHO, 2019). The concentrations of Pb in kale show a significant variation ($p < 0.001$), across the sites and the sites are ranked in the decreasing order $S2 > S10 > S1 > S8 > S7 > S3 > S6 > S4 > S9 > S5$.

Zinc (Zn) concentrations in kales leaves are 24.91-57.86 mg/kg, with the highest concentrations recorded at the sites S2 (41.46-43.33 mg/kg), S7 (37.55-57.86 mg/kg), S9 (39.71-50.28 mg/kg), and S10 (38.95-50.26 mg/kg). The concentrations of Zn recorded in kale leaves from all the sites (100% of the samples) are above the MAC of Zn in vegetable of 5 mg/kg (KEBS, 2016). Besides, Zn concentrations in kale leaves exhibit a significant difference across the sites ($p < 0.001$) and appear in the decreasing order $S7 > S9 > S10 > S2 > S6 > S1 > S8 > S3 > S4 > S5$.

4.3.3.2 Heavy Metals and Trace Elements in Kale Leaves in Wet Season

The concentrations of heavy metals and trace elements in kale leaves for wet season are presented in Table 4.25. The concentrations of As in the leaves range from 0.03 to 0.13 mg/kg. The highest concentrations of As in kale leaves are recorded at the sites S2 (0.09-0.11 mg/kg) and S10 (0.12-0.13 mg/kg). Above the maximum allowable concentrations (MAC) of As of 0.10 mg/kg for vegetable (FAO/WHO, 2019) are recorded in 20% of the samples which originated from the sites S2 (10%) and S10 (10%). The concentrations of As in kale vary significantly across the sites ($p < 0.001$) and the sites considering As concentrations in kale leaves are in the decreasing order $S10 > S2 > S4 > S7 > S1 > S9 > S3 > S8 > S5 > S6$.

Cadmium (Cd) concentrations in kale are between 0.05 and 0.21 mg/kg. The highest Cd concentrations in kale are recorded at the sites S1 (0.18-0.20 mg/kg), S9 (0.05-0.21 mg/kg), and S10 (0.20-0.2). All the samples (100%) have above the MAC of 0.05 mg/kg Cd for vegetable (FAO/WHO, 2019). In addition, Cd concentrations in kale leaves vary significantly across the sites ($p < 0.001$) and the sites are in the decreasing order of Cd concentration $S10 > S1 > S6 > S4 > S9 > S2 > S5 > S7 > S8 > S3$.

Chromium (Cr) concentrations in kale leaves range between 0.04 and 0.69 mg/kg, with the highest concentrations recorded at the S10 (0.64-0.69 mg/kg). The concentrations of Cr in all the sites are below the MAC of 2.3 mg/kg Cr in vegetables (FAO/WHO, 2019). The concentrations of Cr exhibit significant differences across the sites ($p < 0.001$) and the sites are in the decreasing order $S10 > S7 > S2 > S1 > S8 > S9 > S3 > S6 > S5 > S4$. Copper (Cu) concentrations in kale vary between 1.90 and 13.22 mg/kg with the highest concentrations recorded at S10 (2.61-13.22mg/kg). Copper concentrations above the MAC in vegetable of 5 mg/kg (KEBS, 2016) are recorded in 6.7% of the samples originating from the sites S10. The sites show a significant variation in Cu concentrations in kale leaves ($p = 0.017$) and with the decreasing order of Cu concentrations in soil $S10 > S4 > S2 > S5 > S7 > S1 > S9 > S6 > S3 > S8$.

Table 4.25: Concentrations of heavy metals and trace elements in kale leaves in wet season

Sites		AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Mean $\pm$ SD	0.07 $\pm$ 0.00bcd	0.19 $\pm$ 0.01ab	0.26 $\pm$ 0.03b	2.71 $\pm$ 0.39b	7.12 $\pm$ 0.28d	0.34 $\pm$ 0.03de	0.12 $\pm$ 0.01bc	29.82 $\pm$ 2.61bc
	Range	0.06-0.08	0.18-0.20	0.24-0.30	2.31-3.10	6.85-7.4	0.30-0.37	0.11-0.13	27.21-32.43
S2	Mean $\pm$ SD	0.11 $\pm$ 0.01a	0.12 $\pm$ 0.01abc	0.29 $\pm$ 0.04b	3.18 $\pm$ 0.07ab	6.56 $\pm$ 0.37d	0.814 $\pm$ 0.15b	0.21 $\pm$ 0.02a	38.06 $\pm$ 2.44ab
	Range	0.09-0.11	0.11-0.12	0.26-0.33	3.11-3.24	6.21-6.94	0.66-0.95	0.20-0.24	36.28-40.84
S3	Mean $\pm$ SD	0.05 $\pm$ 0.00cd	0.07 $\pm$ 0.01c	0.15 $\pm$ 0.00c	2.39 $\pm$ 0.11b	4.96 $\pm$ 0.21e	0.70 $\pm$ 0.07bc	0.12 $\pm$ 0.01bc	28.50 $\pm$ 0.06bc
	Range	0.05-0.06	0.07-0.08	0.15-0.16	2.29-2.50	4.76-5.18	0.66-0.77	0.11-0.12	28.43-28.56
S4	Mean $\pm$ SD	0.08 $\pm$ 0.00b	0.14 $\pm$ 0.02abc	0.04 $\pm$ 0.00d	4.40 $\pm$ 0.00ab	10.0 $\pm$ 0.14b	1.11 $\pm$ 0.00a	0.03 $\pm$ 0.00d	40.25 $\pm$ 0.15ab
	Range	0.08-0.09	0.12-0.16	0.04-0.04	4.40-4.41	9.87-10.14	1.11-1.12	0.03-0.04	40.09-40.40
S5	Mean $\pm$ SD	0.03 $\pm$ 0.00e	0.11 $\pm$ 0.02bc	0.07 $\pm$ 0.01d	3.17 $\pm$ 0.66ab	7.12 $\pm$ 0.18d	0.77 $\pm$ 0.17b	0.03 $\pm$ 0.00d	32.42 $\pm$ 3.04b
	Range	0.03-0.03	0.09-0.13	0.06-0.07	2.52-3.83	6.95-7.31	0.60-0.95	0.03-0.04	30.01-35.84
S6	Mean $\pm$ SD	0.03 $\pm$ 0.00e	0.14 $\pm$ 0.05abc	0.06 $\pm$ 0.01d	2.48 $\pm$ 0.17b	9.54 $\pm$ 0.17b	0.49 $\pm$ 0.09cd	0.05 $\pm$ 0.00cd	29.57 $\pm$ 2.97bc
	Range	0.02-0.03	0.09-0.18	0.06-0.07	2.31-2.64	9.37-9.71	0.40-0.57	0.05-0.06	27.23-32.91
S7	Mean $\pm$ SD	0.07 $\pm$ 0.02bc	0.07 $\pm$ 0.01c	0.33 $\pm$ 0.03b	2.85 $\pm$ 0.40b	6.71 $\pm$ 0.16d	0.21 $\pm$ 0.02e	0.18 $\pm$ 0.01ab	47.55 $\pm$ 4.24a
	Range	0.05-0.09	0.06-0.07	0.30-0.37	2.45-3.26	6.55-6.87	0.19-0.23	0.16-0.19	43.49-51.94
S8	Mean $\pm$ SD	0.05 $\pm$ 0.00de	0.07 $\pm$ 0.01c	0.17 $\pm$ 0.01c	2.01 $\pm$ 0.11b	7.0 $\pm$ 0.21d	0.18 $\pm$ 0.01e	0.05 $\pm$ 0.01cd	16.85 $\pm$ 0.57c
	Range	0.04-0.05	0.07-0.08	0.16-0.18	1.90-2.13	6.79-7.21	0.17-0.19	0.05-0.06	16.29-17.42
S9	Mean $\pm$ SD	0.05 $\pm$ 0.01de	0.13 $\pm$ 0.08abc	0.15 $\pm$ 0.06c	2.48 $\pm$ 0.20b	10.71 $\pm$ 0.30a	0.25 $\pm$ 0.01e	0.12 $\pm$ 0.06bc	40.48 $\pm$ 7.15ab
	Range	0.04-0.06	0.05-0.21	0.09-0.21	2.29-2.68	10.43-11.02	0.23-0.26	0.06-0.18	33.33-47.63
S10	Mean $\pm$ SD	0.12 $\pm$ 0.00a	0.20 $\pm$ 0.00a	0.66 $\pm$ 0.02a	7.92 $\pm$ 5.30a	7.87 $\pm$ 0.12c	0.20 $\pm$ 0.01e	0.13 $\pm$ 0.06b	37.96 $\pm$ 10.22ab
	Range	0.12-0.13	0.20-0.21	0.64-0.69	2.61-13.22	7.76-7.99	0.19-0.21	0.08-0.19	27.74-48.18
F (p-value)		54.16 (< .001)	6.55 (< .001)	124.11 (< .001)	3.1 (0.017)	189.5 (< .001)	49.32 (< .001)	15.38 (< .001)	10.75 (< .001)
MCA		0.1*	0.05*	2.3*	5**	10 (μ g/kg)**	10*	0.1*	5**

SD = standard deviation; MAC = Maximum allowable concentration, * FAO/WHO (2019); ** KEBS (2016); Means that are not sharing the same letter(s) are significantly different at $\alpha = 0.05$.

Mercury (Hg) concentrations in kale leaves are between 4.76 and 11.03 mg/kg. The highest concentrations of Hg are recorded at S4 (9.87-10.14 mg/kg) and S9 (10.43-11.02 mg/kg). The concentrations of Hg in kale leaves exceed the MAC of 10 µg/kg for vegetable (KEBS, 2016) in 16.7% of the samples, which originated from the sites S4 (6.7%) and S9 (10%). In addition, there is a significant difference in Hg concentrations in kale leaves across the sites ($p < 0.001$), and the sites are ranked in the decreasing order $S9 > S4 > S6 > S10 > S1 > S5 > S8 > S7 > S2 > S3$.

Nickel (Ni) concentrations in kale leaves range from 0.17 to 1.12 mg/kg, with the highest concentrations recorded at S4 (1.11-1.12 mg/kg). The concentrations of Ni in kales leaves from all the sites are within the MAC of 10 mg/kg for vegetable (FAO/WHO, 2019). The sites appear in the decreasing order of Ni concentrations in vegetable as $S4 > S2 > S5 > S3 > S6 > S1 > S9 > S7 > S10 > S8$.

Lead (Pb) concentrations in kale leaves range from 0.03 to 0.24 mg/kg. The highest Pb concentrations in kale leave are observed at the sites S2 (0.20-0.24 mg/kg), S7 (0.16-0.19 mg/kg), S9 (0.06-0.18 mg/kg) and S10 (0.08-0.19 mg/kg). About 53.3% of the samples originating from the sites S1 (10%), S2 (10%), S3 (10%), S7 (10%), S9 (6.7%) and S10 (6.7%) exhibit above MAC of Pb of 0.1 mg/kg for vegetable (FAO/WHO, 2019). The concentrations of Pb in kale exhibit significant difference ($p < 0.001$), across the sites and the sites are ranked in the decreasing order $S2 > S7 > S10 > S9 > S1 > S3 > S8 > S6 > S5 > S4$.

Zinc (Zn) concentrations in kales leaves vary between 16.29 and 51.94 mg/kg, with the highest concentrations recorded at the sites S2 (36.28-40.84 mg/kg), S4 (40.09-40.40 mg/kg), S7 (43.49-51.94 mg/kg), S9 (33.33-47.63 mg/kg), and S10 (27.74-48.18 mg/kg). The concentration of Zn recorded in kale leaves from all the sites are above the MAC of 5 mg/kg Zn for vegetable (KEBS, 2016). Besides, Zn concentrations in kale

leaves show a significant difference across the sites, ranking in the decreasing order S7 > S9 > S4 > S2 > S10 > S5 > S1 > S6 > S3 > S8.

4.3.3.3 Seasonal Variation of Heavy Metals and Trace Elements in Kale Leaves

The results of the two-sample t-test performed on heavy metal and trace element concentrations in kale, comparing for each site dry and wet season (Table 4.26) show that there is a significant difference in the concentration between dry and wet seasons ($p < 0.05$). Heavy metals and trace elements concentrations in kale are significantly higher in dry season compared to wet season for most of the elements across the sites.

However, some of the elements, including Cd at S1, Ni at S3, S4, and S5, and Cu and Zn at S4, show a higher concentration in wet season compared to dry season.

Table 4.26: Seasonal variation in vegetable concentration in vegetable

Elements		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
As	DS-WS	0.028	0.024	0.024	-0.022	0.087	0.041	0.017	0.027	0.012	0.044
	p-value	0.164	0.318	0.003	0.062	0.004	0.062	0.271	0.011	0.190	0.034
Cd	DS-WS	-0.058	0.0587	0.071	-0.006	0.022	-0.007	0.061	0.010	0.111	-0.023
	p-value	0.015	0.077	0.031	0.653	0.200	0.842	0.077	0.303	0.143	0.153
Cr	DS-WS	0.115	0.442	0.294	0.175	0.112	0.202	0.213	0.233	0.034	-0.094
	p-value	0.032	0.096	0.015	0.002	0.016	0.008	0.083	0.006	0.501	0.281
Cu	DS-WS	4.024	3.77	4.55	-2.238	-1.060	0.792	0.373	8.166	-0.173	15.560
	p-value	0.050	0.068	0.017	< .001	0.110	0.064	0.549	0.006	0.368	0.037
Hg	DS-WS	12.545	4.989	11.96	6.567	3.434	-1.216	8.071	2.579	-1.453	41.620
	p-value	< .001	0.002	0.009	0.001	0.007	0.066	0.001	0.002	0.007	0.001
Ni	DS-WS	0.167	-0.214	-0.208	-0.441	-0.398	0.449	0.839	0.161	0.149	0.387
	p-value	0.020	0.120	0.035	0.004	0.057	0.013	0.219	0.022	0.051	0.005
Pb	DS-WS	0.476	3.383	0.313	0.067	0.036	0.298	0.333	0.458	-0.024	1.636
	p-value	0.028	0.014	0.050	0.001	0.005	0.359	0.003	0.156	0.557	0.010
Zn	DS-WS	2.76	4.330	0.502	-15.024	-4.490	5.240	0.150	14.62	4.520	8.530
	p-value	0.205	0.103	0.503	< .001	0.167	0.106	0.983	0.018	0.444	0.303

DS-WS: difference between dry season and wet season values, p-value in bold stand for significant difference between heavy metals and trace elements concentrations in dry Season compared to wet season.

4.3.3.4 Bioaccumulation Factor Soil-Plant

The Bioaccumulation factor soil-plant (BAFs) of heavy metals and trace elements in kale leaves during dry and wet seasons are displayed in Table 4.27 and 4.28. The BAFs of As range between 0.015 and 0.044 for dry season and between 0.009 and 0.040 in wet season. The BAFs of As vary significantly across the sites, with the highest recorded from the sites S2 (0.040), S5 (0.036) and S10 (0.044) for dry season and S2 (0.036), S4 (0.040) and S10 (0.033) in wet season. The BAFs of As is significantly ($p=0.001$) low for the sites S8 (0.017) and S9 (0.015) in dry season and the sites S5 (0.011), S6 (0.009), S8 (0.011) and S9 (0.012) in wet season. Regardless of the sites, the BAFs of As are higher in dry season compared to wet season.

The BAFs of Cd vary from 0.317 to 1.079 in dry season and 0.264 to 1.394 in wet season. The BAFs of Cd exhibit significant variation across the sites during the two seasons ($p < 0.001$ and $p = 0.018$). The highest BAFs of Cd in kale are recorded at the sites S2 (0.952), S3 (0.931), S4 (1.061) and S9 (1.079) in dry season and S4 (1.394) and S10 (0.879) in wet season. The lowest BAFs of Cd are observed at the sites S1 (0.534), S5 (0.578) and S8 (0.566) in dry season and S3 (0.346) and S7 (0.264) in wet season. The BAFs of Cd show mixed trend between dry and wet seasons across the sites (Table 4.27-4.28).

The BAFs of Cr are 0.012-0.047 and 0.004-0.043 for dry and wet seasons, respectively. The highest BAFs of Cr are recorded from the sites S2 (0.044), S7 (0.047) and S10 (0.039) in dry season and S7 (0.028) and S10 (0.043) in wet season. The lowest BAFs are recorded at S5 in dry season and S4 (0.004), S5 (0.006) and S6 (0.006) in wet season. Regardless of the sites, Cr has the lowest BAFs among all the metal elements and with higher values observed in dry season compared to wet season.

Table 4.27: Soil-plant bioaccumulation factor soil-plant of heavy metals and trace elements in kale leaves in dry season

Sites	As	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	0.023bcd	0.534cd	0.029a	0.932bc	0.596b	0.040a	0.032b	0.227a
S2	0.040ab	0.952ab	0.044a	0.552bc	1.056ab	0.036a	0.222a	0.411a
S3	0.029abcd	0.931ab	0.036a	0.646bc	1.457ab	0.042a	0.034b	0.354a
S4	0.027abcd	1.061a	0.018a	0.235c	2.697a	0.065a	0.010b	0.328a
S5	0.036abc	0.578cd	0.012a	0.155c	1.537ab	0.034a	0.004b	0.258a
S6	0.022bcd	0.781abc	0.019a	0.318c	0.770b	0.069a	0.025b	0.386a
S7	0.021bcd	0.317d	0.047a	0.330c	0.827ab	0.142a	0.019b	0.347a
S8	0.017cd	0.566cd	0.034a	1.206ab	0.568b	0.025a	0.022b	0.312a
S9	0.015d	1.079a	0.016a	0.246c	0.351b	0.042a	0.004b	0.356a
S10	0.044a	0.700bc	0.039a	1.807a	1.747ab	0.052a	0.090b	0.395a
F	5.67	13.06	2.52	10.38	3.43	2.04	14.11b	0.98
p-value	0.001	< .001	0.051	< .001	0.010	0.088	< .001	0.483

Table 4.28: Bioaccumulation factor soil-plant of heavy metals and trace elements in kale leaves in wet season

Sites	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	0.015b	0.607ab	0.020c	0.237a	0.216c	0.028bc	0.005bcd	0.200b
S2	0.036a	0.567ab	0.015cd	0.245a	0.598bc	0.056bc	0.013a	0.382b
S3	0.016b	0.346b	0.012	0.266a	0.424bc	0.061b	0.007abcd	0.259b
S4	0.040a	1.394a	0.004f	0.506a	1.625a	0.119a	0.004bcd	0.668a
S5	0.011b	0.637ab	0.006ef	0.277a	1.037ab	0.064b	0.003cd	0.414ab
S6	0.009b	0.643ab	0.006ef	0.319a	0.882bc	0.054bc	0.004bcd	0.255
S7	0.017b	0.264b	0.028b	0.238a	0.375bc	0.025bc	0.009ab	0.383ab
S8	0.011b	0.507ab	0.015cd	0.258a	0.415bc	0.013c	0.002d	0.170b
S9	0.012b	0.558ab	0.014cd	0.331a	0.409bc	0.028bc	0.009ab	0.335b
S10	0.033a	0.879ab	0.043a	0.696a	0.276c	0.011c	0.008abc	0.256b
F	16.44	3.05	68.19	2.24	9.02	11.57	9.08	6.33
p-value	< .001	0.018	< .001	0.063	< .001	< .001	< .001	< .001

The BAF_s of Cu vary between 0.155 and 1.807 in dry season and between 0.237 and 0.696 in wet season. The highest BAF_s are recorded at the sites S1 (0.932), S8 (1.206) and S10 (1.807) for dry season and S4 (0.506) and S10 (0.696) in wet season. Regardless of the sites, the BAF_s of Cu were higher in dry season compared to wet season.

The BAF_s of Hg range between 0.351 and 2.697 in dry season and between 0.216 and 1.625 in wet season. The highest BAF_s of Hg are recorded at the sites S2 (1.056), S3 (1.457), S4 (2.697), S5 (1.537) and S10 (1.747) in dry season and S4 (1.625) and S5 (1.037) in wet season. The BAF_s of Hg are higher in dry season compared to rainy season. The BAF_s of Ni in kale vary between 0.025 and 0.142 for dry season and 0.011 and 0.119 for wet season. The highest BAF_s of Ni are recorded at the site S7 (0.142) in dry season and S4 (0.119) in wet season. The BAF_s of Ni are higher in dry season compared to wet season.

The BAF_s of Pb are 0.004-0.222 in dry season and 0.002-0.013 in wet season. The BAF_s vary significantly across the sites ($p < 0.001$) and the highest values are recorded at the site S2 (0.222) in dry season and S2 (0.013), S9 (0.009) and S10 (0.008) in wet season. The BAF_s of Pb are higher in dry season compared to wet season. The BAF_s of Zn range between 0.227-0.411 in dry season and 0.170-0.668 in wet season. There is no significant difference in the BAF_s of Zn in dry season ($p = 0.483$), while significant differences are noted in wet season ($p < 0.001$). The highest BAF_s of Zn are recorded at the sites S2 (0.395) and S10 (0.411) in dry season and at S4 (0.668), S5 (0.414) and S7 (0.383). The BAF_s of Cd show increase and decrease in some of the sites between dry and wet seasons.

4.3.3.5 Bioaccumulation Factor Water-Plant

The bioaccumulation factor water-plant (BAF_w) of heavy metals and trace elements in kale leaves determined for dry and wet seasons are presented in Table 4.29-4.30. The BAF_w of As in kale are 0.007-0.131 in dry season and 0.021-0.132 in wet season. The BAF_w of As vary significantly across the sites ($p < 0.001$), with the sites S2 (0.095) and S10 (0.131) in dry season and S7 (0.100) and S10 (0.132) in wet season exhibiting the

highest values of BAF_w. The BAF_w of As in kale are slightly lower in dry season compared to wet season.

The BAF_w of Cd in kale are 1.165-4.514 in dry season and 1.049-18.386 in wet season. The BAF_w of Cd vary significantly across the sites ($p = 0.001$) in dry season, but no significant difference is observed in wet season ($p = 0.103$). The BAF_w of Cd in kale are lower in dry season compared to wet season. The highest BAF_w of Cd are recorded at the sites S2 (4.514), S9 (3.888) in dry season S10 (2.962) and S1 (4.383), S4 (4.252), S7 (18.386), S9 (5.179) and S10 (14.106) in wet season. The BAF_w of Cd are substantially higher in wet season compared to dry season.

The BAF_w of Cr are 0.002-0.226 in dry season and 0.007-0.182 in wet season. BAF_w for Cr vary significantly across the sites ($p < 0.001$, $p = 0.022$). The highest values of BAF_w for Cr are recorded at the sites S2 (0.226) and S10 (0.149) in dry season and S7 (0.182) and S10 (0.132) in wet season. The BAF_w of Cr in kale are higher in dry season compared to wet season. The BAF_w of Cu are 0.309-7.624 in dry season and 0.210-2.059 in wet season. The highest values of BAF_w are recorded at S2 (7.624) and S10 (6.167) in dry season and S7 (2.059) and S10 (1.101) in wet season. There is no significant difference in the BAF_s of Cu across the sites in dry season ($p = 0.062$), but significant difference is noted in wet season ($p = 0.001$).

The values BAF_w of Cu are higher in dry season compared to wet season. The BAF_w of Hg are 0.042-0.073 in dry season and 0.017-0.043 in wet season with S2 having a significantly higher BAF_w ($p = 0.028$, $p = 0.002$). The BAF_w of Ni are 0.006-0.202 for dry season and 0.031-0.204 for wet season. The BAF_w vary significantly across the sites ($p < 0.001$), with the highest BAF_w recorded at the sites S2 (0.202), S7 (0.106) and S10 (0.183) in dry season and S4 (0.204) and S7 (0.133) in wet season. The BAF_w of Ni are higher in dry season compared to wet season.

Table 4.29: Water-plant bioaccumulation factor of heavy metals and trace elements in kale leaves in Dry season

Sites	As	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	0.017c	1.835bc	0.086bcd	1.531a	0.042b	0.087bc	0.046b	0.506abc
S2	0.095b	4.514a	0.226a	7.624a	0.073a	0.202a	1.818a	1.044a
S3	0.012c	1.226c	0.047cde	1.151a	-	0.039c	0.072b	0.241c
S4	0.013c	1.810bc	0.030de	0.397a	-	0.089bc	0.022b	0.385bc
S5	0.007c	0.814c	0.002e	0.741a	-	0.006c	0.010b	0.409abc
S6	0.017c	1.968bc	0.020 de	0.340a	-	0.066c	0.088b	0.728abc
S7	0.025c	2.127abc	0.115bc	0.583a	-	0.106abc	0.103b	0.654abc
S8	0.030c	1.165c	0.061cde	2.097a	-	0.054c	0.089b	0.488abc
S9	0.034c	3.888ab	0.020de	0.309a	-	0.086bc	0.012b	0.733abc
S10	0.131a	2.962abc	0.149ab	6.167a	-	0.183ab	0.250b	0.993ab
F	38.48	5.74	18.87	2.26	11.29	8.87	42.88	4.15
p-value	< .001	.001	< .001	0.062	0.028	< .001	< .001	0.004

Table 4.30: Water-plant Bioaccumulation factor of heavy metals and trace elements in kale leaves in wet season

Sites	As	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	0.026d	4.383a	0.019ab	0.497b	0.017b	0.031	0.031a	1.549b
S2	0.064bcd	1.049a	0.042ab	0.690b	0.043a	0.120abc	0.027a	2.595ab
S3	0.029d	1.788a	0.029ab	0.320b	-	0.115abc	0.033a	1.284b
S4	0.088abc	4.252a	0.007b	0.641b	-	0.204a	0.011a	3.288ab
S5	0.026d	2.094a	0.011ab	0.669b	-	0.135ab	0.005a	2.466ab
S6	0.021d	2.277a	0.009b	0.210b	-	0.082bc	0.012a	1.410b
S7	0.100ab	18.386a	0.182a	2.059a	-	0.133ab	1.230a	22.163a
S8	0.029d	3.274a	0.038ab	0.581b	-	0.039bc	0.007a	0.635b
S9	0.045cd	5.179a	0.027ab	0.926b	-	0.060bc	0.023a	3.382ab
S10	0.132a	14.106a	0.132ab	1.101ab	-	0.060bc	0.023a	4.076ab
F	18.67	1.95	2.93	5.75	46.87	7.19	1.06	2.59
p-value	< .001	0.103	0.022	0.001	0.002	< .001	0.434	0.037

The BAF_w of Pb are 0.010-1.818 for dry season and 0.005-1.230 for wet season. The highest BAF_w of Pb are observed at site S2 in dry season and S7 (1.230) in wet season. The BAF_w of Pb are significantly different across the sites in dry season ($p < 0.001$), while no significant different is observed across in wet season ($p = 0.434$). The BAF_w of Pb are higher in dry season compared to wet season. The BAF_w of Zn are 0.241-1.044 in dry season and 0.635-22.163 in wet season. The BAF_w exhibit significant

differences across the sites ($p = 0.004$, $p = 0.037$), with the highest value observed at S2 (1.044) and S10 (0.993) in dry season and at S7 (22.163) and S10 (4.076) in wet season. The BAF_w of Zn are lower in dry season compared to wet season.

4.3.3.6 Daily Intake of Heavy Metals and Trace Element from Kale Consumption

The results of daily intake (DI) of heavy metals and trace elements from daily consumption of kale, estimated for two age groups 7-18 years old (children) and adults (> 18 years old) are presented in Table 4.31-4.32. The DI of As are 0.028-0.073 mg/person/day for children and 0.019-0.050 mg/person/day for adults in dry season and 0.012-0.054 mg/person/day for children and 0.008-0.036 mg/person/day for adults in wet season. The highest DI are observed at the sites S5 (0.064 and 0.044 mg/person/day) and S10 (0.073 and 0.050 mg/person/day) during dry season and S10 (0.054 and 0.036 mg/person/day) during wet season. The DI of As in all the sites for the two seasons are below the maximum allowable daily intake (MADI) of As in food of 0.129 mg/person/day (Marini et al., 2021).

The DI of Cd range between 0.036 and 0.118 mg/person/day for children and between 0.025-0.080 mg/person/day for adults during dry season and 0.028 and 0.092 mg/person/day for children and 0.021 and 0.062 mg/person/day for adults during wet season. The highest DI are recorded at the sites S5 (0.072 and 0.049 mg/person/day), S9 (0.118 and 0.080 mg/person/day) and S10 (0.079 and 0.054 mg/person/day) during dry season and S1 (0.092 and 0.062 mg/person/day) and S10 (0.089 and 0.061) in wet season. The DI of Cd for children in all the site for the two seasons are above the MADI of 0.021 mg/person/day, while for adults DI values are above the MADI for 90% of the sample in wet season.

The DI of Cr are 0.091-0.275 mg/person/day for children and 0.061-0.186 mg/person/day for adults during dry season and 0.018-0.289 mg/person/day for children and 0.012-0.201 mg/person/day for adults during wet season. The highest DI of Cr are recorded from the sites S2 (0.275 and 0.186 mg/person/day), S7 (0.232 and 0.207 mg/person/day) and S10 (0.248 and 0.168 mg/person/day) during dry season and S7 (0.141 and 0.126 mg/person/day) and S10 (0.289 and 0.201 mg/person/day) during wet season. The DI of Cr are above the MADI of 0.2 (Marini et al., 2021) for children for 30% and 10% of the samples and 20 and 10% of the samples for adult, respectively in dry and wet seasons.

Table 4.31: Daily intake of heavy metals and trace elements from kale leaves consumption in dry season

Sites	Age group	AS	Cd	Cr	Cu	Hg*	Ni	Pb	Zn
S1	Children	0.046	0.064	0.178	3.239	9.467	0.242	0.287	15.684
	Adult	0.031	0.043	0.121	2.196	6.417	0.164	0.195	10.632
S2	Children	0.049	0.066	0.275	2.590	4.308	0.224	1.341	15.813
	Adult	0.033	0.045	0.186	1.756	2.920	0.152	0.909	10.719
S3	Children	0.032	0.059	0.182	2.814	6.863	0.198	0.175	11.766
	Adult	0.021	0.040	0.123	1.908	4.652	0.134	0.118	7.976
S4	Children	0.028	0.061	0.100	1.008	7.707	0.312	0.046	11.734
	Adult	0.019	0.041	0.068	0.683	5.224	0.212	0.031	7.954
S5	Children	0.064	0.072	0.097	1.153	5.756	0.205	0.038	15.231
	Adult	0.044	0.049	0.066	0.781	3.902	0.139	0.026	10.325
S6	Children	0.030	0.055	0.115	1.401	3.568	0.402	0.151	14.923
	Adult	0.020	0.038	0.078	0.949	2.418	0.272	0.102	10.116
S7	Children	0.037	0.054	0.232	1.377	6.307	0.448	0.218	20.355
	Adult	0.033	0.048	0.207	1.229	5.629	0.400	0.194	18.167
S8	Children	0.033	0.036	0.174	4.405	4.145	0.148	0.220	13.622
	Adult	0.022	0.025	0.118	2.986	2.809	0.100	0.149	9.234
S9	Children	0.030	0.118	0.091	1.131	4.532	0.193	0.046	22.027
	Adult	0.020	0.080	0.061	0.767	3.072	0.131	0.031	14.931
S10	Children	0.073	0.079	0.248	10.222	21.552	0.256	0.770	20.244
	Adult	0.050	0.054	0.168	6.929	14.610	0.174	0.522	13.722
MADI		0.129 ^A	0.021 ^A	0.2 ^A	10 ^B	34 ^A	0.168 ^A	0.21 ^A	15 ^A
Above MADI (%)	Children	0	100	30	10	0	90	50	60
	Adult	0	100	10	0	0	40	30	10

MADI=Maximum allowable/tolerable daily intake; ^A(Marini et al., 2021); ^B(Russell et al., 2001);

*All values are in mg/person/day except the column of Hg which is expressed in µg/person/day¹

The DI of Cu vary between 0.683 and 10.222 and between 1.153 and 6.929 mg/person/day for children, and adults, respectively in dry season and between 0.871 and 3.447 and between 0.591 and 2.337 mg/person/day for children and adult, respectively in wet season. The highest DI of Cu are recorded at the site S10 for both seasons (10.222, 6.929; 3.447 and 2.337). The DI of Cu are above the MADI of 10 mg/person/day (Russell et al., 2001) only for children in 10% of the samples (S10).

The DI of Hg are 3.568-21.552 and 2.418-14.610 $\mu\text{g}/\text{person}/\text{day}$ for children and adults, respectively in dry season and 2.012-4.652 and 1.364-3.153 $\mu\text{g}/\text{person}/\text{day}$ for children and adults, respectively in wet season. The highest DI of Hg are recorded during dry season at the sites S1 (9.467 and 6.417 $\mu\text{g}/\text{person}/\text{day}$) and S10 (21.552 and 14.610 $\mu\text{g}/\text{person}/\text{day}$). The DI of Hg are below the MADI of 34 $\mu\text{g}/\text{person}/\text{day}$ across the sites (Marini et al., 2021). The DI of Hg are higher for children compared to adults and higher in dry season compared to wet season.

The DI of Ni are 0.148-0.448 and 0.100-0.400 mg/person/day for children and adults, respectively, in dry season and 0.078-0.518 and 0.053-0.351 for children and adults, respectively, in wet season. Above the MADI of 0.168 mg/person/day for children and adults is observed for 90% and 40% of the sample for children and adults in dry season and 50% and 40% of the sample for children and adults in wet season (Marini et al., 2021). The highest DI are observed at S10 in dry season (10.222 and 6.929).

The DI of Pb through kale consumption are 0.038-1.341 and 0.026-0.909 mg/person/day/ for children and adults, respectively in dry season and 0.015-0.079 and 0.010-0.054 mg/person/day for children and adults, respectively in wet season. The sites S2 (0.909 and 1.341) and S10 (0.770 and 0.522) exhibit the highest DI of Pb. The DI of Pb are above the MADI of 0.21 (Marini et al., 2021) in 50% and 30% of the samples, respectively for children and adults in dry season. In contrast, all the DI of Pb in wet

season are below the MADI of Pb. The DI of Zn are 11.766-22.027 and 7.954-18.167 mg/person/day for children and adults, respectively in dry season and 7.293-20.289 and 4.944-18.109 mg/person/day for children and adults, respectively in wet season. The DI of Zn are above the MADI of 15 mg/person/day for children in 60% (dry season) and 50% (wet season) of the samples and for adult in 10% of the samples in dry and wet seasons, respectively. The highest DI of Zn are recorded at the sites S1, S5, S7, S9 and S10.

Table 4.32: Daily intake of heavy metals and trace elements from kale leaves consumption in wet season

Sites	Age group	AS	Cd	Cr	Cu	Hg*	Ni	Pb	Zn
S1	Child	0.032	0.092	0.123	1.302	3.428	0.161	0.058	14.355
	Adult	0.022	0.062	0.083	0.883	2.324	0.109	0.039	9.731
S2	Child	0.040	0.044	0.110	1.184	2.447	0.304	0.079	14.197
	Adult	0.027	0.030	0.074	0.803	1.659	0.206	0.054	9.623
S3	Child	0.022	0.030	0.062	0.968	2.012	0.282	0.047	11.562
	Adult	0.015	0.021	0.042	0.656	1.364	0.191	0.032	7.837
S4	Child	0.038	0.064	0.018	2.048	4.652	0.518	0.015	18.723
	Adult	0.026	0.043	0.012	1.389	3.153	0.351	0.010	12.692
S5	Child	0.017	0.060	0.036	1.731	3.884	0.422	0.018	17.680
	Adult	0.011	0.041	0.025	1.173	2.633	0.286	0.012	11.985
S6	Child	0.012	0.058	0.028	1.061	4.089	0.209	0.023	12.678
	Adult	0.008	0.039	0.019	0.719	2.772	0.142	0.016	8.594
S7	Child	0.030	0.028	0.141	1.218	2.863	0.090	0.075	20.289
	Adult	0.027	0.025	0.126	1.087	2.555	0.080	0.067	18.109
S8	Child	0.021	0.032	0.073	0.871	3.029	0.078	0.022	7.293
	Adult	0.014	0.022	0.050	0.591	2.053	0.053	0.015	4.944
S9	Child	0.024	0.064	0.074	1.216	5.243	0.120	0.058	19.816
	Adult	0.016	0.043	0.050	0.824	3.554	0.081	0.039	13.432
S10	Child	0.054	0.089	0.289	3.447	3.428	0.088	0.058	16.530
	Adult	0.036	0.061	0.201	2.337	2.324	0.059	0.039	11.205
MADI		0.129 ^A	0.021 ^A	0.2 ^A	10 ^B	34 ^A	0.168 ^A	0.21 ^A	15 ^A
Above MADI (%)	Children	0	100	10	0	0	50	0	50
	Adult	0	90	0	0	0	40	0	10

MADI=Maximum allowable/tolerable daily intake; ^A(Marini et al., 2021); ^B(Russell et al., 2001);
 *All values are in mg.person⁻¹.day⁻¹ except the column of Hg which is expressed in µg.person⁻¹.day⁻¹

4.3.4 Discussion

4.3.4.1. Physicochemical Properties of Irrigation Water

Our results on the physicochemical properties of irrigation water samples in vegetable farmlands of Nairobi-Machakos counties interface reveal that most water quality parameters are above admissible threshold for unrestricted irrigation (Ayers & Westcot, 1985; Simsek & Gunduz, 2007). Water parameters including colour, Turb, TSS, TDS and EC are reported to be influenced by local geology (soil and rock types), climate conditions, the volume of hydrologic flow and the extent of existing anthropogenic activities *i.e.* industrial, discharges from WTP and agricultural activities, local sanitation accessibility (Elsayed et al., 2020; Gad et al., 2020). In this study, irrigation water samples from all the sampling stations exhibit high EC, TDS, nutrients' content, water hardness, total alkalinity, which indicate the presence of high salt content and diluted materials. The streams used for irrigation are significantly influenced by discharge of solid waste and wastewater from settlements, industries, WTPs effluent, resulting in significant accumulation of various chemical components in the water column. The extent of water quality degradation varies significantly across the sites due to different influx across the sites. Irrigation water samples are more degraded in the farmland located after wastewater treatment plant discharge points (S5 and S10), the farmlands where irrigation water source is domestic sewage (S1 and S7) or mixture of river water and sewage (S2, S6 and S9).

The physicochemical parameters of irrigation water recorded in Nairobi-Machakos interface are higher compared to those recorded in studies conducted in the Nile River (Elsayed et al., 2020; Gad et al., 2020); Tana River (Njuguna et al., 2017) and Migori River (Opiyo et al., 2022). This is attributable to the fact that urban hydrologic flows (especially in developing countries) are highly exposed to urban pollution from urban

settlements (especially informal settlements) and industrial development. The degraded water physicochemical parameters observed across the farmland is attributable to the presence of high-density urban settlements and industrial areas along with poor sanitary services, waste management and wastewater treatment utilities that lead to significant discharge in urban streams. The findings are consistent with previous studies in Athi River basin that noted an increasing pollution of the basin (Njuguna et al., 2017; Kitheka, 2019; Bagnis et al., 2020). The findings on water quality variables are consistent with those of Kithiia (2012), Zhang et al. (2015) and Butsch et al. (2021) who noted that urban river basins are more exposed to pollution compared to non-urban river basins; thus can pose significant health risks to metropolitan population.

4.3.4.2. Bacterial Contamination in Irrigation Water

The bacteriological characteristics of irrigation water across the farmlands indicate that irrigation water is contaminated in all the sampling stations with significant loads of bacterial pathogens, including *E. coli* (up to 1.5×10^7 CFU/100 mL), *Shigella* spp. (1.6×10^7 CFU/100 mL), *P. aeruginosa* (up to 1.6×10^6 CFU/100 mL), *E. faecalis* (up to 1.8×10^5 CFU/100 mL), and *V. cholerae* (up to 1.6×10^5 CFU/100 mL). The results on bacterial contamination of irrigation water are consistent with the findings of Musyoki et al. (2013b) in Nairobi River and Athi River (Kenya), who reported up to $1.0 \times 10^4 \pm 2.6 \times 10^3$ /100 mL *E. coli*, $1.2 \times 10^1 \pm 1.2 \times 10^1$ /100 mL *Shigella* spp., $3.6 \times 10^3 \pm 3.2 \times 10^3$ /100 mL *E. faecalis*, $6.5 \times 10^2 \pm 1.1 \times 10^2$ /100 *P. aeruginosa*, $1.6 \times 10^1 \pm 1.1 \times 10^1$ /100 mL, *Salmonella typhi*, $5.6 \times 10^2 \pm 1.0 \times 10^2$ /100 mL *V. cholerae*. The globally high average CFU counts of bacterial pathogens recorded in this study indicate the presence of a significant load of faecal materials in the streams used as irrigation water sources. This is attributed to discharge of raw sewage and effluent from informal

settlements and wastewater treatment plants (WTPs) to the urban stream (Musyoki et al., 2013b). The urban streams in the Nairobi-Machakos peri-urban interface are more degraded than they were ten years ago (Kithiia, 2012; Musyoki et al., 2013b).

The CFUs are significantly higher at the stations located after WTPs discharge point (S5 and S10) and those along roads in high density residential areas (S1 and S7). This is attributable to the incoming effluent and sewage, which does not comply with standards for discharge into the environment. The stations along Athi River (S2-S6) have low bacterial load counts compared to those located along Nairobi River (S9 and S10). This is consistent with Bagnis et al. (2020), who stressed that Nairobi River and its two tributaries passing through the city's informal settlements have higher levels of bacterial contamination because of poor sanitation and disposal of waste in the river network compared to Athi River (Letema et al., 2012; Douglas et al., 2022; Kilingo et al., 2022; Vane et al., 2022). In addition, settlements along Athi River are less congested than those along Nairobi River and the total amount of raw sewage and WTPs effluent discharged daily into Nairobi River is greater than the burden imposed on Athi River i.e., 80,000 + 11,000 m³/day Vs 61,943 m³/day of WTP effluent (Ndiritu et al., 2017; Song'oro et al., 2019; Wafula et al., 2020).

Pseudomonas aeruginosa and *E. faecalis* are negative at some of the sampling stations, yet they are positive at some upstream sampling stations. This could be partially attributed to higher inflow of water, which eventually contributes to reduction or increase in bacterial pathogen loads in urban streams. This demonstrates the potential influence of upstream land uses on bacteriological quality of surface water. Socioeconomic activities along streams can quickly alter the quantities of contaminants getting into the stream (Schreiber et al., 2015; Uyttendaele et al., 2015). Unlike chemical contaminants, the spread of bacterial pathogens in surface water is complex

and influenced by water inflows and upstream land uses (Scheuerl et al., 2020; Dai et al., 2021). Bacterial pathogens may show exponential load count across water flow and their load count may significantly decrease after some distance (Scheuerl et al., 2020).

The results show a seasonal influence on bacterial contamination. The bacterial pathogens *Shigella* spp., *P. aeruginosa* and *E. faecalis* are low or undetectable in some of the stations during dry and wet seasons. This can be attributed to the fact that bacterial pathogens can originate from point and non-point source pollution. Although the inflow of fresh water during rain events can dilute streams and so reduce the level of bacterial contamination in the stream, inflow from contaminated stations can lead to higher contamination (Rai & Tripathi, 2007). Furthermore, the amount of effluent discharged into Nairobi River is very high during wet season owing to the clogging power after heavy rains (Kitheka, 2019). As the river tributaries join the main river, depending on their level of contamination, their contribution to bacteria levels will vary accordingly. This is consistent with Wiegner et al. (2017) and Ahmed et al. (2020), who illustrated the influence of rainstorm water inflows on high bacterial contamination of surface water in wet season.

BOD and COD values are high for all the stations and the ratios BOD/COD are low, suggesting that the irrigation water contains high nutrient load, high amount of active biological substance and biologically inactive organic matter. The values of BOD and COD observed in this study indicate poor water quality, which imply that the treatment of such water will incur high costs (Mahapatra et al., 2022). The results showed that the samples with higher BOD and COD exhibited higher pathogen load contamination as well, which confirms that BOD and COD can be used as indicators for primary assessment of bacteriological quality of water in urban streams (Olasoji et al., 2019). The strong positive correlation between bacterial pathogens indicates that they grow in

similar conditions and thus a common source. The strong positive correlation between BOD and COD was expected since BOD measures the amount of organic matter that can be biologically oxidized, while COD measures the amount of organic matter that can be chemically oxidized. The strong positive correlations between BOD and the pathogens suggest that high BOD is associated with a high load of bacterial pathogens in water. The negative correlation between pH and bacterial pathogens is consistent with previous studies (Rincón & Pulgarin, 2004; Krulwich et al., 2011) which showed that *E. coli*, *P. aeruginosa*, *Shigella* spp., *E. faecalis* and *V. cholera* have their optimum growth at neutral pH and reduce as the pH values move from the neutral ranges. The slightly higher pH observed in dry season compared to wet season could be a consequence of high nutrients' content during dry season, which favours algae growth and photosynthesis, followed by CO₂ reduction and release of oxygen and hydroxide alkalinity.

According to the WHO guidelines for wastewater use in agriculture for unrestricted irrigation, *E. coli* count in the water should be less than 1000 CFU/100 mL. For the USEPA (USEPA, 2009) and the NEMA (NEMA-National Environment Management Authority, 2006), it should be free of *E. coli*. By these criteria, irrigation water from the sampling stations in Nairobi-Machakos counties peri-urban interface is unfit for irrigation. The use of such water exposes farmers, consumers and downstream water users to serious health risks (WHO, 2006). *Escherichia coli* is the most commonly used indicator in evaluating bacterial contamination in water (Odonkor & Ampofo, 2013). Therefore, detection of the bacterium implies faecal contamination of water, even though mere detection could be insufficient to understand the extent of bacterial risks. For instance, irrigation water could have below the permissible range for *E. coli* of zero or 1000 CFU/100 mL by the NEMA (NEMA, 2006) and the WHO (WHO, 2006), but

other deadly bacterial pathogens like *Salmonella typhi*, *Shigella* spp. and *Vibrio cholerae* could be present. In a study carried out in Asia by Ahmed et al. (Ahmed et al., 2012), 12% of the water samples had ≤ 1 CFU of *E. coli*, yet the samples tested positive for other pathogenic bacteria such as *S. typhi* and *Enterococcus* spp.

Therefore, the assessment of bacterial contamination of irrigation water for unrestricted irrigation should be expanded to include pathogens that could trigger severe outbreaks such as *Salmonella typhi*, *P. aeruginosa*, *Shigella* spp. and *Vibrio cholerae*. Moreover, there are no explicit regulations for monitoring bacteriological quality of fruits and vegetables supplied to the local market in Kenya. Attention is here drawn to the assessment of irrigation water for bacterial pathogens in order to avert public health emergency, as previously reported, sometimes with several fatalities (Shikanga et al., 2009; Mohamed et al., 2012). Such control and monitoring are determinants for preventing foodborne diseases and ensuring safe and healthy food for metropolitan populations. One cannot overlook the fact that settlements are sited (along the Athi and Nairobi rivers) where settlements are a danger to themselves and to others. Kenya should have an effective housing policy which works together with an effective health policy.

4.3.4.3. Irrigation Water Quality Indices

Irrigation water quality evaluation using the FAO irrigation water quality index (IWQI) showed that irrigation water is classified as doubtful (Marginally suitable) to highly suitable. This suggests that with the use of composite water quality indices, the scores of bad water quality properties are covered up by those of more favourable water quality parameters, concealing low scoring parameters and resulting in a moderate suitability of irrigation water. However, considering the bacterial contamination index (BCI) the

irrigation water samples of all the sites have high load of bacterial pathogens indicating the present of high faecal materials in water column across the sites and are thus unfit for vegetable irrigation. Despite that bacterial contamination is very important for the unrestricted irrigation water, the IWQI by FAO does not include bacterial properties of irrigation water. The results suggest that there is a need of improved irrigation water quality indices for monitoring unrestricted irrigation water quality. Based on the IWQI, the site S5 and S7 have the poorest water quality due to high influxes of wastewater treatment plant effluent, urban wastewater, and domestic sewage. Irrigation water is slightly of better quality in wet season compared to dry season due large influx of fresh water from rainfall events. The quality of surface water in the Nairobi-Machakos interface needs to be improved for use as irrigation water but should be prohibited for domestic use due to high contamination.

4.3.4.4 Heavy Metals and Trace Elements in Soil

The assessment of heavy metals and trace elements contamination in agricultural soil in Nairobi-Machakos counties interface imply the presence of the twelve analysed heavy metals and trace elements (As, Cd, Co, Cr, Cu, Fe, Hg, Mn, Ni, Pb, V, and Zn) in all the farmlands across the catchment. The findings are consistent with previous studies (Mungai & Wang, 2019; Ndungu et al., 2019; Kinuthia et al., 2020; Nyandika et al., 2020), which emphasised the growing trend in different heavy metals and trace elements contamination in Nairobi urban and peri-urban areas. The concentrations of heavy metals and trace elements recorded in this study are higher compared to those recorded by Ndungu et al. (2019) for $Cd \leq 0.1$ mg/kg, $Cr \leq 5.4$ mg/kg, $Cu \leq 3.6$ mg/kg, $Ni \leq 5.3$ mg/kg, and $Zn \leq 11.9$ mg/kg; by Mungai & Wang (2019) for $As \leq 2.28$ mg/kg, $Cd \leq 0.23$ mg/kg, $Cr \leq 4.93$ mg/kg, $Cu \leq 17.22$ mg/kg, $Hg \leq 0.03$ mg/kg, $Ni \leq 1.55$

mg/kg, pb $\leq$ 99.16 mg/kg, Zn $\leq$ 12.54 mg/kg, by Nyandika et al. (2020) for Mn $\leq$ 4752 in Nairobi urban and peri-urban areas. However, the concentrations are found to be lower compared to those recorded by Kinuthia et al. (2020) for Cd $\leq$ 1.9 mg/kg, Cr $\leq$ 81.17 mg/kg, Hg $\leq$ 223.75 μ g/kg, Ni $\leq$ 29.87 mg/kg and Pb $\leq$ 471.17 mg/kg, and those by Nyandika et al. (2020) for Cr $\leq$ 77.5 mg/kg, Cu $\leq$ 69 mg/kg, Ni $\leq$ 33 mg/kg and Zn $\leq$ 590 mg/kg in open drainage canal in Nairobi industrial area and farmland irrigated with WTP effluent, respectively.

The spatial distribution of metal elements across the farmlands are not uniform and the hotspots of the elements are mainly influenced by the characteristics of each sampling station. Despite these dissimilarities in the spatial distribution patterns of the different elements across the catchment, certain homologies were observed between (i) Co and Mn, (ii) Cu and Cr and (iii) As, Cd, Fe, Hg, Pb and Zn, while Ni and V have different distribution patterns. The similarities in the patterns of spatial distribution of the different heavy metals and trace elements can substantially explain their sources and guide in monitoring and remediation measures (Gong et al., 2018; Sun et al., 2019). For all the metal elements in soil except Co, Cu, Cr and Mn, the farmlands along Nairobi River and its tributaries (S8-S10) were more polluted compared to those along Athi River. This is consistent with Bagnis et al. (2020) and Njuguna et al. (2017) who highlighted the higher contamination risk along Nairobi River and its tributaries which are substantially polluted with domestic and industrial waste compared to Athi River.

The combination of the correlation analysis, enrichment factor (EF) index, PCA and HCPC on heavy metals and trace elements concentrations in soil confirm the association observed in the spatial distribution of heavy metal and trace elements. The metal elements Cu, Cr, Ni and V in the farmlands originated primarily from lithogenic or natural sources whereas As, Cd, Co, Fe, Hg, Mn, Pb and Zn showed significant

enrichment from anthropogenic activities. The anthropogenic sources of heavy metals and trace elements in peri-urban agricultural soils include urban wastewater or urban stream irrigation, industrial effluents, aerial emission from industries and traffic network, urban infrastructure construction sites and effluent discharge from wastewater treatment plants and industries (Sellami et al., 2022).

The presence of Cu, Cr, Ni and V in the soils could be attributable to their parent materials' weathering, local pedologic properties, and atmospheric deposition via wind-blown dust (Ghasemi Siani et al., 2022). The elements Cr, Cu, Ni, and V in soil may also occur through aerial deposition from aerosols, continental dust, volcanic emissions, crude coal, petroleum materials or waste and sewage sludge incineration (Chen et al., 2020). Although our findings suggested a natural enrichment of the elements Cr, Cu, Ni, and V, in Nairobi city catchment peri-urban soils, their occurrence has often been associated with wastewater irrigation, urban and industrial waste, leather tanning, industrial effluent and emission (Zhang et al., 2019; Kinuthia et al., 2020).

The metal elements Fe and Mn are the most abundant metal elements in all the farmlands, which is attributed to the concentration of these two elements in the continental crust (Wedepohl, 1995). Indeed, Mn and Fe are abundantly released from their oxides form, resulting in extensive quantities of both elements in soil (Holmström et al., 2001; McMahon et al., 2019). However, anthropogenic activities can also lead to excessive amounts of Fe and Mn in the environment (Liu et al., 2018), especially from waste and effluent from steel production industries and mining activities that can make their way to agricultural soil via wastewater and urban stream irrigation (Yan et al., 2020).

The sites where farm irrigation is primarily based on sewage (S1), urban wastewater or wastewater treatment plant effluents (S5, S9 and S10), and urban open drainage canal

water flow (S7) have the highest heavy metals and trace elements contamination for As, Cd, Hg, Fe, Pb, V and Zn (Fig. 2; Table 3). These findings corroborate those of Arora et al. (2008) and Li et al. (2013) who pointed out that industrial effluents, wastewater and urban waste are the prominent source of heavy metals and trace elements diffusion in African urban areas. The higher contents of Cr and Cu in the farmlands S2, S5 and S10 could be attributed to industrial related activities (S2) and wastewater treatment plant effluents (S5 and S10). The concentrations of Pb and Zn in soil are higher in farmlands along automobile roads or highways (S7). This is consistent with Huang et al. (2015); Fayiga et al. (2018) and Zou et al. (2015), who highlighted that agricultural soils near heavy traffic roads are often contaminated with Pb and Zn. Indeed, Zn and Pb are substantially present in the fuel used in most low and middle-income countries (Maas et al., 2010; Jones et al., 2014; Yang et al., 2020).

The level of Hg contamination is higher in farmland irrigated on urban wastewater and wastewater treatment plant effluent. The occurrence of Hg in the catchment could originate from industrial activities and urban garbage (Xu et al., 2015). These findings corroborate those of Yang et al. (2018) in an industrial region in China and Adeyemi & Ojekunle (2021) in Ogun state in Nigeria, who pointed out that Hg contamination in agricultural soil is substantially associated to industrial activities. The highest concentrations of As, Co and Mn observed at S8 (along Katani Utawala bridge) could be explained by the valley landform of the area that can lead to metal elements' accumulation during rain runoff. The farmlands irrigated with wastewater treatment plant effluent mixed flow (S5 and S10) have generally high concentrations for all the elements. The use of untreated or partially treated wastewater and sewage for irrigation has been proven as the main entry point of heavy metals and traces elements to urban and peri-urban agricultural soil (Sayo et al., 2020). Due to the varying levels of toxicity

of different heavy metals and trace elements, comparing their abundance in soil is not sufficient to provide a meaningful understanding of the subsequent contamination risks. Therefore, various soil pollution indices were used to evaluate soil quality. The Geo-accumulation Index (I_{geo}) and the Single pollution Index (PI) values across the sites have similar results and suggested that the farmlands have low pollution of Co, Cr, Cu, Fe, Hg, Ni, Pb and V, while having moderate to high pollution in As, Cd, Mn and Zn. The findings are in line with Kowalska et al. (2018) who pointed out that I_{geo} and PI have very precise scales and are most effective for soil quality evaluation regarding single elements pollution in soil.

The complex indices PI_{Sum} , PLI and $PI_{Nemerow}$ depict a similar ranking of the overall soil pollution, indicating that S1, S7, S8 and S10 are the most contaminated sites. However, as PI_{Sum} has no precise ranking scale and has more influence from single element pollution index, its interpretation is limited to arithmetic classification of the level of pollution which does not give a specific status of soil contamination. In contrast, PLI and $PI_{Nemerow}$ have precise soil quality classification scales. The $PI_{Nemerow}$ values in this study indicate that most of the soils (90%) are highly contaminated, whereas PLI suggests that 40% of the soil are highly contaminated. This is attributed to the calculation method of $PI_{Nemerow}$, which uses the average single pollution index ($AvePI$) and the maximum single pollution (PI_{max}) of all measured elements. Therefore, higher variability in elements' concentrations in soil can influence the value of $AvePI$ and PI_{max} and will have an important effect on the index value (Kowalska et al., 2018). In the case of this study, PLI provides the most meaningful soil quality evaluation regarding the overall heavy metals and trace elements contamination.

Heavy metals and trace elements can bioaccumulate in edible portion of plants or livestock feeding on grasses or scavenging animals like local pigs, which can later make

their way into the food chains (Ngure & Kinuthia, 2020; Mng'ong'o et al., 2021). Furthermore, farmers in permanent contact with the soil are exposed to metals elements intake through ingestion, inhalation or dermal contact (Oginawati et al., 2022). As heavy metals and trace elements contamination even in minimal concentration can cause serious health risks, efficient and regular monitoring as well as regulations enforcement measures are eminent in urban and peri-urban agro-systems in Nairobi city catchment.

4.3.4.5 Heavy Metals and Trace Elements in kale leaves

Above permissible contaminations of heavy metals and trace elements in dry season and wet season including As (36.7% and 20%), Cd (100% and 100%), Cu (50% and 6.7%), Hg (70% and 16.7%), Pb (83.3% and 53.3) and Cd (100% and 100%) are recorded in kale leaves. The results are consistent with those of Mutune et al. (2014) who illustrated high uptake of heavy metals and trace elements in vegetable in Nairobi metropolitan region. Higher concentrations of heavy metals and trace elements in kale leaves at the sampling stations S1, S2, S5, S7 and S10 could be explained by various factors. These include high accumulation of metals elements in the soils at these sampling stations; irrigation water sources such as sewage (S1 and S7), wastewater treatment effluent (S5, S10); proximity to traffic (S2, S7) and industrial area. Heavy metals and trace elements contamination in vegetable can also originate from aerial deposition (Ngweme et al., 2020). Furthermore, the excessive used of agrochemicals including dangerous pesticides can also contribute to heavy metals accumulation in vegetable.

The Bioaccumulation factor soil-plant and water-plant of heavy metals and trace elements are not uniform across the sampling stations. Metals element bioavailability is generally influenced by factors including pH, soil organic matter, soil redox potential, plant species and the specific metals elements (Mensah et al., 2022). Therefore, the difference in heavy metals and trace elements bioaccumulation across the sites not aligning with the total metal concentration in soil could be attributed to the bioavailability of the metal elements in soil. In this study, the values of bioaccumulation factor (BAF) water-plant are higher compared to the bio-accumulation factor soil-plant. Similar conclusion on BAF was recorded by Kumar et al. (2022) in peri-urban farmland in Sitapur, India. The authors stressed that heavy metals and trace elements in water are in dissolved form, which can be easily available for plant in contrast with metals in soil which can be immobilized and become unavailable. However, in this study the speciation of heavy metals and trace element in soil which infer on metals element bioavailability was not analysed. The significant seasonal variation in heavy metals and trace elements uptake in kale, with high concentrations recorded in dry season can be explained by low metals concentration in irrigation water during wet season, dilution of soil solution in the rhizosphere and chemical components' runoff with soil particles during wet season.

The above maximum allowable daily intake (MADI) of metal elements Cd (up to 90%), Cr (up to 30%), Cu (up to 10%), Pb (up to 50%), Ni (up to 50%) and Zn (up to 60%) recorded from the sites S1, S5, S7 and S10 could be attributed to irrigation water source from this farmland which are sewage (S1, S7), mixture of wastewater treatment plant effluent (S5 and S10). The lower intake of metals in wet season compared to dry season is because of important dilution of contaminant during is soil and irrigation water during the water rainy season. The DI are significantly higher for children, indication more risk

for children compared to adults. The DI observed for kale in this study are higher compared to those recorded in a previous study by on wastewater irrigated kale in Thika town, Kenya. The results indicate that kale from the farmlands in Nairobi-Machakos interface can induce significant intake of heavy metals and trace elements, which can cause harmful health impacts. Therefore, the consumption of vegetables in the metropolitan region could be hazardous for human health conditions and ecology.

4.4 Ecological and Health Risks of Heavy Metals and Trace Elements Contamination in Nairobi-Machakos counties negligible

4.4.1 Potential Ecological Risk in Agricultural Soils

The potential ecological risks (E_r^i and RI) related to heavy metals and trace elements contamination are presented in Table 4.33. The average single metal ecological risk E_r^i (Equation 12) and the cumulative ecological risk RI (Equation 13) show a significant variation among the elements and across the sites ranging from 0.7-96.3 and 63.0-146.20, respectively. The E_r^i for As (11-22.24) in the soils are less than the lowest Hakanson threshold of 40, indicating low ecological risk. The highest E_r^i for As are recorded at the sites S1, S5, S6, S8, S9 and S10. The E_r^i of Cd range from 35.8-96.3 indicating low ecological risk (S4), moderate ecological risk (S2, S3, S5, S6, S8, S9, and S10) and considerable ecological risk (S7 and S1). The E_r^i related to Cr (0.6-1.2), Cu (3.0-4.9), Ni (2.2-4.2), Hg (5.0-34.5), and Pb (2.8-7.1) are less than the lowest risk threshold of 40 and are therefore classified as low risk. However, the E_r^i of Hg in the soil are higher at the site S1 (23.9), S9 (20.0) and S10 (34.5). Among all the metal elements, Cd exhibits the highest contribution to the cumulative ecological risk (RI) with a contribution of 46.1-65.9% (Table 4.34). The contributions of the metals

elements to RI are in the following descending order $Cd > As > Hg > Pb > Cu > Ni > Zn > Cr$ (Table 4.34).

Table 4.33: Potential Ecological Risk E_r^i and RI of heavy metals and trace elements contamination in agricultural soils

E_r^i	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
As	21.9	15.7	15.9	11.1	16.1	15.8	20.5	22.2	20.9	19.5
Cd	82.6	58.5	56.5	35.8	64.1	55.7	96.3	43.6	65.4	73.1
Cr	0.7	1.2	0.7	0.7	0.9	0.7	0.7	0.7	0.7	0.9
Cu	3.3	4.9	3.7	3.4	4.9	3.2	3.8	3.2	3.0	4.3
Hg	23.9	8.1	8.5	5.0	4.9	7.8	13.2	12.1	20.0	34.5
Ni	3.3	4.2	3.2	2.9	3.3	3.0	2.2	3.8	2.4	3.9
Pb	6.6	4.9	4.3	2.8	6.3	4.5	6.9	7.1	5.9	6.5
Zn	2.9	2.0	1.9	1.4	2.2	2.0	2.5	1.9	2.4	2.7
<i>RI</i>	145.1	99.6	94.7	63.0	102.6	92.7	146.2	94.5	120.6	145.6

The overall RI ranged from 63 to 146, which is below the low-risk threshold of 150 (Hakanson, 1980), indicating that the cumulative risk related to all the heavy metals and trace elements contamination in the soils are classified as low ecological risk. However, the sites S1 (145.1), S7 (146.2), S9 (120.6) and S10 (145.6) have the highest ecological risks, which are close to the threshold values of 150 (Table 4.33), while S4 exhibited the lowest ecological risk.

Table 4.34: Single potential ecological risk E_r^i contribution (in %) to cumulative ecological risk *RI*

HMTE	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	Min	Max	Mean
As	15.1	15.8	16.7	17.8	15.7	17.1	14.1	23.5	17.3	13.4	13.4	23.5	16.6
Cd	56.9	58.9	59.7	56.9	62.5	60.1	65.9	46.1	54.2	50.2	46.1	65.9	57.1
Cr	0.5	1.2	0.8	1.1	0.8	0.8	0.5	0.7	0.5	0.6	0.5	1.2	0.7
Cu	2.3	4.9	3.9	5.4	4.8	3.4	2.6	3.4	2.5	3.0	2.3	5.4	3.6
Hg	16.5	8.2	9.0	7.9	4.4	8.4	9.0	12.8	17	23.7	4.8	23.7	11.7
Ni	2.3	4.3	3.4	4.6	3.2	3.3	1.5	4.0	2.0	2.7	1.5	4.6	3.1
Pb	4.5	5.0	4.5	4.5	6.2	4.8	4.7	7.5	4.9	4.5	4.5	7.5	5.1
Zn	2.0	2.0	2.0	2.2	2.1	2.2	1.7	2.1	2.0	1.9	1.7	2.2	2.0
Total	100	100	100	100	100	100	100	100	100	100	-	-	-

HMTE: Heavy metals and trace elements

4.4.2 Health Risk Assessment

4.4.2.1 Non-carcinogenic Health Risk

The results of the non-carcinogenic health risks for each element, computed for children and adults considering dry and wet season are displayed in Table 4.35-4.36 (HQ_k : kale consumption), Table 4.37-4.38 (HQ_{ing} : soil ingestion), Table 4.39 and 4.40 (HQ_{inh} : soil inhalation) and Table 4.41-4.42 (HQ_{dermal} : dermal contact with soil material). The non-carcinogenic health risk is based on the chronic daily intake (CDI) of each metal element. The values of CDI are presented in Appendix 10. The values of CDI for the different exposure route show that the intake via kale consumption is the most prominent over the other exposure routes including soil ingestion, soil inhalation and dermal contact with soil material. The CDI are higher for children compared to adult. As consequence, the hazard quotient (HQ) related to kale consumption is glaringly leading the extent of the non-carcinogenic risk.

a) Hazard quotient from kale leaves consumption

The hazard quotients (HQ_k) related to heavy metals and trace elements intake through kale leaves consumption for dry season and wet season is displayed in Table 4.35-4.36. The values of HQ_k for the different metal elements showed that As has the largest contribution over all the elements. The metals elements are in the decreasing order $As > Cd > Pb > Cu > Zn > Hg > Ni > Cr$. The highest values of HQ_k are recorded at the sites S1, S5 and S10, where irrigation water sources are respectively sewage, mixture of urban river with wastewater treatment effluent. The non-carcinogenic risk observed for kale intake are higher in dry season compared to wet season. In addition, the values show that children are more exposed to non-carcinogenic risk compared to adults. The HQ_k for all the elements and the two age groups are less than one ($HQ_k < 1$) indicating that kale in Nairobi-Machakos counties interface is safe from non-carcinogenic risk.

Table 4.35 Hazard Quotient per element from kale consumption in dry season

Sites	Age group	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Child	1.5E-1	6.4E-2	1.2E-4	8.1E-2	3.2E-2	1.2E-2	8.2E-2	5.2E-2
	Adult	1.0E-1	4.3E-2	8.1E-5	5.5E-2	2.1E-2	8.2E-3	5.6E-2	3.6E-2
S2	Child	1.6E-1	6.6E-2	1.8E-4	6.5E-2	1.4E-2	1.1E-2	3.8E-1	5.3E-2
	Adult	1.1E-1	4.5E-2	1.2E-4	4.4E-2	1.3E-2	7.6E-3	2.6E-1	3.6E-2
S3	Child	1.1E-1	5.9E-2	1.2E-4	7.0E-2	2.3E-2	9.9E-3	5.0E-2	3.9E-2
	Adult	7.0E-2	4.0E-2	8.2E-5	4.8E-2	1.8E-2	6.7E-3	3.4E-2	2.7E-2
S4	Child	6.1E-2	6.1E-2	6.7E-5	2.5E-2	2.6E-2	1.6E-2	1.3E-2	3.9E-2
	Adult	2.0E-2	4.1E-2	4.5E-5	1.7E-2	1.8E-2	1.1E-2	8.9E-3	2.7E-2
S5	Child	2.1E-1	7.2E-2	6.5E-5	2.9E-2	1.9E-2	1.0E-2	1.1E-2	5.1E-2
	Adult	1.5E-1	4.9E-2	4.4E-5	2.0E-2	1.2E-2	7.0E-3	7.3E-3	3.5E-2
S6	Child	1.0E-1	5.5E-2	7.6E-5	3.5E-2	1.2E-2	2.0E-2	4.3E-2	5.0E-2
	Adult	6.8E-2	3.8E-2	5.2E-5	2.4E-2	9.1E-3	1.4E-2	2.9E-2	3.4E-2
S7	Child	1.6E-1	7.1E-2	2.0E-4	4.5E-2	2.8E-2	2.9E-2	8.2E-2	8.9E-2
	Adult	1.1E-1	4.9E-2	1.4E-4	3.1E-2	1.6E-2	2.0E-2	5.6E-2	6.1E-2
S8	Child	1.1E-1	3.6E-2	1.2E-4	1.1E-1	1.4E-2	7.4E-3	6.3E-2	4.5E-2
	Adult	7.4E-2	2.5E-2	7.9E-5	7.5E-2	1.0E-2	5.0E-3	4.3E-2	3.1E-2
S9	Child	9.8E-2	1.2E-1	6.0E-5	2.8E-2	1.5E-2	9.6E-3	1.3E-2	7.3E-2
	Adult	6.7E-2	8.0E-2	4.1E-5	1.9E-2	1.0E-2	6.6E-3	9.0E-3	5.0E-2
S10	Child	2.4E-1	7.9E-2	1.7E-4	2.6E-1	7.2E-2	1.3E-2	2.2E-1	6.7E-2
	Adult	1.7E-1	5.4E-2	1.1E-4	1.7E-1	5.4E-2	8.7E-3	1.5E-1	4.6E-2

Table 4.36: Hazard Quotient per element from kale consumption in wet season

Sites	Age group	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Child	1.1E-1	9.2E-2	8.2E-5	3.3E-2	1.1E-2	8.1E-3	1.7E-2	4.8E-2
	Adult	7.3E-2	6.2E-2	5.6E-5	2.2E-2	7.8E-3	5.5E-3	1.1E-2	3.3E-2
S2	Child	1.3E-1	4.4E-2	7.3E-5	3.0E-2	8.2E-3	1.5E-2	2.3E-2	4.7E-2
	Adult	9.0E-2	3.0E-2	5.0E-5	2.0E-2	5.5E-3	1.0E-2	1.5E-2	3.2E-2
S3	Child	7.3E-2	3.0E-2	4.2E-5	2.4E-2	6.7E-3	1.4E-2	1.4E-2	3.9E-2
	Adult	4.9E-2	2.1E-2	2.8E-5	1.6E-2	4.6E-3	9.6E-3	9.2E-3	2.6E-2
S4	Child	1.3E-1	6.4E-2	1.2E-5	5.1E-2	1.6E-2	2.6E-2	4.2E-3	6.2E-2
	Adult	8.7E-2	4.3E-2	8.4E-6	3.5E-2	1.1E-2	1.8E-2	2.8E-3	4.2E-2
S5	Child	5.6E-2	6.0E-2	2.4E-5	4.3E-2	1.3E-2	2.1E-2	5.1E-3	5.9E-2
	Adult	3.8E-2	4.1E-2	1.6E-5	2.9E-2	8.8E-3	1.4E-2	3.5E-3	4.0E-2
S6	Child	4.2E-2	5.8E-2	1.9E-5	2.7E-2	1.4E-2	1.0E-2	6.6E-3	4.2E-2
	Adult	2.8E-2	4.0E-2	1.3E-5	1.8E-2	9.3E-3	7.1E-3	4.5E-3	2.9E-2
S7	Child	1.3E-1	3.7E-2	1.2E-4	4.0E-2	1.3E-2	5.9E-3	2.8E-2	8.9E-2
	Adult	9.0E-2	2.5E-2	8.4E-5	2.7E-2	8.5E-3	4.0E-3	1.9E-2	6.1E-2
S8	Child	7.0E-2	3.2E-2	4.9E-5	2.2E-2	1.0E-2	3.9E-3	6.4E-3	2.4E-2
	Adult	4.8E-2	2.2E-2	3.3E-5	1.5E-2	6.9E-3	2.7E-3	4.3E-3	1.7E-2
S9	Child	7.9E-2	6.4E-2	4.9E-5	3.0E-2	1.7E-2	6.0E-3	1.6E-2	6.6E-2
	Adult	5.4E-2	4.3E-2	3.4E-5	2.1E-2	1.2E-2	4.1E-3	1.1E-2	4.5E-2
S10	Child	1.8E-1	8.9E-2	1.9E-4	8.6E-2	1.1E-2	4.4E-3	1.7E-2	5.5E-2
	Adult	1.2E-1	6.1E-2	1.3E-4	5.9E-2	7.8E-3	3.0E-3	1.1E-2	3.7E-2

b) Hazard quotient from soil ingestion, inhalation, and dermal exposure

The hazard quotient related to heavy metal intake through soil ingestion (HQ_{ing}), soil inhalation (HQ_{inh}) and dermal exposure (HQ_{dermal}) estimated considering dry season and wet season are presented in Table 4.37-4.42. HQ values for the elements considering the three exposure routes are less than one ($HQ < 1$), indicating there is no significant risk from soil ingestion, soil inhalation, and dermal exposure to soil material. The extent of risks is substantially different considering the elements, the exposure routes, the season, and the age groups. The HQ_{ing} are higher than HQ_{dermal} , which are also higher than HQ_{inh} .

- Hazard quotient from soil ingestion

The values of the elemental non-cancerogenic risk related to soil ingestion (HQ_{ing}) are higher for children compared to adults and the values of HQ_{ing} in dry season compared to wet season are comparable (Table 4.37-4.38).

Table 4.37: Hazard quotient of soil ingestion in dry season

Sites	Age group	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Child	1.4E-2	2.5E-4	8.5E-6	1.8E-4	1.1E-4	6.2E-4	5.3E-3	4.8E-4
	Adult	3.1E-3	5.6E-5	1.9E-6	4.1E-5	2.5E-5	1.4E-4	1.2E-3	1.1E-4
S2	Child	1.1E-2	1.9E-4	1.4E-5	3.6E-4	3.8E-5	8.4E-4	4.7E-3	3.5E-4
	Adult	2.5E-3	4.3E-5	3.2E-6	8.2E-5	8.6E-6	1.9E-4	1.1E-3	7.9E-5
S3	Child	9.0E-3	1.6E-4	8.8E-6	3.0E-4	4.0E-5	6.1E-4	3.6E-3	2.8E-4
	Adult	2.0E-3	3.7E-5	2.0E-6	6.8E-5	9.0E-6	1.4E-4	8.2E-4	6.3E-5
S4	Child	7.4E-3	1.2E-4	8.3E-6	2.3E-4	2.3E-5	5.5E-4	2.8E-3	2.6E-4
	Adult	1.7E-3	2.8E-5	1.9E-6	5.3E-5	5.2E-6	1.2E-4	6.2E-4	5.8E-5
S5	Child	1.2E-2	2.6E-4	1.2E-5	4.1E-4	2.3E-5	6.1E-4	8.5E-3	4.9E-4
	Adult	2.7E-3	5.8E-5	2.7E-6	9.3E-5	5.2E-6	1.4E-4	1.9E-3	1.1E-4
S6	Child	1.0E-2	1.7E-4	9.3E-6	2.6E-4	3.6E-5	6.8E-4	4.2E-3	3.0E-4
	Adult	2.4E-3	3.7E-5	2.1E-6	5.8E-5	8.2E-6	1.5E-4	9.4E-4	6.8E-5
S7	Child	1.4E-2	4.0E-4	7.7E-6	2.4E-4	6.1E-5	4.1E-4	7.8E-3	4.6E-4
	Adult	3.1E-3	9.1E-5	1.7E-6	5.5E-5	1.4E-5	9.2E-5	1.8E-3	1.0E-4
S8	Child	1.5E-2	1.5E-4	8.1E-6	2.4E-4	5.6E-5	7.1E-4	7.7E-3	3.4E-4
	Adult	3.3E-3	3.3E-5	1.8E-6	5.5E-5	1.3E-5	1.6E-4	1.6E-3	7.7E-5
S9	Child	1.4E-2	2.2E-4	8.0E-6	2.3E-4	9.3E-5	4.7E-4	7.5E-3	4.2E-4
	Adult	3.1E-3	5.0E-5	1.8E-6	5.3E-5	2.1E-5	1.1E-4	1.7E-3	9.5E-5
S10	Child	1.3E-2	2.6E-4	1.0E-5	3.3E-4	1.6E-4	5.7E-4	8.7E-3	4.6E-4
	Adult	3.0E-3	5.9E-5	2.3E-6	7.6E-5	3.6E-5	1.3E-4	1.8E-3	1.0E-4

This trend of HQ_{ing} is attributed to the similar trend in heavy metals and trace elements concentrations for the two seasons. The HQ_{ing} values of As are the leading of the extent of the risk and HQ_{ing} values are in the decreasing order $As > Pb > Ni > Zn > Cd > Cu > Hg > Cr$.

Table 4.38: Hazard quotient soil ingestion in wet season

Sites	Age group	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Child	1.5E-2	3.1E-4	8.4E-6	2.9E-4	1.1E-4	6.E-4	7.5E-3	5.1E-4
	Adult	3.4E-3	7.1E-5	1.9E-6	6.5E-5	2.5E-5	1.4E-4	1.7E-3	1.2E-4
S2	Child	1.0E-2	2.1E-4	1.4E-5	3.3E-4	3.8E-5	7.3E-4	4.8E-3	3.3E-4
	Adult	2.3E-3	4.7E-5	3.1E-6	7.5E-5	8.6E-6	1.6E-4	1.1E-3	7.5E-5
S3	Child	1.2E-2	2.2E-4	8.5E-6	2.3E-4	4.0E-5	5.7E-4	4.6E-3	3.7E-4
	Adult	2.7E-3	5.0E-5	1.9E-6	5.2E-5	9.0E-6	1.3E-4	1.0E-3	8.4E-5
S4	Child	7.3E-3	1.2E-4	7.1E-6	2.5E-4	2.3E-5	5.2E-4	2.7E-3	2.2E-4
	Adult	1.7E-3	2.7E-5	1.6E-6	5.6E-5	5.2E-6	1.2E-4	6.2E-4	5.1E-5
S5	Child	9.4E-3	1.8E-4	7.9E-6	2.9E-4	2.3E-5	6.1E-4	3.7E-3	2.6E-4
	Adult	2.1E-3	4.0E-5	1.8E-6	6.5E-5	5.2E-6	1.4E-4	8.5E-4	5.9E-5
S6	Child	1.1E-2	2.1E-4	7.1E-6	2.0E-4	3.6E-5	4.5E-4	4.5E-3	3.9E-4
	Adult	2.4E-3	4.8E-5	1.6E-6	4.5E-5	8.2E-6	1.0E-4	1.0E-3	8.8E-5
S7	Child	1.3E-2	2.5E-4	8.0E-6	3.1E-4	6.1E-5	4.3E-4	5.6E-3	4.2E-4
	Adult	3.0E-3	5.7E-5	1.8E-6	6.9E-5	1.4E-5	9.7E-5	1.3E-3	9.4E-5
S8	Child	1.5E-2	1.5E-4	7.5E-6	2.1E-4	5.6E-5	6.9E-4	6.8E-3	3.3E-4
	Adult	3.4E-3	3.4E-5	1.7E-6	4.8E-5	1.3E-5	1.6E-4	1.5E-3	7.5E-5
S9	Child	1.4E-2	2.2E-4	7.3E-6	2.0E-4	9.3E-5	4.3E-4	3.8E-3	4.1E-4
	Adult	3.2E-3	5.0E-5	1.7E-6	4.5E-5	2.1E-5	9.8E-5	8.6E-4	9.2E-5
S10	Child	1.3E-2	2.3E-4	1.0E-5	2.8E-4	1.6E-4	8.9E-4	4.7E-3	4.9E-4
	Adult	2.9E-3	5.3E-5	2.3E-6	6.3E-5	3.6E-5	2.0E-4	1.1E-3	1.1E-4

- Hazard quotient from soil inhalation

The non-carcinogenic risk from soil inhalation (HQ_{inh}) are higher for adults compared to children (Table 4.39-4.40). The values of HQ_{inh} for Cr are the leading of soil inhalation risk and the HQ_{inh} are in the decreasing order $Cr > As > Pb > Cd > Ni > Zn > Cu > Hg$.

Table 4.39: Hazard quotient soil inhalation in dry season

Sites	Age group	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Child	1.3E-6	4.0E-7	3.0E-5	1.5E-8	1.0E-8	4.7E-8	5.0E-7	3.8E-8
	Adult	1.5E-6	4.8E-7	3.5E-5	1.8E-8	1.2E-8	5.5E-8	5.9E-7	4.5E-8
S2	Child	1.0E-6	3.1E-7	4.9E-5	3.0E-8	3.5E-9	6.3E-8	4.4E-7	2.8E-8
	Adult	1.2E-6	3.7E-7	5.8E-5	3.6E-8	4.2E-9	7.5E-8	5.2E-7	3.3E-8
S3	Child	8.4E-7	2.7E-7	3.1E-5	2.5E-8	3.7E-9	4.6E-8	3.4E-7	2.2E-8
	Adult	1.0E-6	3.2E-7	3.7E-5	2.9E-8	4.4E-9	5.4E-8	4.0E-7	2.7E-8
S4	Child	6.9E-7	2.0E-7	2.9E-5	1.9E-8	2.2E-9	4.1E-8	2.6E-7	2.1E-8
	Adult	8.2E-7	2.4E-7	3.5E-5	2.3E-8	2.6E-9	4.8E-8	3.0E-7	2.5E-8
S5	Child	1.1E-6	4.2E-7	4.2E-5	3.4E-8	2.1E-9	4.5E-8	7.9E-7	3.9E-8
	Adult	1.3E-6	5.0E-7	5.0E-5	4.1E-8	2.5E-9	5.4E-8	9.4E-7	4.6E-8
S6	Child	9.7E-7	2.7E-7	3.2E-5	2.1E-8	3.4E-9	5.1E-8	3.9E-7	2.4E-8
	Adult	1.2E-6	3.2E-7	3.9E-5	2.5E-8	4.0E-9	6.0E-8	4.6E-7	2.9E-8
S7	Child	1.3E-6	6.6E-7	2.7E-5	2.0E-8	5.7E-9	3.0E-8	7.3E-7	3.7E-8
	Adult	1.5E-6	7.8E-7	3.2E-5	2.4E-8	6.8E-9	3.6E-8	8.6E-7	4.4E-8
S8	Child	1.4E-6	2.4E-7	2.8E-5	2.0E-8	5.2E-9	5.3E-8	6.5E-7	2.7E-8
	Adult	1.6E-6	2.9E-7	3.4E-5	2.4E-8	6.2E-9	6.3E-8	7.7E-7	3.2E-8
S9	Child	1.3E-6	3.6E-7	2.8E-5	1.9E-8	8.7E-9	3.5E-8	7.0E-7	3.4E-8
	Adult	1.5E-6	4.3E-7	3.3E-5	2.3E-8	1.0E-8	4.2E-8	8.4E-7	4.0E-8
S10	Child	1.2E-6	4.3E-7	3.6E-5	2.8E-8	1.5E-8	4.3E-8	7.5E-7	3.6E-8
	Adult	1.5E-6	5.1E-7	4.3E-5	3.3E-8	1.8E-8	5.1E-8	8.9E-7	4.3E-8

Table 4.40: Hazard quotient soil inhalation in wet season

Sites	Age group	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Child	1.4E-6	5.1E-7	2.9E-5	2.4E-8	1.0E-8	4.5E-8	7.0E-7	4.1E-8
	Adult	1.7E-6	6.1E-7	3.5E-5	2.8E-8	1.2E-8	5.3E-8	8.3E-7	4.8E-8
S2	Child	9.3E-7	3.4E-7	4.8E-5	2.7E-8	3.5E-9	5.4E-8	4.5E-7	2.6E-8
	Adult	1.1E-6	4.1E-7	5.7E-5	3.3E-8	4.2E-9	6.5E-8	5.4E-7	3.1E-8
S3	Child	1.1E-6	3.6E-7	3.0E-5	1.9E-8	3.7E-9	4.2E-8	4.3E-7	3.0E-8
	Adult	1.3E-6	4.3E-7	3.5E-5	2.3E-8	4.4E-9	5.0E-8	5.1E-7	3.5E-8
S4	Child	6.8E-7	2.0E-7	2.5E-5	2.1E-8	2.2E-9	3.9E-8	2.6E-7	1.8E-8
	Adult	8.1E-7	2.3E-7	2.9E-5	2.5E-8	2.6E-9	4.6E-8	3.0E-7	2.1E-8
S5	Child	8.7E-7	2.9E-7	2.8E-5	2.4E-8	2.1E-9	4.5E-8	3.5E-7	2.1E-8
	Adult	1.0E-6	3.4E-7	3.3E-5	2.8E-8	2.5E-9	5.4E-8	4.1E-7	2.5E-8
S6	Child	9.9E-7	3.5E-7	2.5E-5	1.6E-8	3.4E-9	3.3E-8	4.2E-7	3.1E-8
	Adult	1.2E-6	4.1E-7	2.9E-5	1.9E-8	4.0E-9	4.0E-8	5.0E-7	3.7E-8
S7	Child	1.3E-6	4.1E-7	2.8E-5	2.5E-8	5.7E-9	3.2E-8	5.2E-7	3.3E-8
	Adult	1.5E-6	4.9E-7	3.3E-5	3.0E-8	6.8E-9	3.8E-8	6.2E-7	4.0E-8
S8	Child	1.4E-6	2.4E-7	2.6E-5	1.7E-8	5.2E-9	5.2E-8	6.3E-7	2.7E-8
	Adult	1.7E-6	2.9E-7	3.1E-5	2.1E-8	6.2E-9	6.1E-8	7.5E-7	3.2E-8
S9	Child	1.3E-6	3.6E-7	2.6E-5	1.6E-8	8.7E-9	3.2E-8	3.6E-7	3.2E-8
	Adult	1.6E-6	4.3E-7	3.0E-5	2.0E-8	1.0E-8	3.8E-8	4.2E-7	3.9E-8
S10	Child	1.2E-6	3.8E-7	3.6E-5	2.3E-8	1.5E-8	6.6E-8	4.4E-7	3.9E-8
	Adult	1.4E-6	4.6E-7	4.3E-5	2.8E-8	1.8E-8	7.8E-8	5.2E-7	4.7E-8

- Hazard quotient from dermal exposure to soil

The non-carcinogenic risk from dermal exposure to soil material (HQ_{dermal}) for dry and wet season are displayed in Table 4.41-4.42. The values indicate that the elemental non-cancerogenic risk related to dermal exposure to soil (HQ_{dermal}) are higher for adults compared to children. The values of dermal risk between the two seasons show a similar trend like HQ_{ing} and HQ_{inh} , with no substantial difference between the seasons. The metals elements Pb, As, and Cr exhibited the highest dermal risks and the values of HQ_{dermal} are in the decreasing order $\text{Pb} > \text{As} > \text{Cr} > \text{Ni} > \text{Zn} > \text{Cd} > \text{Cu} > \text{Hg}$.

Table 4.41: Dermal exposure to soil material in dry season

Sites	Age group	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Child	4.5E-5	8.1E-7	1.4E-5	5.9E-7	3.6E-7	2.0E-6	1.1E-4	1.6E-6
	Adult	4.2E-4	7.4E-6	1.3E-4	5.4E-6	3.4E-6	1.9E-5	1.1E-3	1.4E-5
S2	Child	3.6E-5	6.2E-7	2.3E-5	1.2E-6	1.2E-7	2.8E-6	1.E-4	1.1E-6
	Adult	3.3E-4	5.7E-6	2.1E-4	1.1E-5	1.1E-6	2.5E-5	9.4E-4	1.1E-5
S3	Child	2.9E-5	5.3E-7	1.4E-5	9.8E-7	1.3E-7	2.0E-6	7.9E-5	9.1E-7
	Adult	2.7E-4	4.9E-6	1.3E-4	9.0E-6	1.2E-6	1.8E-5	7.2E-4	8.4E-6
S4	Child	2.4E-5	4.0E-7	1.4E-5	7.6E-7	7.5E-8	1.8E-6	5.9E-5	8.4E-7
	Adult	2.2E-4	3.7E-6	1.3E-4	7.0E-6	6.9E-7	1.6E-5	5.5E-4	7.8E-6
S5	Child	3.9E-5	8.4E-7	2.0E-5	1.3E-6	7.5E-8	2.0E-6	1.8E-4	1.6E-6
	Adult	3.6E-4	7.8E-6	1.8E-4	1.2E-5	6.9E-7	1.8E-5	1.7E-3	1.5E-5
S6	Child	3.4E-5	5.4E-7	1.5E-5	8.4E-7	1.2E-7	2.2E-6	9.0E-5	9.9E-7
	Adult	3.1E-4	5.0E-6	1.4E-4	7.7E-6	1.1E-6	2.0E-5	8.3E-4	9.1E-6
S7	Child	4.5E-5	1.3E-6	1.3E-5	7.9E-7	2.0E-7	1.3E-6	1.7E-4	1.5E-6
	Adult	4.2E-4	1.2E-5	1.2E-4	7.3E-6	1.8E-6	1.2E-5	1.5E-3	1.4E-5
S8	Child	4.8E-5	4.8E-7	1.3E-5	8.0E-7	1.8E-7	2.3E-6	1.5E-4	1.1E-6
	Adult	4.4E-4	4.4E-6	1.2E-4	7.3E-6	1.7E-6	2.1E-5	1.4E-3	1.0E-5
S9	Child	4.5E-5	7.3E-7	1.3E-5	7.7E-7	3.1E-7	1.5E-6	1.6E-4	1.4E-6
	Adult	4.2E-4	6.7E-6	1.2E-4	7.1E-6	2.8E-6	1.4E-5	1.5E-3	1.3E-5
S1	Child	4.3E-5	8.6E-7	1.7E-5	1.1E-6	5.3E-7	1.9E-6	1.7E-4	1.5E-6
	Adult	4.0E-4	7.9E-6	1.6E-4	1.0E-5	4.8E-6	1.7E-5	1.6E-3	1.4E-5

Table 4.42: Dermal exposure to soil material in wet season

Sites	Age group	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Child	5.0E-5	1.0E-6	1.4E-5	9.4E-7	3.6E-7	2.E-6	1.6E-4	1.7E-6
	Adult	4.6E-4	9.4E-6	1.3E-4	8.7E-6	3.4E-6	1.8E-5	1.5E-3	1.5E-5
S2	Child	3.3E-5	6.8E-7	2.2E-5	1.1E-6	1.2E-7	2.4E-6	1.0E-4	1.1E-6
	Adult	3.0E-4	6.3E-6	2.1E-4	9.9E-6	1.1E-6	2.2E-5	9.6E-4	1.0E-5
S3	Child	4.0E-5	7.2E-7	1.4E-5	7.5E-7	1.3E-7	1.9E-6	1.0E-4	1.2E-6
	Adult	3.6E-4	6.7E-6	1.3E-4	6.9E-6	1.2E-6	1.7E-5	9.2E-4	1.1E-5
S4	Child	2.4E-5	3.9E-7	1.2E-5	8.2E-7	7.5E-8	1.7E-6	5.9E-5	7.3E-7
	Adult	2.2E-4	3.6E-6	1.1E-4	7.5E-6	6.9E-7	1.6E-5	5.4E-4	6.7E-6
S5	Child	3.1E-5	5.8E-7	1.3E-5	9.5E-7	7.5E-8	2.0E-6	8.1E-5	8.5E-7
	Adult	2.8E-4	5.3E-6	1.2E-4	8.7E-6	6.9E-7	1.8E-5	7.4E-4	7.9E-6
S6	Child	3.5E-5	7.0E-7	1.2E-5	6.4E-7	1.2E-7	1.5E-6	9.8E-5	1.3E-6
	Adult	3.2E-4	6.4E-6	1.1E-4	5.9E-6	1.1E-6	1.3E-5	9.0E-4	1.2E-5
S7	Child	4.4E-5	8.3E-7	1.3E-5	1.0E-6	2.0E-7	1.4E-6	1.2E-4	1.4E-6
	Adult	4.0E-4	7.6E-6	1.2E-4	9.2E-6	1.8E-6	1.3E-5	1.1E-3	1.3E-5
S8	Child	4.9E-5	4.9E-7	1.2E-5	6.9E-7	1.8E-7	2.3E-6	1.5E-4	1.1E-6
	Adult	4.5E-4	4.5E-6	1.1E-4	6.3E-6	1.7E-6	2.1E-5	1.3E-3	1.0E-5
S9	Child	4.6E-5	7.2E-7	1.2E-5	6.5E-7	3.1E-7	1.4E-6	8.2E-5	1.3E-6
	Adult	4.2E-4	6.6E-6	1.1E-4	6.0E-6	2.8E-6	1.3E-5	7.6E-4	1.2E-5
S10	Child	4.2E-5	7.7E-7	1.7E-5	9.2E-7	5.3E-7	2.9E-6	1.0E-4	1.6E-6
	Adult	3.8E-4	7.0E-6	1.6E-4	8.4E-6	4.8E-6	2.7E-5	9.3E-4	1.5E-5

c) Total hazard quotient per element

The total hazard quotients per element (THQ), which represent the sum of HQ values from the different exposure routes for each element are presented in Table 4.43-4.44. The values of THQ are lower than one, suggesting that there are no significant non-carcinogenic health effects per element. As evident from HQ_k values, the highest values of THQ per elements are recorded with As. In addition, the values of THQ are higher for children compared to adults and higher in dry season compared to wet season.

Table 4.43: Total hazard quotient per element in dry season

Sites		AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Children	1.7E-1	6.4E-2	1.7E-4	8.1E-2	3.2E-2	1.3E-2	8.7E-2	5.3E-2
	Adults	1.1E-1	4.3E-2	2.5E-4	5.5E-2	2.1E-2	8.4E-3	5.8E-2	3.6E-2
S2	Children	1.7E-1	6.6E-2	2.7E-4	6.5E-2	1.4E-2	1.2E-2	3.9E-1	5.3E-2
	Adult	1.1E-1	4.5E-2	4.0E-4	4.4E-2	1.3E-2	7.8E-3	2.6E-1	3.6E-2
S3	Children	1.1E-1	5.9E-2	1.7E-4	7.1E-2	2.3E-2	1.1E-2	5.4E-2	3.9E-2
	Adult	7.4E-2	4.0E-2	2.5E-4	4.8E-2	1.8E-2	6.9E-3	3.5E-2	2.7E-2
S4	Children	1.0E-1	6.1E-2	1.2E-4	2.5E-2	2.6E-2	1.6E-2	1.6E-2	3.9E-2
	Adult	6.5E-2	4.1E-2	2.1E-4	1.7E-2	1.8E-2	1.1E-2	1.0E-2	2.7E-2
S5	Children	2.3E-1	7.2E-2	1.4E-4	2.9E-2	1.9E-2	1.1E-2	1.9E-2	5.1E-2
	Adult	1.5E-1	4.9E-2	2.8E-4	2.0E-2	1.2E-2	7.1E-3	1.1E-2	3.5E-2
S6	Children	1.1E-1	5.5E-2	1.3E-4	3.5E-2	1.2E-2	2.1E-2	4.7E-2	5.0E-2
	Adult	7.1E-2	3.8E-2	2.3E-4	2.4E-2	9.1E-3	1.4E-2	3.1E-2	3.4E-2
S7	Children	1.8E-1	7.2E-2	2.5E-4	4.6E-2	2.8E-2	3.0E-2	9.0E-2	9.0E-2
	Adult	1.1E-1	4.9E-2	2.9E-4	3.1E-2	1.6E-2	2.0E-2	5.9E-2	6.1E-2
S8	Children	1.2E-1	3.6E-2	1.7E-4	1.1E-1	1.4E-2	8.1E-3	7.0E-2	4.6E-2
	Adult	7.8E-2	2.5E-2	2.4E-4	7.5E-2	1.0E-2	5.2E-3	4.6E-2	3.1E-2
S9	Children	1.1E-1	1.2E-1	1.1E-4	2.9E-2	1.5E-2	1.0E-2	2.1E-2	7.4E-2
	Adult	7.0E-2	8.0E-2	2.0E-4	1.9E-2	1.0E-2	6.7E-3	1.2E-2	5.0E-2
S10	Children	2.6E-1	7.9E-2	2.3E-4	2.6E-1	7.2E-2	1.3E-2	2.3E-1	6.8E-2
	Adult	1.7E-1	5.4E-2	3.1E-4	1.7E-1	5.4E-2	8.9E-3	1.5E-1	4.6E-2

Table 4.44: Total Hazard Quotient per element in wet season

Sites	Age group	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Child	1.2E-1	9.2E-2	1.3E-4	3.3E-2	1.2E-2	8.7E-3	2.4E-2	4.8E-2
	Adult	7.7E-2	6.2E-2	2.2E-4	2.2E-2	7.8E-3	5.6E-3	1.4E-2	3.3E-2
S2	Child	1.4E-1	4.4E-2	1.6E-4	3.0E-2	8.2E-3	1.6E-2	2.8E-2	4.8E-2
	Adult	9.3E-2	3.0E-2	3.2E-4	2.0E-2	5.6E-3	1.1E-2	1.7E-2	3.2E-2
S3	Child	8.5E-2	3.1E-2	9.4E-5	2.4E-2	6.7E-3	1.5E-2	1.8E-2	3.9E-2
	Adult	5.2E-2	2.1E-2	1.9E-4	1.7E-2	4.6E-3	9.7E-3	1.1E-2	2.6E-2
S4	Child	1.3E-1	6.4E-2	5.6E-5	5.1E-2	1.6E-2	2.6E-2	7.0E-3	6.3E-2
	Adult	8.9E-2	4.3E-2	1.5E-4	3.5E-2	1.1E-2	1.8E-2	4.0E-3	4.2E-2
S5	Child	6.5E-2	6.1E-2	7.3E-5	4.4E-2	1.3E-2	2.2E-2	9.0E-3	5.9E-2
	Adult	4.0E-2	4.1E-2	1.7E-4	2.9E-2	8.8E-3	1.5E-2	5.1E-3	4.0E-2
S6	Child	5.2E-2	5.8E-2	6.2E-5	2.7E-2	1.4E-2	1.1E-2	1.1E-2	4.3E-2
	Adult	3.1E-2	4.0E-2	1.5E-4	1.8E-2	9.3E-3	7.2E-3	6.4E-3	2.9E-2
S7	Child	1.5E-1	3.8E-2	1.7E-4	4.0E-2	1.3E-2	6.3E-3	3.4E-2	8.9E-2
	Adult	9.3E-2	2.5E-2	2.4E-4	2.7E-2	8.6E-3	4.1E-3	2.2E-2	6.1E-2
S8	Child	8.5E-2	3.2E-2	9.5E-5	2.2E-2	1.0E-2	4.6E-3	1.3E-2	2.5E-2
	Adult	5.2E-2	2.2E-2	1.8E-4	1.5E-2	6.9E-3	2.8E-3	7.2E-3	1.7E-2
S9	Child	9.3E-2	6.4E-2	9.4E-5	3.1E-2	1.8E-2	6.4E-3	2.0E-2	6.6E-2
	Adult	5.7E-2	4.3E-2	1.8E-4	2.1E-2	1.2E-2	4.2E-3	1.3E-2	4.5E-2
S10	Child	1.9E-1	8.9E-2	2.6E-4	8.6E-2	1.2E-2	5.3E-3	2.1E-2	5.6E-2
	Adult	1.3E-1	6.1E-2	3.3E-4	5.9E-2	7.8E-3	3.2E-3	1.3E-2	3.8E-2

d) Hazard Index

Figure 4.17 presents the hazard index (HI), that is the overall non-carcinogenic risks, estimated considering all the metals elements analysed. The values of HI for all the sites are less than one ($HI < 1$), indicating no significant non-carcinogenic risk. The highest values of HI are recorded from the sites S1 (0.50 and 0.33), S2 (0.77 and 0.52), S7 (0.53 and 0.35) and S10 (0.97 and 0.66) for dry season and S7 (0.37 and 0.24) and S10 (0.46 and 0.31) for wet season. The values of HI are higher in dry season compared to wet season and higher for children compared to adults.

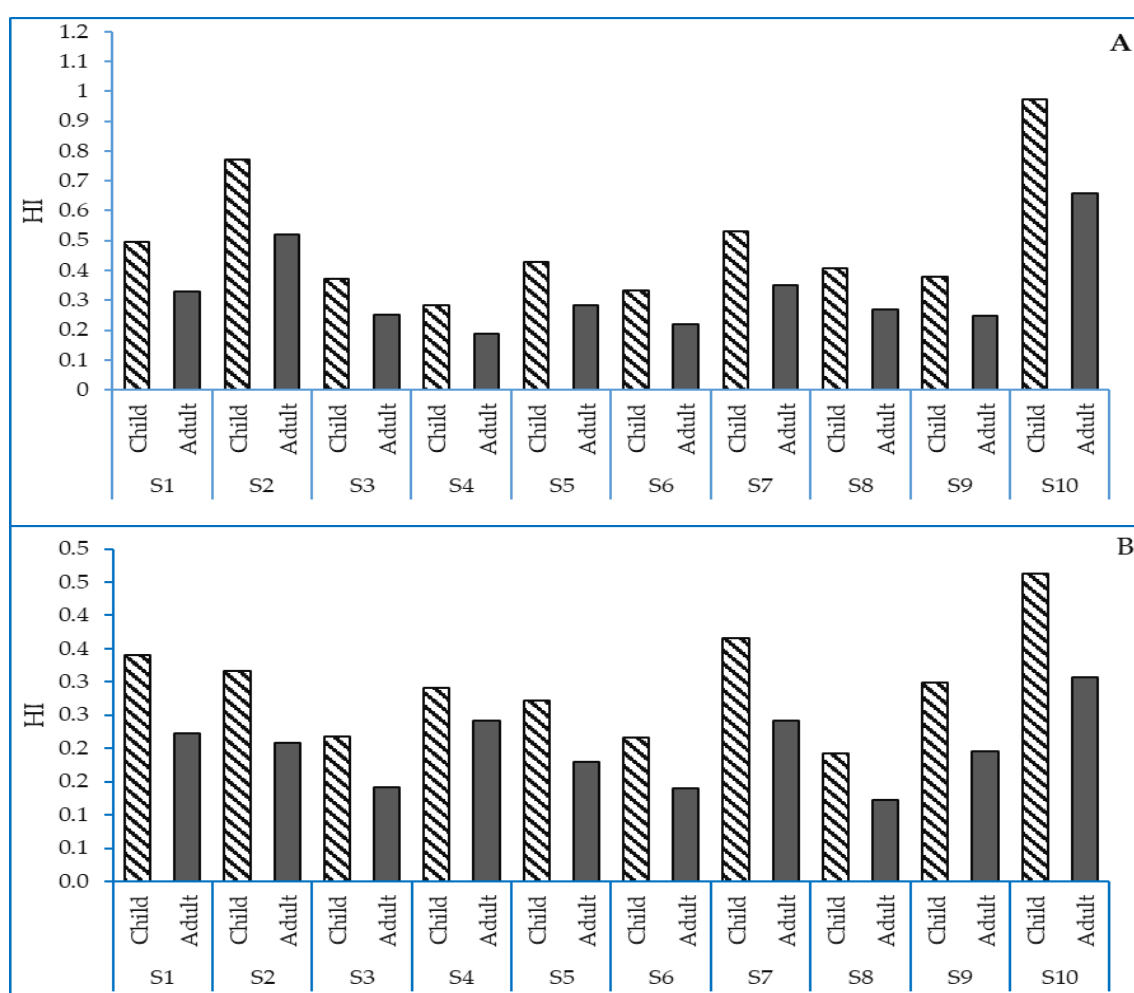


Figure 4.17: Hazard index (HI); A: dry season; B: wet season

4.4.2.2 Carcinogenic Health Risk

a) Carcinogenic Health Risk per element

The carcinogenic risk for single element (CR) and the total carcinogenic risk (TCR) computed for the carcinogens As, Cd, Cr and Pb for children and adults, considering dry season and wet are shown in Table 4.45-4.46 and Fig. 4.18. The values of CR for all the elements are below the threshold of 10^{-4} for children and adults during and the two seasons. The values of CR for adults are higher compared to that of children because of their higher exposure time, which in this study is the lifetime in Kenya (66.7 years). The values of CR for the different carcinogens are higher in dry season compared to wet season, which is primarily due to lower uptake of heavy metals and trace elements in kale in wet season compared to dry season. The extent of carcinogenic risk is prominently led by Cr and As and the values of CR are in the order $Cr > As > Pb > Cd$.

Table 4.45: Carcinogenic risk dry season

Sites	Age group	AS	Cd	Cr	Pb
S1	Child	1.9E-05	1.3E-11	2.5E-05	6.7E-07
	Adult	4.7E-05	6.2E-11	6.1E-05	1.7E-06
S2	Child	2.0E-05	1.0E-11	3.8E-05	3.1E-06
	Adult	5.0E-05	4.7E-11	9.4E-05	7.8E-06
S3	Child	1.3E-05	8.6E-12	2.5E-05	4.1E-07
	Adult	3.3E-05	4.1E-11	6.2E-05	1.0E-06
S4	Child	1.2E-05	6.5E-12	1.4E-05	1.1E-07
	Adult	2.9E-05	3.1E-11	3.4E-05	2.7E-07
S5	Child	2.7E-05	1.4E-11	1.4E-05	1.1E-07
	Adult	6.6E-05	6.5E-11	3.4E-05	2.4E-07
S6	Child	1.3E-05	8.7E-12	1.6E-05	3.6E-07
	Adult	3.1E-05	4.2E-11	4.0E-05	8.8E-07
S7	Child	2.0E-05	2.1E-11	4.2E-05	6.8E-07
	Adult	5.1E-05	1.0E-10	1.0E-04	1.7E-06
S8	Child	1.4E-05	7.8E-12	2.4E-05	5.3E-07
	Adult	3.4E-05	3.7E-11	6.0E-05	1.3E-06
S9	Child	1.3E-05	1.2E-11	1.3E-05	1.3E-07
	Adult	3.1E-05	5.6E-11	3.1E-05	2.8E-07
S10	Child	3.0E-05	1.4E-11	3.4E-05	1.8E-06
	Adult	7.5E-05	6.6E-11	8.5E-05	4.5E-06

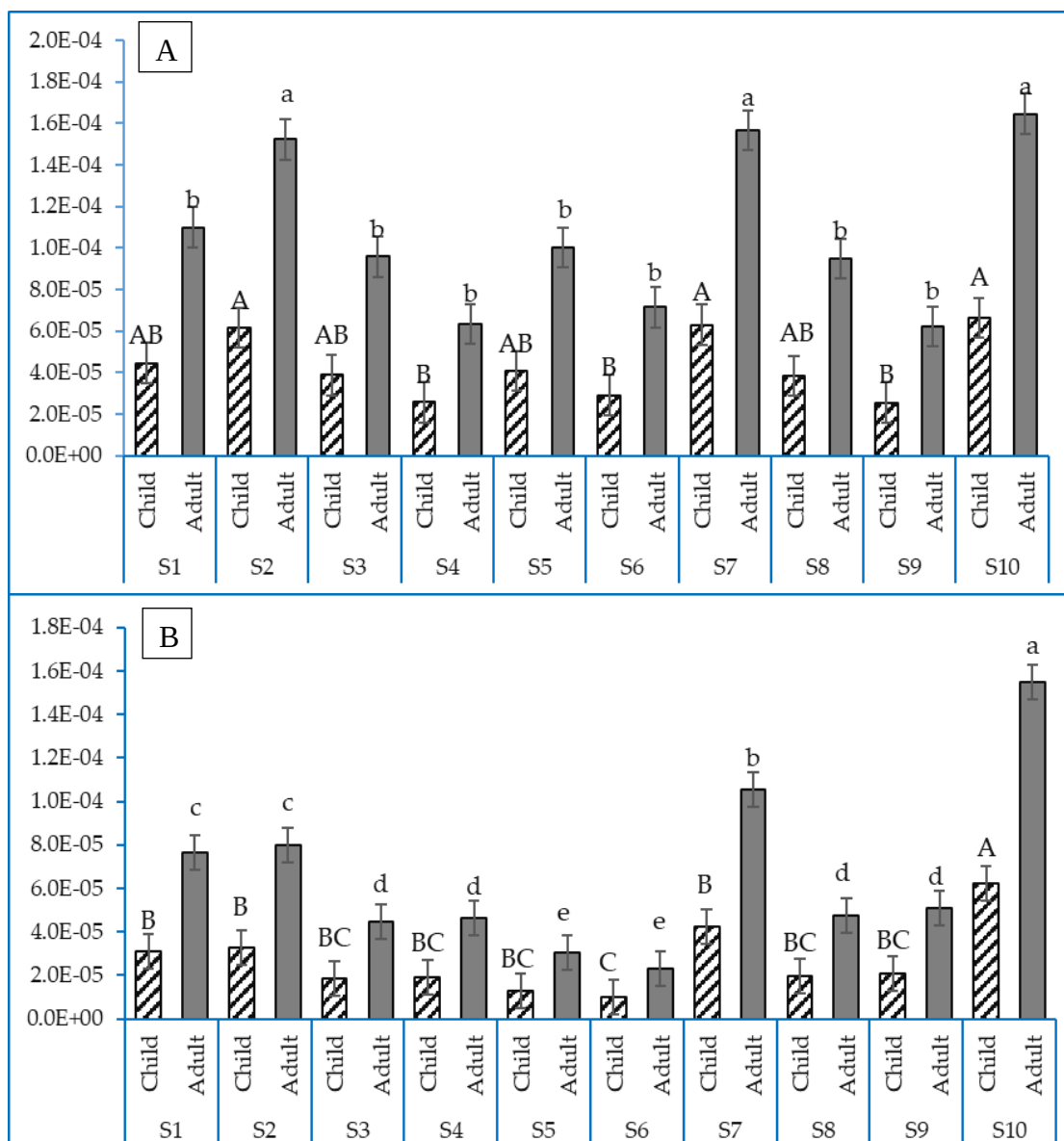
Table 4.46: Carcinogenic risk wet season

Sites	Age group	As	Cd	Cr	Pb
S1	Child	1.4E-5	1.7E-11	1.7E-5	1.5E-7
	Adult	3.4E-5	7.9E-11	4.2E-5	3.5E-7
S2	Child	1.7E-5	1.1E-11	1.6E-5	1.9E-7
	Adult	4.1E-5	5.3E-11	3.8E-5	4.7E-7
S3	Child	9.3E-6	1.2E-11	9.0E-6	1.2E-7
	Adult	2.3E-5	5.6E-11	2.2E-5	2.9E-7
S4	Child	1.6E-5	6.3E-12	3.0E-6	4.1E-8
	Adult	3.9E-5	3.0E-11	6.7E-6	9.1E-8
S5	Child	7.2E-6	9.4E-12	5.4E-6	5.1E-8
	Adult	1.7E-5	4.4E-11	1.3E-5	1.1E-7
S6	Child	5.5E-6	1.1E-11	4.2E-6	6.5E-8
	Adult	1.3E-5	5.3E-11	9.9E-6	1.4E-7
S7	Child	1.7E-5	1.3E-11	2.6E-5	2.4E-7
	Adult	4.1E-5	6.4E-11	6.4E-5	5.9E-7
S8	Child	9.2E-6	7.8E-12	1.0E-5	7.0E-8
	Adult	2.2E-5	3.7E-11	2.5E-5	1.5E-7
S9	Child	1.0E-5	1.2E-11	1.1E-5	1.4E-7
	Adult	2.5E-5	5.6E-11	2.6E-5	3.4E-7
S10	Child	2.2E-5	1.2E-11	4.0E-5	1.5E-7
	Adult	5.5E-5	5.9E-11	9.9E-5	3.5E-7

b) Total Carcinogenic Risk

The total carcinogenic risks (TCR) which combine the four carcinogens As, Cd, Cr and Pb are 2.55×10^{-5} - 6.63×10^{-5} and 6.23×10^{-5} - 1.65×10^{-4} for children and adults, respectively during dry season and 9.82×10^{-6} - 6.23×10^{-5} and 2.32×10^{-5} - 1.55×10^{-4} for children and adults, respectively during wet season (Fig. 4.18). As evident from the values of CR, the values of TCR values are significantly higher in dry season compared to wet season and higher for adults compared to children. The values of TCR for children in dry season are below the threshold of 10^{-4} , indicating no significant risk for children, but for adults the sites S1 (1.10×10^{-4}), S2 (1.52×10^{-4}), S5 (1.01×10^{-4}), S7 (1.57×10^{-4}) and S10 (1.65×10^{-4}), representing 50% of the samples exhibited significant carcinogenic health risks ($\text{TCR} > 10^{-4}$). For dry season, the sites considering the values of TCR are in the decreasing order $\text{S10} > \text{S7} > \text{S2} > \text{S1} > \text{S5} > \text{S3} > \text{S8} > \text{S6} > \text{S4} > \text{S9}$.

For wet season, the values of TCR indicate no significant risk for children for all the stations, however, for adults the sites S7 (1.05×10^{-4}) and S10 (1.55×10^{-4}), representing 20% of the samples, exhibit significant carcinogenic risks. Considering the total level of carcinogenic risk (TCR) risk during wet season the sites are in the decreasing order $S10 > S7 > S2 > S1 > S9 > S8 > S4 > S3 > S5 > S6$.



Histograms that do not share the same alphabetic letter are not significantly different (Tukey's HSD test $p < 0.05$), means comparisons in capital are for children age group while lower letters are for adult age group

Figure 4.18: Total carcinogenic risk; A: dry season; B: wet season

4.4.3 Discussion

4.4.3.1 Potential Ecological Risk

Heavy metals and trace elements contamination in the farmlands show significant ecological risks, implying serious threat to environmental sustainability and human health. The elements As, Cd, Hg and Pb have the highest single metal ecological risk (E_r^i) with Cd and As holding the highest contribution to the cumulative ecological risk (57.1 % and 16.6%). The level of ecological risk observed for each element reflect its spatial distribution pattern across the catchment, with the hotspot sampling sites exhibiting the highest ecological risks. This is consistent with Lv et al. (2022) who concluded that the spatial distribution provides an important basis for contaminated sites remediation and ecological risk management. The single ecological risk observed in this study are higher compared to those reported in previous studies conducted in urban and peri-urban areas in Kenya (Mungai & Wang, 2019; Ndungu et al., 2019; Olando et al., 2020). Nonetheless, our findings are consistent with and add to those of Ndungu et al. (2019), Mungai & Wang (2019), and Olando et al. (2020), who pointed out the high risk of Hg and Cd in and around Nairobi city soils.

The lowest Cd risk factor at S4 could be attributed to decantation and lateral dismissal of particles along river flows, which can naturally make highly polluted stream water less harmful as it flows downstream (Wichelns & Drechsel, 2011). However, the river receives wastewater treatment plant effluent at S5 and becomes more contaminated, hence the higher Cd single ecological risk (Hakanson, 1980). This is clearly illustrated in the variation of the pollution load index (PLI) between the sites (Fig. 4.14), where the values of the PLI decreased with the flow of the river (S1-S4) and became higher at S5.

Despite the significant level of ecological risk exhibited of the single metal elements Cd, As, Hg and Pb, the cumulative ecological risk (*RI*), which represent the overall risk based on the eight heavy metals and trace elements by Hakanson (1980), for all the sites are classified as low ecological risk. The values of the cumulative ecological risk concealed the extent of ecological risk exhibited by the single metal risk index. Thus, an environmental compartment may be considered as having a low cumulative ecological risk, yet one or more elements may be having elevated ecological risk. Therefore, we argue that the cumulative ecological risk index is not completely efficient in evaluating the extent of ecological risk related to heavy metals and trace elements contamination.

4.4.3.2 Carcinogenic and Non-carcinogenic Health Risks

The non carcinogenic risk recorded in this study, revealed that food ingestion remains the prominent route of metal contamination risk for human. The results are consistent with previous studies (Shams et al., 2022), which concluded that the health risk related to heavy metals and traces from soil ingestion, inhalation and dermal contact are negligible. The trend in the non-carcinogenic risk observed in this study are similar to the observation of a previous study in Thika farmlands irrigated with treated wastewater in the outskirt of Nairobi (Njuguna et al., 2019).

Although, the non-cancerogenic risk from kale consumption seems low, our estimation of non-carcinogenic risk is based only on daily consumption of kale with 150 and 100 g (fresh weight) of kale for adult and children, respectively. The level of risk will rise as case the amount of kale ingested increase. In addition, in most, culture, vegetables are generally consumed with staple food, which can be cereal (maize, rice, millet or wheat), tubers (yam, Arrowroot, potato, sweet potato or cassava) or leguminous (beans,

cowpea or lentils), in a proportion vegetable-staple food about 20-80% (Mwesigye et al., 2019). Therefore, if these staple foods would have a certain intake of metal elements, the non-carcinogenic risk may become extremely higher and occasion significant health effect. This confirms the results illustrated by Mwesigye et al. (2019) who recorded significantly higher non-carcinogenic risks with various food rations including yams + beans, yams + ground nuts, yams + Amaranth, cassava + beans, cassava + ground nuts, cassava + amaranth, maize + beans, maize + ground nuts, maize + Amaranthus, sweet potatoes + beans, sweet potatoes + ground nuts, sweet potatoes + amaranth.

The results indicate significant carcinogenic risk across the farmlands with the highest cancer risk factor recorded from the sampling sites S1, S2, S5, S7 and S10. This higher risk can be explained by the source of irrigation water sources of these farmlands and aerial deposit from heavy load traffics and industrial emissions. Carcinogenic and non-carcinogenic risks are higher in dry season compared to wet season due low concentration of metals elements resulting in low uptake in plant tissue during wet season. Considering the age group, children are more vulnerable to non-carcinogenic risks, while adult are more vulnerable to carcinogenic risks. Similar results were reported Shams et al. (2022) in Iran, Mwesigye et al. (2019) in Uganda, Arora et al. (2008) in India and Ogunkunle et al. (2016) in Nigeria.

The carcinogenic risk can be amplified by factors such as genetic vulnerability, environmental conditions, quality of drinking water and type of cancer. Therefore, it is eminently important to establish intervening measures toward the alleviation of heavy metals contamination in peri-urban farmlands. The results call for efficient zoning of agricultural lands in Nairobi-Machakos interface and implicitly in metropolitan regions in developing countries for both permanent and transient agricultural lands. If a land

zoning for vegetable farming should be developed for vegetable farming in Nairobi-Machakos interface, what would be the determinant criteria to be used?

4.5 Modelling Land Suitability for Vegetable Farming in Nairobi-Machakos counties negligible

4.5.1 Land Use Land Cover Classification

The results of land use and land cover (LULC) classification based on the spectral signatures of the PlanetScope 2022 satellite imagery (PS-2022) using the multi-approach decision tree (Fig. 3.7) are presented in Fig. 4.19. Eight LULC classes, namely, sealed area, greenhouse, low vegetation cover, medium vegetation cover, thick vegetation cover, water body, quarry, bare ground, and sparse vegetation, are identified. Bare ground and sparse vegetation are the largest LULC class, with 55.9% of the area (172.5 sq.km) followed by sealed area (18.8%: 58.09 sq.km), which is a combination of all impervious land including urban settlements, industrial infrastructures, and transport infrastructures (essentially tarmacked roads). Expanded sealed areas across the study site are denser along the transport infrastructure of the town centres of Utawala north-east, Kamulu along Kangundo road northwards, and Athi river's industrial area on the south. However, sealed areas are denser in Utawala along the Eastern Bypass Highway towards north-west, in Athi River town in the south, and in Kamulu towards the north. Consistently large portions of bare ground and sparse vegetation are found away from sealed areas, where housing and settlements are scarce in the north and the central part of the study area and away from road infrastructure.

Vegetation cover, which includes shrubs and trees, herbaceous cover, and land with cultivated plants, represents about 20.6% of the area (63.55 sq.km). The stratification of vegetation cover based on its intensity exhibits a decreasing trend with vegetation

thickness with 11.5% (35.64 sq.km), 6.5% (20.1 sq.km) and 2.5% (7.81 sq.km) for low, medium, and thick vegetation cover, respectively. Quarry mining areas are in the central part of the area, isolated from sealed areas and represent 2.6% of the area (7.95 sq.km).

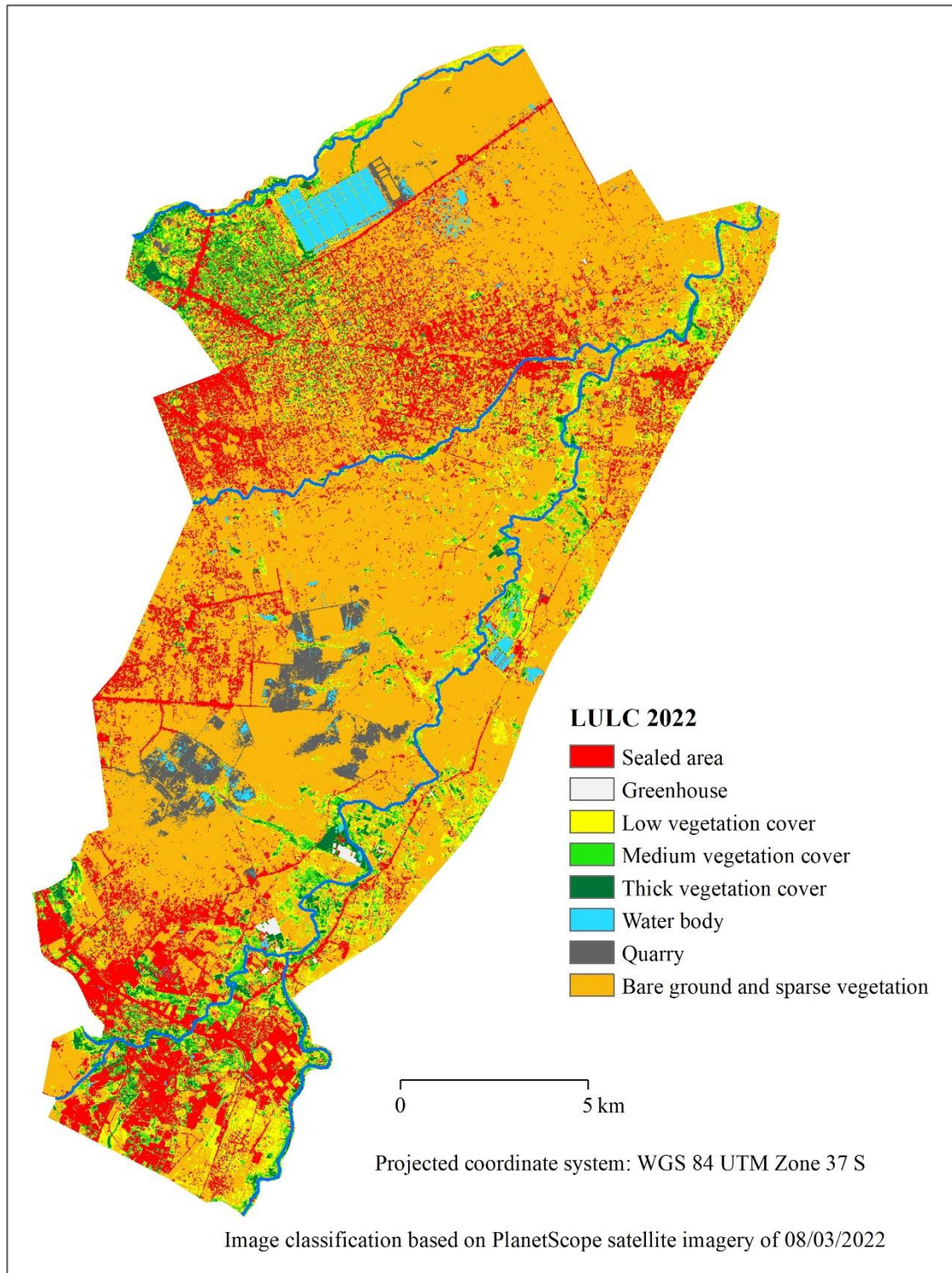


Figure 4.19: Land use land cover classification 2022

Greenhouses cover only 0.1% of the area with 0.45 sq.km, while water bodies assembling all surface water and wastewater represents 2%, *i.e.*, 6.16 sq.km. Vegetation cover appeared to be substantial along the river network. However, surprisingly, a higher portion of vegetation cover is noted in Ruai (north-west). This area is characterised by dispersed building surrounded with relatively large patches of medium to thick vegetation.

4.5.2 Accuracy Assessment

The results of accuracy assessment of land use and land cover (LULC) classification performed on PS-2022 satellite imagery (Table 4.47) showed an overall accuracy of 92.96% and a Kappa coefficient of 0.92. The User's Accuracy (UA) ranged between 83-100%, while producer's accuracy ranged between 68.18-100%. The UA of sealed area and low vegetation cover are the lowest values of UA observed (83.33% and 90%). For sealed area, the low UA is linked to the outcome of PS-2022 segmentation, which resulted in tiny and shapeless segments, thus the misclassification of bright bare ground as sealed area. For low vegetation cover, there are similarities at some place with bare ground and sparse vegetation due to poor phenological status of vegetation. Although, single class errors are observed between sealed area and bare ground and sparse vegetation; quarry and sealed area due to soil brightness, and low vegetation cover and bare ground and sparse vegetation, the overall accuracy (about 93%) indicates that the outcome of LULC classification are acceptable and reliable for the interpretation of occurring socioecological processes (Lillesand et al., 2015; Raab et al., 2018). Accuracy parameters indicate acceptable accuracy, and the LULC analysis provides more detailed land use classes compared to previous studies, which were all based on low resolution Landsat images (Mundia & Aniya, 2005; Katyambo & Ngigi, 2017; Oyugi et al., 2017).

Table 4.47: Classification accuracy assessment results for LULC of PS imagery

LULC classes	User's accuracy (%)	Producer's Accuracy (%)
Sealed area	83.33	96.15
Greenhouse	100.00	100
Low vegetation cover	90.00	96.43
Medium vegetation cover	100.00	100
Thick vegetation cover	100.00	100
Water bodies	100.00	100
Quarry	96.67	93.54
Bare ground and sparse vegetation	100.00	68.18
Overall accuracy	92.96 %	
Kappa Coefficient	0.92	

4.5.3 Spatial Arrangements of Farmland Patches

Agricultural parcel boundaries are used in land use zoning and planning, resource allocation, environmental management, regulatory compliance and enforcement, agricultural extension services, and estimation of subsidies (García-Pedrero et al., 2017). Parcel delineation helps to improve LULC classification results in earth observation applications such as farmland mapping and classification (Willkomm et al., 2019). Figures 4.20-4.21 shows the results of parcel boundaries delineation performed using the Laplacian convolution 5 x 5 on the red band (R) of the PS-2022 satellite imagery. As parcel boundaries can be complex, especially in urban areas with irregular shapes and overlapping features, the accuracy of the parcel boundaries extracted show not only boundaries and vegetation (hedges, preserved vegetation, cultivations) but also part of sealed area, characterised by similar spectral signature with the edges and vegetation. As the functions typically operate on a pixel-by-pixel basis, there are fragmentations and omissions of small edges portions leading to irregularly shaped parcels. In areas with dense vegetation (Fig. 4. 20D and 4.21 D) the vegetation in the parcel exhibits the same spectral signature with the edge vegetation resulting in a representation of large portion of the parcel as parcel boundary. Completely blank areas are areas that have been excluded because of intensive noise and interference from land

features (high density residential area), which made parcel boundaries extraction impossible for these areas (Fig. 4.22).

Despite the limitations incurred, the parcel boundaries extracted provide notorious information for determination of agriculturally used land, which could not be recognised through LULC classification (Fig. 4.20). The parcel boundaries observed in the study site have diverse geometrical shapes and dimensions, that can be classified in three principal categories. The first parcel group (patches type 1) consists of smaller parcels located in highly subdivided medium density residential areas (Fig. 4.20 C, Fig. 4.21 C), where there is substantial development of buildings and settlements interfering with parcel edges, but there is still a few vacant plots or house-backyards, in which vegetable cultivation can be carried out. The average parcel size for this parcel group is 0.065 Ha. The second group (patches type 2) illustrated in Fig. 4.20 A-B and Fig. 4.21 A-B are located in less densely settled areas compared to the first group. This parcel type is characterised by more vacant plots with significant agricultural activities or preserved vegetation and larger parcel size is 0.080 Ha in average. The third group of parcels is (patches type 3) illustrated in Fig. 4.20 D and Fig. 4.21 D and are located in area with low density settlement or areas with large agricultural land. The parcels have low subdivision with large scale farming or dense natural vegetation with an average parcel size of 1.83 Ha. It is worth emphasizing that the three parcel layout groups exhibit three spatial arrangements of the farmland ranging from smaller patches with a remarkable influence of sealed area with high population (Fig. 4.21 C) to area with larger agricultural or dense vegetation patches, without precise shape characterised by absence of building or settlements (Fig. 4.21 D). The land patches type 2 has an intermediate spatial arrangement of parcels between the land patches type 1 and 3 and is characterised by regular patches with accentuated borders.

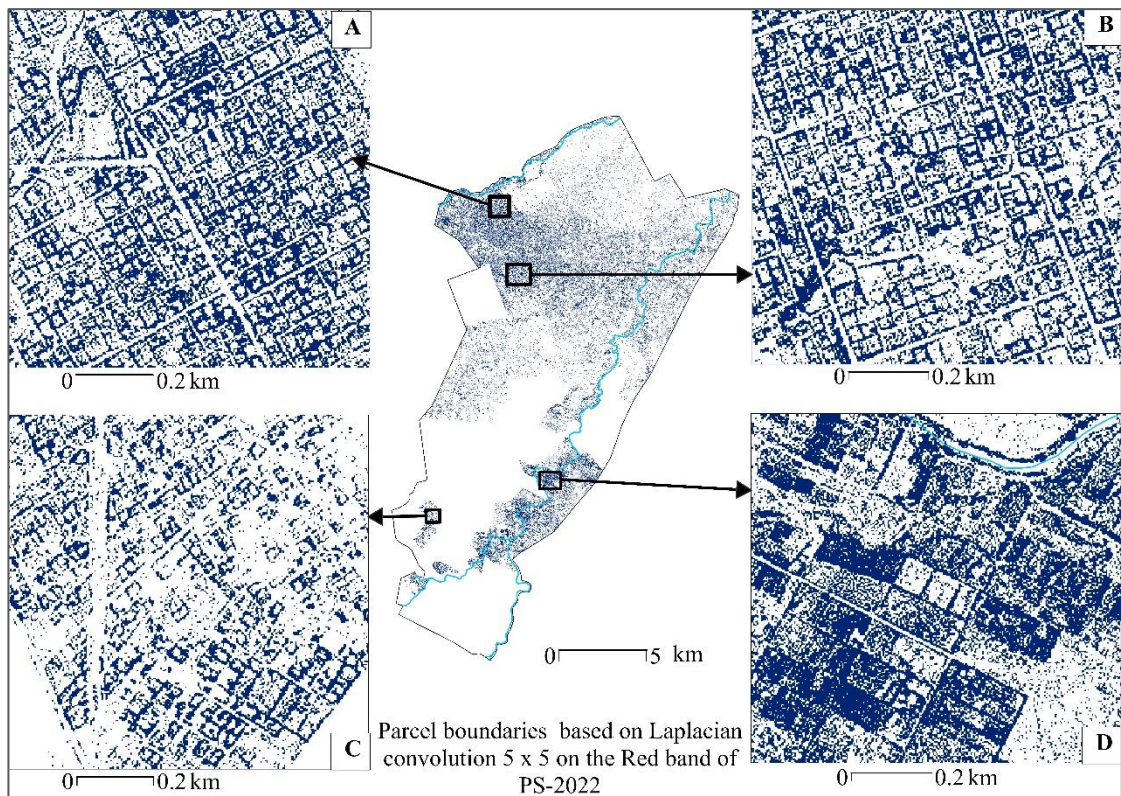


Figure 4.20: Spatial arrangement of land patches

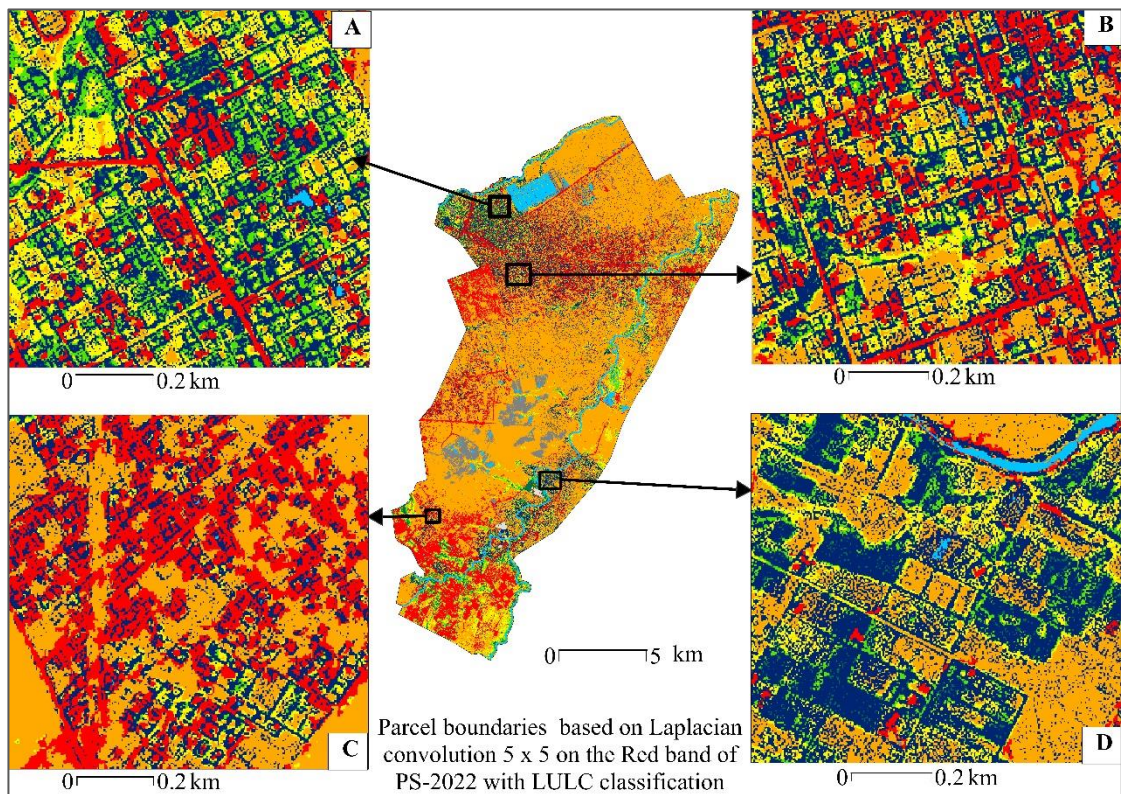


Figure 4.21: Spatial arrangement of land patches with LULC 2022 in background

Parcel boundaries allow further visual analysis of the study site and its subdivision into pertinent land use zones based on the proportion of sealed area, vegetation cover, bare ground, and water bodies.

4.5.4 Land Use Zoning

4.5.4.1 Land Use Zones 2022

The results of visual delineation of land use zones for the year 2022 based on the results of LULC classification, parcel boundaries and the field survey are displayed in Fig. 4.23 and Table 4.48). Residential area, bare ground and sparse vegetation and agricultural land hold the largest proportion of land with 35.96%, 24.69% and 23.97% of the area and 110.77, 76.15 and 74.43 sq.km, respectively. Residential area is subdivided into three subclasses considering the extent of occupation, low density residential (14.48%), medium density residential (10.98%) and high density residential (10.5%). Industrial area is 4.86% (14.98 sq.km), subdivided in light industrial (2.51%) and medium/heavy industrial (2.35%), quarry is 4.17%, while wastewater treatment plant and reserved area for wastewater treatment plant are 2.75% and 3.63%, respectively. High density residential areas are found along road infrastructures, such as the Eastern Bypass Highway along Utawala, in Kamulu along Kangundo Road and around the industries in Athi River on the south. Agricultural lands are located along the urban hydrologic flows (rivers, sewage flow and open drainage canal).

Although the approach of land use zones delineation seems to have lost details over the results of LULC classification (Fig. 4.20-4.22), it increases the level of information regarding land use because all classes in the land use zones inform on what the land is being used for (not just land cover). For example, the area used for agriculture is looking much larger than what it could have been based on LULC classification only.

Furthermore, this approach gives a more meaningful result from urban planning perspective compared to the LULC classification results. Zoning maps, consider specific designations for different land uses and incorporate information related to zoning regulations, development policies, and local regulations (land use guidelines, density requirements, setbacks, building structures, and other regulatory aspects) which are not always reflected in LULC results (Fei et al., 2017; Gao et al., 2020).

Table 4.48: Area covered by land use zones for the year 2022

Land use zone	Area in sq.km	Area in %
High density residential	32.34	10.50
Medium density residential	33.82	10.98
Low density residential	44.61	14.48
Medium/heavy industrial	7.24	2.35
Light industrial	7.74	2.51
Agricultural land	73.7	23.93
Wastewater treatment plant	8.47	2.75
Reserved for wastewater treatment	11.19	3.63
Quarry	12.83	4.17
Bare ground and sparse vegetation	76.05	24.69
Sum	308	100

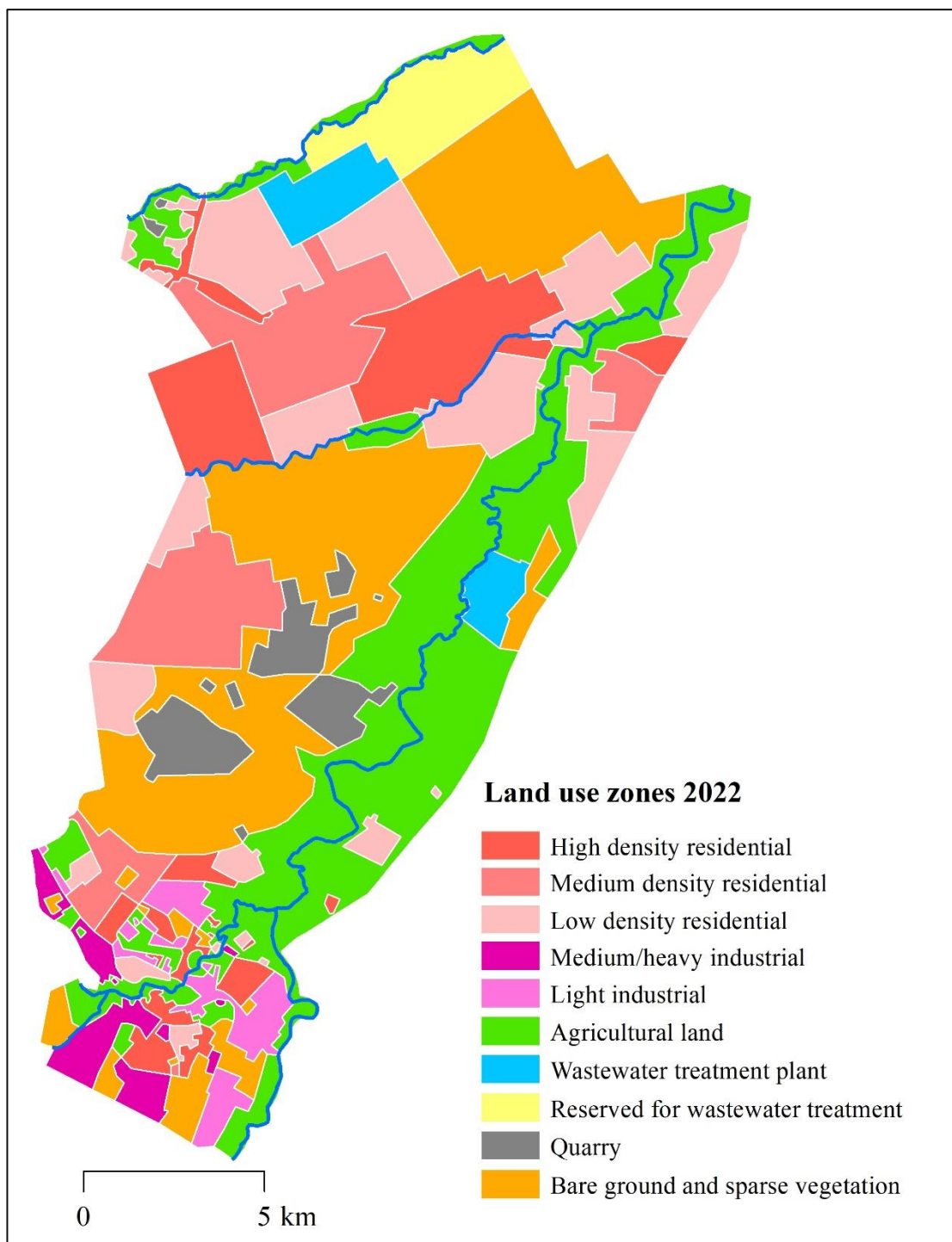


Figure 4.22: Land use zones 2022

4.5.4.2 Land Use Zones 2030

The result of land use zones adapted from the planning map 2030 (see appendix 11) of the area is presented in Table 4.49 and Fig. 4.23. The residential area is intended to

occupy 59.11% of the area (182.07 sq.km) indicating an increase of 23.15% compared to the year 2022. High density residential, medium density residential and low density residential are expected to reach 25.31% (77.96 sq.km), 15.72% (48.42 sq.km) and 18.08% (55.69 sq.km), respectively. Industrial area is expected to increase to 9.50% (29.24 sq.km) with 3.48% and 6.02% for medium/heavy industrial and light industrial area, respectively. A reduction of agricultural land is expected, however agricultural land will still have 20.78% of the area with a coverage of 64.02 sq.km. The area of wastewater treatment plant and the area reserved for wastewater treatment plant expansion remains unchanged as expected, while quarry area is to reduce slightly from 4.17 to 3.03% (12.83 to 9.33 sq.km). The riparian corridor along Nairobi River is planned to become a conservation area with a coverage of 1.20% (3.68 sq.km). The development of high-density residential area is to happen along principal road infrastructures, agricultural lands are reserved along Athi River, while the expansion of industrial settlement is to happen in Athi River Town.

Table 4.49: Land use zone for the year 2030

Land use zone 2030	Area in sq.km	Area in %
High density residential	77.96	25.31
Medium density residential	48.42	15.72
Low density residential	55.69	18.08
Medium/heavy industrial	10.71	3.48
Light industrial	18.53	6.02
Agricultural land	64.02	20.78
Wastewater treatment plant	8.47	2.75
Reserved for wastewater treatment	11.19	3.63
Quarry	9.33	3.03
Conservation and reserve	3.68	1.20
Sum	308.00	100

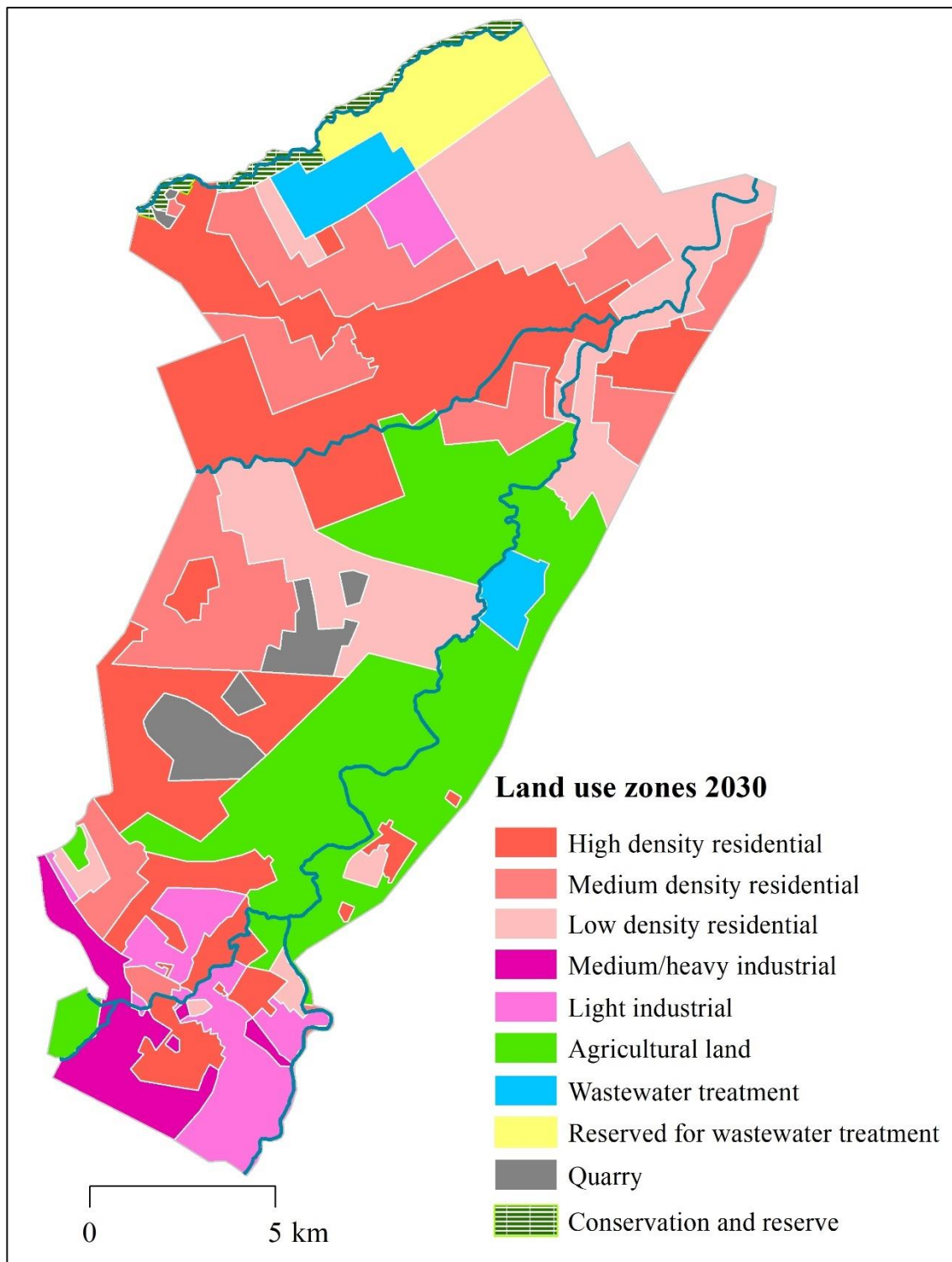


Figure 4.23: Land use zones 2030

In the land use zones 2030 there is no bare ground and sparse vegetation compared to the land use zones 2022, because all areas in the planning map have been assigned a land use. There is an expansion of agricultural land on the upper side of the EPZ-WTP

(Fig. 4.23), which although this is good for the sustainability PUA, a significant part of the area is far from water source (River flow). Therefore, maintaining such agricultural activities will need favourable options or investment for water accessibility for farmers. There is a new industrial area in the north in the land use zones 2030. This area in the 2022 land use zones is under low residential development with scattered settlement across the area. The likelihood of rearranging such an already developed area will substantially depends on land use planning policy and governance, regulations and whether the settlements on this area possess legal occupation right. The agricultural areas along the river in the north-east and the south (land use zones 2022) are going to disappear (land use zones 2030), despite that these areas are located along water sources (Athi River). This change over time seems puzzling considering the sustainability of PUA in the region.

4.5.5 Land Suitability for Vegetable Farming based on AHP-GIS Modelling

4.5.5.1 AHP Weights

Land suitability modelling for safe and sustainable vegetable farming in Nairobi-Machakos counties interface using the integrated AHP-GIS approach is based on six main criteria: land use land cover, irrigation water accessibility and quality, soil suitability, health risk, landform, and market accessibility (see Fig. 3.16 and Table 3.16).

a) Sub-criteria

The pairwise comparison matrices of the sub-criteria of each main criteria for land suitability analysis are presented in Table 4.50-4.55.

- Sub-criteria of land use

The sub-criteria land use has five alternatives, including agricultural land, bare ground and reserve area, low density residential area, medium density residential area, high density residential and light industrial area (Table 4.50). The land use zones medium/heavy industrial, quarry and wastewater treatment plant were excluded from the hierarchy constraint matrix before pairwise comparison based on expert opinion. Agricultural area has the highest weight followed by bare ground and sparse vegetation and reserved areas with 0.4425 and 0.3334, respectively, followed by low density residential (0.1268), medium density residential (0.0662) and high density residential and light industrial area (0.0310).

Table 4.50: Pairwise comparison matrix for the sub-criteria of land use

Criteria	Agricultural	Bare ground/ Reserve area	Low density residential	Medium density residential	High density residential/ Light industrial	Weights
Agricultural	1	2	5	7	9	0.44251
Bare ground/ Reserve area	0.5	1	5	7	9	0.33343
Low density residential	0.2	0.2	1	4	5	0.12679
Medium density residential	0.14	0.14	0.25	1	4	0.06622
High density residential/ Light industrial	0.11	0.11	0.2	0.25	1	0.03104

Max. eigenvalue (λ_{max}) = 5.420801; $n = 5$

Consistency index (CI) = $(\lambda_{max} - n)/(n - 1) = 0.10520$

Random index (RI) = 1.12

Consistency ratio (CR) = $CI/RI = 0.09392$

- Sub-criteria of irrigation water accessibility and quality

The main criterion irrigation water accessibility and quality has three sub-criteria irrigation water accessibility, Irrigation Water Quality Index (IWQI) and Bacterial

Contamination Index (BCI). Irrigation water accessibility has the highest influence with a weight of 0.50, while Irrigation Water Quality Index (IWQI) and Bacterial Contamination Index (BCI) have an equal weight of 0.25 (Table 4.51).

Table 4.51: Pairwise comparison matrix for the sub-criteria of irrigation water accessibility and quality

Criteria	Water accessibility	IWQI	BCI	Weights
Water accessibility	1	2	2	0.50
IWQI	0.50	1	1	0.25
MCI	0.50	1	1	0.25

IWQ: irrigation water quality; MCI: Microbial contamination index

Max. eigenvalue (λ_{max}) = 3; $n = 3$.

Consistency index (CI) = $(\lambda_{max} - n)/(n - 1) = 0$

Random index (RI) = 0.58

Consistency ratio (CR) = $CI/RI = 0$

- Sub-criteria of soil suitability

Soil suitability is based on two sub-criteria soil type and soil contamination in regard to heavy metal and trace elements, which is represented by Pollution Load Index (PLI). The pairwise comparison matrix for soil suitability (Table 4.52) shows that soil contamination in heavy metals and trace elements (PLI) is considered three times more important than the soil type (0.75 versus 0.25) by the experts.

Table 4.52: Pairwise comparison matrix for the sub-criteria of soil suitability

Criteria	PLI	Soil type	Weights
PLI	1	3	0.75
Soil type	0.33	1	0.25

PLI: pollution load index

Max. eigenvalue (λ_{max}) = 1.875; $n = 2$.

Consistency index (CI) = $(\lambda_{max} - n)/(n - 1) = -0.125$

Random index (RI) = 0.

Consistency ratio (CR) = $CI/RI = \text{Not applicable}$

- Sub-criteria of health risk

Health risk have two sub-criteria, the Total Carcinogenic Risk (TCR) and the total non-carcinogenic risk (HI). The pairwise comparison matrix for the sub-criteria of health risk (Table 4.53) reveals that the TCR is three times more prominent than the HI with a value of 0.75 versus 0.25.

Table 4.53: Pairwise comparison matrix for the sub-criteria of health risk

Criteria	TCR	HI	Weights
TCR	1	3	0.75
HI	0.33	1	0.25

HI: Hazard index; TCR: Total Carcinogenic Risk

Max. eigenvalue (λ_{max}) = 2; $n = 2$.

Consistency index (CI) = $(\lambda_{max} - n)/(n - 1) = 0$

Random index (RI) = 0

Consistency ratio (CR) = CI/RI = Not applicable

- Sub-criteria of landform

The main criterion landform has two sub-criteria: slope and elevation. The pairwise comparison matrix for these sub-criteria shows that the slope is given more importance over elevation with a weight of 0.75 versus 0.25 (Table 4.54).

Table 4.54: Pairwise comparison matrix for the sub-criteria of landform

Criteria	Slope	Elevation	Weights
Slope	1	3	0.75
Elevation	0.33	1	0.25

Max. eigenvalue (λ_{max}) = 2; $n = 2$.

Consistency index (CI) = $(\lambda_{max} - n)/(n - 1) = 0$

Random index (RI) = 0

Consistency ratio (CR) = CI/RI = Not applicable

- Sub-criteria of market accessibility

The main criterion market accessibility is evaluated through three sub-criteria: market accessibility, market proximity and road proximity, all based on distance by bird's eye

(Table 4.55). Market proximity have the highest influence (0.45), followed by road proximity (0.30) and residential area proximity (0.25).

Table 4.55: Pairwise comparison matrix for the sub-criteria of market accessibility

Criteria	Market proximity	Road proximity	Residential area proximity	Weights
Market proximity	1	1.4	2	0.45
Road proximity	0.71	1	1.11	0.30
Residential area proximity	0.5	0.9	1	0.25

Max. eigenvalue (λ_{max}) = 3.007; $n = 3$

Consistency index (CI) = $(\lambda_{max} - n)/(n - 1) = 0.00366$

Random index (RI) = 0.58

Consistency ratio (CR) = $CI/RI = 0.006$

b) Main criteria

The results of the hierarchy constraint matrix for the main criteria of land suitability analysis using the nine-point preference scale by Saaty (1994) is presented in Table 4.56. The average scores assigned to each pair of main criteria show that land use and water accessibility and quality have the highest influence on land suitability for vegetable farming with the weights of 0.3326 and 0.2954, respectively, followed by soil suitability (0.1485), health risk (0.0892), landform (0.0878) and finally market accessibility (0.0465), which has the lowest contribution.

Table 4.56: Pairwise comparison matrix for main criteria

Criteria	Land use	Water accessibility and quality	Soil suitability	Health risk	Landform	Market accessibility	Weights
Land use	1	3	5	1	7	4	0.3326
Water accessibility and quality	0.33	1	9	9	5	3	0.2954
Soil suitability	0.20	0.11	1	9	1	5	0.1485
Health risk	1	0.11	0.11	1	1	1	0.0892
Landform	0.14	0.20	1.00	1.00	1	5	0.0878
Market accessibility	0.25	0.33	0.20	1.00	0.20	1	0.0465

Max. eigenvalue (λ_{max}) = 8.43022; $n = 6$

Consistency index (CI) = $(\lambda_{max} - n)/(n - 1) = 0.06146$

Random index (RI) = 1.24

Consistency ratio (CR) = $CI/RI = 0.04956$

c) Overall and partial weights of each criterion and sub-criterion

The overall and partial weights of each criterion and sub-criterion are summarized in Table 4.57. The partial weight expresses the relative contribution of subsequent sub-criteria to their main criterion on a scale from 0 to 1, while the overall weight expresses the absolute contribution of each sub-criterion to land suitability, which reflects the influence of each sub-criteria on the final land suitability. The sub-criteria agricultural area, irrigation water accessibility, PLI, TCR, slope and market proximity exhibit the highest partial weight 0.4425, 0.5000, 0.7500, 0.7500, 0.7500 and 0.4500. Considering the overall weight, the sub-criteria, agricultural area, bare ground/reserved area, irrigation water accessibility and PLI have the highest influence on land suitability, with 0.1472, 0.1109, 0.1477 and 0.1114, respectively.

Table 4.57: Overall and partial weights of land suitability criteria and sub-criteria

Main criteria	Weight of criteria	Sub-criteria	Partial weight	Overall weight
LULC	0.3326	Agricultural	0.4425	0.1472
		Bare ground/ Reserve area	0.3334	0.1109
		Low density residential	0.1268	0.0422
		Medium density residential	0.0662	0.0220
		High density residential/ Light industrial	0.0310	0.0103
		Medium-Heavy industrial/Quarry/ WTP	NA	NA
Irrigation Water accessibility and quality	0.2954	Water accessibility	0.5000	0.1477
		IWQI	0.2500	0.0739
		BCI	0.2500	0.0739
Soil suitability	0.1485	PLI	0.7500	0.1114
		Soil type	0.2500	0.0371
Health risk	0.0892	TCR	0.7500	0.0669
		HI	0.2500	0.0223
Landform	0.0878	Slope	0.7500	0.0659
		Elevation	0.2500	0.0220
Market accessibility	0.0465	Market proximity	0.4500	0.0209
		Road proximity	0.3000	0.0140
		Residential area proximity	0.2500	0.0116

WTP: wastewater treatment plant, NA: not applicable

4.5.5.2 *Spatial AHP Analysis*

For the sub-criteria of each criterion, the hierarchical analyses results were spatially implemented and transferred in levels of suitability and used to derive for each criterion a geospatial dataset, all contributing to the land suitability evaluation.

a) Land use

The land use zones of the years 2022 (Fig.4. 22) and 2030 (Fig.4. 23) were used as input for the main criterion land use in the land suitability analysis for vegetable farming for each of the two years. The suitability of different land use types is derived based on the weighting of the land use zones from the pairwise comparison matrix for land use (Table 4.57) normalized on a scale of 0-100 shows that areas with high score for the land use criterion are located along the rivers, medium score are observed on areas located away from the settlement and river flow.

The statistics of land suitability are presented in Table 4.58. The highest ranked areas with a suitability score of 100 are 23.93% of the area (73.70 sq.km) for the year 2022 and 20.78% of the area (64.02 sq.km) for the year 2030. These areas coincide with agricultural land use, being already under seasonal or year-round cultivation. Bare ground and sparse vegetation and reserved area, which are area not under cultivation, but could be used for agricultural production have a score of 75. These areas occupy 28.32% (87.24 sq.km) in the year 2022 and 4.82% (14.86) as planned for 2030. Low density residential areas occupied 14.48% (44.61 sq.km) and 18.08% (55.69 sq.km) of the area, respectively. These areas have little anthropogenic influence and could encompass substantial agricultural production on vacant plots. Low density residential area has a suitability score of 30. Light industry areas, medium and high-density residential areas are characterised by considerable anthropogenic influence and disturbances. However, these areas could still have some space for

agriculture/gardening within the households' backyard or on vacant plots supporting the households' daily needs for vegetables or adding to their monthly income. Medium density residential area has a score value of 16, while high density residential areas and light industrial areas have a score of 7. Medium density residential area represents 10.98% (33.82 sq.km) and 15.72 (48.42 sq.km) of the area, respectively in the years 2022 and 2030. High density residential and light industrial area are 13.01% (40.08 sq.km) and 31.33% (96.5 sq.km) of the area for the years 2022 and 2030, respectively. The land uses including quarry, wastewater treatment plant (WTP) and heavy/medium industrial areas are classified as unfit for cultivation and rated with a value of 0.

Table 4.58: Area of suitability of the main criterion land use for 2022 and 2030

Suitability	2022		2030	
	Area in sq.km	Area in %	Area in sq.km	Area in %
0	28.54	9.27	28.51	9.26
7	40.08	13.01	96.5	31.33
16	33.82	10.98	48.42	15.72
30	44.61	14.48	55.69	18.08
75	87.24	28.32	14.86	4.82
100	73.70	23.93	64.02	20.78

Only a small area will have a 75 score in 2030. This low area coverage in 2030 land use zones represents a reserved area since there is no bare ground in the 2030 land use zones (Fig. 4.24). A portion of the area with the score 75, on the upper side of the EPZ-WTP in the 2022 are expected to increase to 100 score, while other area along Athi River (river) on south and north will reduce to a score of equal or less than 30. The area with a score of 100 is slightly less in 2030 compared to 2022, but there is a major increase in areas with the score of 7.

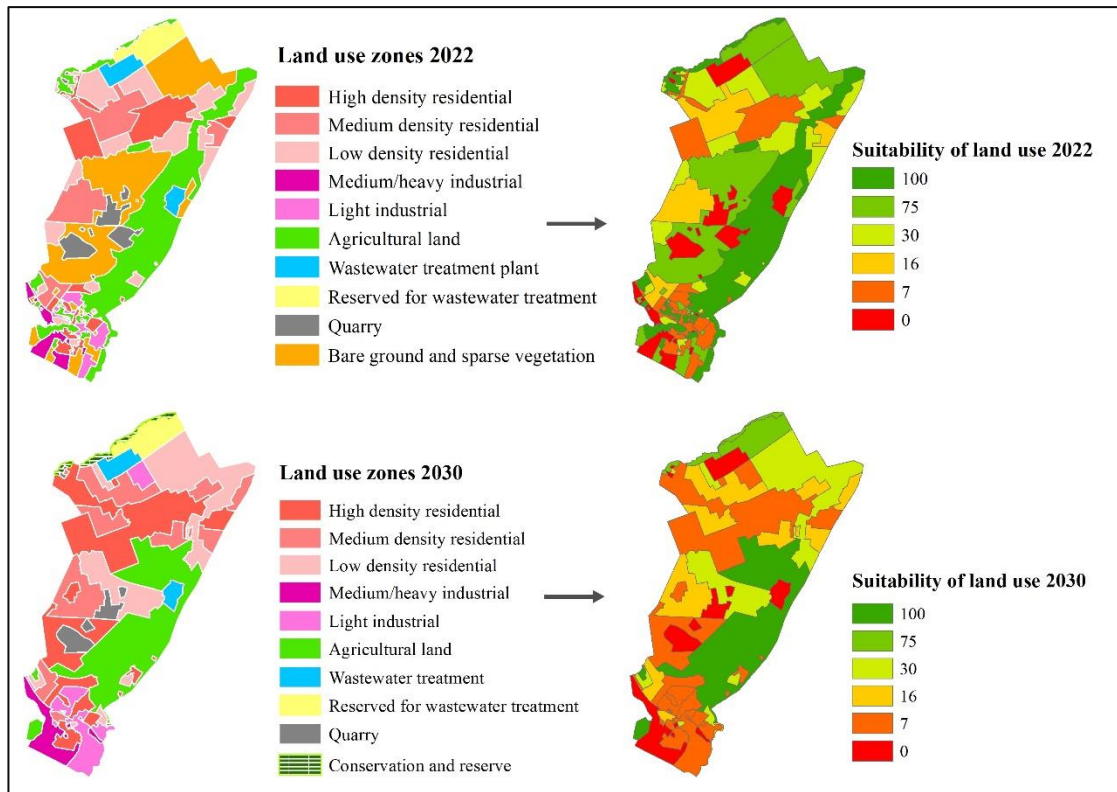


Figure 4.24: Suitability of the main criterion land use for 2022 and 2030

b) Water accessibility and quality

The layer of irrigation water accessibility and quality for land suitability analysis was prepared for dry season and wet season, based on irrigation water accessibility, Irrigation Water Quality Index (IWQI) and Bacterial Contamination Index (BCI). The evaluation of irrigation water accessibility is based on farm proximity to urban hydrological flow including rivers, sewage flow and open drainage canal. In addition, the area around Ruai towards the north-west before Ruai WTP have a particular water accessibility illustrated by year-round presence of cultivation and green vegetation, due to widespread of borehole that support year-round agricultural cultivation on vacant plots and households' backyards. Irrigation water accessibility is higher in area close urban hydrologic flows south to north, along Kangundo Road and area with high borehole edifice (Ruai) and start to become lower as the distance increases (Fig. 4.25-

26). The analysis of irrigation water accessibility revealed that 29.29% (90.30 sq.km) of the area had high accessibility to irrigation water (100), 21.50% 66.22 (sq.km) had fairly good accessibility, while 27.62% (85.08 sq.km) had poor accessibility and 21.56% (66.40 sq.km) had very poor accessibility (Table 4.59). Despite that urban hydrologic flows can encounter some light changes over time, this study assumes the current hydrologic flows (2022) for 2030, because it will be very challenging to predict such changes especially in a relatively complex urban context and a short period of 2022-2030 (Wescoat et al., 2018).

Table 4.59: Area of suitability of irrigation water accessibility

Distance in km	Area in sq.km	Area in %	Suitability
0-0.5	90.30	29.32	100
>0.5-1	66.22	21.50	75
>1-2	85.08	27.62	50
>2-3	42.06	13.66	25
>3-4	20.240	6.57	25
>4-5	4.100	1.33	25

The suitability of irrigation water based on IWQI (Fig. 4.25-26) shows that the highest scores of IWQI are found away from water sources (river, sewage flow and open drainage canal). Table 4.60 shows that 27.15% and 52.70% of the area have a suitability score of 100, respectively for dry and wet season. The area with a suitability score for IWQI of 75 represents 49.08% in dry season and 36.84% in wet season, while the area with the lowest IWQI suitability is 23.78% and 10.46% for wet season and wet season. The suitability score of IWQI is overall higher in wet season compared to dry season. This is associated with seasonal variation in water quality due to influx of significant volume of storm water in rainy season (see section 4.3.1)

Table 4.60: Area of suitability of irrigation water quality index

IWQI	Season	Area in sq.km	Area in %	Suitability
>37	Dry season	83.8	27.15	100
	Wet season	162.33	52.7	
>30-37	Dry season	151.5	49.08	75
	Wet season	113.46	36.84	
>22-30	Dry season	73.41	23.78	50
	Wet season	32.21	10.46	

IWQI: irrigation water quality index

The spatial analysis of BCI across the area shows that the lowest scores are found along water sources (river, sewage flow and open drainage canal) with about 53% and 63% of the area having a BCI suitability score of equal or less than 60 for dry and wet season, respectively (Table 4.61). The highest scores of BCI (> 60) are found away from irrigation water sources with about 47% and 37% of the area for dry and wet seasons, respectively. BCI scores are higher in dry season compared to wet season due to higher bacterial contamination in wet season compared to dry season (see section 4.3.1).

Table 4.61: Area of suitability of Bacterial Contamination Index

E. coli (cfu/100 mL)	BCI	Season	Area in sq.km	Area in %	Suitability
<100	5	Dry season	83.6	27.14	100
		Wet season	83.50	27.11	
100-500	4	Dry season	47.5	15.42	80
		Wet season	30.90	10.03	
500-2500	3	Dry season	138.3	44.90	60
		Wet season	-	-	
2500-20000	2	Dry season	38.6	12.53	40
		Wet season	193.60	62.86	

BCI: bacterial contamination index

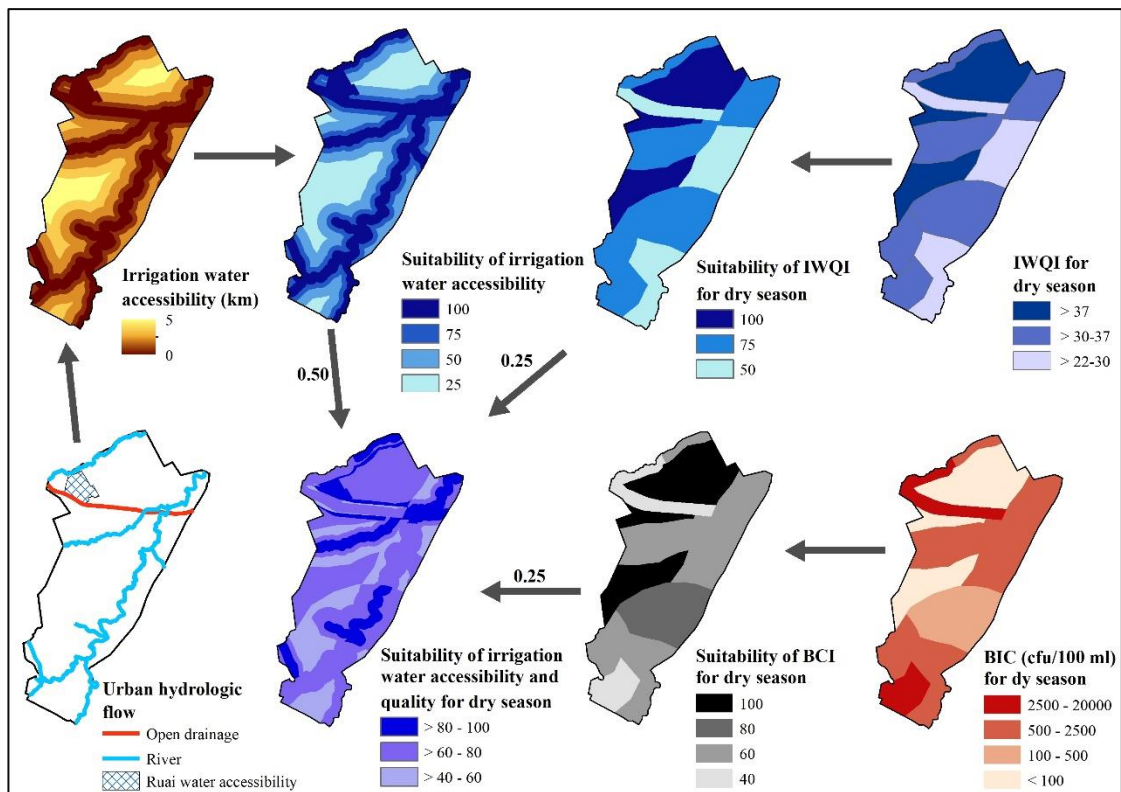


Figure 4.25: Process of deriving the final spatial distribution of irrigation water accessibility and quality for dry season

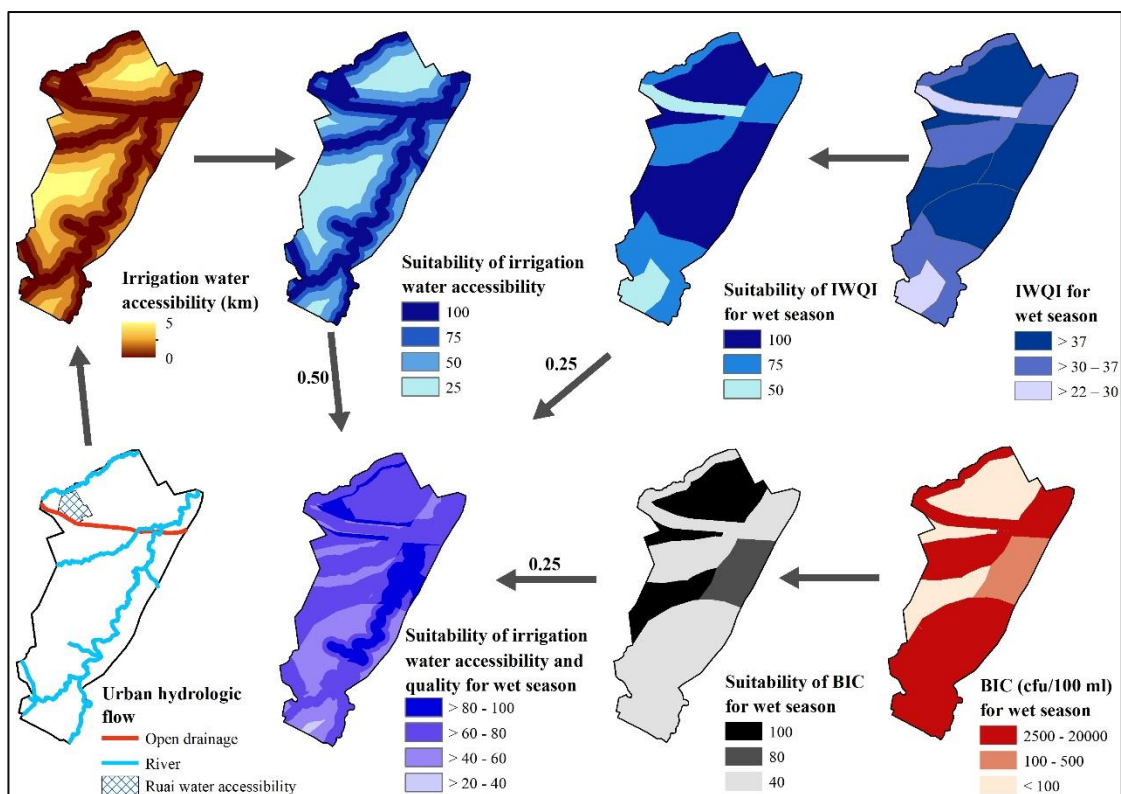


Figure 4.26: Process of deriving the final spatial distribution of irrigation water accessibility and quality for wet season

The overall suitability map for irrigation water accessibility and quality (Fig. 4.25-4.26) which aggregates the three components shows that a major part of the area has a suitability score for irrigation water accessibility and quality above 60, 78.88% (242.96 sq.km) in dry season and 75.89% (233.73 sq.km) in wet season. The areas with the lowest suitability are the area with low access to irrigation water. The patchy patterns of IWQI and BCI along the urban hydraulic flow lines explain why the levels of contamination are different following the rivers downstream (see section 4.3.1). Nevertheless, water quality variables IWQI and BCI seem to have no negative effect on the suitability of the overall suitability of the main criterion irrigation water accessibility and quality across the area. This can be explained by the weight of irrigation water accessibility (0.5) outbalancing that of irrigation water quality parameters IWQI and BCI (twice 0.25). This two-fold weight of water accessibility over water quality is underpinned by the narrative that irrigation water needs to be accessible before the assessment of its quality can be relevant. The levels of suitability observed for irrigation water accessibility and quality across the study site suggest that these areas need to be reserved for agricultural production instead of becoming more and more densely settled. However, this should work together with policy and regulations addressing urban hydrologic flow pollution in the region.

Table 4.62: Area of suitability for the main criterion irrigation water accessibility and quality

Suitability	Season	Area in sq.km	Area in %
20-40	Dry season	-	-
	Wet season	8.07	2.62
40-60	Dry season	65.04	21.12
	Wet season	66.20	21.49
60-80	Dry season	184.74	59.98
	Wet season	186.60	60.58
80-100	Dry season	58.22	18.90
	Wet season	47.13	15.30

c) Soil suitability

Soil suitability map (Fig. 4.27) was prepared from soil types and the Pollution Load Index (PLI). The soil types of the area were extracted from "*The soils of the Nairobi-Thika-Yatta- Machakos*" 1/100,000 by Scott (1963, 1985). The area of interest of this study encompasses eight soil types (see Fig. 3.3 in section 3.2). All the soil except soil 2 (stony soils with rock outcrops/Lithosols and Regosols) and soil 3 (red friable clay with laterite horizon) have medium to high nutrients and soil organic carbon contents (Scott, 1965). These soils represent 93.75% of the area and are scored with a value of 100 because they don't have limitations for agricultural production. Stony soils with rock outcrops, also called Lithosols and Regosols, are shallow soils with gravels very near the surface, light textured with high rate of infiltration, generally reddish brown in colour (Yenni et al., 2017). Cultivation is restricted on these soils because of a limited lithosphere for root development. Red friable clay with laterite horizon soils are rusty, acidic and coarse in texture, with very low nutrients and soil organic carbon contents, thus infertile for crop cultivation (Adedokun & Oluremi, 2019). However, despite their low fertility, some crops especially vegetable can be grown when the soils are irrigated and manured. In line with the limitations highlighted, stony soils with rock outcrops have a score of 25, while red friable clay with laterite horizon soils have a score of 50. These soil cover 3.59% and 2.66% of the area, respectively.

The spatial analysis of PLI using the suitability range presented in Table 4.63 exhibits scores varying between 1 and 50 only. The result shows that PLI score in the area decrease east to west, with the lowest scores recorded on the north-west along Nairobi River. About 68% (210 sq.km) of the area has a score of less or equal to 20 (Table 4.63).

Table 4.63: Area of suitability of Pollution Load Index

PLI values	Suitability	Area in Sq.km	Area in %
>1	1	12.1	3.93
>0.9-1	10	82.1	26.66
>0.8-0.9	20	115.7	37.56
>0.7-0.8	30	68.8	22.34
>0.6-0.7	40	21.83	7.09
>0.5-0.6	50	7.47	2.43

PLI: Pollution Load Index

Soil suitability combining the two sub-criteria (soil type and PLI) show that a larger portion of the area 69.22% (213.2sq.km) has a suitability score of 20-60 (Table 4.64, Fig. 4.27). The lowest soil suitability range of 0-20 is recorded at 1.25% of the area, while 27.54% has a soil suitability of 40-80 and only 1.99% a suitability of 60-100. The areas with low suitability are located around the sampling stations S1, S2, S5, S7, S8, S9 and S10 (Table 3.2 and Fig. 3.5 in section 3.2), where there is substantial heavy metals and trace elements contamination with $PLI > 0.8$ (see section 4.3.2).

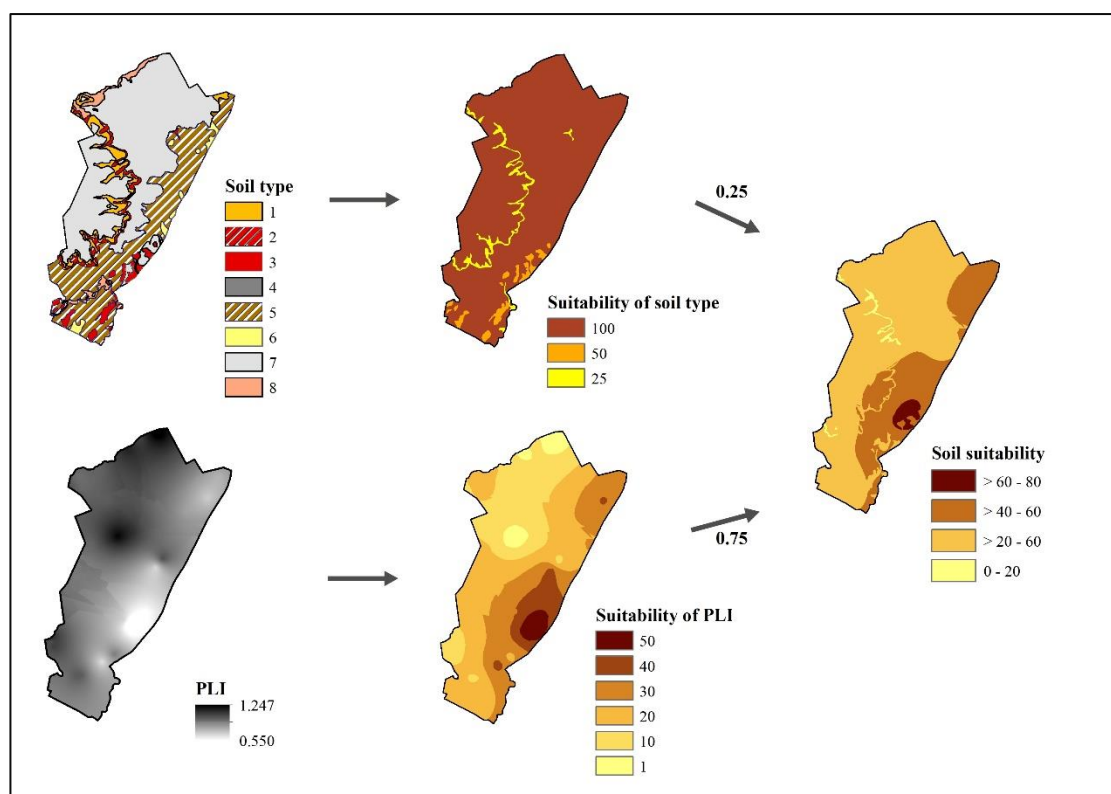


Figure 4.27: Process of deriving the final spatial distribution of Soil suitability

Table 4.64: Area of suitability for the main criterion soil suitability

Soil suitability	Area in sq.km	Area in %
0-20	3.84	1.25
> 20-40	213.2	69.22
> 40-60	84.83	27.54
> 60-80	6.13	1.99

d) Health risk

The spatial analysis of health risk is based on the total non-carcinogenic risk (Hazard Index HI) and the Total Carcinogenic Risk (TCR) using the suitability scale in Table 4.65-4.66. Since health risk variables have a seasonal variability due to different intake of heavy metals and trace elements in dry and wet season (section 4.4.2), the spatial analysis of health risk was performed separately for dry season (Fig. 4.28) and wet season (Fig. 4.29). For the non-carcinogenic risk about 70% and 100% of the area for dry season and wet season, respectively, have a suitability score equal or above 60 with different distribution within the score ranges (60-100) between dry and wet season.

Table 4.65: Area of suitability of Hazard Index

HI values ($\times 10^{-4}$)	Suitability	Season	Area in sq.km	Area in %
0.8-0.9	20	Dry season	5.54	1.80
		Wet season	-	-
0.7-0.8	30	Dry season	10.05	3.26
		Wet season	-	-
0.6-0.7	40	Dry season	35.89	11.65
		Wet season	-	-
0.5-0.6	50	Dry season	45.48	14.77
		Wet season	-	-
0.4-0.5	60	Dry season	120.54	39.14
		Wet season	11.50	3.73
0.3-0.4	70	Dry season	90.50	29.38
		Wet season	102.00	33.12
0.2-0.3	80	Dry season	-	-
		Wet season	192	62.34
0.1-0.2	90	Dry season	-	-
		Wet season	2.5	0.81

HI: Hazard Index

The spatial analysis of TCR across the area shows that land suitability regarding the Total Carcinogenic Risk range from 1-40 during dry season and 1-80 during wet season. In dry season, large proportion of the area (92%) has a suitability score of less or equal to 20, while in wet season 58.7% of the area has a suitability score of 50-80 (Table 4:66). The lowest suitability scores are recorded around the sites S1, S2, S7, S8, S9 and S10 because of their significant Total Carcinogenic Risk (Table 3.2 and Fig. 3.5). The suitability scores of both HI and TCR are higher in wet season compared to dry season because of lower values of HI and TCR in wet season compared to dry season (section 4.4.2.2).

Table 4.66: Area (% and sq.km) of suitability of Total Carcinogenic (TCR)

TCR values	Suitability	Season	Area in sq.km	Area in %
1	1	Dry season	141.69	46.00
		Wet season	26.33	8.55
10	10	Dry season	97.7	31.72
		Wet season	16.91	5.49
20	20	Dry season	44.08	14.31
		Wet season	12.89	4.19
30	30	Dry season	18.23	5.92
		Wet season	37.4	12.14
40	40	Dry season	6.3	2.05
		Wet season	33.7	10.94
50	50	Dry season	-	-
		Wet season	43.87	14.24
60	60	Dry season	-	-
		Wet season	71.5	23.21
70	70	Dry season	-	-
		Wet season	40.5	13.15
80	80	Dry season	-	-
		Wet season	24.9	8.08

TCR: Total Carcinogenic Risk

The spatial analysis of the overall health risk across the area (Table 4.67, Fig. 4.28-4.29) shows that the suitability scores of health risk vary between 0-60 for dry season, while it is up to 80 for wet season. Besides, about 98% of the area has a suitability score of health risk equal or less than 40 in dry season and about 72% exhibited a suitability equal or above 40 in wet season.

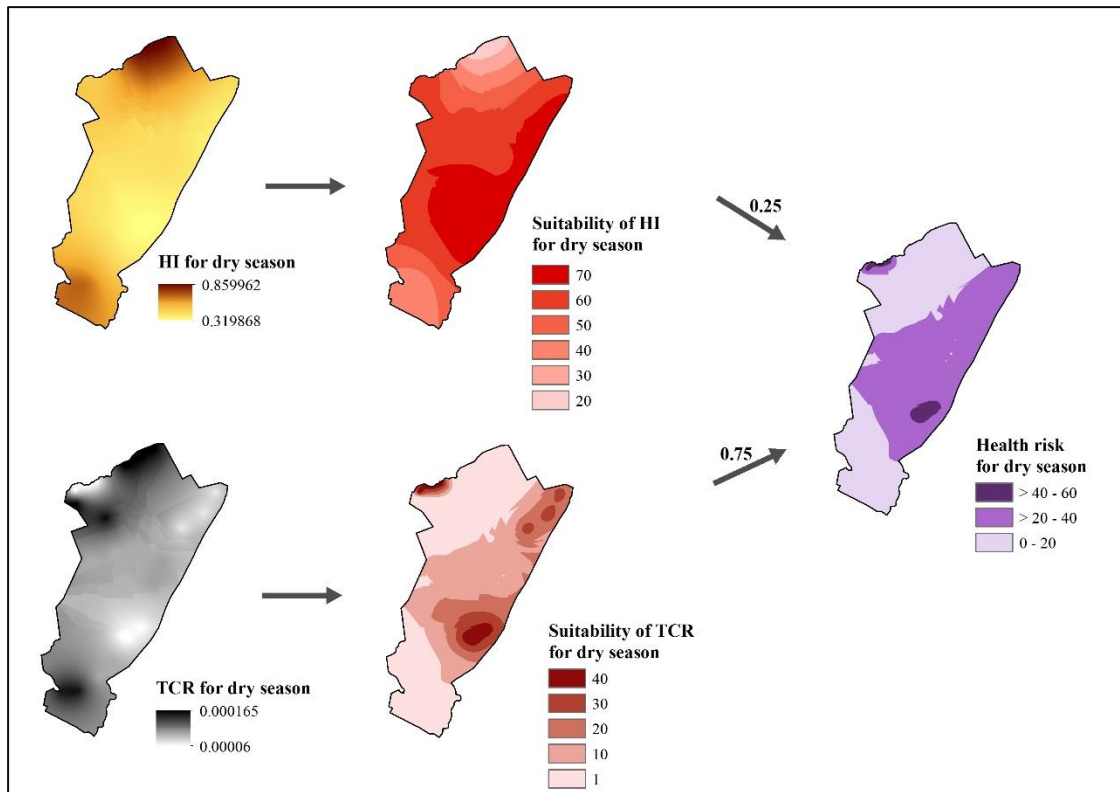


Figure 4.28: Process of deriving the final spatial distribution of health risk in dry season

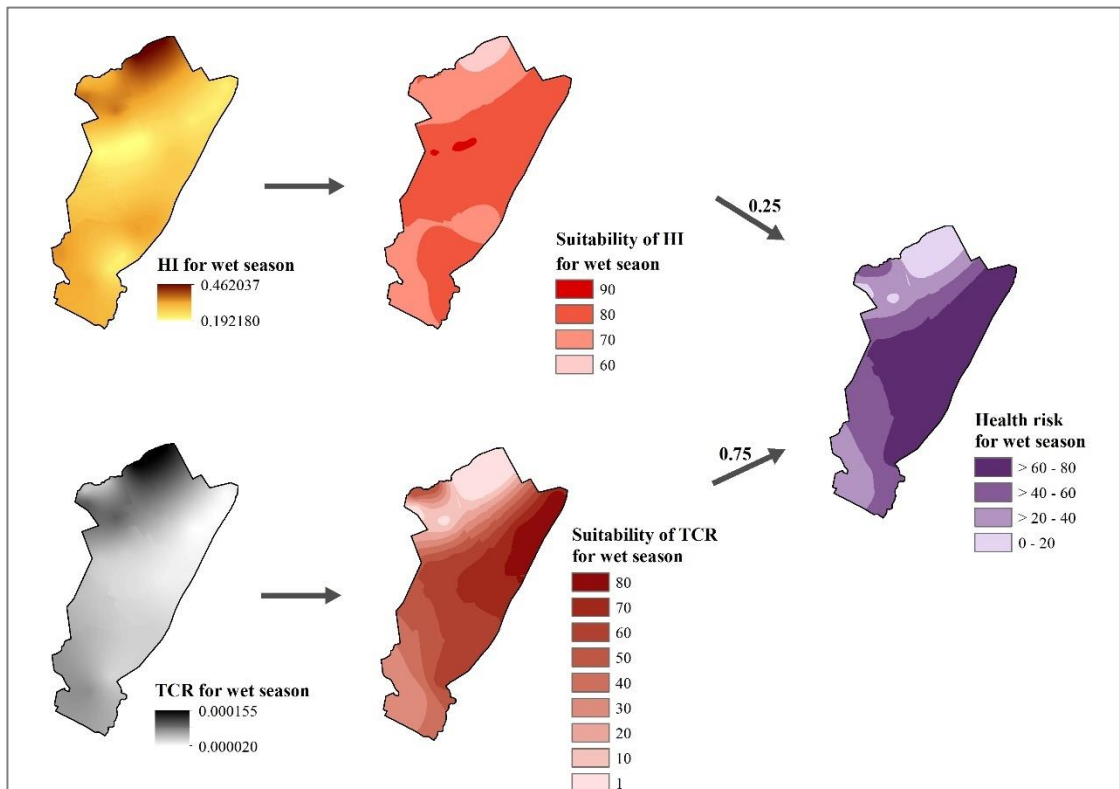


Figure 4.29: Process of deriving the final spatial distribution of health risk in wet season

The areas with the lowest suitability in regard to health risk are found on south and north-west along the sampling stations S1, S2, S7 S8 and S10 in dry season, whereas in wet season the lowest suitability is observed at S7 and S10 (Table 3.2 and Fig. 3.5), due to their higher intake of the carcinogens As, Cd, Cr and Pb in kale leaves (section 4.4.2.2). Although TCR suitability values are generally lower, due to its 3 times the weight as compared to HI, the overall result of health risk mimics the pattern of TCR, although with lesser classes.

Table 4.67: Area of suitability for the main criterion health risk

Suitability	Season	Area in sq.km	Area in %
0-20	Dry season	144.80	47.01
	Wet season	26.19	8.50
>20-40	Dry season	157.00	50.97
	Wet season	59.51	19.32
>40-60	Dry season	6.20	2.01
	Wet season	85.30	27.69
>60-80	Dry season	-	-
	Wet season	137	44.48

e) Landform

Elevation in the area varies between 1446-1614 m above sea level. The translation of the elevation into suitability results in scores of 60 and above (Table 4.68). Two third of the area has a score of 100 and the remaining split almost evenly between 80 and 60. The slope of the area ranges between 0-69.46%. The slope is classified into five classes (Table 4.68). The spatial analysis of the slope over the area (Fig. 4.30) shows that 82.30% of the area has a suitability above or equal to 60. The area with the lowest suitability of landform is located on the west of the study and demarcated by a concave structure in the hillshade south-west to north-west (Fig. 4.30). The overall pattern of landform shows a spatial pattern close to slope suitability pattern, but with higher overall scores due to elevation suitability impact.

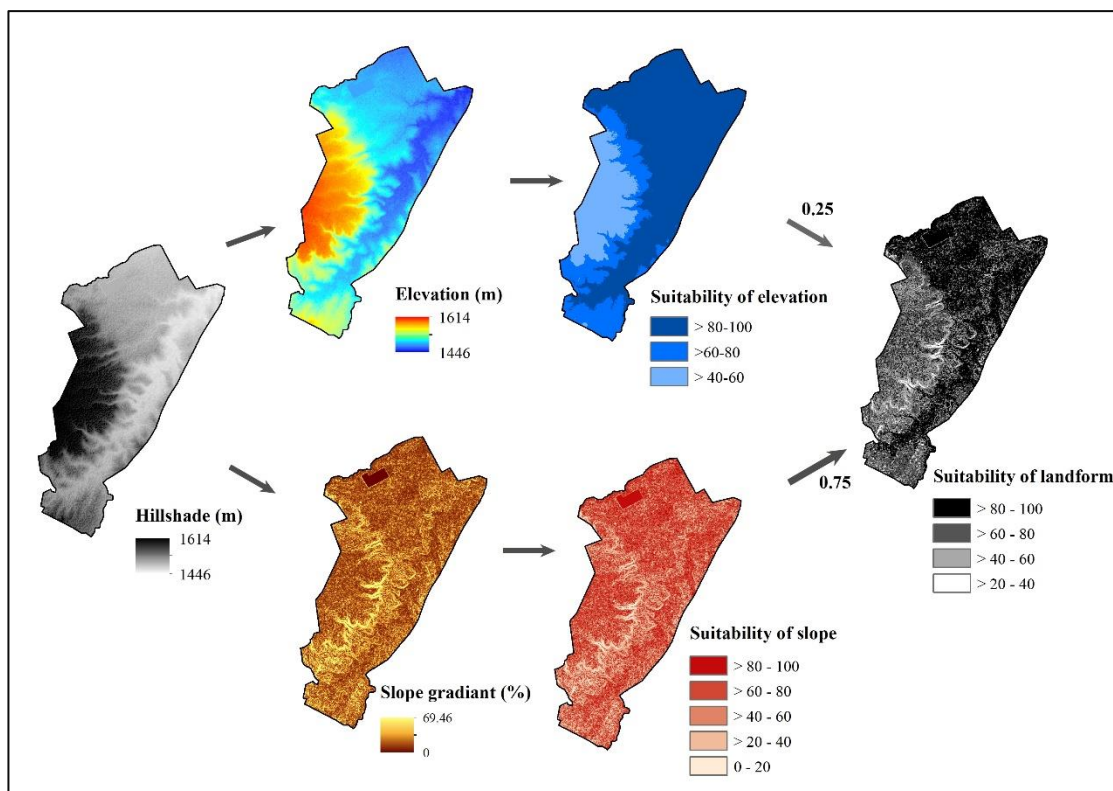


Figure 4.30: Process of deriving the final spatial distribution of landform

Table 4.68: Statistics for spatial analysis of elevation

Landform parameters	Suitability	Area in sq.km	Area in %
Elevation	60	55.90	18.15
	80	62.30	20.23
	100	189.8	61.62
slope	20	5.50	1.79
	40	49.01	15.91
	60	78.10	25.36
	80	128.78	41.81
	100	46.61	15.13
Landform	20-40	5.59	1.81
	40-60	63.11	20.49
	60-80	107.1	34.77
	80-100	132.2	42.92

f) Market accessibility

The evaluation of market accessibility is based on knowledge gathered during peri-urban farmland investigation and ground truth (section 4.2). This evaluation is focused

on the marketing of fresh product farm towards the local markets (air-open market and supermarket), which represent about 92% of the market orientation of farming units in the study site (see Table 4.1 in section 4.2.1). The marketing of fresh vegetable can be influenced by access to transport infrastructures and markets' (air-open markets, supermarkets and retailers' shops) locations (Reardon & Timmer, 2012; Krishnan, 2018). The cost of transportation related to farm product marketing can be influenced by the distance to main and secondary roads and the distance to the markets. Farmers in the study area generally use a motorbike to take their products to the markets, however, they also use a motorbike for connecting to the main road from where they can access public transport, which is generally cheaper although less convenient. The proximity of the farmlands to the markets, roads and residential areas also increases the likelihood of influx of customers for on-farm selling.

The spatial analysis of market accessibility was prepared using a combination of market proximity, road proximity and residential area proximity. Since settlements are expected to expand, the analysis of market accessibility was performed for the years 2022 (Fig. 4.31) and 2030 (Fig. 4.32). Eight relevant air-open markets are found in the area or in its immediate neighbourhood. Three of the markets are located in the south in Athi River town centre, three in Ruai town centre in the north-west and two in Kamulu town centre in the north-east (Fig. 4.1, Fig. 4.31-32). The eight air-open market were used for the two-time steps 2022 and 2030, because the planning map indicate that the markets will remain the same by 2030 (Appendix 11). The results of market proximity show a zoning of the study site around the markets and the linear distance to the closest market ranges from 0.2-11.4 km.

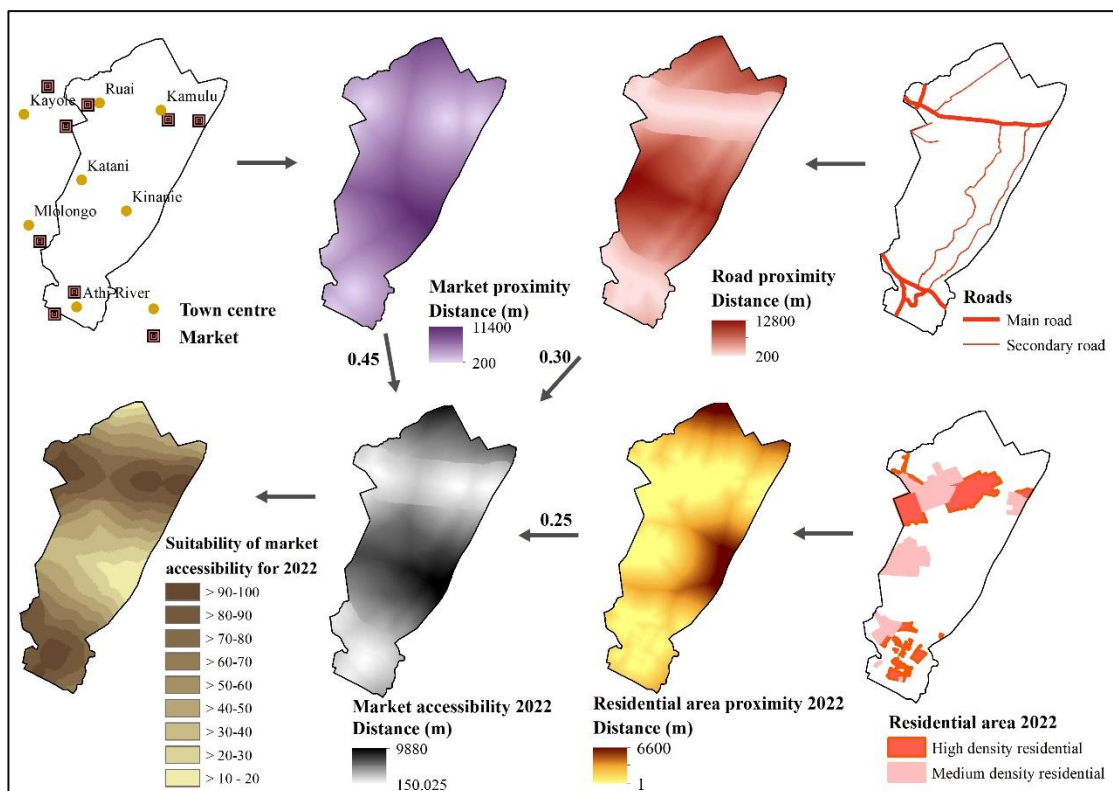


Figure 4.31: Process of deriving the final spatial distribution of market accessibility 2022

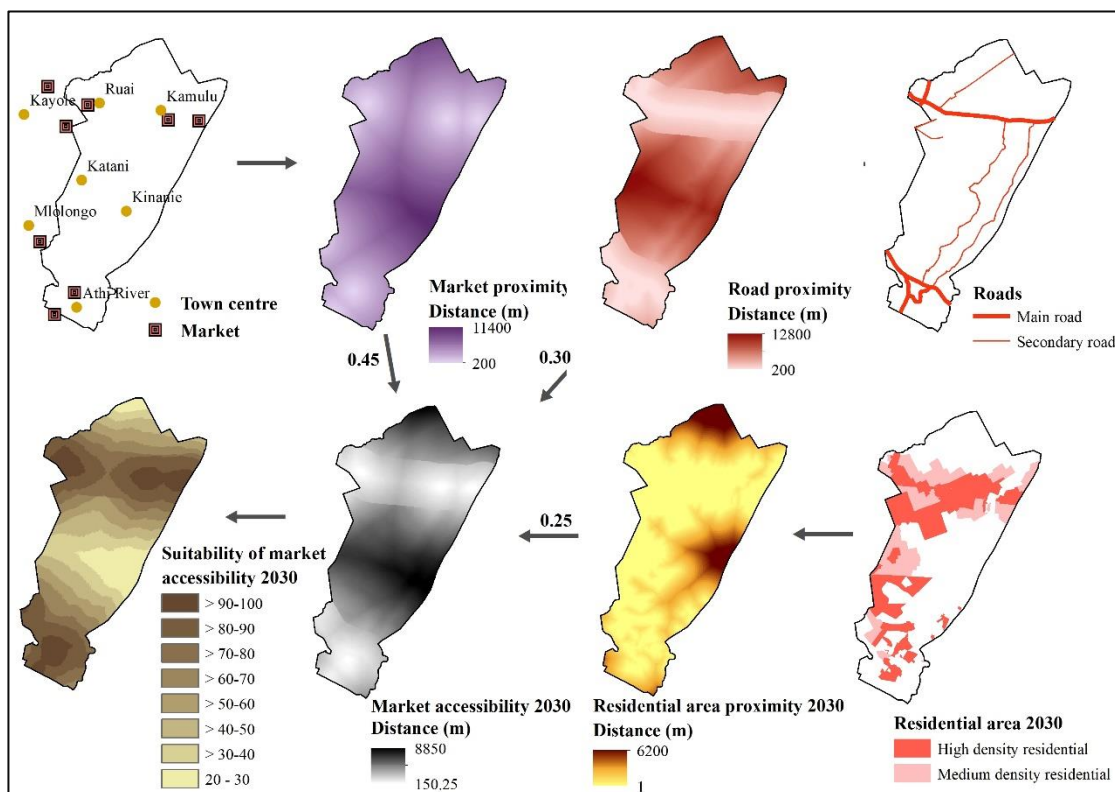


Figure 4.32: Process of deriving the final spatial distribution of market accessibility 2030

The main roads in the area include the Eastern Bypass in the north-west, Kangundo Road and Mombasa Road, Athi River Road and Nairobi-Namanga Road in the south. The secondary roads include two long dirt roads (approximately 25 km) connecting Kangundo road to Mombasa Road, south to north, a tarmacked road secondary road connecting to Kangundo Road in the north (Ruai centre) and a short road in the high-density residential area of Utawala town centre on the upper middle of the study site (Fig. 4.1, Fig. 4.33-4.34). The spatial analysis of road proximity reveals patterns created by different weights for main roads (east-west) versus secondary roads (north-south). The spatial patterns of road proximity vary between 0.2 and 12.8 km. The proximity analysis considering residential areas based on medium- and high-density residential areas (section 4.5.4) shows that residential areas are located between 0.001 and 6.6 km for the year 2022 and between 0.001 and 6.2 km for 2030. Besides, residential area proximity reveals effects due to limiting the modelling to the study area only since residential areas next to study area are not included.

The results of the spatial analysis of market accessibility for land suitability suggest that 41.77% (131.51 sq.km) and 42.70% (131.51 sq.km) of the area for the year 2022 and 2030, respectively, have high market accessibility (80-100) with a distance equal or less than 3 km (Fig. 4.32-4.33). About 22% (67.33 sq.km) and 24% (75.26 sq.km) of the area for the years 2022 and 2030, respectively, fall in medium suitability with a score ranging between 60 and 70 for 4-5 km (Table 4.71). The remaining areas have low market accessibility, with suitability scores between 50 and 10 for 6 to 10 km distances (Fig. 4.33-4.34). The difference in pattern between market accessibility for 2022 and 2030 is solely due to differences in residential proximity.

Table 4.69: Statistics for spatial analysis for market accessibility

		2022		2030	
Distance in km	Suitability	Area in sq.km	Area in %	Area in sq.km	Area in %
1	100	27.25	8.85	29.64	9.62
2	90	63.9	20.75	65.76	21.35
3	80	37.5	12.18	36.11	11.72
4	70	30.62	9.94	35.42	11.50
5	60	36.71	11.92	39.84	12.94
6	50	42	13.64	40.46	13.14
7	40	36.4	11.82	33.34	10.82
8	30	19.8	6.43	20.68	6.71
9	20	10.8	3.51	6.75	2.19
10	10	3.02	0.98	NA	NA

4.5.5.3 Integrated AHP-GIS land Suitability for Peri-urban Vegetable Farming

The results of land suitability analysis for vegetable farming in Nairobi-Machakos counties interface using the integrated AHP-GIS approach based on the six main criteria including land use (Fig. 4.24), irrigation water accessibility and quality (Fig. 4.25-4.26), soil suitability (Fig. 4.27), health risk (Fig. 4.28-4.29), landform (Fig. 4.30) and market accessibility (Fig. 4.31-32) are displayed in Fig.4.33-4.34 and Table 4.70-4.71.

Suitable to highly suitable lands in the area accounts for 38.3% and 45.3% in dry season and wet season, respectively for 2022 and 25.2% and 26% in dry season and wet season, respectively for 2030. These suitable lands are located along Athi River (River), while less suitable lands are located in medium/high density residential industrial areas, quarry and wastewater treatment plant areas. Moderately suitable lands are found in low and medium density residential areas with low water accessibility. The areas suitable for vegetable farming are larger during wet season compared to dry season and this is attributable to better water quality and low health risk during wet season compared to dry season as the uptake of chemical contaminant are higher in dry season. However bacterial contamination was proven higher in wet season compared to dry season,

therefore water treatment or stabilisation before used for irrigation remain very important for food safety during dry and wet season.

Table 4.70: Statistics of land suitability analysis for vegetable farming 2022

Suitability degree	Season	Area in sq.km	Area in %
Highly suitable	Dry season	8.74	2.84
	Wet season	25.87	8.40
Suitable	Dry season	109.21	35.46
	Wet season	113.75	36.93
Moderately suitable	Dry season	140.41	45.59
	Wet season	131.46	42.68
Marginally suitable	Dry season	49.64	16.12
	Wet season	36.92	11.99
Unsuitable	Dry season	-	-
	Wet season	-	-

Table 4.71: Statistics of land suitability analysis for vegetable farming 2030

Suitability	Season	Area in sq.km	Area in %
Highly suitable	Dry season	5.57	1.81
	Wet season	17.57	5.70
Suitable	Dry season	71.88	23.34
	Wet season	62.46	20.28
Moderately suitable	Dry season	145.7	47.31
	Wet season	164.65	53.46
Marginally suitable	Dry season	84.85	27.55
	Wet season	63.32	20.56

The results indicate that nearly half of the area (45.59% and 42.68%) for 2022 and 47.31% and 53.46% in 2030) fall under moderate suitability. Land suitability for vegetable farming appears to be low towards Nairobi on the west compared to Athi River towards the east. This is attributable to denser development and higher contamination risks along Nairobi compared to Athi River. The comparison between the land suitability maps of the years 2022 and 2030 show a decrease in land suitable towards the north-east and the south-west along the river. This decrease in land suitability is due to intensive development planned for these areas by 2030, despite the

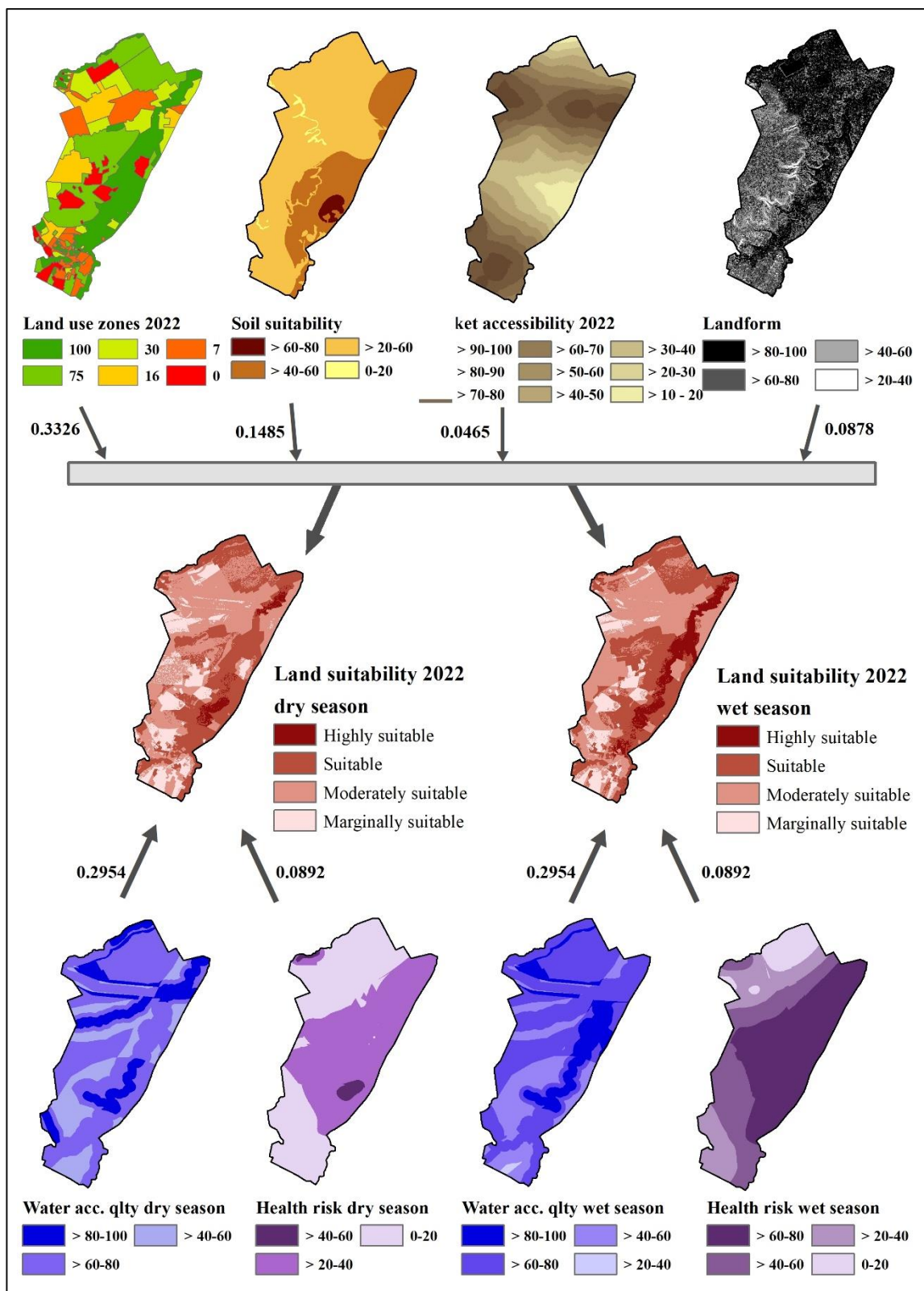
availability of irrigation water. Such development appears to be a threat for the sustainability of PUA. The analysis of the spatial pattern of moderately suitable lands (Fig. 4.33-34) indicates that moderately suitable areas have low suitability regarding land use, irrigation water accessibility and quality and soil suitability. This confirms the overall influence of the main criteria land use, irrigation water and soil suitability on the overall land suitability (Table 4.57). Despite that a larger portion of the area has low suitability for vegetable farming, essentially because of settlement development and poor irrigation water quality, suitable to highly suitable land represents 25-40% of the area, with the lowest proportion for the year 2030. These results imply that there is a non-negligible potential for the production of healthy and safe vegetables in Nairobi-Machakos counties interface. However, there is a need for rational land zoning of agricultural land, which works together with sound urban waste management, farmers' sensitization, regulations, and enforcement of phytosanitary and regulatory measures.

The land use zone map based on VHR-GE imagery (Fig. 4.1) have less details of land use zones and border precisions compared to the one based on VHR-PS imagery (Fig. 4.23). This is attributable to the fact that PS satellite imagery have four spectral bands (B-G-R-NIR), which allow the use of different spectral band combinations for better land use features extraction compared to VHR-GE imagery, which is a single band imagery. Although the land use zones map emanating from VHR-GE and the one from the VHR-PS do not have the same patterns, they convey similar information. The first provides a global overview of land use zones and can be use by operator with low expertise in remote sensing and Geographical Information System (GIS) since based on visual interpretation.

The study provides a scenario of the land suitability for vegetable farming for the year 2030 (Fig. 4.34). Although only land use related variables (land use zones and market

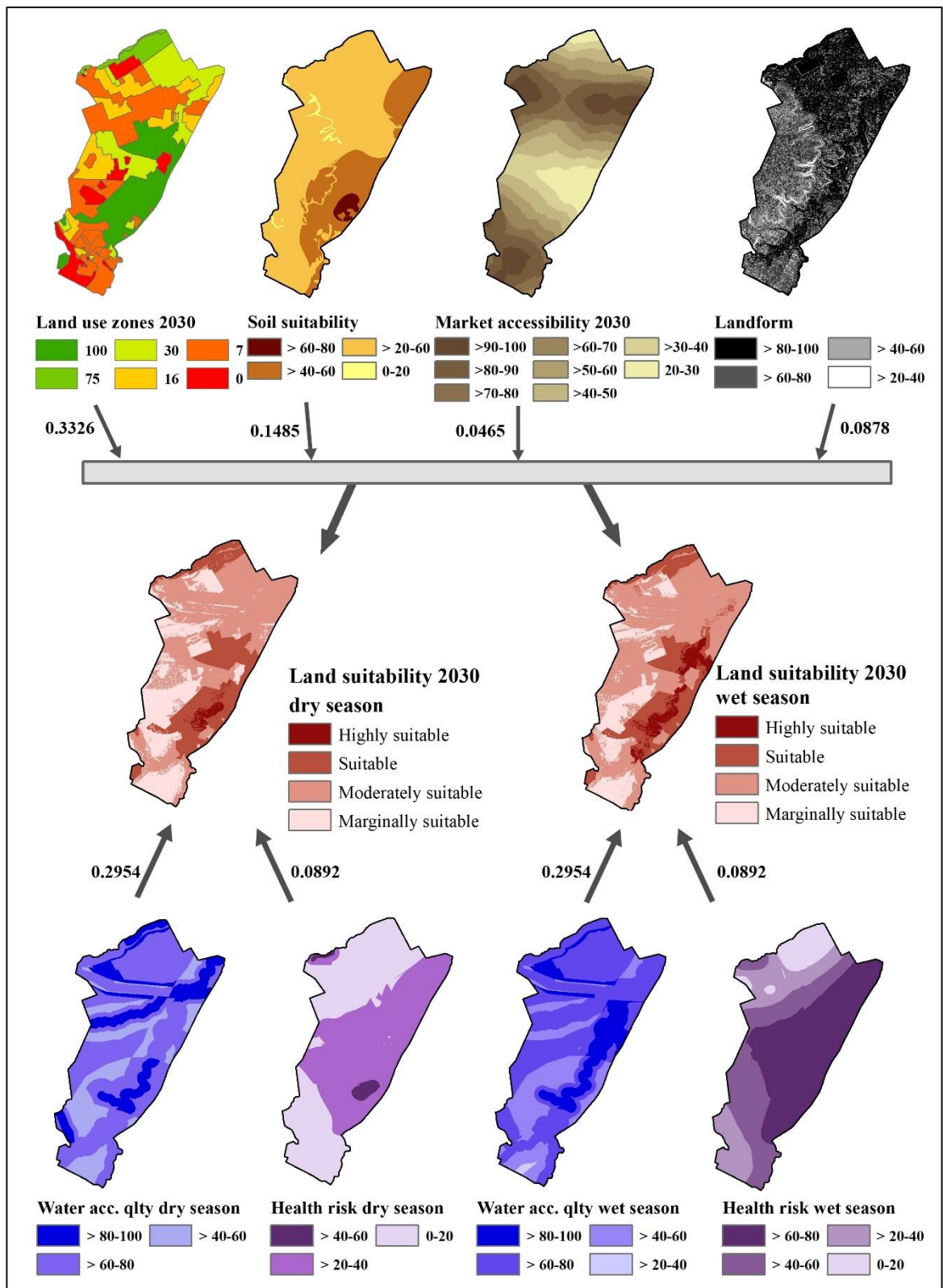
accessibility) changed in the 2030 modelling, the results give insight to urban researchers and planners for better measures and policies in line with the achievement of the sustainable development goals and the chapter 4 of Kenya Vision 2030 focusing on food security; affordable housing; manufacturing and affordable healthcare. The study stresses that urban planners and policy makers have a remarkable role to play for the sustainability of PUA building resilient and sustainable urban centres in Nairobi metropolitan region but also implicitly in similar regions in all developing countries.

The findings are valuable for policymakers and planners in identifying and protecting areas favourable for peri-urban farming, improve knowledge of unsuited area for agriculture, which can serve for other land use and thus minimise the urban and industrial development on land with high suitability that can be used for peri-urban farming. Furthermore, the study unveil that the utilization of the AHP-GIS approach has the potential to enhance the decision-making process of policy makers and planners in Kenya and at large in developing countries. The merging of AHP and GIS substantially support contribute to efficient land use planning, and our study substantiates its potency for the benefit of healthy and sustainable vegetable farming in peri-urban landscapes. The findings are consistent with previous studies highlighting the use of the AHP-GIS approach for agricultural land use planning (Thapa & Murayama, 2008; Koschke et al 2012; Bozdağ et al., 2016; Memarbashi et al., 2017).



Water acc. qlty: irrigation water accessibility and quality

Figure 4.33: Process of deriving the final land suitability maps for vegetable farming for 2022



Water acc. qlty: irrigation water accessibility and quality

Figure 4.34: Process of deriving the final land suitability maps for vegetable farming for 2030

4.6 Reflecting on the integrative methodological approach and the findings

This study aimed at assessing the dynamics of peri-urban agrosystems and their implication on land suitability for vegetable farming in Nairobi-Machakos counties interface. The research used a descriptive correlational research design integrating different approaches and combining different datasets. This included:

- socioeconomic data of peri-urban farming units collected during survey,
- farmland mapping based on Very High-Resolution Google Earth (VHR-GE) imagery and ground truth data,
- determination of ecological and health risks by testing physicochemical, bacterial and metals elements in irrigation water, soil and vegetable samples
- use of VHR PlanetScope imagery in combination with all previous datasets to provide a spatially explicit modelling of land suitability for vegetable farming in the study area base on GIS.

The process began with characterisation of peri-urban agrosystems in Nairobi-Machakos counties interface resulting in two typologies. The first typology is based on the spatial arrangement of the farmlands and provides a broader perception of current land use zones (Table 4.6, Fig. 4.1), while the second based on the socioeconomic attributes of the farming units, provides more insights on socioeconomic variables, including type of actors, market orientations and production resources integration and endowment, which is relevant for developing specific intervention and regulatory measures targeting specific group of farmers (Table 4.2). The assessment of water quality, heavy metals and trace elements contamination in irrigation water, soil and vegetable allowed to establish the extent of health risks related to peri-urban agrosystems and raise awareness on the urgent need of rational zoning for PUA, sound

waste management, and enforcement of phytosanitary and regulatory measures for food safety in the metropolitan region.

The last-step of the study is the AHP-GIS integrated approach, which allowed to resourcefully combine the data collected in all the previous steps: farmland typology, social and environmental opportunities, and challenges of PUA plus experts' opinions, with modern geospatial data and techniques to assess land suitability for vegetable farming. The approach enabled empirical and spatially explicit modelling of land suitability over time which can help planners, decision-makers, and policy-makers to improve land use planning, policies and regulations for sustainable management of peri-urban agrosystems in metropolitan areas. As noted in the introduction, few studies focused on land suitability evaluation for vegetable farming in metropolitan regions, especially in sub-Saharan Africa. Although, the AHP-GIS approach has been implemented in different fields (Akıncı et al., 2013; Bagheri et al., 2013) and more so with some applications in agricultural land suitability (Thapa & Murayama, 2008; Bozdağ et al., 2016), few studies on land suitability tackled the health risk concerns of PUA, especially in the global south. The benefit of this study resides particularly in the set of many criteria combined as well as the integrative approach used in combining them to achieve land use suitability that reflect the prevailing socioecological, resource endowments and environmental systems. Previous studies using the AHP-GIS based land suitability analysis (Thapa & Murayama, 2008; Akıncı et al., 2013; Bozdağ et al., 2016) focused on high productivity with criteria such as land use, irrigation water quality, climatic patterns, market orientation and the accessibility to transport infrastructures. In addition to these parameters, this study includes food safety parameters such as irrigation water contamination (irrigation water quality index:

IWQI, bacterial contamination index: BCI), soil pollution (Pollution Load Index: PLI) and health risks (carcinogenic risk: TCR and non-carcinogenic risk: HI).

The study aligns with the contemporary shift in the promotion of PUA, which not goes beyond promoting fresh fruits and vegetables production in metropolitan regions but emphasises more on safe and healthy fresh fruits and vegetables production (Drechsel & Karg, 2013; Marshall et al., 2018; Surendran et al., 2020). Furthermore, the study provides a look into a most likely future scenario (2030), reflecting on the need of an integrative approach for rational and sustainable zoning of agricultural land with a supportive policy framework for safe, sustainable, and inclusive urban food systems in line with SDG 2 and 11 and the goal 4.2 of Kenya's Vision 2030. The approach makes it possible to incorporate a broader range of criteria and assigning varying degrees of importance, when formulating strategies, policies, or decisions pertaining to the preservation or alteration of agricultural land use. The overall integrated AHP-GIS is very relevant for improving agricultural land zoning in Nairobi metropolitan region and more so for other instances of peri-urban landscapes, albeit with the need to fine-tune individual specific local socioeconomic and environmental conditions. However, the achievement of these results by implementing the AHP-GIS integrative approach was subject to a number of challenges, which are worth to be highlighted to serve as a guide for future studies.

One of the principal challenges of the study is the sensitivity of the research subject, which created difficulties in getting farming units to take part in the survey or to accept to be part of the sampling stations. Most of the farmers feared to take part in the survey because of illegal occupation of public spaces or the use of obviously contaminated urban water flows (sewage flows, rivers, WTPs effluents) for farm irrigation. Some farmers are also reluctant towards allowing sampling of irrigation water, soil and

vegetable on their farm due to the fear over the outcomes, in case this could lead to stopping them from conducting their farming activities. Despite these encounters, it was possible to spread 130 farming units across the ten vegetables production zones identified (Fig. 3.4-3.5, Table 3.2). The sampling sections were carried out upon understanding and with the aim of upscaling the data for a better zoning of PUA, which will contribute to secure their activities in the study site.

Another challenge of the study is the high cost of laboratory analysis for heavy metals, trace elements and bacterial pathogens analysis. This led to a reduced sampling frame and low number of sampling sites as well as the number of samples collected from each site. Although, limited samples were collected for bacteriological, heavy metals and trace elements testing (30 x 2), the selection of the sampling stations and sampling methods were thoroughly conducted to provide a representative view of contamination across the study sites. For bacterial pathogens isolation, molecular methods which are very accurate, could not be used for bacteriological characterisation due to funding constraints. Instead, bacteriological isolations were carried out using specific selective media and each of the bacterial isolate was taken through an internal protocol of laboratory quality control that included a range of microscopic and biochemical tests which allowed to confirm the isolates (Table 3.3).

An interpolation approach was used for analysing the spatial patterns of soil pollution (PLI) and health risks (HI and TCR) across the study area, but for irrigation water quality variables (IWQI and BCI) the study area was subdivided into sub-catchment areas based on knowledge of the area gathered during survey and ground truth data collection. The use of sub-catchment areas suited the water quality variable better because of different hydraulic regimes across the study site. However, both approaches were only limited to the study area and therefore could not account for potential effects

of influencing factor originating from outside the study area (Luederitz et al., 2015). Nevertheless, the understanding of the dynamics of the metropolitan region, existing literature and the extended ground truth allowed to minimize the impact of these uncertainties on the results.

The remote sensing data *i.e.*, PlanetScope (PS) imagery has a very good resolution (3 m) but is limited to four spectral bands B-G-R-NIR and therefore it limited geospatial applications that could be explored for enhanced LULC features extraction. For example, the Middle Infrared band (MIR) would enhance vegetation – soil differentiation. Moreover, the implementation of object-based methods for LULC classification requires the use of more advanced tools like the feature analyst, (Gu et al., 2017; Willkomm et al., 2019) being a complex and time-consuming process (Blaschke et al., 2014; Dronova, 2015). In the face of these constraints for a timely completion of an explicit LULC classification based on the VHR-PS imagery, a decision tree approach combining various rather simplistic remote sensing and GIS analysis methods was elaborated, tested and nevertheless allowed to successfully extract land use features with an overall accuracy above 90% (Fig. 3.7, Table 4.47).

The LULC classification could not allow to distinguish agricultural land, which was included under the broader classes of vegetation cover. Therefore, the extraction of the parcel boundaries using the Laplacian convolution filter on the R band of PS-2022, subdividing the area in subregions allowed to identify parcel arrangement, which were combined with LULC results to provide substantiated information on land use and allowed to derive land use zones (Fig. 3.7). Willkomm et al. (2019) acknowledged the difficulty of extracting agricultural patches using RapidEye imagery, a satellite image of the same family with PS-2022. The authors stressed that the use of suitable input

setting per subregion consisting of relatively uniform spatial arrangement of parcels contributes to better demarcation of land use patches.

The other issues in the integrated AHP-GIS based land suitability approach are related to the use of disparate data sources *i.e.*, river network, roads, DEM and soil type, which have different levels of quality (scale, resolution or level of details). The integration of such data can create discrepancies or noise in the results (Du et al., 2015). For example, the Digital Elevation Model (DEM) has a spatial resolution of 30 m, while for PlanetScope imagery it is 3 m (see section 3.7.2.1 geospatial dataset). It was necessary to integrate and manage different levels of quality of the different data sources, also incorporating ground truth data and knowledge of the study site and logical assumptions *i.e.*, on catchment zones and manual digitizing to reduce this type of error. Since the area of focus of the study is relatively small (308 sq.km), it was possible to check thoroughly each dataset, but this level of scrutinizing can be more challenging for larger areas.

In the AHP-GIS modelling for the year 2030, only land use related variables *i.e.*, land use zones and residential areas proximity have been modified, while other components of the model maintained the state of 2022. This is because predicting the changes of these parameters for the year 2030 is not easily possible. The conditions of water quality, soil contamination and health risks in 2030 will most likely worsen or improve in case of implementation of efficient intervention measures. As this is difficult to predict, a range of scenarios would be required to infer on under different circumstances. Moreover, the land use development in the planning map 2030 is already overruled for some areas in the current state of land use development (2022). This indicating that the planning policies in Nairobi and Machakos counties lack enforcement, and this could have a substantial impact on the sustainability of PUA.

Therefore, the state of land suitability for vegetable farming by 2030 will be much more affected (lower) if land use development by 2030 is significantly overruled compared to the planning map as noticed in the 2022 situation.

The results of the weighing process based on the 12 experts resulted in the following weights: land use (0.3326), irrigation water accessibility and quality (0.2954), soil suitability (0.1485), health risk (0.0892), landform (0.0878) and market accessibility (0.0465). The results of the modelling show a strong influence of land use over the other criteria which are all composites of at least two sub-criteria. Considering the importance of health risks and irrigation water quality in peri-urban farming (Na Zheng et al., 2010; Lindahl & Magnusson, 2020; Kumar et al., 2022; Zaynab et al., 2022), one could expect that these variables would be having higher weight in the overall land suitability (Table 4.57). The results of the modelling will be different if the variables describing the state of contamination risks (irrigation water quality index, bacterial contamination index, pollution load index) and health risks (hazard index and total carcinogenic risk) have the highest weights. This is attributable to the judgement of the experts, which depend on their level of understanding of the topic. Despite of being from relevant fields (public health, medical sciences and environmental sciences) the majority of the expert perceived land use as the prominent factor influencing land suitability for vegetable farming. This point to the need of more awareness and sensitization of farmers, urban and peri-urban population consuming the fresh products as well as experts and decision makers, whose opinions influence policy and regulations elaboration, implementation, and enforcement.

The results provide a substantive idea of how AHP-GIS can be extensively used for scenarios modelling. As illustrated in Fig. 4.33-4.34, the approach is tangible, easy to implement and flexible for land suitability analysis regarding safe and healthy vegetable

production. In contrast to most studies looking back into how environmental phenomenon had evolved overtime, this study looked ahead, providing a most likely scenario, thus raising awareness and attention on urgent intervention measures. However, the modelling of different scenarios under various circumstances is required to give more insights for resilient peri-urban agrosystems with production of safe and healthy products in urban and peri-urban landscapes. The findings confirm that the AHP-GIS land suitability modelling is a promising approach that will contribute to improve decision making and Agricultural land use zoning in Nairobi-Machakos counties interface but also in all developing countries (Thapa & Murayama, 2008; Bozdağ et al., 2016; Memarbashi et al., 2017; Mazahreh et al., 2019; Amini et al., 2020; Tashayo et al., 2020; Kumar et al., 2021).

5 CHAPTER FIVE: SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary of Findings

Objective 1 characterised peri-urban farmland in Nairobi-Machakos counties interface. The spatial distribution of peri-urban farmlands in the peri-urban interface reveals five farmland types: residential garden (RG), small-scale open field (SOF), small-scale greenhouse (SGh), large-scale open field (LOF) and large-scale greenhouse (LGh). Peri-urban farmland typology based on socioeconomic characteristics exhibits four farmland types. The two classifications seem different, but they share some similarities. The farm type 1 encompasses predominantly SOF and LOF, whereas farm type 4 is exclusively made of LGh and large scale intensive and export market-oriented greenhouse farming. Farm type 3 is a combination of LGh and SGh and are generally greenhouse farming system and share features related to type of actors and market orientation. Farm type 2 is predominated by RG. The typology based on visual interpretation of very high-resolution Google Earth imagery gives a spatial perspective of peri-urban farmland arrangement that can inform urban planning and land use zoning; whereas the typology derived from multivariate analysis of socioeconomic variables is more appropriate for developing specific intervention measures targeting specific groups of farmers and actors. Peri-urban agriculture (PUA) in Nairobi-Machakos interface is mostly market oriented with various market destination: local air-open market, supermarket, and export market. Local air-open markets remain the dominant marketing systems of PUA produce with above 90% of the overall production. The biggest production in the peri-urban interface originates from the farm type 1 (69%) and farm type 2 (23%). The main factors underpinning PUA in Nairobi-Machakos interface are the type of peri-urban agriculture (RG, SOF, LOF, SGh and LGh), irrigation water sources, the presence of stream nearby the farm, and land tenure system.

Objective 2 assessed irrigation water quality and heavy metals and trace elements contamination in irrigation water, soil and edible part of kale (*Brassica oleracea*). Physicochemical parameters show that irrigation water is degraded across the peri-urban interface with varying quantities of dissolve materials, salts, and nutrients. Irrigation water in all the sampling sites is contaminated with varying intensity of liquid and solid waste, effluent of wastewater treatment plants and faecal materials from urban settlement, which exceed the WHO (2006) guidelines for wastewater use for unrestricted irrigation. Water quality in the peri-urban interface is essentially influenced by influx of soiled waste, wastewater, effluent discharges and sewage flows. The suitability of irrigation water in the interface based on irrigation water quality index ranges from marginally suitable to highly suitable. However, considering bacterial contamination index, most irrigation water exhibits strong bacterial contamination. The bacterial characteristics of irrigation water in the interface exceeds the permissible threshold set by WHO and Kenya's NEMA for *Escherichia coli*, *Shigella* spp., *Pseudomonas aeruginosa*, *Enterococcus faecalis*, and *Vibrio cholerae* in unrestricted irrigation water. Therefore, irrigation water in all the sites is classified as unfit for vegetable cultivation. Although *E. coli* testing is the most used indicator in evaluating bacterial contamination in irrigation water, it remains insufficient in apprehending the extent of health risks since its compliance with national and international standards does not imply the absence of deadly microbial pathogens like *Salmonella typhi*, *Shigella* spp., and *Vibrio cholerae*. This suggests that the monitoring of bacterial contamination in irrigation water for unrestricted irrigation should be extended to other bacterial pathogens that trigger severe outbreaks such as *Salmonella typhi*, *Pseudomonas aeruginosa*, *Enterococcus faecalis*, *Shigella* spp., and *Vibrio cholerae*.

The assessment of heavy metals and trace elements contamination in agricultural soils reveals that all the tested elements are detectable, with As, Cd, Mn, Pb and Zn exceeding allowable limits in agricultural soil at 1.7%, 13.3%, 80%, 1.7% and 11.7%, respectively. Although the concentrations of some of the elements including As (43.3%), Cd (55%) and Zn (13.3%) are within the permissible ranges for agricultural soil at many sites, these concentrations are close to the threshold values and may accumulate with time and pose serious risks. The spatial distribution of heavy metals and trace elements exhibits three similar distribution patterns with slight variations between the hotspot sites of the different elements: (i) Co and Mn, (ii) Cu and Cr and (iii) As, Cd, Fe, Hg, Pb and Zn, while Ni and V exhibited singular spatial distributions compared to other elements. Elements such as As, Cd, Co, Fe, Hg, Mn, Pb and Zn in soil appear to be of anthropogenic enrichment, whereas Cr, Cu, Ni and V originate mainly from lithogenic and natural sources.

Above maximum allowable concentrations of heavy metals and trace elements are recorded in kale leaves for dry season and wet season: As (36.7% and 20%), Cd (100% and 100%), Cu (50% and 6.7%), Hg (70% and 16.7%), Pb (83.3% and 53.3) and Cd (100% and 100%). Heavy metals and trace elements concentrations in kale leaves are higher in samples from sewage irrigated farmlands (S1 and S7), wastewater treatment effluent irrigated farms (S5, S10), farmlands close to busy traffics roads (S2, S7) and industrial area (S2). The highest bioaccumulation factor soil-plant (BAFs) of heavy metals and trace elements are recorded with Hg (up to 2.70), Cu (up to 1.81) and Cd (up to 1.1) in dry season and Hg (up to 1.63) and Cd (up to 1.1) in wet season. The highest bioaccumulation factor water-plant (BAF_w) are Cd (up to 4.5), Cu (up to 7.62), Pb (1.82), Zn (up to 1.04) in dry season and Cd (up to 4.12), Cu (up to 2.06), Pb (up to 1.23) in wet season with significant variability across the sites. The bioaccumulation

factor (BAF) water-plant are higher compared to the bioaccumulation factor soil-plant suggesting that the source of irrigation water have a substantial impact on heavy metals and trace elements uptake in kale leave. Thus, heavy metals and trace elements contamination in peri-urban farmlands in Nairobi-Machakos interface is associated to urban wastewater irrigation, discharge of sewage and industrial effluent and wastewater treatment plant effluents in urban streams used for farm irrigation, which can lead to high intake of metals elements through food consumption.

Above maximum allowable daily intake of metal elements are recorded for Cd (up to 90%), Cr (up to 30%), Cu (up to 10%), Pb (up to 50%), Ni (up to 50%) and Zn (up to 60%) recorded from the sites S1, S5, S7 and S10 and is attributed to irrigation water sources of these farmlands, sewage (S1 and S7) and wastewater treatment plant effluent (S5 and S10). Therefore, the consumption of kale leaves from the farmlands in Nairobi-Machakos interface could induce significant intake of heavy metals and trace elements, which can cause detrimental health impacts. These are further confirmed with the findings from the estimations of ecological risks, carcinogenic and non-carcinogenic health risks investigated in objective three.

Objective 3 informs on ecological and health risks from heavy metals and trace elements. Heavy metals and trace elements contamination in soil exhibits significant ecological risks, demonstrating serious threat to environmental sustainability and human health across the peri-urban interface. The elements As, Cd, Hg and Pb show high ecological risks, with Cd contributing about 46-66% of the overall ecological risk. The sampling sites S1, S5, S7, S9 and S10 depicts the highest ecological risks of 145, 103, 146, 121 and 146, respectively. The estimation of health risks related to heavy metals and trace elements reveals that oral intake through kale consumption is the most prominent exposure route compared soil ingestion, inhalation or dermal contact.

Arsenic (As) exhibits the highest values of non-carcinogenic risk, while Cr followed by As have the highest carcinogenic risks. The estimated values of total non-carcinogenic risk (HI) are less than the threshold of non-carcinogenic risk, indicating low risk of non-carcinogenic health conditions. However, as the estimation of the non-carcinogenic risk (HI) is based on the ingestion on a certain amount of kale, a vegetable that is generally consumed with staple food like maize, cassava, rice and bananas, the level of non-carcinogenic risk could become significant if the staple crop has a certain concentration of heavy metals and trace elements. The values of the carcinogenic risks (TCR) show significant carcinogenic risks across the farmlands with the highest cancer risk recorded from farmlands with sewage irrigation (S1, S7), farmlands located in industrial area (S2), farmlands with wastewater treatment plant effluent irrigation (S5, S10). The HI and TCR are higher in dry season compared to wet season because of low metal elements' uptake by plant in wet season. The HI are higher for children compared to adults, while the TCR are higher for adults compared to children.

Objective 4 models land suitability for vegetable farming using an integrated AHP-GIS based approach. Land suitability modelling for vegetable farming in Nairobi-Machakos interface is based on six main criteria: land use, irrigation water accessibility and quality, soil suitability, health risk, landform and market accessibility, considering a current situation (2022) and a likely scenario for the year 2030. The results show that land use, irrigation water accessibility and quality, and soil suitability are the most prominent factors influencing land suitability for vegetable farming. Land suitability analysis shows that 38.3% in dry season and 45.3% in wet season for 2022 and 25.2% in dry season and 26% in wet season for 2030 are suitable to highly suitable for vegetable farming. The overall integrated AHP-GIS approach is relevant for improving agricultural land use zoning in Nairobi metropolitan region and more so for other peri-

urban environment albeit with fine-tuning to local environmental conditions. The approach empowers planners and policy maker to incorporate different criteria and assigning varying degrees of importance when formulating strategies, policies, or decisions pertaining to preservation or alteration of agricultural land use in metropolitan regions. The findings of this study contribute to the design of a more sustainable model for determining and conserving the appropriateness of peri-urban land for agricultural production in urban landscapes.

5.2 Conclusion

This study was conducted to assess the dynamics of peri-urban agrosystems and their implications for land suitability for vegetable farming in Nairobi-Machakos counties interface. The study demonstrates that vegetable farming in the outskirts of Nairobi has a substantial importance for food security for the metropolitan population and urban household farmers are the principal suppliers of fresh vegetables to metropolitan markets. Peri-urban agriculture in Nairobi-Machakos interface takes on various forms determined by farming profile, land tenure, irrigation water sources and market orientation. They play a determinant role in the local urban food systems. Despite their role for urban food systems resilience and sustainability, their access to land and quality irrigation water is challenging. Most peri-urban farmers rely on urban hydrologic flows, which are polluted with urban and industrial waste, sewage and wastewater treatment plant (WTPs) effluent for farm irrigation.

The evaluation of irrigation water quality showed that most physicochemical variables of irrigation water quality are above the maximum permissible limits for vegetable irrigation. Irrigation water used in the farmland is contaminated and therefore dangerous

for the farmers and the metropolitan populace consuming cultivated fresh fruits and vegetable from these farms. The study emphasises that the monitoring of bacterial contamination in irrigation water for unrestricted irrigation should be extended to other microbial pathogens that trigger severe outbreaks such as *Salmonella typhi*, *Pseudomonas aeruginosa*, *Enterococcus faecalis*, *Shigella* spp., and *Vibrio cholerae*. In the current context of general climatic variability, especially with widespread drought spells in Kenya at large, the potential of reusing urban hydrologic flows would be a great opportunity if the associated health risk could be tackled.

The concentrations of heavy metals and trace elements in soil, irrigation water and kale are above the maximum allowable thresholds due to urban wastewater irrigation, discharge of sewage and industrial and wastewater treatment plant effluents in urban streams used for farm irrigation. The estimated carcinogenic risks and single element ecological risks from the farmland are significant and pose hazardous threat to public health, urban food security and safety. The study notes that the consumption of kale leaves from the farmlands in Nairobi-Machakos interface poses significant carcinogenic risks and thus efficient and regular monitoring, zoning of agricultural land and regulations are imperative in urban and peri-urban agrosystems.

The implementation of the AHP-GIS integrated land suitability analysis approach shows that land use, irrigation water accessibility and soil suitability are the prominent factors that affect land suitability for vegetable farming in Nairobi-Machakos counties interface. Therefore, maintaining the numerous benefits of PUA in metropolitan landscapes will need strategic and efficient intervention measures toward these three determinant components of land suitability. The results of land suitability modelling reveal that about 40% of peri-urban area is suitable to highly suitable for vegetable farming but is likely to drop to 25% by 2030, indicating a significant threat for urban

food systems, city resilience and sustainability. The findings suggest that fresh vegetable farming in Nairobi-Machakos interface and implicitly all peri-urban interfaces in developing counties can be healthy, safe and sustainable if well zoned and regulatory requirements enforced in metropolitan regions with rational resources arrangement and accessibility.

5.3 Recommendations

In line with the findings of this study, the following recommendations are made to guide intervention measures:

i. Integration of peri-urban agriculture into urban planning:

Peri-urban agriculture plays a crucial role in local food systems and income generation but is often overlooked in urban planning and resource allocation. Recommendations include upscaling data at the ecosystem scale to properly zone agricultural land, linking potential risks to their source, and integrating ecosystem considerations for effective management of ecological and public health risks associated with vegetable production in peri-urban areas.

ii. Improvement of waste management protocols:

Urban and peri-urban areas require sound waste management protocols to reduce surface water pollution. Recommendations involve increasing sewer line coverage, enhancing sanitation services to prevent household waste diversion into open water networks, and improving the efficiency of wastewater treatment processes at plants like Ruai and EPZ to ensure compliance with environmental discharge standards.

iii. Inclusion of Peri-urban Stakeholders in Decision-making:

Peri-urban farmers and stakeholders must have their voices adequately represented in decision-making processes related to land use planning.

iv. Regular monitoring of agrosystems:

Peri-urban agrosystems should undergo regular monitoring of soil, water, and plant contamination to inform farmers and policymakers about waste management implications and ecological risks, facilitating prevention or remediation measures.

v. Enforcement of regulations for local market vegetables:

While only 4% of horticultural production in Kenya is for export markets, the majority of produce supplied to local markets remains unregulated. Recommendations include enforcing regulations and standards for fresh vegetables sold in local markets to ensure food safety, sensitizing farmers about the implications of their farmland locations and irrigation water sources on food quality and public health and implementing controls for compliance with health requirements even for local markets.

vi. Utilization of AHP-GIS Approach for Land Use Planning:

The AHP-GIS land use suitability model provides a framework for sustainable and participative land use planning, integrating expert and local stakeholder opinions. The study recommends the adoption of the AHP-GIS approach for agricultural land zoning in metropolitan regions to achieve environmentally and ecologically sustainable solutions.

5.4. Perspectives for Further Research

For future research perspective, the following recommendation are made.

- i. There is a need for understanding of the efficiency of existing institutional arrangements and actors affecting irrigation in peri-urban landscape for better monitoring-regulation enforcement for food safety and sustainability.
- ii. There is need for exploration of suitable remediation measures for heavy metals and trace elements remediation in contaminated sites.
- iii. Comprehensive experiments on heavy metals and trace elements uptake by different crops and different varieties of the same species in order to provide farmers with crops and varieties with very low risk of heavy metals and trace elements accumulation.
- iv. Evaluation and validation of the AHP-GIS land suitability model in different peri-urban contexts to better use planning.

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APPENDICES

Appendix 1: Questionnaire for Farming Unit Survey

Consent form

A. Introduction	
Dear Respondent, We are conducting academic research to understand the dynamic of peri-urban agriculture in Nairobi-Machakos interface. The research is seeking to highlight the different challenges regarding peri-urban farming and compliance to food safety and propose a set of farm management strategy and upscaling data to improve and sustain peri-urban farming which play a multifunctional role in urban and peri-urban landscape. We hereby seek your assistance towards gathering the required data for this study. The information acquired from this research will be handled confidentially and will only be utilized for purposes of this academic study. The results of this research will support decision-making process for safe and sustainable vegetable farming in peri-urban environment. Filling the questionnaire for this survey should take utmost 20 minutes of your time. You are kindly request to respond to all the questionnaire items as honestly as possible. Thank you! Filling the questionnaire for this survey should take utmost 20 minutes of your time. You are kindly request to respond to all the questionnaire items as honestly as possible. Thank you. Arcadius Agassin Ahogle Kenyatta University, Department of Environmental Planning and Management.	
B. Respondent's Declaration	
I, the undersigned, hereby declare that having been sufficiently informed of the purpose of this research and my obligations, I freely agree to participate in the study as requested. I will provide accurate and honest responses to all the questionnaire items.	
Signature Initials of the respondent	Date (Optional)
C. Enumerator's Declaration	
I, ... hereby declare that I have vividly explained to the respondent the purpose of this research, and that the data contained herein is a true representation of the actual views provided freely and willingly by the respondent.	
Signature	Date

Questionnaire n°.....

Date Name Initial County: 1. Nairobi 2. Machakos
 Location Sub-location.....

Ward:..... phone number Farming Unit

(FU) head. GPS Coordinates E.....S. Household

head gender: 1.F 2.M. Household head Age years Household size:

Number of female of FU..... (Number)

Respondent gender: 1.F 2.M Marital status: 1.Single 2.married

3.divorcee 4.widow

Education: 1.None 2.Primary 3.Secondary 4.Certificate 5.Diploma

6.University

FU characteristics

Residence ownership 1. Yes 2. No

What is your main source of water for domestic use?

1. Piped water in the compound
3. Community stand pipe
5. Borehole
2. River/stream
4. Rainwater reservoir
6. Others

Sanitation

What type of sanitation facility do you use?

1. Sewer connexion 2. Pit latrine 3. Septic Tank 4. Open defecation

5. Others (please specify)

Farm owner profile: 1. Urban household 2. Private local institution/Church

3. Public urban professional 4. International investor/institution

Main source of income

1. Farming 2. Animal husbandry 3. Business 4. Formal employment

5. Informal employment 6. Causal labour 7.

Other.....

Second source of income:

1. Farming 2. Animal husbandry 3. Business 4. Formal employment

5. Informal employment 6. Causal labour 7.

Other.....

Monthly income

Income (US\$)	<100	100-150	150-200	200-300	300-400	400-500	500-600	600-800	800-1000	> 100 000
Tick										

Contribution of Peri-urban agriculture to monthly income:

1_10% 2_25% 3_50% 4_75%
5_100%

Experience in peri-urban agriculture years

Farming mode: 1. Permanent 2. Seasonal 3. Other (specify)
.....

Membership to farmers' organization/cooperative 1. Yes 2. No

If Yes which one

Are you member of an out-grower Scheme? 1. Yes 2. No

If yes which ones?

Out grower Schemes companies	Criteria: 1. Water quality, 2. Pesticides residues, 3. heavy metals, 4. biological pathogens

Access to trainings: 1. Yes 2. No How many trainings have you gotten?
.....

Focus of training:

- a. Access to high quality seed 1. Yes 2. No
- b. Soil fertility management: 1. Yes 2. No
- c. Irrigation water quality Safe handling/treatment of Wastewater: 1. Yes 2. No
- d. Safe handling of pesticides: 1. Yes 2. No
- e. Meeting requirements for various markets 1. Yes 2. No
- f. Marketing 1. Yes 2. No
- g. Others

Percentage of peri-urban agricultural production used for household subsistence:

1_10% 2_25% 3_50% 4_75% 5_100%

Main source of labour: 1. Family members 2. Casual workers 3. Permanent workers

4. Seasonal Workers (Specify period) months

Targeted markets 1. Local open 2. Local supermarkets 3. Export market

Crops exported (if 3 above)
.....

Main marketing systems: 1. On farm selling 2. Self-engagement in open market 3.
Involvement as aggregator 4. External aggregators 5. Exportation 6.
Others (Specify)

To which local open market do you supply your product to
.....

Marketing and aggregators' specification

Agricultural products	1.Supermarket 2.Aggregators(local) 3.Export	Regulation 0. None; 1. Water; 2. Fertilizer 3. Pesticides; 4. Farm hygiene	Testing the product 1. Yes 2. No
Leafy vegetable (cabbage, Kales)			
Fruits Vegetable (Tomato, ...)			
Staple crops (Maize, beans, ...)			
Herbs (mint, ...)			
Others (Specify)			

To which local supermarket do you supply your products

.....

How do you ensure you meet the requirements?

.....

Are you paying any fees or tax for any services or facilitation? 1. Yes 2. No

If yes, how much KES, Which services?

Which services?

Have you been given any awards for the safety of your products or good farming practices implementation?

1. Yes 2. No Which one?

Are your products subjected to certification? 1. Yes 2. No

If yes, which ones?

Are your inputs certified? 1. Yes 2. No;

If yes, which on: 1.Water 2.Soil 3.Organic Amendments 4. Chemical
fertilizer 5.Pesticides 6.Seeds

Do you conduct pathological analysis on your irrigation water before using? 1.
Yes 2. No

Do you conduct pathological and nutrients analysis on your soil before planting? 1. Yes
2. No

Do you apply any treatment to your irrigation water before using? 1. Yes 2. No

If yes, Which treatments?

Do you apply any treatment to soil to reduce or monitor soil contamination or acidity 1. Yes 2. No

If yes which treatments

Had your products been rejected once for local market? 1. Yes 2. No

Had your products been rejected once for local supermarket? 1. Yes 2. No

Had your products been rejected once for exportation? 1. Yes 2. No

If yes, why was it reject? 1. Water quality 2. Pesticides residues 3. Fertilizers' residues

4. Heavy metals 5. Microbial pathogens 6. Farm location hygiene

7. Other (Specify)

C- Biophysical resources

Land tenure

Land tenure	Inherited	Gift	Purchased	Leased		Free hold	Total land
					Cost (US\$,year)		
Area (acre)							

How long have you been farming on this land? months/years

Were you farming somewhere else before? 1. Yes 2. No

If yes, why did you shift here?

Were you farming somewhere else before? 1. Yes 2. No

If yes, why did you shift here? 1. Abandon farming 2. Land shortage

2. Other (Precise)

Have you ever reduced your farmland area? 1. Yes 2. No

If yes, for which purpose did you dedicated the subdivided land?

.....

What is the distance from your farm to the nearest:

industry? km; which industry

Principal Road? km; which principal road

Secondary road km, which Secondary road

Cropping site characteristics

Land (acre)	Farm location 1.Home garden 2.Private Land 3.Public land 4.Road reserve 5.Railway's reserve 6.River reserve 7.Others (Specify)	Presence of stream or river 1. Yes 2. No	Farm position 1.Up stream 2.Middle stream 3.Down stream	Water source 1.Borehole 2.River water 3.Sewer 4.Domestic Wastewater 5.Industry effluent 6.Community dam 7.Others (Specify)	Cultivation methods 1.Open field 2.Green house 3.Plastic tunnel 4.Other (specify)

What do you plant? 1. Vegetable 2. Fruits 3. Staple crops
(maize, Beans) 4. Herbs 5. Cut flowers 6. Others:
.....

Specify the vegetable you plant

Vegetable	Area (Acre)	Yield /Acre	Range of Price
Kales			
Spinach			
Tomato			
Cabbage			
Coriander (Dhania)			
Cucumber			
Carrot			
Sweet corn			
Onion			
Beetroot			
French bean			
Maize			
Beans			
Cowpea			

Irrigation patterns

How frequent do you irrigate?

-In Dry season 1. Daily 2. A Week 3. Not at all
 -In rainy season 1. Daily 2. A Week 3. Not at all

Irrigation water source

Source	Infrastructures used 1. Open basin 2. On site storing pan 3. On site tank 4. Other (specify)	Irrigation system 1. Yes 2. No	Water pumping engine 1. Yes 2. No
Tap water			
Borehole			
River water			
Sewage			
Domestic Wastewater			
Industry effluent			
Community dam			
Other(specify)			
Other(specify)			

Irrigation water characteristic

Irrigation water source	Availability 1. Scarce 2. Periodic 3. Permanent	Water quality 1. Very poor 2. Poor 3. Average 4. Good 5. Very good	Reliability for farming 1. Very poor 2. Poor 3. Average 4. Good 5. Very good	Have you ever used one of these sources for irrigation? 1. Yes 2. No
Tap water				
Borehole				
River water				
Sewer				
Domestic Wastewater				
Industry effluent				
Community dam				
On site pan				

Soil fertility management

Crop	Poultry manure	Cow manure	Pig manure	Goat/ Sheep manure	Wastewater	Compost	Urea	NPK
Leafy vegetable								
Fruit (Tomato, ..)								
Tubers								

Do you used pesticide for pest management for leafy vegetable? 1. Yes 2. No

Do you used pesticide for pest management for fruit vegetable? 1. Yes 2. No

Do you used pesticide for pest management for tubers vegetable? 1. Yes 2. No

Do you have any awareness of heavy metal contamination? 1. Yes 2. No

Heavy metals	Coper	Zinc	Chrome	Lead	Cadmium	Nickel	Arsenic	General awareness
Tick where applicable								

Do you have any awareness of

Microbial pathogens	Worms, bacteria's infestation	Salinity	Acidity	Other (Specify)
Tick where applicable				

In a scale of one to five how do you rank the profitability of Peri-urban agriculture?

1=not profitable;
profitable

2=marginally profitable;

3=moderately

4=Above average profitable;

5=highly profitable

What are the major bottleneck challenges you encounter during?

.....
.....

THANK VERY MUCH!!!

Appendix 2: Questionnaire for Experts' Opinion for Pairwise Comparison of Land Suitability Factors for Vegetable Farming

1. Name initials 2. Profession:

3. Field of specialization:

☐ Agriculture sciences	☐ Chemistry/ Biochemistry/ Biotechnology/ Microbiology	☐ Ecology/Environmental Sciences/ Urban/Spatial/ Regional/ Environmental Planning/Management
☐ Public health/ Pharmacy/ Medicine	☐ Geography & Earth sciences	☐ Others (specify)

3. Age

☐ < 35	☐ 35 - 60	☐ > 60

4. Read Table 2 by following Y axe versus X axe and fill in the importance of Y parameters versus X parameters for land suitability for vegetable farming, based on the AHP priority scale provide in Table 1.

Table 1: Intensity of importance

Intensity of importance	Definition
1	Equal importance
2	Equal to moderate importance
3	Moderate importance
4	Moderate to strong importance
5	strong importance
6	Strong to very strong importance
7	Very strong importance
8	Very to extremely strong importance
9	Extremely importance

Table 2: Main criteria of land suitability for vegetable farming

X axis →

↓ **Y axis**

Criteria	Land use	Water accessibility and quality	Soil suitability	Health risk	Landform	Market accessibility
Land use types	1					
Water quality		1				
Soil contamination			1			
Health risk				1		
Topography					1	
Market accessibility						1

5. Read Table 3 by following Y axis versus X axis and fill in the importance of Y parameters versus X parameters for land suitability analysis for vegetable farming, based on the AHP priority scale provide in Table 1.

Table 3: Pairwise comparison matrix for the sub-criteria of land use

→ **X axis**

↓ **Y axis**

Sub-criteria	Agricultural	Bare ground	Reserve area	Low density residential	Medium density residential	High density residential	Light industrial
Agricultural	1						
Bare ground		1					
Reserve area			1				
Low density residential				1			
Medium density residential					1		
High density residential						1	
Light industrial							1

6. Read Table 4 by following Y axis versus X axis and fill in the importance of Y parameters versus X parameters for land suitability analysis for vegetable farming, based on the AHP priority scale provide in Table 1.

Table 4: Pairwise comparison matrix for the sub-criteria irrigation water accessibility and quality

Y axis  X axis 

Sub-criteria	Water accessibility	IWQI	MCI
Water accessibility	1		
IWQI		1	
MCI			1

7. Read Table 4 by following Y axis versus X axis and fill in the importance of Y parameters versus X parameters for land suitability analysis for vegetable, based on the AHP priority scale provide in Table 1.

Table 5: Pairwise comparison matrix for the sub-criteria of soil suitability

Y axis  X axis 

Criteria	PLI	Soil type
PLI	1	
Soil type		1

8. Read Table 6 by following Y axis versus X axis and fill in the importance of Y parameters versus X parameters for land suitability analysis for vegetable, based on the AHP priority scale provide in Table 1.

Table 6: Pairwise comparison matrix for the sub-criteria of health risks

Y axis  X axis 

Criteria	TCR	HI
TCR	1	
HI		1

9. Read Table 7 by following Y axis versus X axis and fill in the importance of Y parameters versus X parameters for land suitability analysis for vegetable, based on the AHP priority scale provide in Table 1.

Table 7: Pairwise comparison matrix for the sub-criteria of health risks

Y axis  X axis 

Criteria	Slope	Elevation
Slope	1	
Elevation		1

10. Read Table 8 by following Y axis versus X axis and fill in the importance of Y parameters versus X parameters for land suitability analysis for vegetable, based on the AHP priority scale provide in Table 1.

Table 8: Pairwise comparison matrix for the sub-criteria of market accessibility

Y axis  X axis 

Criteria	Market proximity	Road proximity	Residential area proximity
Market proximity	1	1.4	2
Road proximity	0.71	1	1.11
Residential area proximity	0.5	0.9	1

Thank you very much!!!

Appendix 3: Substantive PhD Registration Letter



KENYATTA UNIVERSITY

OFFICE OF THE REGISTRAR (ACADEMIC)

FAX: 811242/811575
E-mail: admissions-pg@ku.ac.ke
Website: www.ku.ac.ke

P.O. Box 43844-00100
NAIROBI, KENYA
Tel: 020-873000 Ext. 3222/23

Our Ref: N85F/28008/2018

Date: 31st March, 2021

Arcadius Martinien Ahogle,
P.O BENIN.

Dear Arcadius,

RE: SUBSTANTIVE REGISTRATION (Ph.D)

Following the recommendation by the Dean, Graduate School, you are hereby granted substantive Ph.D. registration.

Please note that your registration number and all rules and regulations remain the same as per your admission letter.

Thank you.

MR. R. A. CHWEYA,
FOR REGISTRAR (ACADEMIC)

cc Dean, School of Environmental Studies
 Dean, Graduate School
 Chairman, Department of Environmental Planning & Management

RAC/hk

Transforming Higher Education....Enhancing Lives
Kenyatta University is ISO 9001:2015 Certified



Appendix 4: NACOSTI Research Permit

 REPUBLIC OF KENYA	 NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION
Ref No: 884917	Date of Issue: 17/March/2021
RESEARCH LICENSE	
	
This is to Certify that Mr.. Martinien Arcadius AHOGLE AGA of Kenyatta University, has been licensed to conduct research in Machakos, Nairobi on the topic: PERI-URBAN AGRO-SYSTEMS DYNAMICS AND THEIR IMPLICATIONS ON VEGETABLE CONTAMINATION IN NAIROBI-MACHAKOS COUNTIES INTERFACE, KENYA for the period ending : 17/March/2022.	
License No: NACOSTI/P/21/9601	
884917	
Applicant Identification Number	Director General NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION
	Verification QR Code
	
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Appendix 5: ICP-MS Analysis Order for Heavy Metals and Trace Elements



The University of
Nottingham

School of Biosciences
Division of Agriculture and Environmental Science
Sutton Bonington Campus
Sutton Bonington
Loughborough
Leicestershire
LE12 5RD
United Kingdom

www.nottingham.ac.uk/biosciences

Tel: +44 (0)115 951 6255
Email: liz.bailey@nottingham.ac.uk

3rd November 2021

Ref: ICP-EHB-21-15

Dear Arcadius,

Re: Quotation for soil, plant and water samples for ME and Hg analysis

Thank you for the opportunity to provide a quotation for this work. Details are provided below.

For ground soil samples requiring total or 'pseudo total' elemental analysis we can offer (i) digestion in boiling aqua regia (trace element grade acids) to provide 'pseudo-totals' using 2 mm sieved soil or finely ground soil, or (ii) a mixed acid digestion approach (HF, HClO₄, HNO₃) on finely ground soil. We need c. 2 g of homogeneous appropriately ground soil for a single digestion. Milli-Q water (18.2 MΩ cm) is used for all dilutions undertaken prior to analysis. For plant materials we have both microwave digestion (Multiwave Pro; Anton Paar) and hotplate facilities (Multicube 48; Anton Paar) and use Primar Plus™ grade nitric acid either alone or in combination with hydrogen peroxide. Milli-Q water (18.2 MΩ cm) is used for dilutions prior to analysis. We need c. 1 g finely ground material for a single acid digestion.

We report a standard range of major and trace elements including: Al, As, B, Ba, Cd, Ca, Co, Cr, Cs, Cu, Fe, K, Mg, Mn, Mo, Na, Ni, P, Pb, Rb, S, Se, Sr, Ti, U, V and Zn and can provide a detailed methodological description of the procedures undertaken including details of quality control.

Analysis is undertaken using two ICP-MS instruments: Thermo-Fisher iCAP-Q (single quadrupole) and iCAP-TQ (triple quadrupole); both are equipped with a 'Flatapole collision cell' (typically charged with helium gas) upstream of the analytical quadrupole to reduce polyatomic interferences. The triple quadrupole instrument is routinely used to 'mass-shift' very low concentrations of selected elements away from interfering species (e.g. Se) using an oxygen cell between the quadrupoles. Multiple internal standards are introduced to the sample stream via a T-piece, to correct for instrument drift, and typically include Sc (50 µg L⁻¹), Ge (20 µg L⁻¹), Rh (10 µg L⁻¹), Re (10 µg L⁻¹) and Ir (5 µg L⁻¹) in a matrix of 2% HNO₃; a similar concentration of HCl is also acceptable. Direct spiking of internal standards into samples and the use of a single line delivery approach is

**Appendix 6: KEPHIS Clearance Certificate for Water, Soil and Plant Tissue
Samples Shipping to School of Biosciences, The University of
Nottingham UK**

No. 3572649		 PHYTOSANITARY CERTIFICATE No. KEPHIS/9166/2021	 KEPHIS CERT 3572649
MINISTRY OF AGRICULTURE KENYA PLANT HEALTH INSPECTORATE SERVICE PHYTOSANITARY CERTIFICATE FOR SOIL, ORGANIC MANURES, ROOTING AND/OR POTTING MIXTURES AND REGULATED ARTICLES (Agricultural Produce (Export) Act Cap. 319)			
1. Name and Address of Exporter Martinien Arcadius Ahogle Agassin Kenyatta University P.O. Box 43844-00100 Nairobi, Kenya		2. Dealer's name and address of Consignee School of Biosciences Sutton Bonington Campus Loughborough, Leicestershire LE 12 5RD, United Kingdom	
3. Place of origin: Kenya		4. To Plant Protection Organization of United Kingdom	
		5. Declared means of Conveyance Air	
6. Declared point of Entry: Airport		7. Distinguishing marks Labelled	
8. Number and description of packages: 3 Packages of Assorted Samples		9. Name of regulated Article(s) Plant, Soil and Water Samples	
10. Scientific identity of Regulated Article(s) Brassica Oleracea, Soil and Water		11. Quantity declared 1Kg, 1.2Kg, 1Kg	
12. This is to certify that the Article(s) described above has/have been inspected according to appropriate procedures and are considered to be free from quarantine pests and practically free from other injurious pests in conformity with the current phytosanitary regulations of the importing country.			
13. Additional declaration: For Research purposes only.			
14. Disinfestation and/or disinfection treatment: None		Place of issue KEPHIS HEADQUARTERS	
15. Chemical (Active ingredient): None		Date: 24/11/2021	
16. Duration and temperature: None		Name of Inspector: BERNARD MUKOYE	
17. Concentration None 18. Date		Signature 	
19. Any additional information		of Authorizing officer	



Note: The certificate shall be completed in typescript or in block capitals
 No financial liability with respect to this certificate shall attach to Kenya Plant Health Inspectorate Service or to any of its officers or representatives.

Appendix 7 Coordinate of Sampling Stations

Sampling stations	Samples	Coordinates		Stations description	Irrigation water sources
		X	Y		
S1	S1A	272149.7	9844413	Residential-industrial mixed area, Pridelands,	Raw domestic sewage
	S1B	272161.4	9844055		
	S1C	272403.8	9843519		
S2	S2A	273585.6	9840367	Athi River Town industrial area	Mixture of domestic sewage and river water (Athi River)
	S2B	274674.2	9840388		
	S2C	275425	9840482		
S3	S3A	277554.2	9841851	High-density residential area, Athi River town	Mixture of domestic sewage and river water (Athi River)
	S3B	278853.2	9842707		
	S3C	279132.5	9843642		
S4	S4A	280663.5	9845797	Before the EPZ wastewater treatment plant, Kinanie	Mixture of domestic sewage and river water (Athi River)
	S4B	279916	9846353		
	S4C	282279	9847206		
S5	S5A	283326.2	9851985	After the EPZ wastewater treatment plant, Kinanie	Mixture of domestic sewage, river water (Athi River) and WTP effluent 61,943 m ³ /day
	S5B	284021	9852820		
	S5C	284421.9	9854336		
S6	S6A	286377.2	9857803	Muthwani-Kamulu Nairobi-Machakos	Mixture of domestic sewage, river (Athi River) and WTP effluent
	S6B	288794.6	9859336		
	S6C	290059.2	9861680		
S7	S7A	274342.1	9860498	Kangundo Road, Nairobi	Open drainage canal, mixture of domestic sewage
	S7B	275236.8	9860462		
	S7C	278290.7	9858849		
S8	S8A	276535.7	9854450	Stream, Katani-Utawala bridge	Mixture of domestic sewage and urban stream water
	S8B	279212	9855264		
	S8C	280965.7	9855730		
S9	S9A	274975.4	9861746	Before the WTP discharge point, Ruai	Mixture of domestic sewage, river water (Nairobi River)
	S9B	276377.1	9862336		
	S9C	277399.9	9862740		
S10	S10A	280334.9	9864567	Downstream after the WTP discharge point, Ruai	Mixture of domestic sewage, river water (Nairobi River) and WTP effluent 80,000 m ³ /day
	S10B	281688.1	9865655		
	S10C	283476.3	9866353		

WTP = wastewater treatment plant; EPZ = export processing zone

Geographic projection system: WGS 84 / UTM zone 37S

Appendix 8: Pictorial of Field Work



Appendix 9: Pictorial of Samples Processing and Laboratory Analysis



Appendix 10: Principal Component Loading for PCA Analysis Performed on Heavy Metal and Trace Element Concentration in Soil

Heavy metals	PC1	PC2	PC3
As	17.01	4.22	4.47
Cd	14.26	1.26	3.66
Co	0.04	4.12	41.97
Cr	5.76	22.23	1.59
Cu	4.67	16.49	0.95
Fe	15.58	0.17	0.00
Hg	3.65	2.43	0.28
Mn	2.10	3.59	38.04
Ni	0.29	26.06	5.02
Pb	15.74	1.33	0.97
V	0.52	17.29	0.22
Zn	20.36	0.80	2.81
Eigenvalues	4.23	2.63	1.97
% Variance	35.2	22	16
Cumulative variance	35.2	57.2	73.2

The coefficients in bold indicate the principal component on which an element loading is the highest

Appendix 11: Chronic Daily Intake CDI from Kale Consumption

Table 1: Chronic daily intake CDI from kale consumption in dry season

Sites	Age group	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Child	4.6E-5	6.4E-5	1.8E-4	3.2E-3	9.5E-6	2.4E-4	2.9E-4	1.6E-2
	Adult	3.1E-5	4.3E-5	1.2E-4	2.2E-3	6.4E-6	1.6E-4	2.0E-4	1.1E-2
S2	Child	4.9E-5	6.6E-5	2.7E-4	2.6E-3	4.3E-6	2.2E-4	1.3E-3	1.6E-2
	Adult	3.3E-5	4.5E-5	1.9E-4	1.8E-3	2.9E-6	1.5E-4	9.1E-4	1.1E-2
S3	Child	3.2E-5	5.9E-5	1.8E-4	2.8E-3	6.9E-6	2.0E-4	1.7E-4	1.2E-2
	Adult	2.1E-5	4.0E-5	1.2E-4	1.9E-3	4.7E-6	1.3E-4	1.2E-4	8.0E-3
S4	Child	2.8E-5	6.1E-5	1.0E-4	1.0E-3	7.7E-6	3.1E-4	4.6E-5	1.2E-2
	Adult	1.9E-5	4.1E-5	6.8E-5	6.9E-4	5.2E-6	2.1E-4	3.1E-5	8.0E-3
S5	Child	6.4E-5	7.2E-5	9.7E-5	1.2E-3	5.8E-6	2.1E-4	3.8E-5	1.5E-2
	Adult	4.4E-5	4.9E-5	6.6E-5	7.8E-4	3.9E-6	1.4E-4	2.6E-5	1.0E-2
S6	Child	3.0E-5	5.5E-5	1.1E-4	1.4E-3	3.6E-6	4.0E-4	1.5E-4	1.5E-2
	Adult	2.0E-5	3.8E-5	7.8E-5	9.5E-4	2.4E-6	2.7E-4	1.0E-4	1.0E-2
S7	Child	4.9E-5	7.1E-5	3.1E-4	1.8E-3	8.3E-6	5.9E-4	2.9E-4	2.7E-2
	Adult	3.3E-5	4.9E-5	2.1E-4	1.2E-3	5.6E-6	4.0E-4	1.9E-4	1.8E-2
S8	Child	3.3E-5	3.6E-5	1.7E-4	4.4E-3	4.1E-6	1.5E-4	2.2E-4	1.4E-2
	Adult	2.2E-5	2.5E-5	1.2E-4	3.0E-3	2.8E-6	1.0E-4	1.5E-4	9.3E-3
S9	Child	3.0E-5	1.2E-4	9.1E-5	1.1E-3	4.5E-6	1.9E-4	4.6E-5	2.2E-2
	Adult	2.0E-5	8.0E-5	6.2E-5	7.7E-4	3.1E-6	1.3E-4	3.1E-5	1.5E-2
S10	Child	7.3E-5	7.9E-5	2.5E-4	1.0E-2	2.2E-5	2.6E-4	7.7E-4	2.0E-2
	Adult	5.0E-5	5.4E-5	1.7E-4	7.0E-3	1.5E-5	1.7E-4	5.2E-4	1.4E-2

Table 2: Chronic daily intake from kale consumption in wet season

Sites	Age group	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Child	3.2E-5	9.2E-5	1.2E-4	1.3E-3	3.4E-6	1.6E-4	5.8E-5	1.4E-2
	Adult	2.2E-5	6.2E-5	8.4E-5	8.9E-4	2.3E-6	1.1E-4	3.9E-5	9.8E-3
S2	Child	4.0E-5	4.4E-5	1.1E-4	1.2E-3	2.4E-6	3.0E-4	7.9E-5	1.4E-2
	Adult	2.7E-5	3.0E-5	7.5E-5	8.1E-4	1.7E-6	2.1E-4	5.4E-5	9.7E-3
S3	Child	2.2E-5	3.0E-5	6.2E-5	9.7E-4	2.0E-6	2.8E-4	4.7E-5	1.2E-2
	Adult	1.5E-5	2.1E-5	4.2E-5	6.6E-4	1.4E-6	1.9E-4	3.2E-5	7.9E-3
S4	Child	3.8E-5	6.4E-5	1.8E-5	2.0E-3	4.7E-6	5.2E-4	1.5E-5	1.9E-2
	Adult	2.6E-5	4.3E-5	1.3E-5	1.4E-3	3.2E-6	3.5E-4	9.9E-6	1.3E-2
S5	Child	1.7E-5	6.0E-5	3.6E-5	1.7E-3	3.9E-6	4.2E-4	1.8E-5	1.8E-2
	Adult	1.1E-5	4.1E-5	2.5E-5	1.2E-3	2.6E-6	2.9E-4	1.2E-5	1.2E-2
S6	Child	1.2E-5	5.8E-5	2.8E-5	1.1E-3	4.1E-6	2.1E-4	2.3E-5	1.3E-2
	Adult	8.5E-6	4.0E-5	1.9E-5	7.2E-4	2.8E-6	1.4E-4	1.6E-5	8.6E-3
S7	Child	4.0E-5	3.7E-5	1.9E-4	1.6E-3	3.8E-6	1.2E-4	9.9E-5	2.7E-2
	Adult	2.7E-5	2.5E-5	1.3E-4	1.1E-3	2.6E-6	8.0E-5	6.7E-5	1.8E-2
S8	Child	2.1E-5	3.2E-5	7.3E-5	8.7E-4	3.0E-6	7.8E-5	2.2E-5	7.3E-3
	Adult	1.4E-5	2.2E-5	5.0E-5	5.9E-4	2.1E-6	5.3E-5	1.5E-5	5.0E-3
S9	Child	2.4E-5	6.4E-5	7.4E-5	1.2E-3	5.2E-6	1.2E-4	5.8E-5	2.0E-2
	Adult	1.6E-5	4.3E-5	5.0E-5	8.3E-4	3.6E-6	8.2E-5	3.9E-5	1.3E-2
S10	Child	5.4E-5	8.9E-5	2.9E-4	3.4E-3	3.4E-6	8.8E-5	5.8E-5	1.7E-2
	Adult	3.7E-5	6.1E-5	2.0E-4	2.3E-3	2.3E-6	6.0E-5	3.9E-5	1.1E-2

Table 3: Chronic daily intake from intake from soil particle ingestion in dry season

Sites	Age group	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Child	4.2E-6	2.5E-7	1.3E-5	7.2E-6	3.3E-8	1.2E-5	1.9E-5	1.4E-4
	Adult	9.4E-7	5.6E-8	2.9E-6	1.6E-6	7.6E-9	2.8E-6	4.2E-6	3.2E-5
S2	Child	3.3E-6	1.9E-7	2.1E-5	1.4E-5	1.1E-8	1.7E-5	1.7E-5	1.1E-4
	Adult	7.5E-7	4.3E-8	4.8E-6	3.3E-6	2.6E-9	3.8E-6	3.7E-6	2.4E-5
S3	Child	2.7E-6	1.6E-7	1.3E-5	1.2E-5	1.2E-8	1.2E-5	1.3E-5	8.4E-5
	Adult	6.1E-7	3.7E-8	3.0E-6	2.7E-6	2.7E-9	2.8E-6	2.9E-6	1.9E-5
S4	Child	2.2E-6	1.2E-7	1.2E-5	9.3E-6	6.9E-9	1.1E-5	9.6E-6	7.8E-5
	Adult	5.0E-7	2.8E-8	2.8E-6	2.1E-6	1.6E-9	2.5E-6	2.2E-6	1.8E-5
S5	Child	3.6E-6	2.6E-7	1.8E-5	1.7E-5	6.9E-9	1.2E-5	3.0E-5	1.5E-4
	Adult	8.2E-7	5.8E-8	4.1E-6	3.7E-6	1.6E-9	2.8E-6	6.7E-6	3.3E-5
S6	Child	3.1E-6	1.7E-7	1.4E-5	1.0E-5	1.1E-8	1.4E-5	1.5E-5	9.1E-5
	Adult	7.1E-7	3.7E-8	3.1E-6	2.3E-6	2.5E-9	3.1E-6	3.3E-6	2.1E-5
S7	Child	4.2E-6	4.0E-7	1.2E-5	9.7E-6	1.8E-8	8.1E-6	2.7E-5	1.4E-4
	Adult	9.4E-7	9.1E-8	2.6E-6	2.2E-6	4.2E-9	1.8E-6	6.2E-6	3.1E-5
S8	Child	4.4E-6	1.5E-7	1.2E-5	9.8E-6	1.7E-8	1.4E-5	2.4E-5	1.0E-4
	Adult	1.0E-6	3.3E-8	2.8E-6	2.2E-6	3.8E-9	3.2E-6	5.5E-6	2.3E-5
S9	Child	4.2E-6	2.2E-7	1.2E-5	9.4E-6	2.8E-8	9.4E-6	2.6E-5	1.3E-4
	Adult	9.4E-7	5.0E-8	2.7E-6	2.1E-6	6.3E-9	2.1E-6	6.0E-6	2.9E-5
S10	Child	4.0E-6	2.6E-7	1.6E-5	1.3E-5	4.8E-8	1.1E-5	2.8E-5	1.4E-4
	Adult	9.0E-7	5.9E-8	3.5E-6	3.0E-6	1.1E-8	2.6E-6	6.3E-6	3.1E-5

Table 4: Chronic daily intake from soil particle ingestion in wet season

Sites	Age group	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Child	4.6E-6	3.1E-7	1.3E-5	1.2E-5	3.3E-8	1.2E-5	2.6E-5	1.5E-4
	Adult	1.0E-6	7.1E-8	2.8E-6	2.6E-6	7.6E-9	2.7E-6	5.9E-6	3.5E-5
S2	Child	3.0E-6	2.1E-7	2.1E-5	1.3E-5	1.1E-8	1.5E-5	1.7E-5	1.0E-4
	Adult	6.8E-7	4.7E-8	4.6E-6	3.0E-6	2.6E-9	3.3E-6	3.8E-6	2.2E-5
S3	Child	3.6E-6	2.2E-7	1.3E-5	9.2E-6	1.2E-8	1.1E-5	1.6E-5	1.1E-4
	Adult	8.2E-7	5.0E-8	2.9E-6	2.1E-6	2.7E-9	2.6E-6	3.6E-6	2.5E-5
S4	Child	2.2E-6	1.2E-7	1.1E-5	1.0E-5	6.9E-9	1.0E-5	9.6E-6	6.7E-5
	Adult	5.0E-7	2.7E-8	2.4E-6	2.3E-6	1.6E-9	2.4E-6	2.2E-6	1.5E-5
S5	Child	2.8E-6	1.8E-7	1.2E-5	1.2E-5	6.9E-9	1.2E-5	1.3E-5	7.8E-5
	Adult	6.4E-7	4.0E-8	2.7E-6	2.6E-6	1.6E-9	2.8E-6	3.0E-6	1.8E-5
S6	Child	3.2E-6	2.1E-7	1.1E-5	7.9E-6	1.1E-8	9.0E-6	1.6E-5	1.2E-4
	Adult	7.2E-7	4.8E-8	2.4E-6	1.8E-6	2.5E-9	2.0E-6	3.6E-6	2.6E-5
S7	Child	4.0E-6	2.5E-7	1.2E-5	1.2E-5	1.8E-8	8.6E-6	2.0E-5	1.3E-4
	Adult	9.1E-7	5.7E-8	2.7E-6	2.8E-6	4.2E-9	1.9E-6	4.4E-6	2.8E-5
S8	Child	4.5E-6	1.5E-7	1.1E-5	8.4E-6	1.7E-8	1.4E-5	2.4E-5	1.0E-4
	Adult	1.0E-6	3.4E-8	2.6E-6	1.9E-6	3.8E-9	3.1E-6	5.4E-6	2.3E-5
S9	Child	4.2E-6	2.2E-7	1.1E-5	8.0E-6	2.8E-8	8.7E-6	1.3E-5	1.2E-4
	Adult	9.5E-7	5.0E-8	2.5E-6	1.8E-6	6.3E-9	2.0E-6	3.0E-6	2.8E-5
S10	Child	3.8E-6	2.3E-7	1.6E-5	1.1E-5	4.8E-8	1.8E-5	1.6E-5	1.5E-4
	Adult	8.6E-7	5.3E-8	3.5E-6	2.5E-6	1.1E-8	4.E-6	3.7E-6	3.3E-5

Table 5: Chronic daily intake from soil dust inhalation in dry season

Sites	Age group	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Child	3.9E-10	2.3E-11	1.2E-9	6.7E-10	3.1E-12	1.2E-9	1.7E-9	1.3E-8
	Adult	4.6E-10	2.7E-11	1.4E-9	8.0E-10	3.7E-12	1.4E-9	2.1E-9	1.6E-8
S2	Child	3.1E-10	1.8E-11	2.0E-9	1.3E-9	1.1E-12	1.6E-9	1.5E-9	9.8E-9
	Adult	3.7E-10	2.1E-11	2.3E-9	1.6E-9	1.3E-12	1.9E-9	1.8E-9	1.2E-8
S3	Child	2.5E-10	1.5E-11	1.2E-9	1.1E-9	1.1E-12	1.1E-9	1.2E-9	7.8E-9
	Adult	3.0E-10	1.8E-11	1.5E-9	1.3E-9	1.3E-12	1.4E-9	1.4E-9	9.3E-9
S4	Child	2.1E-10	1.2E-11	1.2E-9	8.7E-10	6.5E-13	1.0E-9	9.0E-10	7.2E-9
	Adult	2.5E-10	1.4E-11	1.4E-9	1.0E-9	7.7E-13	1.2E-9	1.1E-9	8.6E-9
S5	Child	3.4E-10	2.4E-11	1.7E-9	1.5E-9	6.4E-13	1.1E-9	2.8E-9	1.4E-8
	Adult	4.0E-10	2.9E-11	2.0E-9	1.8E-9	7.6E-13	1.4E-9	3.3E-9	1.6E-8
S6	Child	2.9E-10	1.5E-11	1.3E-9	9.6E-10	1.0E-12	1.3E-9	1.4E-9	8.5E-9
	Adult	3.5E-10	1.8E-11	1.5E-9	1.1E-09	1.2E-12	1.5E-9	1.6E-9	1.0E-8
S7	Child	3.9E-10	3.7E-11	1.1E-9	9.0E-10	1.7E-12	7.5E-10	2.5E-9	1.3E-8
	Adult	4.6E-10	4.4E-11	1.3E-9	1.1E-9	2.0E-12	9.0E-10	3.0E-9	1.5E-8
S8	Child	4.1E-10	1.4E-11	1.1E-9	9.1E-10	1.6E-12	1.3E-9	2.3E-9	9.5E-9
	Adult	4.9E-10	1.6E-11	1.4E-9	1.1E-9	1.9E-12	1.6E-9	2.7E-9	1.1E-8
S9	Child	3.9E-10	2.1E-11	1.1E-9	8.7E-10	2.6E-12	8.8E-10	2.5E-9	1.2E-8
	Adult	4.6E-10	2.5E-11	1.3E-9	1.0E-9	3.1E-12	1.0E-9	2.9E-9	1.4E-8
S10	Child	3.7E-10	2.4E-11	1.4E-9	1.2E-9	4.5E-12	1.1E-9	2.6E-9	1.3E-8
	Adult	4.4E-10	2.9E-11	1.7E-9	1.5E-9	5.3E-12	1.3E-9	3.1E-9	1.5E-8

Table 6: Chronic daily intake from soil dust inhalation in wet season

Sites	Age group	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Child	4.3E-10	2.9E-11	1.2E-9	1.1E-9	3.1E-12	1.1E-9	2.4E-9	1.4E-8
S1	Adult	5.1E-10	3.5E-11	1.4E-9	1.3E-9	3.7E-12	1.3E-9	2.9E-9	1.7E-8
S2	Child	2.8E-10	1.9E-11	1.9E-9	1.2E-9	1.1E-12	1.4E-9	1.6E-9	9.3E-9
S2	Adult	3.3E-10	2.3E-11	2.3E-9	1.5E-9	1.3E-12	1.6E-9	1.9E-9	1.1E-8
S3	Child	3.4E-10	2.1E-11	1.2E-9	8.6E-10	1.1E-12	1.1E-9	1.5E-9	1.0E-8
S3	Adult	4.0E-10	2.5E-11	1.4E-9	1.0E-9	1.3E-12	1.3E-9	1.8E-9	1.2E-8
S4	Child	2.1E-10	1.1E-11	9.9E-10	9.3E-10	6.5E-13	9.7E-10	8.9E-10	6.3E-9
S4	Adult	2.4E-10	1.3E-11	1.2E-9	1.1E-9	7.7E-13	1.2E-9	1.1E-9	7.4E-9
S5	Child	2.6E-10	1.7E-11	1.1E-9	1.1E-9	6.4E-13	1.1E-9	1.2E-9	7.3E-9
S5	Adult	3.1E-10	2.0E-11	1.3E-9	1.3E-9	7.6E-13	1.4E-9	1.5E-9	8.7E-9
S6	Child	3.0E-10	2.0E-11	9.9E-10	7.3E-10	1.0E-12	8.3E-10	1.5E-9	1.1E-8
S6	Adult	3.5E-10	2.4E-11	1.2E-9	8.7E-10	1.2E-12	9.9E-10	1.8E-9	1.3E-8
S7	Child	3.8E-10	2.4E-11	1.1E-9	1.1E-9	1.7E-12	8.0E-10	1.8E-9	1.2E-8
S7	Adult	4.5E-10	2.8E-11	1.3E-9	1.4E-9	2.0E-12	9.5E-10	2.2E-9	1.4E-8
S8	Child	4.2E-10	1.4E-11	1.1E-9	7.8E-10	1.6E-12	1.3E-9	2.2E-9	9.3E-9
S8	Adult	5.0E-10	1.6E-11	1.3E-9	9.3E-10	1.9E-12	1.5E-9	2.6E-9	1.1E-8
S9	Child	3.9E-10	2.1E-11	1.0E-9	7.4E-10	2.6E-12	8.1E-10	1.2E-9	1.1E-8
S9	Adult	4.7E-10	2.4E-11	1.2E-9	8.8E-10	3.1E-12	9.6E-10	1.5E-9	1.4E-8
S10	Child	3.6E-10	2.2E-11	1.5E-9	1.0E-9	4.5E-12	1.6E-9	1.5E-9	1.4E-8
S10	Adult	4.2E-10	2.6E-11	1.7E-9	1.2E-9	5.3E-12	2.0E-9	1.8E-9	1.6E-8

Table 7: Chronic daily intake from dermal contact with soil material in dry season

Sites	Age	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Child	1.4E-8	8.1E-10	4.2E-8	2.4E-8	1.1E-10	4.1E-8	6.1E-8	4.7E-7
	Adult	1.3E-7	7.4E-9	3.8E-7	2.2E-7	1.0E-9	3.8E-7	5.6E-7	4.3E-6
S2	Child	1.1E-8	6.2E-10	6.9E-8	4.7E-8	3.7E-11	5.5E-8	5.4E-8	3.4E-7
	Adult	9.9E-8	5.7E-9	6.3E-7	4.4E-7	3.4E-10	5.1E-7	5.0E-7	3.2E-6
S3	Child	8.8E-9	5.3E-10	4.3E-8	3.9E-8	3.9E-11	4.0E-8	4.2E-8	2.7E-7
	Adult	8.1E-8	4.9E-9	4.0E-7	3.6E-7	3.6E-10	3.7E-7	3.8E-7	2.5E-6
S4	Child	7.3E-9	4.0E-10	4.1E-8	3.0E-8	2.3E-11	3.6E-8	3.1E-8	2.5E-7
	Adult	6.7E-8	3.7E-9	3.8E-7	2.8E-7	2.1E-10	3.3E-7	2.9E-7	2.3E-6
S5	Child	1.2E-8	8.4E-10	6.0E-8	5.4E-8	2.2E-11	4.0E-8	9.7E-8	4.8E-7
	Adult	1.1E-7	7.8E-9	5.5E-7	5.0E-7	2.1E-10	3.7E-7	9.0E-7	4.4E-6
S6	Child	1.0E-8	5.4E-10	4.5E-8	3.4E-8	3.5E-11	4.4E-8	4.8E-8	3.0E-7
	Adult	9.4E-8	5.0E-9	4.2E-7	3.1E-7	3.3E-10	4.1E-7	4.4E-7	2.7E-6
S7	Child	1.4E-8	1.3E-9	3.8E-8	3.2E-8	6.0E-11	2.6E-8	8.9E-8	4.5E-7
	Adult	1.3E-7	1.2E-8	3.5E-7	2.9E-7	5.5E-10	2.4E-7	8.2E-7	4.2E-6
S8	Child	1.4E-8	4.8E-10	4.0E-8	3.2E-8	5.5E-11	4.6E-8	8.0E-8	3.3E-7
	Adult	1.3E-7	4.4E-9	3.7E-7	2.9E-7	5.1E-10	4.2E-7	7.3E-7	3.1E-6
S9	Child	1.4E-8	7.3E-10	3.9E-8	3.1E-8	9.2E-11	3.1E-8	8.6E-8	4.1E-7
	Adult	1.3E-7	6.7E-9	3.6E-7	2.8E-7	8.4E-10	2.8E-7	7.9E-7	3.8E-6
S10	Child	1.3E-8	8.6E-10	5.1E-8	4.4E-8	1.6E-10	3.8E-8	9.2E-8	4.5E-7
	Adult	1.2E-7	7.9E-9	4.7E-7	4.0E-7	1.5E-9	3.5E-7	8.4E-7	4.1E-6

Table 8: Chronic daily intake from dermal contact with soil material in wet season

Sites	Age group	AS	Cd	Cr	Cu	Hg	Ni	Pb	Zn
S1	Child	1.5E-8	1.0E-9	4.1E-8	3.8E-8	1.1E-10	3.9E-8	8.5E-8	5.0E-7
	Adult	1.4E-7	9.4E-9	3.8E-7	3.5E-7	1.0E-9	3.6E-7	7.9E-7	4.6E-6
S2	Child	9.8E-9	6.8E-10	6.7E-8	4.3E-8	3.7E-11	4.8E-8	5.5E-8	3.3E-7
	Adult	9.0E-8	6.3E-9	6.2E-7	4.0E-7	3.4E-10	4.4E-7	5.1E-7	3.0E-6
S3	Child	1.2E-8	7.2E-10	4.2E-8	3.0E-8	3.9E-11	3.7E-8	5.3E-8	3.7E-7
	Adult	1.1E-7	6.7E-9	3.8E-7	2.8E-7	3.6E-10	3.4E-7	4.9E-7	3.4E-6
S4	Child	7.2E-9	3.9E-10	3.5E-8	3.3E-8	2.3E-11	3.4E-8	3.1E-8	2.2E-7
	Adult	6.6E-8	3.6E-9	3.2E-7	3.0E-7	2.1E-10	3.1E-7	2.9E-7	2.0E-6
S5	Child	9.2E-9	5.8E-10	3.9E-8	3.8E-8	2.2E-11	4.0E-8	4.3E-8	2.6E-7
	Adult	8.5E-8	5.3E-9	3.6E-7	3.5E-7	2.1E-10	3.7E-7	3.9E-7	2.4E-6
S6	Child	1.0E-8	7.0E-10	3.5E-8	2.6E-8	3.5E-11	2.9E-8	5.2E-8	3.8E-7
	Adult	9.6E-8	6.4E-9	3.2E-7	2.4E-7	3.3E-10	2.7E-7	4.8E-7	3.5E-6
S7	Child	1.3E-8	8.3E-10	3.9E-8	4.0E-8	6.0E-11	2.8E-8	6.4E-8	4.1E-7
	Adult	1.2E-7	7.6E-9	3.6E-7	3.7E-7	5.5E-10	2.6E-7	5.9E-7	3.8E-6
S8	Child	1.5E-8	4.9E-10	3.7E-8	2.7E-8	5.5E-11	4.5E-8	7.7E-8	3.3E-7
	Adult	1.3E-7	4.5E-9	3.4E-7	2.5E-7	5.1E-10	4.2E-7	7.1E-7	3.0E-6
S9	Child	1.4E-8	7.2E-10	3.6E-8	2.6E-8	9.2E-11	2.8E-8	4.4E-8	4.0E-7
	Adult	1.3E-7	6.6E-9	3.3E-7	2.4E-7	8.4E-10	2.6E-7	4.0E-7	3.7E-6
S10	Child	1.2E-8	7.7E-10	5.1E-8	3.7E-8	1.6E-10	5.8E-8	5.4E-8	4.8E-7
	Adult	1.1E-7	7.0E-9	4.7E-7	3.4E-7	1.5E-9	5.3E-7	4.9E-7	4.4E-6

Appendix 12: Planning Maps

The planning maps used in the study were collected from the Lands and Physical Planning department of Machakos county and are also available online at <https://machakos.go.ke/download/strategic-integrated-action-plans-for-konza-kenol-kangundo-tala-komarock-ruai-eastern-by-pass-transport-corridor/>

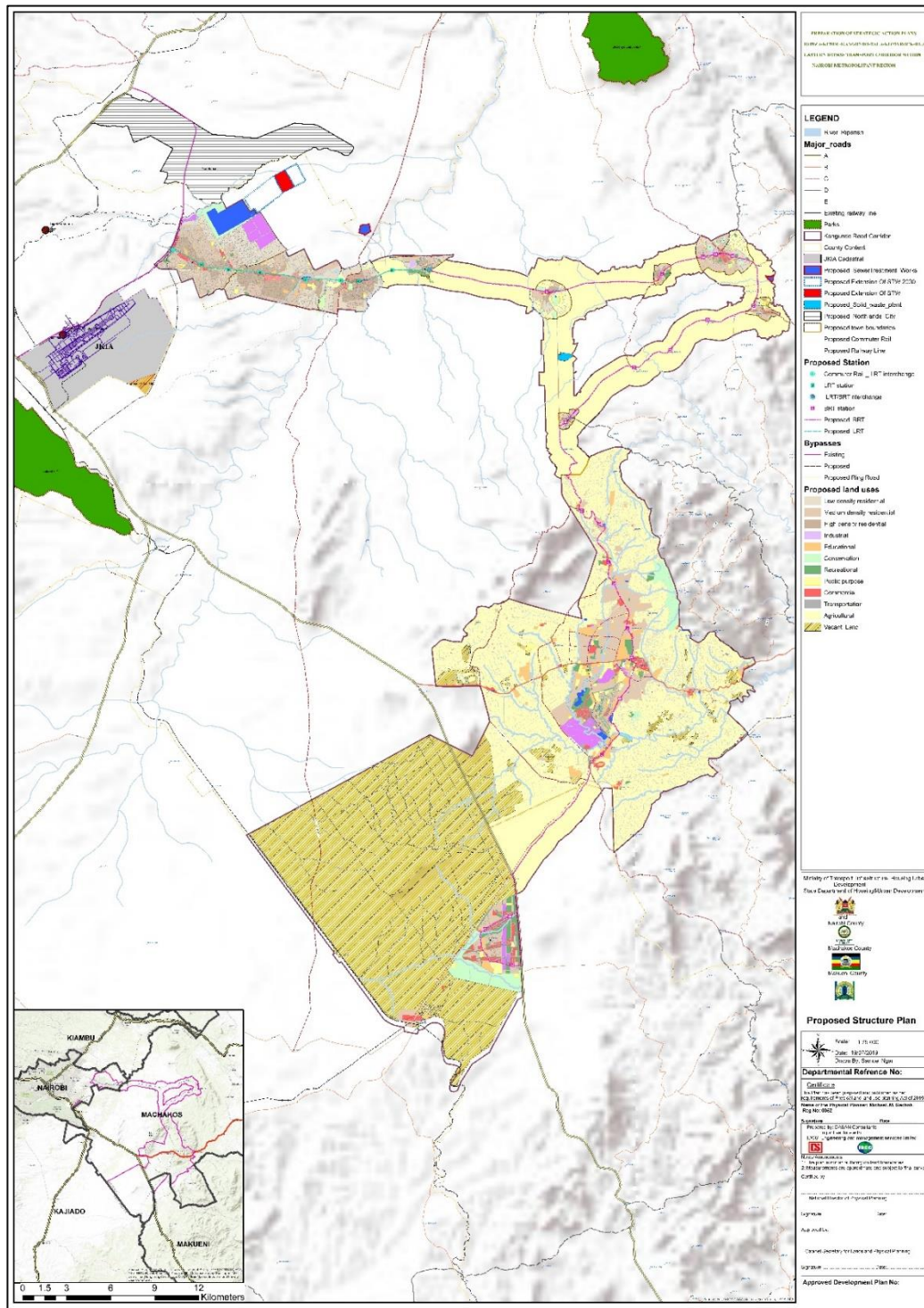


Figure 1: Strategic Integrated Action Plans for Konza-Kenol-Kangundo-Tala-Komarock-Ruai-Eastern By-Pass Transport Corridor

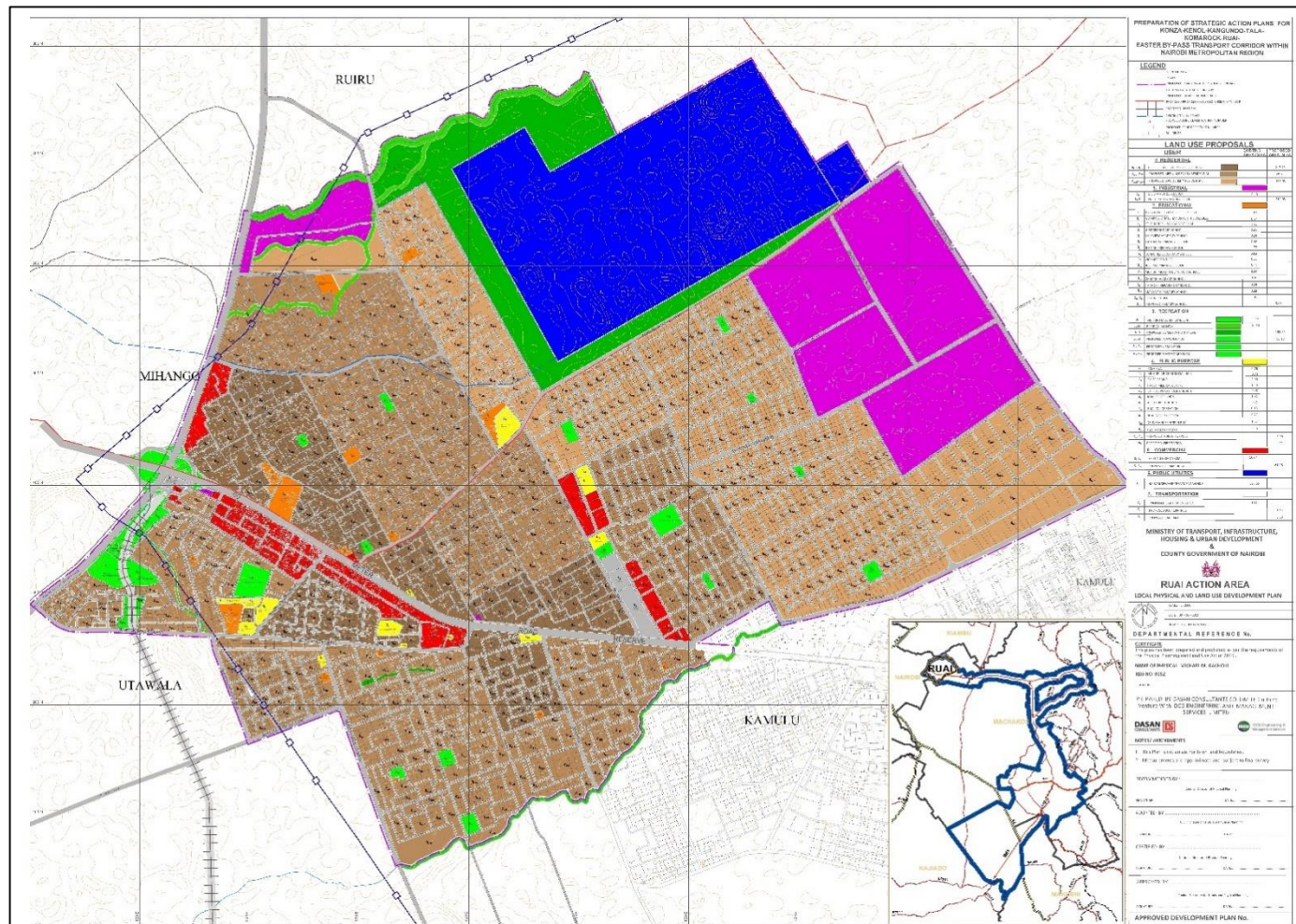


Figure 2: Ruai strategic land use plan 2030

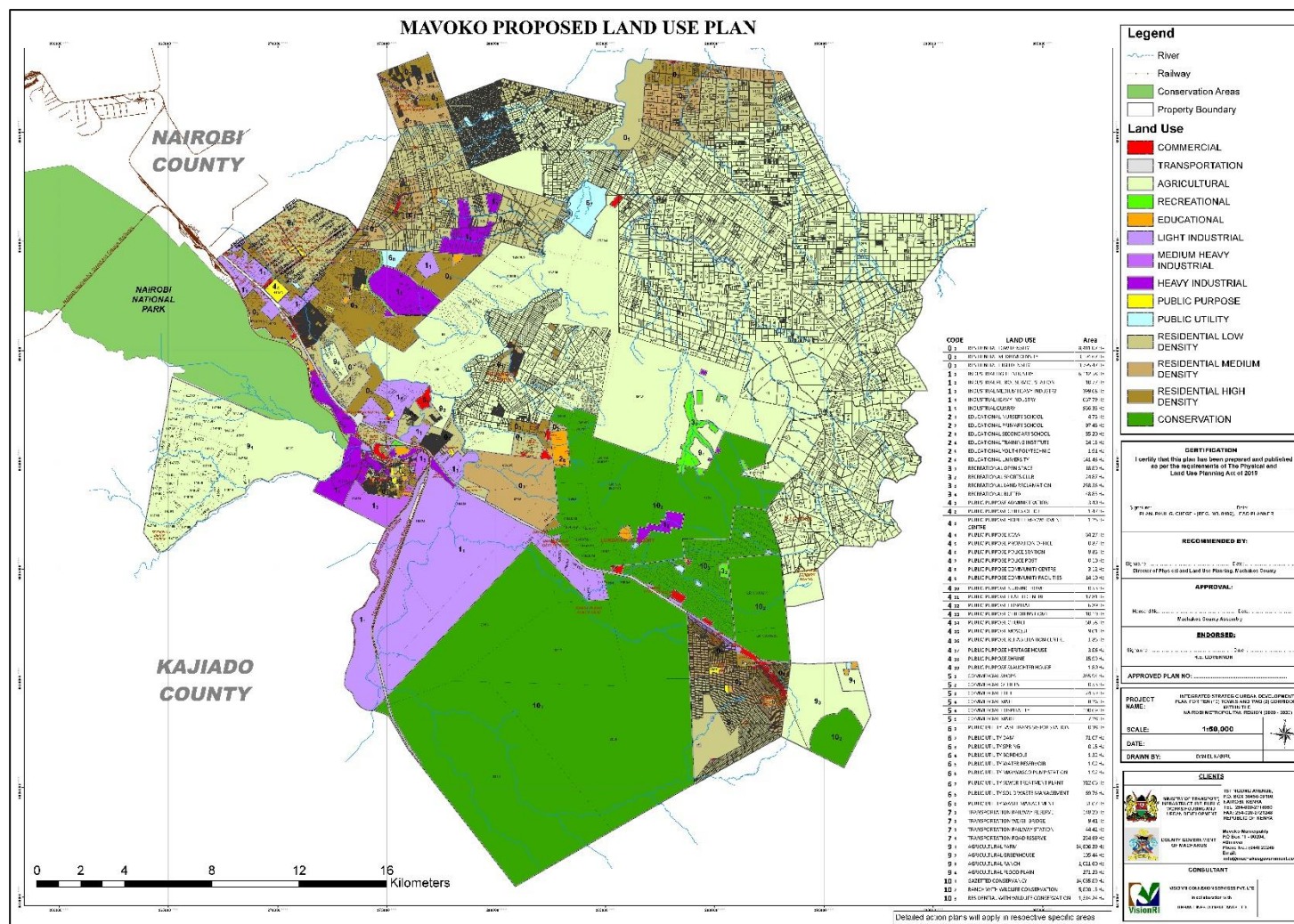


Figure 3: Mavoko proposed land use plan 2030

Appendix 13: Papers emanating from this Thesis

1. Ahogle, A. M. A., Letema, S., Schaab, G., Ngure, V., Mwesigye, A. R., & Korir, N. K. (2023). Heavy metals and trace elements contamination risks in peri-urban agricultural soils in Nairobi city catchment, Kenya. *Frontiers in Soil Science*, 2, 1048057. <https://doi.org/10.3389/fsoil.2022.1048057>
2. Ahogle, A. M. A., Korir, N. K., Houngnandan, P., Abu-Ghunmi, L., & Letema, S. (2023). Bacterial hazards in urban stream irrigation in peri-urban interface of Nairobi-Machakos counties, Kenya. *International Journal of Environmental Studies*, 1-17. <https://doi.org/10.1080/00207233.2023.2216605>
3. Ahogle, A. M. A., & Letema, S. (2024). Irrigated urban agriculture: A mixture of farming scales, water flows and actors in Nairobi, Kenya. *Water International*, 49(2), 144–163. <https://doi.org/10.1080/02508060.2024.2320002>