The Spatial Dimension of Agriculture and Food Security

Mathenge, Mwehe

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A GIS-based spatially explicit approach for integration of smallholder agriculture into agribusiness

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THE SPATIAL DIMENSION OF AGRICULTURE AND FOOD SECURITY:
A GIS-based Spatially Explicit approach for Integration of smallholder agriculture into Agribusiness

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Chapter 1

Introduction

Picture: A smallholder farmer with brokers weighing potatoes in a farm in Timau, Kenya. Source: Author.

1.1 Introduction

This chapter provides the background information, the problem statement, and the aim of the thesis and ends with the scientific and social implications of the thesis. In addition, the chapter contextualizes the challenges that prevent smallholders from effectively competing and participating in the local, national and international agri-foods markets. In brief, the chapter presents the pertinent challenges smallholder production systems in Low-and Middle-income countries (LMICs) face in their endeavor to meet their food demands and that of a growing population. The chapter contextualizes the interplay of spatial 'geographic' explicit factors and how they influence smallholders' agriculture productivity, food security, and participation in agribusiness markets.

1.2 Background and problem definition

Globally, approximately 98% of family-owned farms [1] and 75% of smallholder farmers [2–4] owning less than two hectares, control most of the agricultural land and are to be found in Low-and Middle-income countries (LMICs). In many LMICs, agriculture and food production are heavily reliant on spatially fragmented smallholder agriculture systems [2–4]. In sub-Saharan Africa, subsistence and semi-subsistence farming dominate the food production segment of rural-based agriculture [5] and account for up to 80% of the food consumed [6,7]. In Kenya for instance, smallholder households constitute 75% of rural households and account for about 75% of agricultural output and 70% of the marketed agricultural produce [8–10]. This is in contrast to the high-income countries, where the modern agri-foods 'output' market is mostly dominated by highly efficient farms or large-scale commercial land holdings (greater than 20 hectares) that belong to well-organized agribusiness value chains. [11,12]. Despite the volume of agricultural production smallholder farmers generate and the crucial role they play in feeding a large subsection of the global population, most smallholders are facing serious sustainability challenges, and remain fundamentally food insecure [13]. They also constitute the most disadvantaged and vulnerable groups and face an uphill challenge of accessing the emerging agribusiness and agri-food markets.

The demand for food globally has risen tremendously and is expected to increase even higher; between 59-98% by the year 2050 [14]. Many others indicate that future food supply (production) is not the issue (especially when people are consuming less meat) but accessibility (poverty) is the real problem [15]. In LMICs, the increasing food production gap is raising food insecurity for the majority of the poor population, with more than 800 million people facing food shortages [16] and in effect are periodically hungry. The high dominance of poor rural smallholders in the food production segment in LMICs means that they are unable to match the high food demands exerted by a growing population, especially among those residing in urban areas [17,18]. Furthermore, food producers in the agricultural value chains are experiencing increasing competition for land, water, and energy from the mounting urbanization [19–21]. The big challenge for government policies is how to address the agriculture sustainability paradox by bridging the critical food supply-demand deficit without jeopardizing the carrying capacity of the natural resource base [22]. The majority of poor smallholders in LMICs lack resources, appropriate skills, and motivation to enable them to shift from subsistence-oriented agriculture to more income-oriented and sustainable agricultural practices. To the smallholder farmers, the adoption of income-generating agribusiness production would enable them to exploit and access opportunities provided by growing local and international agri-food markets [23,24]. Such emerging agribusiness markets represent a good opportunity for poor smallholder farmers in rural areas to diversify their livelihoods and incomes thus reducing food insecurity and poverty.

However, poor smallholder farmers face a myriad of challenges that prevent them from effectively competing and participating in the local, national and international agri-foods markets. What can governments, policymakers, and other stakeholders do to improve poor smallholder farmers' agriculture productivity, food security, and competitive advantage in participating in the local and global agribusiness value chain and markets? This question constitutes a pertinent basis for this thesis.

1.3 The complexity of integrating poor subsistence smallholders into the agribusiness value chains

The increasing level of poverty in recent decades has led to a large percentage of poor smallholder farmers becoming trapped in a vicious cycle of food poverty [25–27]. The majority of rural poor smallholder households are characterized by marginal productivity, and rudimentary production methods, with little or no commercialization [28,29]. Furthermore, rural smallholder households are often spatially heterogeneous, operating at the intersection of complex socio, political, biophysical, and economic environments [30–33] which influence their farming decisions to participate (or not) in agribusiness. This complexity presents formidable challenges to policymakers in their endeavor at integrating poor smallholders into the emerging agribusiness value chains and mainstream agriculture policy.

A growing body of research on improving smallholder agriculture and food security is focused on pro-poor agricultural value chain development and the transformation of smallholder systems from 'traditional' subsistence-centered production to 'modern' agribusiness-oriented value chains. This is intended to shift the fragmented spot-market transactions of poor smallholders to a more direct-market network [11], thus enabling them to participate in, and benefit from, the contemporary agri-food markets [34–36]. However, academic discourse on the link between rural poverty, access to livelihood capital assets, and participation in agribusiness markets suggests that poor smallholders have too few livelihood capital assets to effectively participate in agri-food markets [37,38]. Van der Heijden & Vink [39] found that the main hindrances to market participation of smallholders in LMICs were their limited livelihood capital assets (human, physical, financial, socio, and natural capital) and fragmented production. For a large subset of rural smallholders who derive their main livelihood from small-scale subsistence agriculture, they directly or indirectly depend upon the accumulated livelihood capital assets to diversify in income-oriented agribusiness. Consequently, as Donovan & Poole [37] note, the stronger a livelihood capital asset base, the greater its ability to expand and intensify its livelihood activities, with those highly endowed having a higher probability of being food secure and participating in agribusiness than those who are resource-poor.

Though pro-poor agriculture policies advocate for the inclusion of the productive potentials of poor smallholder's accumulated livelihood assets, many rural smallholders in Sub-Sahara Africa are tragically the most asset-poor and food-insecure group [40]. Several studies [41–45] have found that if livelihood capitals are properly utilized, they can help diversify subsistence agriculture into income-oriented agribusiness. Cognizant of this reality, academic discourse has pressed for more attention to the role livelihood capitals play in livelihood diversification strategies employed by poor smallholders to achieve food security [37]. However, how these livelihood capitals catalyze smallholders' participation in agribusiness has only been partially researched. Additionally, although much literature shows livelihood capitals influence smallholders' choices in different ways, it is rarely understood what combination of livelihood capitals could result in a higher probability of smallholders diversifying their subsistence production into more probable income-generating agribusiness.

1.4 The influence of spatially explicit factors on smallholder agricultural production

Agricultural production is intrinsically a spatially complex system. The spatial manifestation of agricultural activities could cumulatively be considered to be a result of local geographic specificities [46]. A study by Głębocki, Kacprzak, & Kossowski [47] revealed that the spatial organization of farming activities was a result of complex spatial interactions between farmers and local geography. From a local-level perspective, predominant-agricultural production systems in an area can be construed as a coherent element of the spatial organization of agricultural production that, to a larger extent, is shaped by the interaction of local geographic specificities and livelihood capitals [43,46]. Depending on households' location-specific conditions, livelihood capitals endowment, farm management decisions, and policy influences [45], smallholder household everyday farming decisions are influenced and compounded by the complex interactions emanating from variabilities of socio-economic, cultural, agroecological, biophysical, and institutional variables [48–51]. The impact of these variable interactions on smallholder households at a local level creates diverse, spatially heterogenous farming patterns and production systems adopted to, and distinct to the local context. These resulting farming typologies and production systems can be conceptualized as spatial manifestations of individual household decisions that respond to actions resulting from many spatial and nonspatial factor interactions and constraints.

At the lowest spatial levels (farm and neighborhoods level), varying biophysical and agroecological constraints (soil variability, water scarcity, topography, pests and diseases, climatic variability, etc.) act as primary determinants of smallholder households' agricultural productivity [52]. Their negative variabilities hamper smallholders' productivity by constraining their capacity to generate quality and quantity marketable surplus [53]. When socio-economic variables are included in the system (e.g., family size, landholding size, labor, skills, education, etc.), a clear variation in the characterization of smallholder systems emerges, distinct from one farm to another and across geographic landscapes. At a higher spatial level, exogenous variables like market structures, transport, technology, etc. interact to influence smallholders' decisions, but when mapped and visualized at that scale, they produce a blurred spatial pattern and mask some of the important underlying factors that influence households' decision-making processes. Studies like that of Nthiwa [54] and Réjou-Méchain et al. [55] posit that over-reliance on spatial analysis outputs that use aggregated spatial data at higher spatial levels could obscure local spatial patterns. As a consequence, the interpretability of resultant spatial patterns and factors causing these patterns at the local level becomes difficult, thus likely to mislead government policymakers.

1.5 The challenge of spatialization of agriculture policy

In its broadest sense, spatialization of agriculture policy means that for every agriculture policy, plan, or strategy, its formulation and implementation ought to be anchored on spatially relevant information. Spatial data is that which is "geographically-referenced" to the real physical location where it was collected through the GPS coordinates. Many of the agriculture policies and interventions are contextually 'spatially blind policies, i.e., they rarely have a clear consideration and inclusion of local geographic specificities in their formulation and implementation. To start with, agriculture policies and interventions are usually uncoordinated and tend to follow generic recommendations that miss the local spatial variation/aspects of agricultural productivity. This lack of spatial contextual awareness of agriculture policies narrows the highly context-specific and place-based nature of agricultural production. In contrast, food insecurity reduction per se has not been a priority of spatial planning policies, at any rate, not sufficient to adequately address hunger, food inequality, and related disparities. The traditionalist 'centralized' spatial development policies widely adopted by many LMICs are overly biased toward promoting land-use economic development, especially in urban territories over rural [56]. This is despite the popular belief that rural territories serve as 'breadbaskets' for feeding the growing urban population in the world's fastest urbanizing regions of sub-Saharan Africa [19]. The issue of food security and food production in urban areas is still largely invisible and has long been neglected by urban planners [57]. Accordingly, food security and food production have been misconstrued as a rural development policy agenda, creating a rural-urban dichotomous divide in food provision planning.

The marginalization and economic segregation of the rural areas mean that there is a shortage of supportive physical and institutional infrastructure for agribusiness development [58]. This impedes many poor rural smallholders' access to, and participation in, agribusiness. It is such unbalanced spatial and territorial development patterns of growth [59] that limit poor smallholder farmers' capacities to respond to food insecurity while at the same time undermining their capacities to respond to opportunities created by emerging agri-food value chains and markets. Various authors blame this continuous socio-spatial policy disconnect for perpetuating the rural-urban dichotomous divide, and this divide has also been blamed for perpetuating food insecurity, territorial food inequality, and poverty [58,60,61]. To tackle these challenges, a multisectoral and multifaceted policy response is necessary. However, the inadequacy of government policies to comprehensively address these problems emanate from a rather disjointed sectoral approach and a lack of an integrated development framework for policy coordination. This makes integration of the spatial dimension of agriculture and development planning frameworks a difficult but necessary condition for proper policy-making [62,63]. Hence, there is a need for the adoption of spatially integrated agriculture policies and interventions.

1.6 Problem statement and objective of the thesis

As the previous sections have shown, smallholder production systems are highly diverse and spatially heterogeneous and operate at the intersection of complex socio-economic and spatial environmental dynamics [30–33]. As such, many of the factors that influence smallholders' everyday farming decisions are dependent on prevailing spatially 'geographic' heterogenous local specificities. These geographic specificities vary across and within territories. This implies that smallholder farmers and their farming decisions are to an extent influenced by the spatial variability of the spatially-explicit factors and how these factors interact with each household's livelihood capital endowments. The manifestation of the spatial interactions between local geographic specificities and smallholder farmers' livelihood capitals is manifested by the resulting spatial organization of farming typologies, agriculture productivity, and resulting spatial patterns of food insecurity in a locality [47,51,64]. These spatially heterogenous specificities can be mapped and analyzed using spatial explicit methodologies in GIS [47,65,66]. The results would reveal local spatial patterns of food insecurity and geographic factors that impede poor smallholder households' from raising their agriculture productivity, impede their participation in agribusiness, and the root causes of food insecurity. However, how the interaction of spatial heterogeneity of household livelihood capital endowments with geographically heterogenous specificities influences poor smallholder participation in agribusiness has rarely been investigated. In addition, existing empirical approaches mostly used in agriculture research lack spatially explicit methodologies that can map, analyze and visualize local spatial factors. This makes many policymakers in the agriculture sector turn a blind eye to the spatially explicit determinants that influence agricultural production and market participation at the local level [47,49]. As a consequence, it has been difficult for policymakers in the agriculture sector to design spatially targeted interventions for addressing local-level challenges that hinder many resource-poor smallholders, particularly in the marginalized rural areas, from participating in the agribusiness market. The overall objective of the thesis is thus to investigate, map, analyze and visualize spatially explicit factors that influence smallholders' food production, and market participation.

1.7 Scientific and social implications of the study

Scientific implication

Factors that influence smallholder farmers to participate in, and benefit from, agribusiness markets are spatially heterogeneous, meaning that they manifest differently in various local geographical contexts and at various spatial levels [11]. In geographic information systems (GIS), we can deconstruct the spatial heterogeneity of agricultural production and food security by analyzing the spatial dependence, that is, the spatial autocorrelation of factors influencing agriculture productivity or food security. The spatial autocorrelation can be mapped and analyzed using specific Local Indicators of Spatial Association (LISA) models. Some of these spatially-explicit LISA models include Geographically Weighted Regression (GWR), Getis-Ord Gi* Hot spot analysis, and Local Moran's I. However, in the agriculture sector, the lack of adoption of spatially explicit methodologies remains a serious caveat in the spatialization of agriculture policy. Most of the empirical studies in agriculture have socio-economic empirical methods that lack spatial explicitness in interrogating the spatial dimension of agriculture.

This study is an attempt to fill this gap by developing a spatially explicit method to map and analyze the spatially explicit factors that impede smallholder farmers to participate in agribusiness and those that contribute to food insecurity. Using a set of GIS-based indicators and a spatially explicit method, we map the spatial dimension of agriculture and food insecurity not only to unearth the spatial manifestation of food insecurity but also to identify local causative factors that impede smallholders from participation in agribusiness. Spatialization of agriculture can be used to inform place-based policies and local-based interventions in facilitating smallholder farmers' entry into the agribusiness value chains and their integration into agribusiness markets. The output of this study will enrich public policy makers, spatial planners, and agriculture stakeholders in formulating better local-based policies and in designing spatially targeted interventions that could play a crucial role in improving the sustainability of smallholder systems.

Social implication

The constraints poor smallholder farmers face in producing enough food to cater to their food security needs and surplus to sell to agribusiness markets can be perceived as an interplay of complex interactions between local geographical factors and their daily decisions to improve their farming activities. These complex interactions are often embedded in complex socio-spatial processes and are unique to a particular locality – with the lowest at the farm level and the highest at the territorial level. The local geographical factors are dynamic and continuously influence the day-to-day households' farming decision-making processes. These factors either produce barriers or facilitate household agriculture productivity depending on an individual household's interaction with them. The role of policymakers and relevant stakeholders in society is to manage or minimize the negative effects emanating from these complex interactions between farmers and geographical factors. If poor smallholders are to be empowered to participate in the agribusiness value chain, there is a need for governments and policymakers, especially in LMICs to harness the synergy of these socio-spatial interactions and designed spatially integrated agriculture policies and interventions. Doing so would require a better understanding of how these spatially explicit factors can be harnessed, mapped analyzed, and integrated into agriculture policy-making in improving smallholder agriculture productivity and food security.

1.8 Structure of the dissertation

This thesis is organized into eight chapters. Although each thesis chapter deals with a particular subject, the research questions of the thesis bind the different chapters into one thesis. It should be taken into regard that each thesis chapter is 'self-contained' and stand-alone, based on a published or submitted article, and can be interpreted independently. Therefore, to a little extent, certain overlap and repetition might occur. The next chapter, **Chapter 2**, provides the theoretical background of the thesis, while **Chapter 3** describes the research approach and methodologies used, the main research questions, and details the study design. **Chapter 4** provides the results of a systematic literature review on GIS application in agriculture. The review provides recent trends and future perspectives on the application of GIS to improve agriculture sustainability and provides insights into the spatialization of agriculture policy. **Chapter 5** appraises the catalytic role the household livelihood capitals (asset base of households) could play in influencing poor smallholders' decisions and choices to diversify their farming activities in agribusiness. Recommendations inform policymakers on the design of pro-poor policy strategies for improving smallholder agriculture. In **Chapter 6**, a spatially explicit methodology is developed for mapping, and analyzing spatially explicit factors that impede poor smallholders from participating in agribusiness markets. **Chapter 7** deconstructs the complex and multidimensional aspect of food insecurity and provides policymakers with an approach for mapping the spatial dimension of food security at a local level. Specifically, this chapter discusses how spatially disaggregated data, GIS-based indicators, and a place-based approach can be combined to map the spatial patterns of food insecurity and their causal determinants. **Chapter 8** presents an in-depth analysis of the structural and practical inhibitors and facilitators for agriculture and spatial 'agri-spatial' policy integration and develops a multilevel and multisectoral framework for agri-spatial policy integration. Finally, **Chapter 9** summarizes the research findings and draws conclusions and recommendations for policy and practice, and provides recommendations for further research.

Chapter 2

Theoretical background

Picture: Assorted fruits packaging at ABC Westland agri & food warehouse, Amsterdam. Source, Author.

2.1 Introduction

This chapter describes the theoretical background of the thesis. We elaborate on the spatial dimension of agriculture and food security, and the role of the livelihood capital assets on household food production. Further, we discuss how GIS and spatial geostatistics methods can be combined in mapping and analyzing the spatially explicit factors that constrain or facilitate smallholder agriculture productivity at the local level. The chapter ends with an elaboration of a spatially explicit conceptual framework for the integration of the spatial dimension of agriculture into policy.

2.2 The spatial dimension of agriculture and food security

According to FAO, food security "exists when all people, at all times, have physical, social, and economic access to sufficient safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life." (FAO, 1996). Equally, the dimension of food security includes both endogenous and exogenous factors that constrain a household's decisions and choices on availability, access, utilization, and stability of food. This definition captures the complex and multi-dimensional causal interactions of the factors that influence individuals' and households' food security. In literature, some of the proxy variables used for assessing a household's food security status (figure 2.1) include (1) availability dimension (e.g., domestic production, import capacity, food stocks, food aid); (2) accessibility dimension (e.g., poverty, purchasing power, transport and market infrastructure, food distribution); (3) utilization dimension (e.g., food safety & quality, clean water, health & sanitation), and (4) stability dimension (e.g., weather variability, price fluctuations, political factors, economic factors).

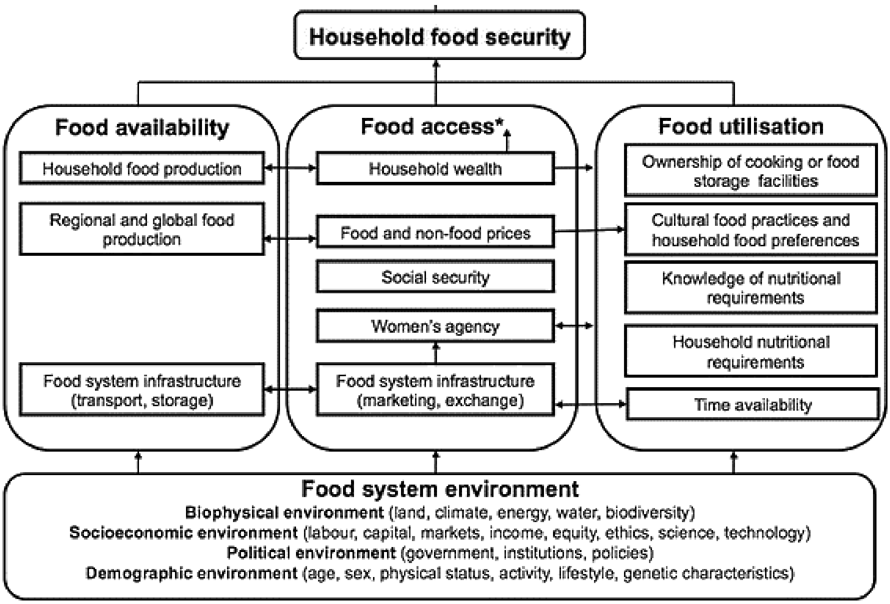

Figure 2.1: Some of the dimensions of household food security with their proxy variables. Adopted from [67]

Agricultural production is intrinsically connected to the local geographic conditions of smallholders' places of residence. It can be constructed as a coherent element of the spatial organization of the agriculture ecosystem predominant in a particular local geographic space [43,46]. Nonetheless, local geographic environments vary from place to place due to a myriad of factors including geographic specificities, territorial capitals, place-based development policies, and demographic characteristics. As such, empirical investigation of a spatial relationship between smallholder agriculture productivity and local territorial characteristics has revealed an inherent spatial varying relationship between local geographic characteristics in the smallholder's place of residence and key explanatory factors influencing food security. From a local spatial perspective, smallholder agricultural production can be constructed as a coherent element of the spatial organization of the agriculture ecosystem predominant in a particular geographic space [43,46]. Equally, studies like that of Głębocki, Kacprzak, & Kossowski, [47] have shown that spatial organization of household farming activities influences or is influenced by local spatial interactions of geographic specificities and farmers' livelihood capital assets. To summarize, agricultural production thus takes place within a complex interaction of socioeconomic and biophysical processes operating within nested spatial layers of local geographic specificities [46].

2.3 The influence of livelihood capital on smallholders' participation in agribusiness markets

Low livelihood capital 'assets base of a household' has been identified as a considerable constraint [24] to exploiting the opportunities of expanding agribusiness and agri-food markets. Academic discourse on the link between access to productive livelihood assets, and market participation show that poor smallholders have too few livelihood capital assets to effectively participate in agribusiness [11,27]. The ability (or lack thereof) of households to productively exploit livelihood capital to improve their agricultural production and food security can be spatially manifested by local spatial patterns of food insecurity and farming typologies predominant in a geographic locality. At a higher spatial level, different territories exhibit spatially heterogeneous characteristics due to the levels of territorial capital endowment [68,69].

Several studies have used the sustainable livelihood approach as a theoretical and analytical framework to bring a deeper understanding of the way individuals and households, in different contexts, use their livelihood capital assets to diversify their livelihoods into the farm and non-farm activities [12,29]. At the local 'household' level, agricultural production is influenced by the dynamic interactions of each household's livelihood capital assets and local geographic specificities. The livelihood capital assets-based approach (Figure 2.2) conceives six classes of resources held at the individual, household, or collective levels to include a combination of physical, human, financial, natural, social, and cultural capital assets [30,31]. Livelihood capitals are defined as the "asset base" upon which individuals and households build their livelihoods [11,32]. all these are paramount to households' agricultural productivity and food security levels.

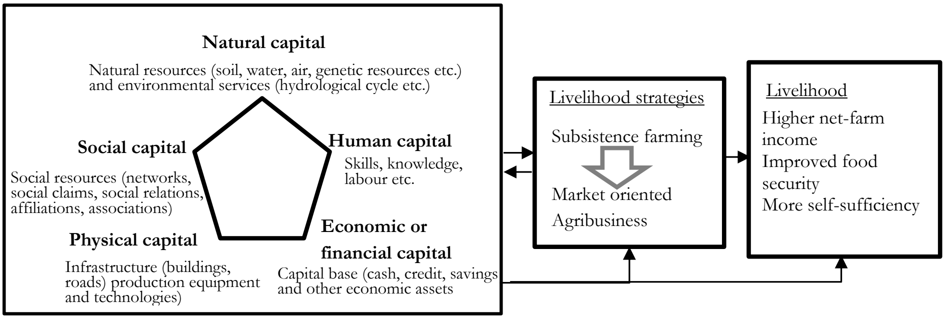

Figure 2.2: Sustainable Livelihood capitals framework (adopted from Morse & McNamara, 2013; Rakodi, 2002)

The *physical capitals* include basic infrastructure households need to support livelihoods including infrastructure-availability, transportation, buildings, water supply and sanitation, energy, technology, access to information (e.g., radio or mobile phones), and access to agricultural implements [1,33]. *Social capital* represents the ability of individuals or households to secure benefits through membership and relationships [30,41]. They are accrued from shared norms and values embedded in social networks that enable individuals or households who belong to them to access and exchange different resources [42]. *Natural capital* consists of land, water, biodiversity, air quality, and agroecological conditions [30]. Some studies report that the associated costs of mitigating the negative impact of natural capital (e.g., climate change) could far outstrip the benefits accrued from agribusiness [20,43]. thereby making agribusiness less attractive for poor smallholders. *Financial capital* includes fiscal resources individuals or households use in constructing their livelihoods including savings, access to credit, inflows like pensions, and remittances [32]. In addition to livelihood capitals, exogenous factors exert a lot of influence on the development and spatial organization of farming systems. Exogenous factors include institutional development and institutional policies [68,72] like market regulations, trade policies, property rights, land tenure, and proximity to input and output markets [35,45–47]. These influence farmers' choices to participate in agribusiness, even though they are not confined by spatial boundaries. The institutional factors influence how individuals and households use their livelihood assets in shaping their different livelihood strategies and outcomes [31,32,48].

2.4 Modeling the spatial dimension of food security

Spatial patterns of food insecurity disparities bear a closer relation to the spatial heterogeneity or homogeneity of household farming typologies, due to local geographical specificities and household livelihood capital endowment (at a local level) and at a higher spatial level, due to territorial capital endowment [47,64]. Methods that use geographically disaggregated parameters of localities to analyze the local spatial heterogeneity have been advocated as an effective entry point to identify local causative factors of food insecurity and inequality (OECD/FAO/UNCDF, 2016). Spatially explicit methods that model the local spatial dimension of agriculture and food security combine GIS-based indicators and a place-based approach in spatial patterns analysis. However, Barret (2010) notes that most empirical approaches for measuring food insecurity constraints tend to formulate multidimensional indicators from the four major dimensions of food security – availability, access, utilization, and stability. According to Martinez [73], the advantage of using GIS-based indicators in constructing food security indicators enables the mapping of food insecurity hot spots and the identification of local geographic areas with the greatest need. This in turn guides local authorities in prudent resource (re)allocation, setting priorities, and targeting policies and programs to local areas facing high food insecurities.

Often, composite indicators frequently apply aggregated data generated at a higher spatial level of aggregation e.g., global, national, regional, or city levels to monitor spatially linked problems. A criticism of using aggregated data is that they can produce a misleading output and representation of the problem they address and quantify [73]. This emanates from the problem called ecological fallacy – a situation whereby inferences made from geographically aggregated data e.g., indicators constructed exclusively from census data, can produce misleading outcomes. Outputs from such indicators may mask important spatial differences at the local level and often hide the stark contrast between better-off and poor households, since not every person living in a better-off area is necessarily well-off and vice versa. Because of this, resources and interventions may be directed to areas in which inhabitants do not necessarily need them [74]. These limitations can be overcome by combining disaggregated spatial data and GIS to construct GIS-based indicators or spatially based indicators. Several studies [73,75] have demonstrated that the use of a small area approach and GIS-based composite indicators diminishes the extent of measurement error and reveals the accurate spatial manifestation of problems under study [74,76]. However, the lack of quality spatial data at a local scale has hindered the effective identification and spatial targeting of geographically deprived areas.

2.5 Using spatially-explicit GIS approach in modeling food insecurity

With an increasing realization that many social problems are linked to and embedded in local spatial processes, better methods for mapping and analysis of the spatial varying relationship from spatial data have been developed [77,78]. The increasing advancement of geospatial technologies; Geographic Information Systems (GIS), Remote Sensing (RS), and Geographic Position Systems (GPS), is not only providing more geographically referenced data but also permitting an ever-more granular spatial analysis at the lowest spatial levels [77,78]. These technologies have made it easier to acquire high-resolution satellite imagery that has simplified the mapping and investigation of spatially explicit factors and complex socio-spatial and environmental dynamics that influence agriculture productivity [30–33]. GIS technology provides an operational platform to integrate spatial and non-spatial data in deconstructing the spatial complexity by modeling the spatial dependence (spatial autocorrelation) of current and prospective decision problems [78]. GIS has the inbuilt capability to organize, analyze, and geo-visualize indicators at a local spatial scale and enables the lowering of the geographic unit of analysis, e.g., from administrative polygon to neighborhood, depending on a particular indicator and level of localization of the decision problem [73].

Spatially explicit approaches and placed-based analysis provide a powerful conceptual entry point for a better understanding of the spatial relationship between local geographic factors and their influence on agricultural production. The spatially explicit approach uses a geographically targeted area as a primary entry point to build a deeper context in understanding the spatial complexity of a problem facing the inhabitants of that locality [73].

In a spatially-explicit GIS approach, the socio-economic and livelihood assets proxy indicators of a household can be deconstructed, mapped, and conceptualized as nested spatial layers of variables that are embedded in a real geographic location within a GIS system by way of geographic referencing [32,79,80]. Their interaction can be mapped at different spatial and temporal scales to identify local-specific enablers or barriers to smallholders' agriculture productivity, food security, and agribusiness. The nested spatial layers can be analyzed in GIS to reveal spatial patterns, trends, spatial impediments, or even new opportunities for agribusiness development within a certain locality. The use of the placed-based approach enables identification and spatial targeting of geographically poor 'deprived' areas, and impoverished local populations. These approaches provide researchers and policymakers with localized insights and an understanding of spatial interactions in revealing hidden spatial patterns from hitherto unknown local spatial processes [81].

Spatial location is a powerful conceptual entry point for the improved understanding of the interplay of human welfare and agricultural production. Waldo Tobler's First Law of Geography posits that "everything is related to everything else, with near places more likely to be related than distant ones". Inferring from this, the influence of spatially explicit factors on agricultural production could be most pronounced or clustered at the local level 'neighborhood', and influence is likely to diminish as territorial distance increases. For instance, several studies to investigate the geographic context of poverty and inequality have found coalescing factors that cause poverty, with a higher spatial concentration of poverty in "poverty hot spots areas" deprived rural areas and urban slums [82,83]. Likewise, there is a higher probability of finding groupings of food-insecure households in geographical clusters as a result of coalescing of proxy variables of similar values that cause food insecurity. If this spatial relationship could be accurately determined and mapped, there would be a higher probability of policymakers designing spatial targeted policies and interventions that specifically focus on the hot spots of food insecurity and deprived households.

Nonetheless, the complexity of modeling local spatial relationships cannot be fully deciphered from simple statistical and 'economic' theoretical frameworks [84]. This is because many of the societal problems are embedded in socio-spatial complexity. The inherent difficulty emanates from the lack of clear, spatially explicit methodologies that can detect location-specific spatial patterns and spatial variability (heterogeneity or homogeneity). In addition, Wiggins, [85] says that there hardly exists comprehensive spatial data disaggregated at a local level to support localized spatial patterns analysis.

2.6 GIS spatial statistics for modeling local-level spatial autocorrelation

There are several local spatial statistics models used to analyze local-level spatial autocorrelation. These include Local Indicators of Spatial Association (LISA), cluster and outlier analysis (Anselin Local Moran's I), hot spot analysis, and geographically weighted regression [86–88] These methods have enabled researchers to integrate the theoretical and spatial dimensions of the relationship among spatial entities in analyzing local-level spatial autocorrelation. Several studies in agriculture [47], land use [89], environment [42,43], urban planning [90], etc. have employed these models to not only analyze the local spatial varying relationships but also to predict spatial patterns and trends. The results from such analysis have provided policymakers with better spatial decision support systems for (1) identifying geographic clustering of social problems, (2) visualizing alternative planning scenarios, (3) prioritizing resources, and (4) designing spatially targeted interventions.

Box 2.1: Several GIS spatial statistics for modeling local spatial autocorrelation are described below.

- **Global Morans I** spatial autocorrelation method assesses the presence or absence of spatial patterns in a dataset. According to Goodchild and Getis [91,92], the method calculates the z score and p-value which indicate whether to reject or accept the null hypothesis. The null hypothesis usually is complete spatial randomness of data. Global Morans I result only reveals spatial autocorrelation 'spatial patterns' at a global level (i.e., the entire dataset) but not at a local level (households and their neighbors).
- **The Cluster and Outlier Analysis (Anselin Local Moran's I)** method is used to detect the presence of local spatial patterns and clusters and map spatial patterns [87]. It does so by identifying concentrations of high values (hotspots), concentrations of low values (cold spots), and spatial outliers [86,87]. It also determines if those local spatial patterns and clusters are statistically significant or are a result of complete spatial randomness of data. Spatial units are either categorized to have positive or negative spatial patterns at a significance level ($p < 0.05$) [86].
- **Getis-Ord GI* Hot Spot Analysis** is one of the commonly used Local Indicator of Spatial Association (LISA) methods in ArcGIS [91]. According to Anselin [86], the LISA method uses geostatistical calculations to analyze local spatial autocorrelation by measuring the similarity of attribute points in locations. The method uses spatial statistics to calculate statistically significant spatial clusters of high (hot spots) and low values (cold spots) by measuring the similarity of attribute points in locations [65,86,93]. This can be used to map the existence and concentrations of local geographical clusters of phenomena like food insecurity, and poverty.
- **Geographically Weighted Regression (GWR**) identifies statistically significant geographic factors causing local spatial autocorrelation (i.e., factors behind the observed spatial patterns), thus enabling us to locate and geo-visualize specific localities with a statistically significant concentration of high values (hotspots) and concentrations of low values (cold spots), of spatial patterns[66,94,95]. According to Brunsdon, Fotheringham, & Charlton [94], the GWR model is a non-stationary technique that measures spatially varying inherent relationships for a set of coefficients. Since the variables being estimated vary continuously over the study area, their "surface can be geo-visualized and interrogated for relationship heterogeneity" [94].

In GIS, spatial dependency and spatial autocorrelation [81] are commonly used spatial statistics models to analyze the influence of local spatially explicit factors, in uncovering spatial relationships and detecting spatial patterns. Spatial dependency is described as a condition where values are observed at one location depending on the values of neighboring observations at nearby locations [47,86,96]. In GIS, spatial dependence is analyzed using spatial autocorrelation. Spatial autocorrelation uses the same principle and is defined as a situation whereby observations at locations closer to each other in geographic space are more likely to be similar in attributes than observations farther apart that tend to have dissimilar attributes [64,95]. An assumption is made that due to the effect of spatial autocorrelation, relationships between neighboring spatial units are much stronger than between distant ones [47], with influences diminishing with territorial distance. Thus, households residing in a particular locality would tend to bequeath that geographical area with the same characteristics/attributes. Thus, by analyzing local spatial autocorrelation of the factors in households in a certain locality, one can be able to detect clusters by spatial clustering (hot spots) of food insecurity and localities with clustering of poor households (those lowly endowed with livelihood capital assets).

2.7 Difference between GIS spatial statistics and normal statistics models

Unlike normal statistics, the spatial statistics models conceptualize spatial relationships by calculating spatial autocorrelation based on two parameters (1) spatial unit of analysis, and (2) territorial distance [97]. The spatial unit of analysis is the extent of a geographic area to which a phenomenon or underlying spatial process occurs [98]. The territorial distance value defines the appropriate spatial unit of analysis. The assumption is that the optimal territorial distance value will be where the underlying processes promoting spatial clustering are most pronounced. According to Getis and Aldstadt [99], the intensity of spatial clustering is determined by the z-score returned, with the most optimal territorial distance symbolized graphically as the peak z-score value. These models assume that relationships between neighboring spatial units are much stronger than between distant ones[47,86]. This is done by first calculating spatial weights for each data point in the study area or calculating the most optimal statistically significant peak z-scores, which indicate distances where spatial processes promoting clustering are most pronounced.

2.8 A spatially explicit conceptual framework for modeling the spatial dimension of agriculture

The constraints smallholders face can be perceived as an interplay of the driving forces emanating from social, biophysical, economic, agroecological, and cultural variables. These variables are dynamic and continuously shape or influence smallholders' rational or irrational decision-making processes through their daily interactions. This prompts the need for a spatially explicit analysis of the localized context within which agricultural food production takes place. By using spatially explicit variables and spatial analytical models, the extent to which smallholders are influenced by the spatially explicit factors can be mapped, analyzed, and visualized. Subsequently, 'local adoptive' solutions can be formulated.

In food security literature, the influence of local geographic specificities as a potential contextual explanation of low agriculture productivity and food insecurity among smallholders has received little attention. Similarly, the spatial influence of spatially explicit factors on agriculture productivity has rarely been investigated. Additionally, food insecurity reduction per se has not been a priority of spatial planning policies. At any rate, spatial planning policy interventions have not been sufficient to adequately address the spatial dimension of agriculture and food security. Factors influencing each smallholder's decision to participate (or not) in agri-food value chains are difficult to comprehend, especially when they are analyzed using aggregated data and at a higher spatial unit analysis [100]. Consequently, a lack of linking factors to their specific geographical setting and analyzing their spatial manifestation may not bring out the real picture of a decision problem, which can lead to misdiagnosis. This study postulates that interventions for improving smallholder market participation ought to be based on a nuanced understanding deduced from a holistic, interdisciplinary analysis of local factors, using disaggregated data and indicators.

Deconstructing social-spatial complexity can be done by first getting a holistic understanding of local factors' interactions and then developing a spatially explicit framework to model the socio-spatial interactions. Some of the research methodologies that have been used in past studies are of course valuable but tend to lack the spatial explicitness component. Thus, this study explores the spatially varying relationship between local geographic context and agriculture productivity in understanding the underlying causes of food insecurity and low agricultural productivity amongst poor smallholder households. Likewise, we identify and map spatially explicit factors that influence or impede smallholders to participate in agribusiness markets. we then develop a conceptual framework for integrating the spatial dimension of agriculture into the agri-spatial policy. Our results have implications for policy in that they support policymakers in designing location-specific strategies, improving spatial targeting of interventions, prioritization of resource allocation, and informing approaches for spatialization of agriculture policies. Developing a deeper and more detailed understanding of the spatial dimension of agriculture and food security inequality can contribute to inclusive, multi-sectoral, and spatially integrated policies for strengthening the development of sustainable smallholder agriculture systems.

Chapter 3

Research design

Picture: Author interviewing women belonging to Mama Simba women group in Samburu, Kenya. Source: author.

3.1 Introduction

This chapter presents the central research question and sub-research questions. We then discuss the research approach, describe the study settings, study design, and data collection approaches, and conclude with a presentation of ethical considerations, research validity, and an outline of the thesis.

3.2 Research questions

The central research question of the study is formulated as follows:

> How do spatially 'geographic' explicit factors influence smallholders' agricultural productivity, food security, and decisions to participate (or not) in agribusiness, and how can these factors be mapped, analyzed, and integrated into the agriculture and spatial planning policies in improving smallholders' agriculture sustainability, food security and participation in agribusiness?

Five sub-research questions were formulated to answer the central research question;

1. **How has GIS technology been used and applied in the agriculture sector in promoting spatially integrated agriculture policies in improving agriculture sustainability?**

Efforts for enhancing smallholder agriculture sustainability require that farmers are empowered with practicable information that enables them not only to make evidence-informed decisions but also to implement them in activities that could increase their farm productivity and sustainable production practices. These practices would need to be complemented by better technologies that enhance production efficiency enhancement and better agronomic practices. GIS technologies can integrate and synthesize social-spatial, economic, and environmental data that is rooted in local geography in producing spatial-based knowledge. This research question guided the researcher in investigating and consolidating various ways GIS technology has been used and applied in the agriculture sector. The output of this research question is consolidated knowledge that can be used to support evidence-based decision-making. In subsequent research questions, presented in individual chapters of this thesis, the researcher demonstrates how GIS can be integrated into agriculture sector policymaking to support spatially integrated agriculture policies and spatially targeted (policy) interventions for enhancing the sustainability of smallholder farmers.

2. **How do differentiated livelihoods capital owned by poor smallholder farmers influence their decisions to participate (or not) in agribusiness activities?**

The spatial context of agriculture can be viewed from the perspective of farmers' differentiated access to livelihood capitals, local resources, and access to essential infrastructure and services existing in a locality.

The spatial heterogeneity of household livelihood capital endowments has been used to characterize the spatial diversity of smallholder farming typologies in a given territory and explain their decision choices. Whereas various studies have highlighted the lack of livelihood capital as a reason for most smallholders not to diversify into agribusiness, it is rarely understood what combination of these livelihood capitals could result in a higher probability of poor smallholders diversifying their subsistence production into more probable income-generating agribusiness given different contexts. This research question guided our study in examining the extent to which differentiated livelihood capitals owned by households interact to influence poor smallholders' decisions and choices to participate in agribusiness activities.

3. **How can spatially "geographically" explicit factors and GIS be used to identify and map poor smallholders' households and local spatial factors that impede their participation in agribusiness markets?**

Spatially explicit factors play an important role in shaping smallholder decision-making processes. Studies have found a link between the spatial characterization of smallholder farming typologies and the spatial dependence of variable values existing at different spatial locations. However, most empirical studies in the agriculture sector do not account for spatial dependency and spatial heterogeneity. The inherent difficulty emanates from the lack of a clear, spatially explicit methodology that can detect location-specific spatial dependence (spatial patterns) and spatial variability (heterogeneity or homogeneity) from spatially explicit factors. The lack of a method to analyze local spatial dependence makes many existing empirical approaches turn a blind eye to the geographical reality of the spatial context of determinant that influences agricultural production. As a consequence, it is difficult for policymakers to design spatially targeted interventions for addressing local-level challenges that hinder many poor smallholders from participating in the agribusiness market. This research question guided the researcher in designing a GIS-based spatially-explicit methodology that was then used in mapping, analyzing, and geo-visualizing spatially explicit factors, and in identifying poor smallholder households. The use of GIS and disaggregated spatial data helped in unearthing local spatially explicit factors that smallholder participation in agribusiness.

4. **How can the spatial dimension of food insecurity be mapped, analyzed, and geo-visualized (using GIS) to identify the spatial patterns of food insecurity and to provide a contextualized understanding of local-level causative factors of food insecurity?**

The spatial inequality of food insecurity, its multifactorial causation, and the complexity associated with addressing this critical societal problem require a localized and contextualized understanding of factors. In addition, an understanding of location-specific patterns of food insecurity could offer important insights into the causes of local spatial disparities. However, in many food security studies, little focus has been devoted to mapping the resultant spatial patterns and disparities in food insecurity at the local level. Importantly, the prominence of spatially explicit factors as a possible contextual explanation of the spatial pattern of food insecurity has received little attention. Yet, agriculture productivity and food insecurity cannot be delinked from the influence exerted by local geographic specificities existing at smallholder households' places of residence. The answer to this research question was intended to elicit a contextualized understanding of how geographic specificities at the local levels influence agricultural production and by extension, food insecurity. Knowledge gained from the question is crucial for spatial targeting of interventions, and for designing place-based policies that are aligned to specific challenges and opportunities of a defined geographic area.

5. **How can the spatial dimension of agriculture be integrated into the spatial development policy frameworks to improve the sustainability of smallholder agriculture, and what factors enable or constrain agriculture and spatial 'agri-spatial' policy integration?**

Achieving smallholder agriculture sustainability is a multicausal and multidisciplinary challenge that requires integrated agriculture policy responses at different spatial scales and across policy domains. However, albeit many LMICs governments advocate for integrated policy responses in addressing the multidimensional challenges that hinder small-scale agriculture sustainability, the majority of agriculture policies have been criticized for not being sufficiently integrated. Rather, many of these policies are usually sector-specific oriented, devoid of multi-level, multisectoral, and multi-actor policy integration. Importantly, policymakers rarely consider and integrate the spatial dimension of agricultural production in their formulation and implementation. This research question guided our research in examining the existing agriculture and spatial planning policy frameworks in identifying the structural and practical inhibitors and facilitators for agri-spatial policy integration.

3.3 Method of inquiry

We used a mixed-methods approach in this research to collect data. This approach enabled us to apply a variety of robust data collection methods (surveys, interviews, group discussions, document analysis, systematic review, and spatial mapping), followed by triangulation. All these methods permitted the collection of data that allowed us to gain a comprehensive understanding of the interplay of factors that influence smallholders' decisions and choices on agricultural production, food security, and market participation.

The research setting

Most of the research for this thesis was conducted in Kisumu and Vihiga Counties located in the western region of Kenya (figure 3.1).

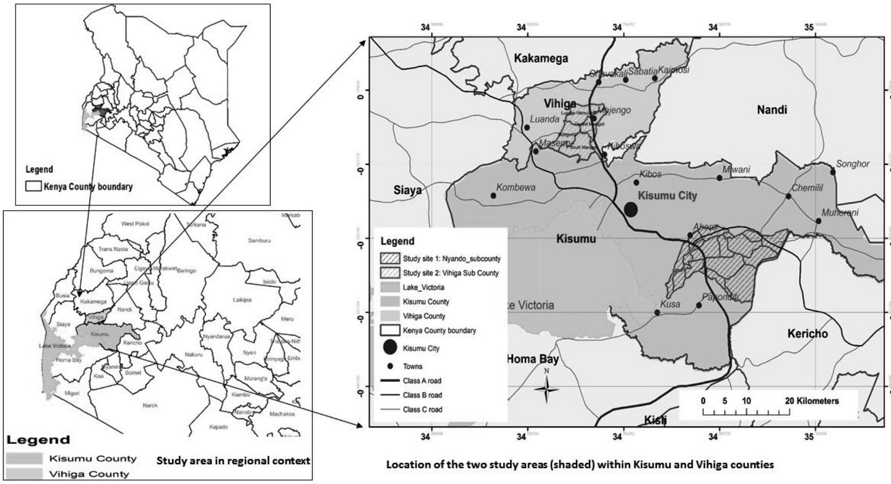

Figure 3.1: Map of the study area

Vihiga County

Vihiga County is one of the 48 devolved county governments located in Western Kenya, a few kilometers from Lake Victoria and the main city of Kisumu. The County covers an area of 563.8 km^2 with 90% of the area categorized as rural and only 10% urban. The County has five administrative Sub-Counties: Hamisi, Emuhaya, Luanda, Sabatia, and Vihiga. According to the 2019 National Population and Housing Census, the County had a population of 590,013 with one of the highest population densities at 1,046 persons per square kilometre compared to the national average of 92 persons per km^2. Vihiga County is categorized into two main agroecological zones, the upper and lower midlands. These zones dictate land-use patterns and population settlement. The county's altitude ranges between 1,300m and 1,800m above sea level. It slopes gently from East to West with undulating hills and valleys. The average farm size is 0.4 ha for small-scale and 3 ha for large-scale farming. In regards to land use, 98.7% of the arable land is under farming, mostly subsistence, while 1.3% is under housing. The major land-use types include livestock, crop farming, tree planting fish farming, and settlements. The County experiences an equatorial type of climate with fairly well-distributed rainfall throughout the year with an average annual precipitation of 1900mm. Temperatures range between 14-32 ^{0}C with a mean of 23 ^{0}C. Rain is experienced in March, April, and May with short rains in September, October, and November. Driest and hottest months are December, January, and February.

Kisumu County

Kisumu County covers an area of 2,010 km^2 of land and 567 km^2 of water mass. The County has seven sub-counties: Kisumu East, Kisumu West, Kisumu central, Nyando, Seme, Nyakach, and Muhoroni. The population of the county according to the 2019 Population and Housing Census was estimated at 1,115,574 persons with 556,942 males and 594,609 females. The county's average population density was 550 persons per Km^2. The County has diverse economic potential; it has one of the four cities in Kenya (Kisumu city), and it is situated on the shores of Lake Victoria (which is a trading hub that connects Kenya, Uganda, and Tanzania). Additionally, it has a vibrant agriculture sector which is boosted by good climatic conditions. The average annual rainfall ranges between 450mm and 600mm with long rains occurring in March and May while short rains occur from September to November. The mean annual maximum temperature ranges from 25^{0}C to 35^{0}C and the mean annual minimum temperature ranges between 9^{0}C to 18^{0}C. The altitude in the County varies from 1,144 meters above sea level on the plains to 1,525 meters above sea level in the Maseno and Nyakach areas. This altitude range greatly influences temperatures and rainfall in the County. There are three topographical zones: the Kano Plains, the upland area of Nyabondo Plateau, and the midland areas of Maseno. The Kano Plains lie on the floor of the Great Rift Valley, bordered to the North and East by escarpments, while the upland area comprises ridges that rise gently to an altitude of 1,835m above sea level. Below is a summary of the salient characteristics of the two study areas.

Table 3.1: Salient characteristics of the study areas

	Study areas	
Characteristics	*Vihiga County*	*Kisumu County*
Biophysical and spatial		
Altitude (ma.s.l)	1,600	1,114
Average precipitation (mm/yr) *	1,900	1,300
Dominant soil	Red loamy sand soil	Black cotton soil
Rainfall type	Bimodal pattern	Bimodal pattern
Climate type	Equatorial	Tropical
Annual temperature (^{0}C) **	18-21 degrees	21-24 degrees
Topography	Undulating	Flat
Agro-ecological zones	Upper midlands	Lower midlands
Socio-economic		
Population density (person/ km^2)	1,300	400
Agricultural production	70% (small scale)	90% (small scale)
Farm sizes (ha)	0.4–3	0.6
Agriculture employment	62%	70%
Absolute Poverty	40%	39%
Land use		
Main food crops	Maize, beans	Maize, beans, rice
Main cash crops	Tea, coffee	Sugarcane
Main Livestock system	Tethered, zero grazing	Tethered

*Rainfall is a bimodal pattern of long and short rainy seasons. **Lowest monthly temperature and warmest monthly temperature
Data source: Vihiga and Kisumu County development Plan (2018-2022).

The selection strategy of the case studies

Kenya's new constitutional dispensation in the year 2010 reorganized government structures by creating one national government and 47 semiautonomous devolved county governments. Each of the 47 county governments formulates policies to guide agriculture and spatial development in its jurisdiction. Among the functions that were devolved from national to the counties in the new constitutional dispensation include agriculture and spatial planning functions. Upon this basis, one criterion for case study selection was that the selected areas were to be located in two different decentralized county governments. The choice of using this parameter was to enable a comparative analysis of how different policies and strategies formulated by these two devolved governments influenced and impacted smallholder agriculture at the local level. Based on this, Vihiga and Kisumu counties were chosen. The following parameters were further considered in selecting the two sites for this study;

- Areas with an urban center or close (5-10 km) to a major urban center. An assumption was made that smallholders in residing those areas have higher proximity to markets than those in rural areas.
- Areas with a spatially heterogeneous landscape that is predominated by small-scale agricultural activities. This strategy hypothesized that the researcher would get diverse data to support a robust analysis that can support the valorization of the research findings.

Additionally, Vihiga County was selected for various reasons. First, the county has made significant strides in terms of establishing governance and institutional frameworks to support the implementation of the devolved government system. Second, since the devolution of agriculture and spatial planning functions from national to county government in the year 2010, the county is listed among those that have formulated and implemented legislation, policies, spatial plans, and supportive institutional mechanisms to anchor and guide the agriculture and spatial planning sectors. Third, in Vihiga County relevant information is easily accessible. The high adoption of information technology and e-government in the county enables it to publish all its policies, legislation, fiscal strategies, and other relevant information on its website (https://vihiga.go.ke/downloads.html). Fourth, the county has high agroecological potential for agricultural production. In terms of land use, the county is characterized by heterogeneous land-use systems with farming typologies ranging from pure subsistence, and mixed subsistence, to cash-crop oriented. Agriculture activities in the county are predominated by small-scale agriculture with the majority of households average farm sizes ranging between 0.1 to 2.0 ha. However, the county experiences a high prevalence of food insecurity and high population pressure, and agricultural production faces several challenges that require a pragmatic and multifaceted approach to addressing them.

In addition to the salient characteristics of Kisumu County discussed in table 3.1 for Kisumu city, the county was chosen based on its proximity to Kisumu city which has many supermarkets and open-air markets. The high population of Kisumu city also provides a ready market for many smallholders' agricultural produce, and its productive hinterlands provide fertile land for many small-scale farmers to grow crops that are then sold in the city. In addition, Kisumu city hosts the devolved government headquarters.

3.4 Research Design

Studies of the thesis

Overall research design comprised five separate studies. Table 3.2 below shows the linkage between data collection methods, research designs, research questions, and analytical tools of the different studies.

Table 3.2: Research designs and research questions addressed in the different chapters of the thesis

Name of study	Research question	Research approach used	Analytical tool	Chapter number
Application of GIS in agriculture in promoting spatially integrated agriculture policies for improving agriculture sustainability: A systematic review	In what ways (application areas) has the GIS technology been used in the agricultural sector in the last decade in promoting spatially integrated policies in improving agriculture sustainability?	Systematic literature review	- Systematic literature review - Descriptive statistics	**4**
Can livelihood capitals promote the diversification of resource-poor smallholder farmers into agribusiness?	How do households' livelihood capitals influence poor smallholders' decisions on whether to participate in agribusiness markets?	Cross-sectional study	- Livelihood survey - Multinomial logistic regression - Key informant interviews	**5**
A GIS-based spatially explicit approach for targeting resource-poor smallholders	How can spatially "geographically" explicit factors and GIS be used to identify and map poor smallholders' households and local spatial factors that impede their participation in agribusiness markets?	GPS spatial mapping	- Spatial geostatistical analysis - GIS mapping	**6**
Mapping the spatial dimension of food insecurity using GIS GIS-based indicators and a place-based approach.	How can the spatial dimension of agriculture and food insecurity be mapped, analyzed, and geo-visualized (using GIS) to identify the spatial patterns of food insecurity, and to provide a contextualized understanding of local-level causative factors of food insecurity?	GPS spatial mapping	- Spatial geostatistical analysis - Geocoded Surveys - Principal Component Analysis	**7**

Integration of agriculture and spatial planning frameworks in policies on improving the sustainability of smallholder Agri-food systems	How can the spatial dimension of agriculture be integrated into the spatial development policy frameworks to improve the sustainability of smallholder agriculture, and what factors enable or constrain agriculture and spatial 'agri-spatial' policy integration?	Qualitative case study	- Policy document analysis - Key informant interviews - Observation	**8**

Below we briefly describe the methods used to collect data, with the detailed description provided in the corresponding chapters of the thesis.

Non-spatial data collection methods

Several methods were used to collect non-spatial data including, livelihood analysis, key informant interviews, and focus group discussions. These are briefly described below.

Livelihood survey

A livelihood survey was used for acquiring an in-depth understanding of the influences, barriers, and facilitators of smallholder farming decisions at the household level. A comprehensive questionnaire was developed that captured various variables of a household's livelihood capital assets. We profiled each household's farming activities, then collected data on livelihood assets to assess how the farming activities and decisions to participate in agribusiness were influenced by those livelihood capital endowments. The purpose was to understand the extent to which differentiated asset configurations of each household impact its decisions to participate (or not) in agribusiness activities. A related critical question for our investigation in this study was how differentiated livelihood capital endowments create different outcomes necessary for the transition of rural poor smallholders' subsistence into market-oriented agribusiness.

Key informant interviews and focus group discussions

Key Informant Interviews (KIIs) and Focus Group Discussions (FGD) were conducted with various stakeholders, including county and national government agriculture officials, the private sector, and traders in the agribusiness value chains. Structured and unstructured interviews were conducted with key informants in the agriculture and spatial planning sector. Policy decision-makers from county government officials and the Ministry of Agriculture were selected using snowballing sampling for interviews. Particular attention was paid to questions on factors affecting the participation of poor smallholder farmers in agribusiness. Key informant interviews were scheduled first to get focus on broad issues. then the discussions from these interviews enabled the refining of the household questionnaires that were administered to sampled households in the case study area.

Several FGDs were conducted to gather an in-depth understanding of the perceptions, opinions, and experiences of farmers and stakeholders. FGDs "allow participants an opportunity to narrate their personal experiences and to test their interpretations of events and processes with others" [101]. According to Sagoe [102], the result is a multiplicity of voices speaking from a variety of subject positions. FGD is a powerful method that enables local communities to collaboratively produce local knowledge through organized group discussions. Such knowledge produced in a collaborative performance, according to Nyumba et. al., [101] "better reflects the social nature of knowledge than a summation of individual narratives extracted in interviews" (p. 29).

Systematic literature review

A systematic literature review was conducted in the databases SCOPUS, Web of Science/Clarivate, Bielefeld Academic Search Engine (BASE), COnnecting REpositories (CORE), and google scholar. The objective of the review was to synthesize existing evidence on GIS technology application in the agriculture sector to inform evidence-based policy.

Spatial data collection method

Geocoded household survey

The geocoded household survey was used to collect georeferenced spatial data of households. It comprised of two parts: Part one used face-to-face interviews and Part two used a geocoded household questionnaire. In total 392 households were included in the two study areas. A semi-structured questionnaire was our main survey instrument and was designed to have both open and close-ended questions. The questionnaire covered diverse topics and captured data on biophysical, socio-economic, and technical aspects of each household. Socioeconomic information collected included age, gender, marital status household head, family structure, labor availability, sources of income, access to agricultural inputs, food security, livestock system, links to markets, and production orientation. Agroecological and biophysical information collected included, among other variables slope, flooding, erosion, pests, and diseases.

The second part, the geocoding of the household survey questionnaire entailed a step-by-step approach, comprising the following steps.

1. In the first step, we rasterized each study area (administrative polygon) into equal grid cells of 50 by 50 meters using ArcGIS software.

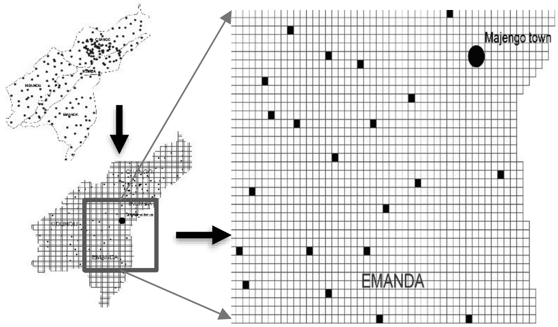

Figure 3.2: Rasterizing the administrative polygon into grid cells.

2. In the second step, using the previously calculated sample size, we randomly distribute this sample size within the study area polygon using the ArcGIS software function. To achieve a spatial uniform distribution of these points, a rule-based algorithm was used to restrict the minimum distance between any two random points to 25 meters.

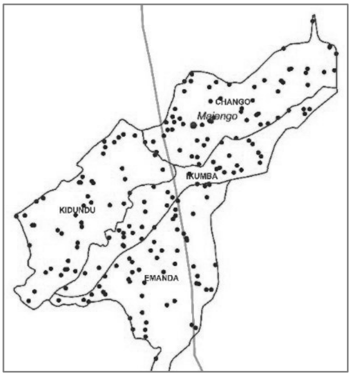

Figure 3.3: A GIS randomly distributed sample point in the study area.

3. In the third step, the randomized points, grid cells layer, and study area boundary layers were converted into Keyhole Markup Language (KML) layers and superimposed on a high-resolution satellite image in the Google Earth browser.

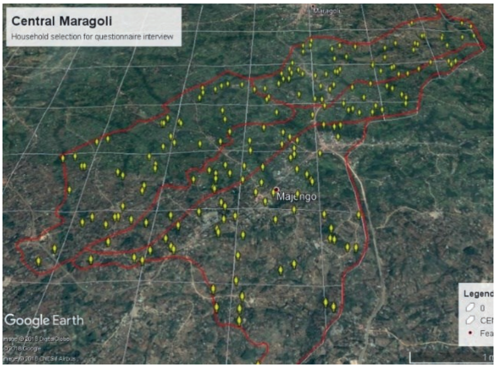

Figure 3.4: KML layer of the randomized points superimposed on a high-resolution satellite image of the study area

4. In the fourth step, we copied the KML layers in the research assistant's Android phone App. 'GPS Essential App' and used it as our mapping and navigation tool during data collection. The grid cells helped the research assistant to easily and accurately identify the exact locations of sampled households (each randomized point) for interviewing during fieldwork.

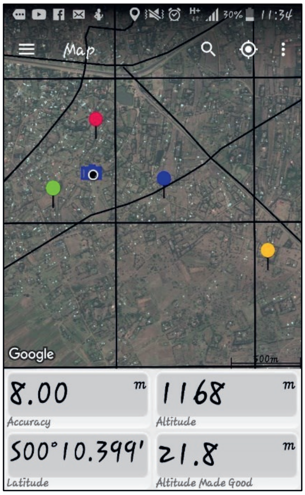

Figure 3.5: A phone screenshot of the 'GPS Essential App' showing the actual GPS coordinates of interviewed households.

5. In the fifth step, we used the android phone's 'GPS Essential App' to geolocate the randomized sample points. Simple random sampling was used to select any household amongst those enclosed by the square grid cell. The household to which each randomized point fell was prioritized for an

interview before making another selection. Handheld GPS devices recorded the coordinates of the sampled households.

6. During fieldwork, spatial data verification was addressed by projecting GPS coordinates of administered questionnaires in ArcGIS at the end of each day and uploading the projected shapefiles as layers on the android phones of the research assistant before the start of the next day's fieldwork. This facilitated data verification and identification of interview gaps.

7. To ensure a spatially and evenly distributed sample, the GPS coordinates for each administered questionnaire were projected in ArcGIS daily. Then a buffer analysis for each GPS point was performed using a 250 meters buffer. This helped to spatially identify areas covered (inside of the buffer zone) and not covered (outside of the buffer zone) by research assistants and to avoid research assistants interviewing too close to previously interviewed household points.

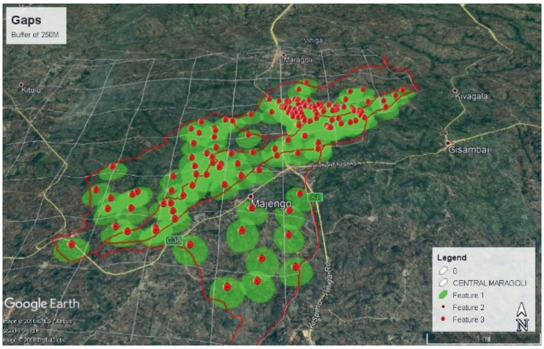

Figure 3.6: A buffer analysis results of the sampled household GPS points, showing the gaps for interviews.

The collection of georeferenced spatial data was carried out by the use of Geographical Information Systems (GIS) and Geographical Positioning Systems (GPS). The strong spatial analytic capability of GIS provided tools and techniques for the identification, mapping, and analysis of spatial and non-spatial factors that influence agricultural production [103].

The spatial data layers (GPS coordinates of households, administrative boundaries, road networks, rivers, markets centers, and, towns) were superimposed on Google earth's high-resolution satellite image to aid fieldwork data collection. The researcher also digitized road networks, rivers, markets centers, and, towns from the high-resolution satellite image of the case studies provided by the Digital Globe Foundation. Integration of GIS, GPS coordinates, and geocoded spatial data helped in building a detailed Spatial data collection framework (Figure 3.7) and GIS database for studies presented in chapters 5 and 6.

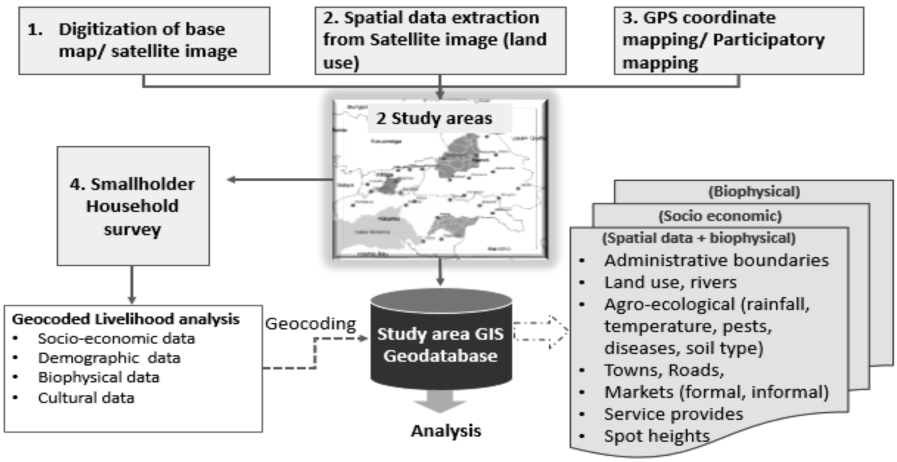

Figure 3.7: Spatial data collection framework

3.5 Data analysis

KII and FGD data were organized and managed using digital voice recorders and field notebooks. All audio files were transcribed verbatim. In study chapters 4 and 7, non-spatial data (quantitative data) was coded and input into the Statistical Package for the Social Science (SPSS) software. Several statistical analyses were conducted for study 4 including descriptive statistics (ANOVA, frequencies, percentages), multinomial logistic regression, and principal component analysis. For studies chapters 5 and 6, the spatial data (GPS coordinates of household questionnaires) were exported into the developed geodatabase of each study area where they were integrated with other spatial data layers through georeferencing. In study chapters 5 and 6, spatial data were analyzed using several spatial analytic techniques including Global Moran's I, Cluster and Outliers Analysis (Anselin Local Moran's I), Hot Spot Analysis (Getis-Ord GI*), and Geographically Weighted Regression (GWR) analysis. For a detailed explanation of the application of these methodologies, see studies chapters 5 and 6 of the thesis.

3.6 Internal and external validity of the thesis

The validity and reliability of the study are determined by the careful consideration and articulation of the methodology employed to gather quality data and the instruments developed to collect data. Since we used mixed methods to collect and analyze data, we addressed the internal and external validity in multiple ways.

Quality control during fieldwork

To ensure quality data was collected, a clear guideline for the data collection procedure was developed for the fieldwork. The use of triangulation with mixed methods allowed for the 'convergent validation of our data thus enhancing the validity of our results. The research instruments (questionnaires, GPS, and recording instruments) were tested and calibrated beforehand to ensure reliable, and accurate data is collected. The fieldwork research assistants were trained and incorporated from the initial designing of the questionnaire, pretesting, translating it to the local dialect, and pre-testing. The research assistants were selected based on familiarity with the study area, and who could speak the local dialect of the inhabitants of the study area. Before data collection, the principal researcher and the research assistants discussed the data collection formalities, etiquette, emerging issues, and proposed solutions.

To minimize data entry mistakes, data entry assistants were trained beforehand and a quality check was adhered to during entry. Preliminary sorting of collected data was done based on the main data collection methods. Data from the key informant interviews and FGDs were sorted according to the broad theme of discussion and also according to research questions. Data from farmers' questionnaires were sorted, coded, and entered into SPSS statistical software for analysis. Immediately after data entry, a preliminary analysis using SPSS software was conducted in checking data consistency, completeness, missing data, and outliers. All data sets were prepared to facilitate a swift repeat of the inference process. Before conducting multinomial regression analysis, nonspatial data were screened for basic assumptions of multinomial logistic regression including missing values, outliers, and normality of distribution, using SPSS software. Furthermore, we screened the data for multicollinearity using the Variation Inflation Factor (VIF) and tolerance coefficient.

Checking the reliability and predictive accuracy of the regression model

We employed two methods to check for the validity of the multinomial regression model: *10-fold cross-validation* and *hit ratio analysis*. The 10-fold cross-validation method was used to estimate the predictive performance of our logistic regression model. First, we randomly partitioned our sample size into 10 folds, with a training data set to train the model and a testing data set to validate it. We then performed 10 rounds of model cross-validation using different partitions. The results of the 10-fold cross-validation and hit ratio analysis are detailed in chapter 5 (figures 5.3 to 5.5 and Table 5.4).

Checking the validity and suitability of the constructed composite indicators to map food insecurity

We constructed GIS-based indicators to measure and map food insecurity. However, composite indicators used to monitor spatially linked problems, frequently apply aggregated data collected at global, national, regional, or city levels. A criticism of using indicators generated at a higher spatial level of aggregation is that they may mask important spatial differences at the local level and often hides the stark contrast between better-off and poor households in a locality. We overcame this by collecting household data at the household level. This diminished the extent of measurement error and improves the measurement of local spatial heterogeneity of problems under investigation. In addition, the constructed composite indicator should first be assessed for its fitness and its reliability. The Kaiser-Meyer-Olkin (KMO) coefficient is used to investigate the validity and suitability of the constructed indices [104]. According to OECD, the standard practice when constructing composite indicators is to extract and retain only those factors that meet the following criteria; eigenvalues greater than one, total variance more than 10%, cumulative variance greater than 60%, Kaiser-Meyer-Olkin (KMO) coefficient greater than 0.5 and with a statistically significant Bartlett test of sphericity. The KMO normalization coefficient determines the sampling adequacy by measuring the proportion of variance among variables that might be caused by underlying factors [104]. This ensures that the variables used to measure a particular concept are measuring the concept as intended. High values above 0.5 generally indicate that factor analysis may be useful with the data. The results (see table 6.3) suggests that our data was suited for PCA.

Checking the validity of the spatial data and spatial analysis methods

Before performing spatial analysis in ArcGIS, the geocoded household data were tested for normality, multicollinearity, and goodness of fit. We used the Exploratory Regression Statistics in ArcGIS software to test these variables for residual spatial autocorrelation, residual normality, and global multicollinearity (of less than $VIF < 7.5$). In modeling local spatial relationships, two crucial factors should explicitly be determined before spatial analysis can be carried out because they affect the spatial analysis output. These are (1) geographical unit of analysis and (2) territorial distance. In determining the most appropriate spatial unit of analysis, we rasterized the administrative polygon of the study areas into small cell grids to lower the spatial unit of analysis. Spatial analysis was based on rasterized cell grids with their associated attribute data. We then transposed the sampled households' GPS points and their associated attribute data into the rasterized layer to allow cell-by-cell spatial analysis. We used the "Incremental Spatial Autocorrelation tool" in ArcGIS to calculate the most optimal territorial distance value.

To improve the accuracy of spatial regression results and interpretability of the output statistics, two problems associated with modeling spatial relationships should be addressed beforehand; (1), the problem of the heterogeneity of the spatial relationship and (2), the problem where local data artificially inflate the spatial statistical significance (i.e., type 1 error). In reality, the spatial relationships are not homogeneous, since factors promoting spatial autocorrelation have different potentials for interactions [88]. To improve the accuracy of the spatial analysis, we used a row-standardized spatial weight matrix for our dataset in ArcGIS to quantify the spatial relationships that exist among the features. Row standardization creates proportional weights to account for where certain features may have an unequal number of neighbors [66,99]. The spatial weights matrix quantifies the spatial relationships that exist among the features in the dataset and row standardization creates proportional weights to account for where certain features may have an unequal number of neighbors [66,99]. This method is popularly used by different authors as it is effective [99]. To address the second problem (i.e., type 1 error) we applied a False Discovery Rate (FDR) correction that adjusts the critical p-value thresholds in our spatial analysis.

External validity

A common concern for empirical studies is the generalizability and replicability of study findings to a broader context in informing public policy. Principally, spatially explicit studies highly depend on the quality of spatial data and the clarity of methods used in their analysis. The quality of spatial data used, and by extension, the methods used to collect it should be among the most important considerations for researchers if the study outputs are to be relied upon in informing policy and being able to be reproducible elsewhere. For our study, we designed a well-articulated data collection strategy to collect quality georeferenced household survey data. First, we designed a household survey questionnaire with clear, and simple-to-understand closed and open-ended questions. Secondly, for difficult-to-understand questions, we translated them into local dialects to make it easy for households to understand the question. Equally, the quality of our household survey was enhanced by incorporating web-based geospatial tools that helped us to easily and accurately geolocate sample households in collecting georeferenced data. The step-by-step description of the process of designing a spatially explicit methodology in chapters 5 and 6 of this study could enable other researchers to replicate the study elsewhere.

3.7 Ethical considerations

Ethical approval for this research was obtained from Maseno University Ethical Review Committee, reference number (MSU /DRPI/ MUERC/00633/18). In addition, informed consent was sought from all interviewees and respondents. Ten research assistants from Maseno University were trained and helped in the face-to-face interviews of households. The research assistants were incorporated from the initial designing of the questionnaire, pretesting, translating it to the local dialect, and pre-testing. The research assistants were selected based on familiarity with the study area, and who could speak the local dialect of the study area. Interviews were conducted at individual homes of the sampled households. Before the start of each day's interviews, the principal researcher briefed the research assistants on data collection formalities and etiquettes, and at the end of each day, we met to discuss the challenges, emerging issues, and how to address them

Chapter 4

Application of GIS in Agriculture in Promoting Evidence-Informed Decision Making for Improving Agriculture Sustainability: A systematic review

Picture: Author interviewing a small-scale tea farmer in Kiambu, Kenya.

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Abstract

The objective of this review was to synthesize existing evidence on GIS and RS application in agriculture in enhancing evidence-informed policy and practice for improving agriculture sustainability and identifying obstacles to their application, particularly in low- and middle-income countries. Systematic searches were conducted in the databases SCOPUS, Web of Science, Bielefeld Academic Search Engine, COnnecting REpositories (CORE), and Google Scholar. We identified 2113 articles published between 2010–2021, out of which 40 articles met the inclusion criteria. The results show that GIS technology application in agriculture has gained prominence in the last decade, with 66% of selected papers being published in the last six years. The main GIS application areas identified included: crop yield estimation, soil fertility assessment, cropping patterns monitoring, drought assessment, pest and crop disease detection and management, precision agriculture, and fertilizer and weed management. The use of GIS technology has the potential to enhance agriculture sustainability by integrating the spatial dimension of agriculture into agriculture policies. In addition, GIS's potential in promoting evidence-informed decision-making is growing. There is, however, a big gap in GIS application in sub-Saharan Africa, with only one paper originating from this region. With the growing threat of climate change to agriculture and food security, there is an increased need for the integration of GIS in policy and decision-making in improving agriculture sustainability.

Keywords: GIS, agriculture sustainability, place-based policy, spatial knowledge, spatial decision support system

4.1 Background

The demand for food globally has risen tremendously and is expected to increase to 59-98% by the year 2050 [14]. However, the growing concerns are that the agricultural food production systems are unable to match the high demand, especially in poor nations, causing an intensifying level of food insecurity [17]. How best to facilitate increased food production without jeopardizing land and water resources, energy, and the environment is a momentous task that governments and policymakers have to address [22].

In many low- and middle-income countries (LMICs), most of the food production is rural-based, dominated by smallholder and subsistence farmers. Enhancing smallholders' sustainability requires that farmers are empowered with practicable information that enables them not only to make evidence-informed decisions but also to implement them in activities that could increase their farm productivity and sustainability. In efforts toward transforming the weak and often inefficient traditional subsistence production practices, sustainable production approaches [18,105] that support production-efficiency-enhancement and better agronomic practices are needed. These include planting climate-resilient crops, high-yielding crop varieties, crop yield forecasting, integrated pest management, as well as integrating biodiversity solutions in sustainable food production systems [106]. Ultimately, these novel interventions would require comprehensive, up-to-date datasets (spatial and non-spatial) and the adoption of advanced GIS technologies that can synthesize and integrate social, spatial, economic, demographic, and environmental data in agriculture. The output of this synthesis would be evidence-based spatial knowledge that improves our understanding of agriculture sustainability and in supporting better policies and decision-making processes.

Contemporary advances in Geographic Information Systems (GIS), Remote Sensing (RS), and Geographic Positioning Systems (GPS) technologies present an opportunity to acquire and operationalize high-resolution satellite imagery and digital spatial data [107]. In the agriculture sector, these spatial data have aided in the investigation of the spatial linkages of social, physical, agroecological, and environmental complexities and how they affect agriculture sustainability. GIS technology provides users with a mixture of geo-spatial information management tools and methods that allow users to collect, store, integrate, query, display, and analyze geospatial data at various scales [92]. Remote sensing technology acquires images and other information about crops and soil from sensors mounted on different platforms including satellites, airborne remote sensing (manned drones and unmanned aerial vehicles), and ground-based equipment that is then processed by computers to aid agricultural decision-making systems [108,109].

The spatial context of agriculture can be viewed from the perspective of farmers' differentiated access to livelihood capitals, local resources, and access to essential infrastructure and services existing in a locality. In a GIS system, the data containing each of these aspects can be deconstructed as nested spatial layers, each rooted in local geography by geographic coordinates captured using GPS [64]. These spatial layers can then be processed and analyzed in a GIS system in multiple ways to reveal crop and soil conditions, and spatial interactions, predict crop trends, monitor land-use change, monitor pests, and in biodiversity conservation [110–113]. They can also be used to map and reveal spatial impediments to agricultural production, or even new information for improving agricultural sustainability.

In recent times, the increasing complexity associated with agricultural production systems has aroused policymakers' interest in investigating how the spatial aspect 'dimension' of agriculture can be exploited using advanced GIS, RS, and GPS technologies to improve agricultural productivity and better production practices [114,115]. The integration of GIS technologies in agriculture has increased the opportunities for the development of even better spatial explicit frameworks that support the creation of dynamic agriculture databases and interactive systems [116]. Such database systems allow users to interact with spatially referenced agriculture data in real-time, while accurately providing precise positional data, thus providing enhanced frameworks for decision-making. New fields that apply GIS in agriculture have emerged as a result. These include precision agriculture, automated farm systems, crop yield forecasting, climate change detections, and the real-time monitoring of crop production [108,109,117]. These have the capability of improving agricultural production and food security.

In this regard, several recent systematic literature reviews have been conducted to illuminate and consolidate various ways GIS, RS, and GPS technologies have been applied in the agriculture sector. García-Berná et al. [108] used a systematic mapping study to focus on the current trend and what new opportunities remote sensing techniques offer in agriculture. Their study found increased uptake of RS technologies in the acquisition and extracting of georeferenced data from satellite imagery and unmanned aerial vehicles. Spatial data from these technologies have been applied in several areas including crop growth and yield estimation, cropland parameter extraction, weed, and disease detection, and the monitoring of water and nutrients in plants. How this application could be integrated to improve spatial-based agriculture policymaking was not elaborated by the authors. The Al-Ismaili [118] review highlighted the integrated application of RS and GIS techniques in precision agriculture, and in mapping, detection, and classification of the greenhouse through aerial images and satellites. How such a technique could be assimilated into enhancing policymaking was not mentioned. In yet another meta-review, Weiss et al., [109] research highlighted the emerging development in RS that strengthens the specific application of RS in crop breeding, agricultural land use monitoring, crop yield forecasting, and biodiversity loss. Sharma, Kamble, and Gunasekaran [119] focused on how GIS data applications have assisted in the development of precision agriculture. The authors proposed a framework, "Big GIS Analytic" to guide how big GIS data should be applied in the agriculture supply chain. Their framework also lays a foundation for a theoretical structure for improving the quality of GIS data application in agriculture to elevate productivity. These studies help us to understand how GIS and RS applications in agricultural production systems have advanced. However, the available systematic reviews seem not to explicitly provide how GIS and RS technologies could enhance the integration of the spatial dimension of agriculture into policy frameworks and interventions.

There is an increasing demand for evidence-supported decision-making to assist policymakers in assessing the local needs of farmers, improving production and supply value chains, and developing spatial based-interventions. In this regard, this review aimed at synthesizing existing evidence on GIS and RS application in agriculture in enhancing evidence-informed policies for improving agriculture sustainability and identifying obstacles to their application, particularly in LMICs. The review draws on a decade of literature, from 2011 to 2021, to examine the current and future perspectives on integrating GIS in policies that support agriculture sustainability. The main contributions of the study are to provide readers and policymakers with evidence on how GIS technology has been used in the agriculture sector to improve agricultural production practices and inform how the technology can be adopted to improve evidence-based decision-making and policies. This paper is structured as follows: after the introduction, we describe the methodology applied to select and review the articles; then, we detail the findings in Section 3. In Section 4, we highlight obstacles to applying GIS in agriculture policy and practice. Lastly, Sections 5 and 6 give the conclusion and the limitations of the study.

4.2 Review Methodology

Process of screening

The search used the bibliographic databases SCOPUS, Web of Science/Clarivate, Bielefeld Academic Search Engine (BASE), and COnnecting REpositories (CORE), as well as Google Scholar. The following inclusion criteria were employed to screen for titles and abstracts: (1) full articles in peer-reviewed journals; (2) articles published between January 2010 and October 2021; (3) written in the English language; and (4) those associated with the application of GIS or RS in agriculture. The following search string was applied as index terms to search: "*TITLE, ABSTRACT (*Agriculture* OR Plant OR Crop*) AND (GIS or Geographic OR Information OR Systems) AND (Remote OR Sensing OR RS)". The full search syntax is found in Figure A1 in the appendix. Following the eligibility criteria, a total of 2113 articles were found; 701 articles were identified from SCOPUS, 104 from Web of Science, 468 from Bielefeld Academic Search Engine (BASE), 68 from CORE, and 238 records from Google Scholar. After excluding duplicates and studies for which no full text or access was available (988 articles), 1,223 articles were eligible for further screening.

The flow of the screening process is shown in figure 4.1. The first screening was based on the title and abstract checking for relevance to the purpose of this article, based on which a substantial number of articles (n = 554) were excluded. Further exclusion criteria were based on (1) articles focusing on the general application of GIS, i.e., suitability analysis and site selection analysis (n = 81) and (2) irrelevant topics or focus (n = 171). After the exclusion of these articles, 97 articles were subjected to secondary screening through full article reading, which resulted in the exclusion of 57 articles. After the final screening, 40 articles were selected for analysis.

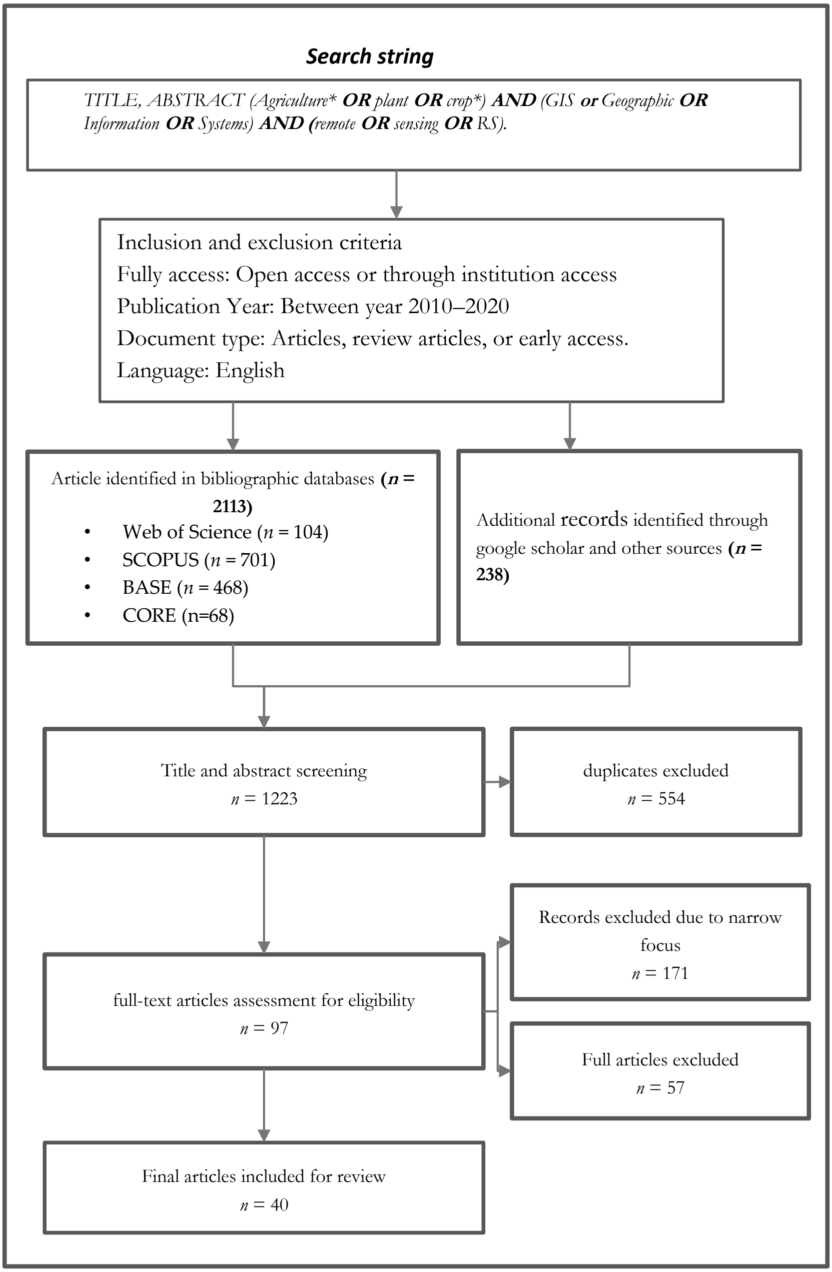


Figure 4.1: Flow diagram of the screening process

Data extraction and analysis

Full reference records for selected articles were exported to the Mendeley reference manager and Microsoft Excel to enable coding and analysis. We extracted data using a standardized form and included the following descriptive data: author(s); year of study; journal; location; research objectives/questions; and main methods, findings, and conclusions. The included articles were analyzed through thematic analysis, combining both deductive and inductive coding.

4.3 Results and Discussion

Characterization of the selected papers

In total, 20 journals published the selected papers (figure 4.2), with the top four publishers being Elsevier (26% of the articles), Springer (21%), MDPI (9%), and PLOS ONE (9%). Affiliates publishers of Elsevier where the papers were published included (Agricultural Systems, Chemosphere, Science of the Total Environment, Agricultural Water Management, Field Crops Research, Computers and Electronics in Agriculture, Applied Geography, Computers and Electronics in Agriculture, and Catena). The Springer publisher affiliates included (Nature, Earth Systems and Environment, Nutrient Cycle Agroecosystem, Precision Agriculture, and Environment Monitoring Assess) while the MDPI affiliate publishers included (Sustainability, and Agriculture).

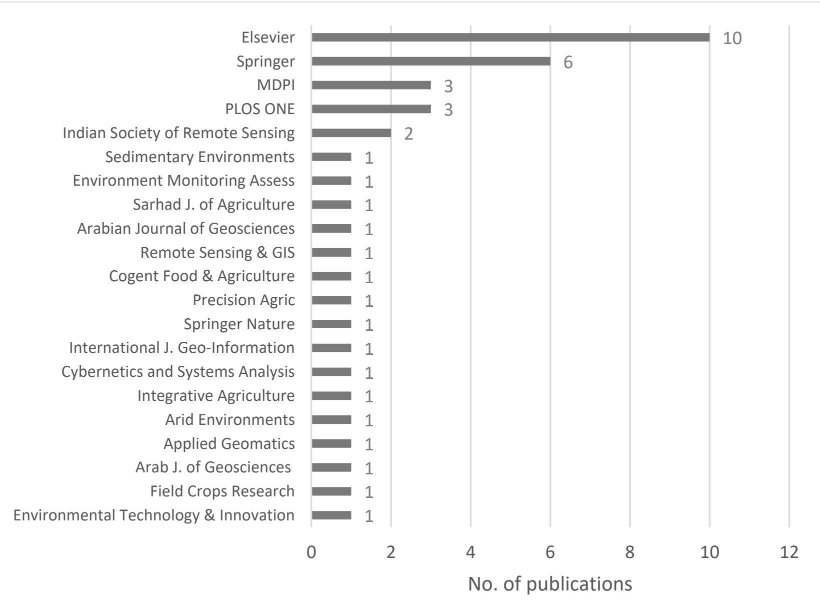
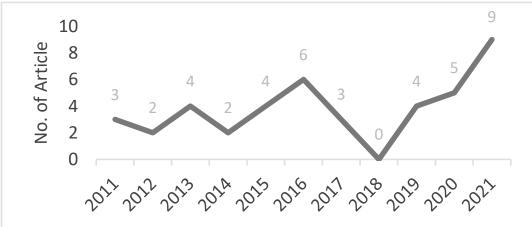


Figure 4.2: Publication sources of selected papers

The selected articles covered diverse fields of GIS applications that were published in various years and based in diverse regions as shown in Table 4.1.

Table 4.1. Characteristics of the included records

Criteria	Category	No. of Articles	%
Field of GIS application	Crop yield estimation/forecasting	12	30%
	Soil fertility assessment	9	22.5%
	Cropping pattern and monitoring	4	10%
	Drought risk assessment	3	10%
	Pest and crop disease detection	3	7.5%
	Precision agriculture	3	7.5%
	Fertilizer and weed management	2	5%
Publication year			
Region of case study	East Asia and pacific	14	35%
	Europe and Central Asia	3	7.5%
	South Asia	11	27.5%
	North America	4	10%
	The Middle East and North Africa	7	17.5%
	Sub-Sahara Africa	1	2.5%

The most frequent fields of application were crop yield estimation and forecasting (30%) and soil fertility assessment (22.5%). Eighteen countries were identified in the selected papers where the research was conducted. Grouped by region, we found that East Asia and Pacific countries were the most frequent, accounting for 35% of the total, including Australia (n = 4); Bangladesh (n = 1); Indonesia (n = 1); China (n = 7); and Russia (n = 1). South Asia accounted for 27.5% including India, (n = 7); Pakistan, (n = 1); and Iran (n = 3). North America accounted for 10% of the total, including the USA (n = 3) and Canada (n = 1). Middle East and North Africa accounted for 17.5% including Saudi Arabia, (n = 2); UAE, (n = 1); Morocco, (n = 1); and Egypt, (n = 3). GIS applications in Europe and Central Asia accounted for 7.5% of the total, including Ireland, Ukraine, and Turkey, each with (n = 1). Sub-Saharan Africa had the least articles, with only one (Ethiopia, n = 1) accounting for 2.5%.

The most frequent type of GIS application methodologies identified in the selected papers are presented in Figure 4.3. More than half (27 papers) accounted for 67.5% of the selected papers that used GIS in their methodologies, 8 papers (20%) integrated both GIS and RS, while 5 papers (12.5%) used RS techniques.

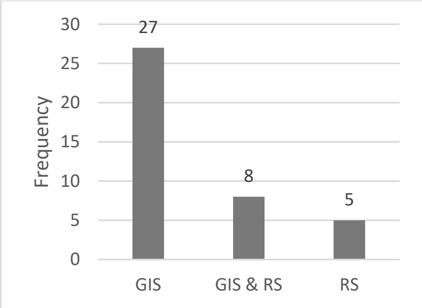


Figure 4.3: Number of papers using GIS, RS, or a combination of the two in their methodology.

GIS application in agriculture and the implication to policy

The main field of study for the selected papers was categorized into seven application areas (Table 4.2). These include crop yield estimation/forecasting (26% of the papers), soil fertility assessment (18%), cropping patterns and agricultural monitoring (13%), drought assessment (16%), pest and crop disease detection and management (11%), precision agriculture (8%) and fertilizer and weed management (8%).

Table 4.2. Classification of main types of research topics addressed in the selected papers

	Research topic/ GIS application areas	Reference	No. of publications
1.	Crop yield estimation/ Forecasting	[120–127]	12
2.	Soil fertility assessment	[128–134]	7
3.	Cropping patterns and agricultural monitoring	[112,135–138]	5
4.	Drought assessment	[139–144]	6
5.	Pest and crop disease detection and management	[145–148]	4
6.	Precision agriculture	[149–151]	3
7.	Fertilizer and weed management	[117,152,153]	3

We expound on how GIS was applied in the selected papers according to the research topic in the sections below.

Crop yield estimation/ forecasting

Monitoring crop growth and early crop yield forecasting over agricultural fields is an important procedure for food security planning and agricultural economic return prediction. The continued advancement in RS and GIS technologies has improved the process and techniques of monitoring the development of crops and estimating their yields [122,125,127]. Several studies demonstrate the application of integrated GIS and RS technologies in crop yield estimation. Memon et al.'s [120] study demonstrated how integrating multispectral Landsat satellite imagery and comparing different RS-based spectral indices were effective in measuring the percentage of wheat straw cover and successively determining its effect on the yields of rice crops. The knowledge can inform long-term planning of agriculture sustainability in rice-wheat cropping systems. The result of the research by Hassan and Goheer [123] showed that the accurate early estimation of wheat crop yield before harvesting can be determined by using vegetation indices derived from moderate resolution imaging spectroradiometer satellite imagery and crop yield data and the GIS modelling approach. In yet another study, Hassan and Goheer [124] used a GIS-based environment policy integrated climate model that provided a practical tool for simulating rice crop yield. The model combined regional level crop level data, soil data, farm management data, and climatic data to spatially estimate variations in crop yield. Likewise, Al-Gaadi et al. [125] extracted the normalized difference vegetation index and soil-adjusted vegetation index from Landsat satellite images acquired during the potato growth stages to predict potato tuber crop yield. GIS and RS-based crop yield forecasting models could have a wider application in informing spatially based agriculture policies. For example, based on the output of these models, policy intervention can be designed to manipulate the specific contributors to crop yields (which include farm management techniques, weather conditions, water availability, altitude, terrain, plant health, and policy intervention [121,126]. Forecasting crop yields well before harvest is crucial, especially in a region characterized by climatic uncertainties. Monitoring agricultural crop growth conditions and the prediction of potential crop yield is important in planning and policymaking for food security and agricultural economic return prediction [122,124,127]. This could include developing policies for improving agriculture productivity and sustainability [124]. In feeding a growing population in LMICs agricultural production systems must strive to reduce the food production yield gap between current yields achieved by farmers and those potentially attainable in rainfed subsistence farming systems. In addressing this mismatch, the study by Hochman et al., [126] developed a model that integrated statistical yield and cropping area data, remotely sensed data, cropping system simulation, and GIS mapping to assess and map wheat yield gaps.

Soil quality/ fertility assessment

Soil quality assessment is critical for designing sustainable agricultural practices (optimal agricultural use) that can help bridge the current food production and demand gap in overcoming the food security problem. The availability of RS datasets and GIS spatial modelling techniques provides new opportunities for measuring/evaluating soil quality at different spatial scales [129,132]. Shokr et al., [131] developed a spatially-explicit soil quality model by combining soil's physical, chemical, and biological properties and integrating these with a digital elevation model and Sentinel-2 satellite image to produce digital soil maps. Abdelfattah and Kumar, [128] describe the application GIS-enabled web-based soil information system that provides a descriptive, quantitative, and geospatial soil database in a simple interface. The system was applied to determine the sufficiency potential of soils for plant growth and management. Using GIS and RS technologies, Abdellatif et al. [134] developed a spatial model for the assessment of soil quality. His model combined four main soil quality indices (soil fertility index, soil physical index, soil chemical index, and geomorphological properties Index) and GIS ordinary kriging spatial interpolation to map the soil quality index. The application of these GIS-based models provides evidence-based ways to improve soil quality management. This would enable decision-makers, policy formulators, land-use planners, and agriculturalists to efficiently manage soil resources, to ensure the sustainable use of agricultural lands according to their potential [130,132,133]. Thus, assessing soil quality indicators would be important for sustainable agricultural practices and in achieving food security.

Crop mapping and monitoring decision support systems

In an era of unpredictable climate changes, agricultural crop monitoring analysis could help government policymakers and farmers plan and design cropping patterns that adapt to water availability. Agricultural monitoring systems integrate multiple geospatial data sets and cropping system models into computer algorithms to spatially compute and simulate optimum scenarios for site-specific conditions for crop production [138]. A crop monitoring system is developed by integrating geospatial data obtained by high-resolution remote sensing with a web GIS geoportal interface [137]. Santosh and Suresh [135] demonstrated the uniqueness of combining GIS and RS in a tool for crop selection and rotation analysis at the farm level to improve crop management decisions. Cropping patterns simulation is determined by irrigation water availability which in turn is affected by changes in climate and irrigation water extraction policies. Wang et al., [112] combined GIS and irrigation water availability simulation models to analyze the cropping patterns based on the forecast of irrigation water availability. A GIS web-based crop mapping and monitoring decision support system at the farm level could help farmers to access information and take appropriate measures to improve crop production [135]. Such a system can have a wider application in supporting agronomic decision-making including optimizing land and labor productivities, enhancing higher cropping intensities, and producing better crop yield [136]. This can increase crop production and ensure better crop management in the long run, and precision irrigation management.

Agricultural drought assessment

Using spatial datasets generated by satellite RS and GIS technologies offers very useful information for assessing and modelling agricultural drought-risk patterns, monitoring drought conditions, and producing drought vulnerability (risk) maps [144]. Hoque et al. [139] integrated geospatial techniques with fuzzy logic to develop a comprehensive spatial drought risk inventory model for operational drought management. This model successfully identified the spatial extents and distribution of agricultural drought risk. Sehgal and Dhakar [140] used GIS and high spatial resolution RS-derived indicators of crop sensitivity to develop a methodology that assessed and mapped at a local scale key biophysical factors contributing to agricultural drought vulnerability. The drought vulnerability maps could inform policymakers in formulating spatially explicit policies for drought mitigation and intervention strategies [141,142]. In addition, vulnerability maps could be used to indicate where socioeconomic development policy programs should be given priority [143].

Pest and crop disease detection and management

Several geospatial tools and techniques continue to be developed to aid farmers in crop disease control and management strategies. Several studies [145–148] provide practical application of satellite RS data and Geospatial techniques for sustainable crop disease detection and management. RS technology including Airborne and satellite imagery acquired during growing seasons has been used for early and within-season detection, mapping of some crop diseases, the control of recurring diseases in future seasons, and assessing economic loss caused by frost damage [145]. Santoso et al., [146] used high-resolution QuickBird satellite imagery to effectively detect spatial patterns of oil palm plants infected by basal stem rot disease. They used six vegetation indices derived from visible and near-infrared bands satellite imagery to successfully discriminate between healthy and infected oil palms. Using precision agriculture technologies and remote sensed imagery Yang [148] showed how site-specific fungicide application to disease-infested areas has been implemented for effective control of the disease. In the future, new approaches that apply geoinformation technologies in monitoring and management of pest and crop disease detection could reduce the effect of pesticides and herbicide chemicals on the environment.

Precision agriculture

In precision agriculture, automated geospatial analysis and decision-support algorithms-can provide valuable scientific information to policymakers for better agriculture policy development. Precision agriculture practices, which employ integrated GIS, RS, and GPS technologies have gained prominence in their ability to optimize crop production, facilitate site-specific crop management and reduce the application of agrochemicals. Toscano et al. [154] demonstrated the usefulness of Sentinel-2 and Landsat-8 images to depict the within-field spatial variability of wheat yield, which is key for adopting precision farming techniques. This provided a potential alternative to traditional farming practices by improving site-specific management and agricultural productivity. García et al. [155] tested the performance of remote sensing drones as mobile gateways to provide a guide to the optimal drone parameters for successful Wi-Fi data transmission between sensor nodes and the gateway in precision agriculture systems. The study successfully demonstrated that drones, (flying at the lowest velocity, at a height of 24 meters, and with an antenna with 25 meters of coverage) can be used as a remote sensing tool to gather the data from the nodes deployed on the fields for crop monitoring and management. This had the potential to increase the adoption of precision agriculture by even smallholder farmers. Segarra et al., [156] study specifically focused to understand the European Space Agency's twin Sentinel-2 satellites' features and their application in precision agriculture. Their study highlights that Sentinel-2 has dramatically increased the capabilities for agricultural monitoring and crop management, abiotic and biotic stress detection, improved the estimation of crop yields, enhanced crop type classifications, and provided a variety of other useful applications in agriculture. All of these contribute to increasing the adoption of precision agriculture, which leads to more productive and sustainable agriculture management, and environmental sustainability. In precision agriculture, plantation-rows extraction using satellite image-based solutions is essential in crop harvesting, pest management, and plant grow-rate predictions. The study of Fareed and Rehman [151] used GIS and RS to design an automated method to extract plantation rows from a drone-based image point clouds-based digital surface model. The automatic plantation rows extraction can be used to quantify plantation-row damage assessment in precision agriculture.

Weed management and fertilizer decision support system

Accurate weed distribution mapping could greatly enhance efficiency in weed management, and reduce weed damage, overhead costs of herbicide application, and the rationalization of fertilizers [153]. Dunaieva et al. [117] used GIS technologies to produce accurate weed distribution maps in rice farms. This information improved the efficiency of input application thus reducing the consumption of inputs including herbicides, fungicides, and weeding labor costs. This in turn reduced the weed damage and crop production overhead costs. Xie et al. [152] demonstrated the application of GIS in the development of a GIS-based Fertilizer Decision Support System (FDSS) by integrating RS data, field surveys, and expert knowledge to develop a soil spatial database on the SuperMap platform for crop management systems. The application of FDSS in agricultural production had benefits, such as increasing fertilizer utilization efficiency, thus lowering production costs.

Obstacles to applying GIS in agriculture policy and practice

Generally, the use of GIS and RS technologies is not a panacea to successful evidence-based policy and practice and has its downside. The success of the geospatial technology application depends on its proper use, quality data, and considerable resources in its management. In countries that suffer low resources, such as LMICs, the cost of the technology and lack of appropriate skills jeopardize its wider use and adoption [157]. Simulating crop yield production is always challenging due to the variety of cropping systems and levels of technology used. Accurate crop yield gap assessment would require improvements in input data quality, including accurate weather parameters, better soil characterization, and spatially distributed land use data [124]. It would also demand the setting up of instrumented geo-referenced validation sites that provide comprehensive survey data to inform a continuous improvement cycle for yield gap assessment [126]. As such, future improvements in current remote sensing technology and the development of better-integrated cropping systems models would provide more accurate inputs for yield gap assessment.

In drought vulnerability assessment and mapping, most studies reported in the literature tended to use aggregated spatial data at higher spatial scales (national or regional level), but not at a finer scale. Since the intensity of drought hazards is more felt and manifested at the local level, a detailed drought-risk mapping at a finer scale would require high-resolution remote sensing and the use of locally contextual indicators to yield a full picture of vulnerability. This would have more relevance to policymakers whose intent is to formulate and implement mitigation interventions at the local level. With the prediction that more severe and frequent drought uncertainties due to climate change scenarios, drought-risk mapping that incorporates all the spatially explicit risk components would be a highly efficient contribution to drought mitigating strategies. More skills and knowledge on the use of geospatial techniques for agricultural drought risk are needed.

In crop disease detection, challenges still exist in mapping them using airborne or satellite imagery. Although many crop diseases can be successfully detected and mapped using satellite imagery, each disease has its characteristics that would require different procedures for detection and management. According to Yang, [148] “some diseases are difficult to detect, especially when multiple biotic and abiotic conditions with similar spectral characteristics exist within the same field" (pg. 531). Recurring diseases would require consistent historical imagery and spatial-temporal data while emerging diseases are more difficult to detect. Yang argues that more advanced RS imaging sensors and image-processing techniques for differentiating diseases from other confounding factors are needed. In less developed countries, very few farmers have the necessary skills required to use RS technologies in creating their prescription maps, in the implementation of disease management, and the site-specific fungicide application. More research is needed in the development of integrated geospatial analytical methodologies and tools for aiding farmers in different crop disease detection and management strategies detection.

Although precision agriculture technologies can aid in optimizing crops and facilitating agricultural management decisions in solving food insecurity challenges in LMICs, precision farming requires the adoption of geospatial technology and a large amount of high-resolution spatiotemporal data. A lack of skills to technological know-how and skills to use GIS and RS software can be augmented by the dissemination of precision agricultural technologies not only from institutions but the transfer of practical geospatial technologies from developed countries [147]. However, considerable investments in ICT infrastructure are needed for the effective adaptation of precision agricultural approaches in LMICs.

Soil fertility assessment is considered one of the most important indicators of precision farming and for sustainable use of agricultural lands according to their potential. This requires a comprehensive soil information system. However, according to Abdelfattah and Kumar [128], much of the world has very poor coverage of soil quality data. In LMICs, the fragmentation of agricultural land into small uneconomical plots and unsustainable farming practices is happening at a much higher rate, geostatistical approaches would require field data with high sampling density for completeness and accuracy. In such a rapidly changing environment, the potential of active remote sensors to determine soil quality requires further research.

Other obstacles to the use and adoption of GIS and RS in agriculture include a lack of commonly agreed data interoperability standards. Though there is increasing availability of spatial data usage in LMICs, many of these data are prone to error and are often collected and stored with different spatial units, formats, metadata, time, and space intervals. This makes some data unusable, prevents spatial data integration, and hinders a unified analysis of data, especially those collected from multiple sensors and platforms. A need exists on developing standardized guidelines for agriculture spatial data. Training for researchers, practitioners, and farmers on how to collect quality and accurate spatial data that can be usable in multi-platform systems is paramount. Developing spatial data repositories with better interoperability can enable data integration and improve the efficiency of data analyses. In this regard, crowdsourced data collection would be a promising contribution to developing cost-effective agri-spatial data repositories.

Limitations of the study

The results of this study are purely based on the 40 articles spanning 10 years (2010–2021) and the learning obtained from them. As a result, we might not have included some significant research papers published in earlier years. However, the purpose of this review was to analyze the most recent trends and relevant publications in the application of GIS in agriculture. For this reason, we argue that the 40 papers are comprehensive, and it is unlikely that the content of previously published papers would have substantially altered our findings. Furthermore, the selection criteria only included peer-reviewed papers. However, reflections on GIS methodologies are sometimes published in books or grey literature since they have more space for in-depth reflections. To reduce this limitation, we formulated our search string to include a broad range of the most relevant terms of interest in this study. In addition, we performed the search in the largest indexed databases of SCOPUS, BASE, CORE, and Clarivate. To account for significant papers that might have not been indexed in these databases, we also included the search results from Google Scholar. Notwithstanding these few limitations, the insights provided in this review provide valuable information and knowledge on GIS and RS application in enhancing evidence-based policy interventions for enhancing agriculture sustainability, as well as identifying barriers to their application in the LMIC context.

4.4 Conclusion

This paper has explored various ways GIS technology has been integrated into agriculture to improve agriculture decisions and policymaking. GIS and RS technologies present better methods for the analysis of spatial factors that affect agricultural production as compared to approaches where spatially explicit data are absent. If well exploited, the spatially integrated knowledge provided by GIS and RS can be applied to enhance agriculture policy and evidence-based interventions geared towards improving agriculture sustainability. Though GIS technologies provide a promising pathway for improving agronomic practices, they remain underexploited in many LMICs where a dire need for enhancing agriculture and food production practices is most needed. For LMIC governments and farmers to better exploit the benefit of GIS and RS technologies, there is a need for an increased level of awareness and potential use of spatial data related to agriculture. Further advances in geoinformatics techniques and computing infrastructure will allow a more collaborative framework amongst scientists, policymakers, researchers, extension personnel, crop consultants, and farm equipment and chemical dealers with practical guidelines for effective management of crop yield estimations, soil fertility, cropping pattern and monitoring, drought risks, and fertilizer and weed management.

In enhancing evidence-based agriculture policy, government and policymakers would require hard evidence that brings a clear understanding of the complexity and interconnectedness of factors affecting agriculture productivity. This would in turn enable the designing of concrete intervention strategies. Additionally, a broad spectrum of stakeholders and practitioners in the agriculture sector would need location-specific agricultural data in implementing a wide array of decisions that improve agricultural production potential. Equally, smallholder farmers would require synthesized information to empower them not only to make evidence-informed decisions but also to implement practicable activities that increase agricultural productivity. This raises the demand for GIS integration in agriculture policy formulation and implementation.

GIS and RS technologies provide a big potential in the assessment, storage, processing, and production of agriculture data. The data could be useful in precision agriculture, site-specific farming, and disease detection, among others, all geared toward improving agriculture food production and food security issues. Unfortunately, the lack of quality spatial data in many local governments has continued to undermine decision-making, policy formulation, and effectiveness in their implementation. Where such data exists, there is a general lack of skills in the use of GIS and RS spatial analytical techniques. Achieving spatially integrated agriculture policies demands comprehensive, up-to-date spatial datasets and better methods that combine and analyze complex data from various sources to produce useful information. This would necessitate national as well as local governments to adopt methods, strategies, and techniques that facilitate the collection and analysis of diverse agricultural datasets in providing comprehensive insights to policymakers, planners, farmers, and a broad spectrum of stakeholders in the agriculture sector. GIS thus provides a promising pathway for the acquisition of comprehensive, up-to-date spatial databases and better spatial analysis methods that are capable of analyzing complex data to produce useful information. If properly adopted and implemented, GIS can enhance the spatial decision support system in improving the efficiency and effectiveness of agriculture policy formulation and planning. Nonetheless, policy change can guide and catalyze actions but requires public and political will to actualize it. Thus, the adoption of GIS technology in policymaking would require local government to commit public funds to set up the required software, hardware, supportive infrastructure, and training of staff to use them. Future studies can focus on how GIS and RS technology could promote a collaborative framework amongst scientists, policymakers, researchers, and extension agriculture officers in promoting sustainable, and climate-smart farming practices, especially in LMICs.

Appendix A1: search syntax

CORE database search string: (date of search: 25.10.2021): 68 articles found
title:((Agriculture, AND GIS, AND Remote AND sensing,)) AND year:[2010 TO 2021]
Web of Science query (date of search: 26.10.2021): 104 articles found
https://www.webofscience.com/wos/woscc/summary/79c860ee-207f-46ca-8db2-f70df81462ed-0eff1eca/relevance/1 Search refined by: **Publication Years**: Between 2021 and 2010: **Document Types**: Articles or Review Articles or Early Access: **Languages**: English: **Open Access:** All Open Access or Gold or Gold-Hybrid or Green Published or Free to Read: **Document Types:** Articles **Web of Science Categories:** Remote Sensing or Geosciences Multidisciplinary or Green Sustainable Science Technology or Multidisciplinary Sciences or Agronomy or Ecology or Geography Physical or Plant Sciences or Agriculture Multidisciplinary or Computer Science Information Systems or Soil Science or Agricultural Engineering or Agricultural Economics Policy or Food Science Technology or Horticulture or Nutrition Dietetics or Environmental Sciences or Environmental Studies.
SCOPUS search query (date of search: 26.10.2021)
TITLE-ABS-KEY (*gis,* AND *agriculture,* AND *remote* AND *sensing,* OR *rs* OR *geographic* OR *information* OR *systems*) AND (LIMIT-TO (PUBYEAR , *2022*) OR LIMIT-TO (PUBYEAR , *2021*) OR LIMIT-TO (PUBYEAR , *2020*) OR LIMIT-TO (PUBYEAR , *2019*) OR LIMIT-TO (PUBYEAR , *2018*) OR LIMIT-TO (PUBYEAR , *2017*) OR LIMIT-TO (PUBYEAR , *2016*) OR LIMIT-TO (PUBYEAR , *2015*) OR LIMIT-TO (PUBYEAR , *2014*) OR LIMIT-TO (PUBYEAR , *2013*) OR LIMIT-TO (PUBYEAR , *2012*) OR LIMIT-TO (PUBYEAR , *2011*) OR LIMIT-TO (PUBYEAR , *2010*)) AND (LIMIT-TO (DOCTYPE , *"ar"*)) AND (LIMIT-TO (LANGUAGE , *"English"*)) AND (LIMIT-TO (EXACTKEYWORD , *"Remote Sensing"*) OR LIMIT-TO (EXACTKEYWORD , *"GIS"*) OR LIMIT-TO (EXACTKEYWORD , *"Agriculture"*) OR LIMIT-TO (EXACTKEYWORD , *"Geographic Information Systems"*) OR LIMIT-TO (EXACTKEYWORD , *"Agricultural Land"*) OR LIMIT-TO (EXACTKEYWORD , *"Geographic Information System"*) OR LIMIT-TO (EXACTKEYWORD , *"Remote Sensing And GIS"*) OR LIMIT-TO (EXACTKEYWORD , *"Remote Sensing Technology"*) OR LIMIT-TO (EXACTKEYWORD , *"Spatial Analysis"*) OR LIMIT-TO (EXACTKEYWORD , *"Agricultural Robots"*) OR LIMIT-TO (EXACTKEYWORD , *"Soils"*) OR LIMIT-TO (EXACTKEYWORD , *"Sustainability"*) OR LIMIT-TO (EXACTKEYWORD , *"Decision Making"*) OR LIMIT-TO (EXACTKEYWORD , *"Soil"*) OR LIMIT-TO (EXACTKEYWORD , *"Precision Agriculture"*) OR LIMIT-TO (EXACTKEYWORD , *"Prediction"*) OR LIMIT-TO (EXACTKEYWORD , *"Crop Production"*) OR LIMIT-TO (EXACTKEYWORD , *"Agricultural Production"*) OR LIMIT-TO (EXACTKEYWORD , *"Crop Yield"*) OR LIMIT-TO (EXACTKEYWORD , *"Agricultural Development"*) OR LIMIT-TO (EXACTKEYWORD , *"Drought"*) OR LIMIT-TO (EXACTKEYWORD , *"Irrigation (agriculture)"*) OR LIMIT-TO (EXACTKEYWORD , *"Geographic Information System (GIS)"*) OR LIMIT-TO (EXACTKEYWORD , *"Alternative Agriculture"*) OR LIMIT-TO (EXACTKEYWORD , *"Food Security"*))

.

Chapter 5

Can Livelihood Capital Promote Diversification of Resource-Poor Smallholder Farmers into Agribusiness? Evidence from Nyando and Vihiga Counties, Western Kenya

Picture: Women selling fresh farm produce in an open-air market in Kano, Kisumu. Source: Author

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Abstract

The push towards the transformation of subsistence smallholder farming into market-oriented agribusiness has been in the public policy debates of many low- and middle-income countries, including Kenya. While various studies have highlighted the lack of livelihood capital as a reason for most smallholders not to diversify into agribusiness. Livelihood capital is defined as the "asset base" upon which individuals and households build their livelihoods. These include a combination of physical, human, financial, natural, social, and cultural capital. How this livelihood capital influences smallholders' decisions and choices has, however, only been partially researched Using systematic random sampling, 392 households in Western Kenya were interviewed through a researcher-administered questionnaire. The multinomial logistic regression method was used to analyze the data. The findings reveal that livelihood capitals acted in parallel and jointly to determine the decisions of smallholders to participate in agribusiness. Results show that education level, gender, landholding size, distance to markets, farm input access, and agriculture extension services positively and significantly influenced the decision choices of households to participate in agribusiness. Households with higher livelihood capital accumulation resulted in a higher probability of participating in agribusiness while those with limited livelihood capital resulted in a lower probability to participate in agribusiness. We argue that designing appropriate pro-poor targeted policy interventions to improve households' livelihood capital could address the problem of non-participation of poor rural smallholders in agribusiness markets.

5.1 Background

Presently, there is increased opportunity at the local and global levels for agribusiness due to increased demands for food and the globalization of agri-food markets[158]. Although the greatest benefits have been felt by the better-off households including medium and large-scale farmers, the poor rural smallholders, who constitute the majority of food producers globally, are largely excluded from participation in the emerging agribusiness markets [37,159]. In sub-Saharan Africa, rural smallholders account for the largest proportion of food sources [160] and dominate the production segment of a rural and locally oriented agri-food supply [5]. In contrast, the national and regional input and output markets have mostly been dominated by commercial 'medium and large' agribusiness supply chains. Empirical studies have attributed smallholders' exclusion in agribusiness to a multiplicity of barriers that limit their participation in modern agribusiness and food supply chains [161]. Amongst the barriers is their high poverty levels that manifest in their lack of or insufficient access to productive capital assets [37,162,163] which significantly jeopardizes their ability to pull themselves out of the vicious cycle of poverty.

Many studies report that the majority of poor smallholders in Low- and Middle-Income Countries (LMICs) lack resources, appropriate skills, and motivation to enable them to move out of food insecurity and poverty traps [25–27]. In addressing these challenges, governments and policymakers in many LMICs, such as Kenya, are actively promoting sustainable agriculture and agriculture sector transformation geared toward farm modernization, rural-urban market integration, and inclusive local food value chains. Strategies such as bottom-up initiatives, market development, state parastatals, producer organizations, cooperative movements, contractual arrangements, value chain financing, and multi-actor supply chain governance are used to boost smallholder agribusiness development [158,164–166]. Implementation of these strategies is premised on the belief that they will ultimately promote a paradigm shift in existing smallholder production practices from subsistence toward highly market-oriented agribusiness practices. The push for smallholder commercialization is also considered a possible driver of rural economic growth and pro-poor poverty reduction strategies [167]. This is expected to stimulate rural entrepreneurship for small agribusinesses, raise their agriculture productivity, improve the quality of production, and create surplus thus increasing their chances of participating in agri-food markets [163,168]. However, much of the efforts to address the problem of smallholder non-participation have been biased towards the provision of technical-based solutions to improve agriculture productivity and less on improving the livelihood capital base of the resource-poor smallholders.

Academic discourse on the link between rural poverty, access to productive livelihood assets, and market participation suggest that poor smallholders have too few livelihood capital assets to effectively participate in agribusiness and agri-food markets [37,38]. A large number of rural smallholders who derive their main livelihood from small-scale subsistence agriculture, directly or indirectly depend on accumulated productive capital assets to diversify into income-oriented agribusiness. However, the challenge for many rural smallholders in Sub-Sahara Africa is that they are peculiarly and tragically the most asset-poor and food-insecure demographic group. Thus, the critical question is how differentiated livelihood capital endowments create different outcomes necessary for sustenance and well-being for rural households in terms of incomes, and food security.

In Kenya, the majority of subsistence-oriented smallholders, who account for the bulk of agricultural food production, are inherently poor. Most own on average 0.2–3 acres and are to be found in the marginalized rural areas, where 70% of rural households are dependent on subsistence agriculture as their main livelihood pillar [169]. However, in the last 2 decades, there have been sustained efforts by both government and private entities to address the high poverty levels and the high non-participation of rural smallholders in agribusiness through the commercializing of agriculture [165]. Despite such efforts, the majority of rural smallholders remain inherently poor, aloof, and mainly excluded from participation in contemporary agribusiness markets. The high poverty levels mean that poor smallholders are lowly endowed with critical productive capital assets and resources that are crucial in entrepreneurial efforts [37] like starting new on-farm and off-farm ventures or in upgrading their peasant livelihoods to more income-generating agribusiness ventures. Thus, they are constrained to effectively exploit the opportunities of contemporary agribusiness markets.

Whereas literature shows livelihood capitals influence smallholders' choices in different ways, it is rarely understood what combination of livelihood capital assets could result in a higher probability of smallholders diversifying their subsistence production into more probable income-generating agribusiness given different contexts. For this study, we apply the livelihood capital analysis approach to understand the extent to which differentiated asset configurations impact smallholder households' ability to participate in agribusiness activities. Though there is evidence from the literature that suggests better-off smallholders with sufficient assets are more likely to achieve successful integration in agribusiness [170], not much research has been conducted to investigate at the micro-level, how livelihood capitals affect the participation of poor households in agribusiness activities. Yet, a critical investigation of this is important because empirical findings have shown that higher productive-capital assets endowment has been associated with increased diversification in farm and non-farm livelihood activities and as a source of higher dietary diversity [163,169,171]. Therefore, this study aims to explore how household capital endowments influence smallholders' decisions to participate in agribusiness in the study area in the study areas of Kisumu and Vihiga counties of Western Kenya. The study contributes to the knowledge gap toward a better understanding of the causative relationships between livelihood capital assets and their influence on smallholders to participate in agribusiness. It contributes to a more nuanced identification of systemic interventions that are required for successful pro-poor smallholder agribusiness development in LMICs.

Sustainable livelihood capital framework

Several studies have used the sustainable livelihood approach as a theoretical and analytical framework to bring a deeper understanding of the ways individuals and households, in different contexts, use their livelihood capital assets to diversify their livelihoods into the farm and non-farm activities [163]. The sustainable livelihood assets-based approach conceives six classes of resources held at the individual, household, or collective levels to include a combination of physical, human, financial, natural, social, and cultural capital assets [71,172]. Recent literature suggests that low livelihood assets have been identified as a considerable constraint [37,159] to livelihood diversification and exploiting the opportunities of expanding agri-food markets.

Livelihood capitals are defined as the "asset base" upon which individuals and households build their livelihoods [37,70]. The physical capitals include basic infrastructure households need to support livelihoods including transportation, roads, buildings, water supply and sanitation, energy, technology, access to information (e.g. radio or mobile phones), and access to agricultural implements [158,173]. It has been found that higher asset holdings are essential for marketable surplus production at a smallholder level and hence could positively influence smallholder decisions to invest in local agribusiness [61,174]. At the macro level, rural-urban connectivity, market opportunities, off-farm employment, and technology adoption [175] have contributed to shaping food production decisions and strategies of smallholder agriculture.

The Department for International Development (DFID) considers human capital as the generic assets or "sufficient conditions" that serve as building blocks for the achievement of livelihood outcomes. Human capitals include age, gender, education level, years of experience, skills, training, family size, dependency ratio, labor power, and ability to adopt new technology [173,176]. A Household's human capital endowment and utilization can generate multiple benefits toward achieving sustained small-scale agribusiness success [174,177]. Some studies [178] assert that human capital is amongst the effective strategies that enhance knowledge production and agronomic skills that smallholders could capitalize on to diversify into agribusiness.

Social capital represents the ability of individuals or households to secure benefits through membership and relationships. They are accrued from shared norms and values embedded in social networks that enable individuals or households who belong to them to access and exchange different resources [83]. Empirical findings show that higher social capital could positively facilitate increased agricultural productivity outcomes. For example, Wagah & Mwehe [83] found that social capital positively contributed to improving the food security of poor peri-urban households in Kisumu city, Kenya, and recommended the improvement of smallholders' informal social networks. Additionally, social capital has contributed to the dissemination of locally adopted farmer-led innovations that complement externally promoted agriculture technologies for improving agriculture and food security [179,180].

Natural capital consists of land, water, biodiversity, air quality, and wild resources. Some studies [168] report that the associated costs of mitigating the negative impact of natural capital (e.g. climate change) could far outstrip the benefits accrued from agribusiness thereby making agribusiness less attractive for poor smallholders. Financial capital includes fiscal resources individuals or households use in constructing their livelihoods including savings, access to credit, inflows like pensions, and remittances [70]. Additionally, livestock assets, crop sales, wages, and on-off farm employment are also considered financial capital. Several studies have found that access to financial capital by households, including affordable credit, and agricultural extension services to have a positive relationship with market participation [83,181].

In addition to livelihood capitals, exogenous variables like institutional factors exert a lot of influence on the development of farming systems. These factors include market regulations, trade policies, property rights, land tenure, and proximity to input and output markets [174,182,183] influence farmers' choices to participate in agribusiness, even though they are not confined by spatial boundaries. The institutional factors influence how individuals and households use their livelihood assets in shaping their different livelihood strategies and outcomes.

5.2 Methods

Study area

This study was conducted in two study sites (Figure 5:1) located in Kisumu and Vihiga counties in the Western part of Kenya. The Nyando study site is located in Kisumu County along the shores of Lake Victoria while the Central Maragoli site is located in Vihiga County along the equator in the upper Lake Victoria basin. Both areas receive fairly well-distributed rainfall throughout the year. The motivation for selecting these study sites is that they experience a very high prevalence of food insecurity, and high population pressure, and are located in the peri-urban hinterlands of Kisumu city. Additionally, these two areas are predominated by a high level of small-scale agricultural activities and have a spatially heterogeneous landscape.

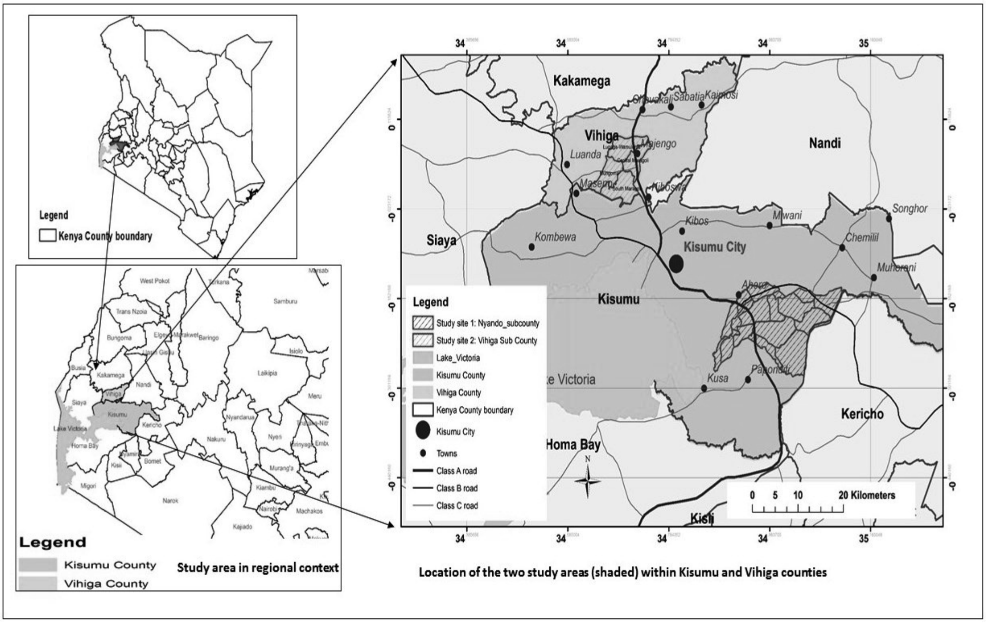

Figure 5.1: Geographical location of the two study sites in Western Kenya

Method and variables used

We used a multistage sampling method to select study sites and sample households. After choosing Kisumu and Vihiga counties, we used a stratified sampling technique to select Nyando and Central Maragoli wards as our study sites. Before actual fieldwork, we conducted an exploratory study through field reconnaissance visits to identify main farming types and various livelihoods capitals assets available in the study area. Subsequently, 392 sample households were selected using a systematic random sampling technique from the two areas for the survey. Research assistants helped to administer the closed and open-ended questionnaires to these households. Permission to interview was sought from every participant before the commencement of the interviews and only adult members of households above 18 years of age were interviewed.

Table 5.1 describes the variables selected for this study. We categorized household production orientation into three main types; Horticulture, semi-commercial, and subsistence (either mixed 'with livestock' or pure 'crop only'). These categorizations were derived from the tabulation of the types of food production practices that were observed in the study area during fieldwork data collection. The categorization was deduced from analyzing each household's farming activities; food crops grown, cash crops grown, fruit and vegetable crops grown and livestock kept (cows, goats, chickens).

Table 5.1: Description of Variables Used in the Multinomial regression model

Variable	Variable explanation	Expected sign	Mean	Std Dev
Dependent variables				
Production orientation choices	0. Semi-commercial	n/a	n/a	n/a
	1. Horticulture	n/a	n/a	n/a
	2. Subsistence	n/a	n/a	n/a
Independent variables			**Descriptive statistics**	
(a.) Human capital			**Mean**	**Std Dev**
GENDER	Binary, 1 if the head is male and 0 if female	+/-	1.50	.50
AGE	Continuous, HH head age in years	+	49.86	14.89
OCCU	Categorical, HH head occupation	+	3.55	1.29
EDULVL	Categorical, HH head education level	+	2.41	.81
SCHLYRS	Continuous, household head years of schooling		9.18	4.22
(c.) Financial capital				
FINCOME (in Kshs)	Continuous, Natural Log, On-farm income	+/-	8,356	28,310
LVTKASSET (in Kshs)	Continuous, Natural Log, the value of livestock assets	+/-	63,404	64,98
CHKASSET (in Kshs)	Continuous, value of chicken assets		10.80	14.64
AGRIC CREDIT	Binary, 1 if the head has access to agric. Credit and 0 otherwise	+	1.83	0.38
(d.) Natural and Physical capital				
LANDSIZE (in Ha)	Continuous, Natural Log, land size	+	.396	.240
SFERTILITY	Categorical, soil fertility level	+/-	2.39	.54
FINPUT	Categorical, Farm input availability		1.61	1.07
CLIM	Ordinal, Climate change variability (drought and famine)		1.99	1.04
RAINAVAIL	Ordinal, Rainfall availability		2.40	.763
(e.) Social capital				
SNTWK	Binary, 1 if the head belongs to a social network and 0 otherwise	+	1.43	.50
SAVINGS	Binary, 1 if head saves money, 0 otherwise	+	1.43	.50
LABOR	Binary, 1 if HH has enough family labor and 0 otherwise	+	1.48	.50
(f.) Economic capital				
TRAINING	Binary, 1 if the head has the training, 0 otherwise	+	1.73	.45
SKILLS	Binary, 1 if the head has relevant agribusiness skills, 0 otherwise	+	1.78	.41
(g.) Transaction costs				
DISMKT	Ordinal, effect of proximity to market on a household, little, to very high effect	+	4.74	1.51

By combining different choices of the household made, four farming production orientations were arrived at:

- Horticulture-oriented households: mostly grew high-value crops (fruits and vegetables) specifically for selling to the markets, but also grew staple food for their consumption.

- Commercially oriented households: mostly grew commercial crops (tea, coffee, and sugarcane) and sold their products through marketing cooperatives, but also grew staple crops for consumption.
- Mixed subsistence-oriented households: mostly kept livestock in addition to growing various crops.
- Pure subsistence households: grew crops only for their consumption and hardly ever sold any to the markets.

Data analysis was done by use of Statistical Package for the Social Sciences (SPSS) software. The multinomial logistic regression model in SPSS was applied to identify various factors that influence smallholder households to participate in agribusiness market activities. Before conducting multinomial regression, the explanatory variables were examined through various SPSS analytical techniques for basic assumptions of multinomial logistic regression including missing values, outliers, normality of distribution, and multicollinearity [184]. Household annual income, with missing values on more than 20% of the cases, was deleted. The normality test identified five continuous cases to be univariate outliers with extremely high z scores over 3.29($p<.001$, two-tailed). To improve the normality of their distribution, livestock assets, household assets, farm tools assets, on-farm income, and land size variables were logarithmically transformed. However, household assets and farm tools assets still returned a high skewness and kurtosis after transformation and were subsequently omitted. Using the Mahalanobis distance function, four cases were found to be multivariate outliers with $X^2(7) = 24.322$, ($p< .001$) and were deleted.

Nine continuous explanatory variables were screened for multicollinearity using the Variation Inflation Factor (VIF) and tolerance coefficient where off-farm income, off-farm employment, and livestock assets were greater than 10 indicating high multicollinearity. After model iteration, off-farm income was left out of the analysis. After satisfying all the assumptions of multinomial regression analysis, SPSS version 20 was used to analyze the data. Out of the 20 hypothesized variables (Table 1) presumed to influence smallholder's agricultural production choices, only 9 were found to be statistically significant at 0.05, 0.01, and 0.1 alpha levels and are further discussed in the results section.

5.3 Results

Demographic characteristics of respondents

A total of 392 sample household heads were interviewed comprising 21% of youths (18-35 years), 55% of adults (36-60 years), and 24% aged (61 years and above). The sample size was comprised of an almost equal number of males (49.7%) and females (50.3%). The average household size was found to be 7 persons with households having 5 persons and above comprising 85% of the total sample. This is above the national average household size of 3.9 persons, as per the Kenya National Bureau of Statistics 2019 census report [185]. It is presumed that large family sizes would ideally require larger parcels of land, agriculture intensification on smaller ones, or even diversification of food production choices in meeting their food demands. However, the average landholding sizes in the study area were 2 acres, with 62% of the sampled household falling below the average. The main farming practices observed in both study areas included subsistence farming (90.9%), commercial (5.1%), and horticulture (4.8%) farming (Table 5:2)

Table 5:2: Farming production orientation practiced by sampled households

Farming production choices	Frequency	Marginal Percent
Horticulture oriented	16	4.8
Commercial oriented	17	5.1
Subsistence (mixed)	146	44.5
Subsistence (crops only)	149	46.4

The crops grown by the majority of households were maize, vegetables, and beans (Figure 5:2). We found a little level of agriculture intensification and crop diversification in the sampled households.

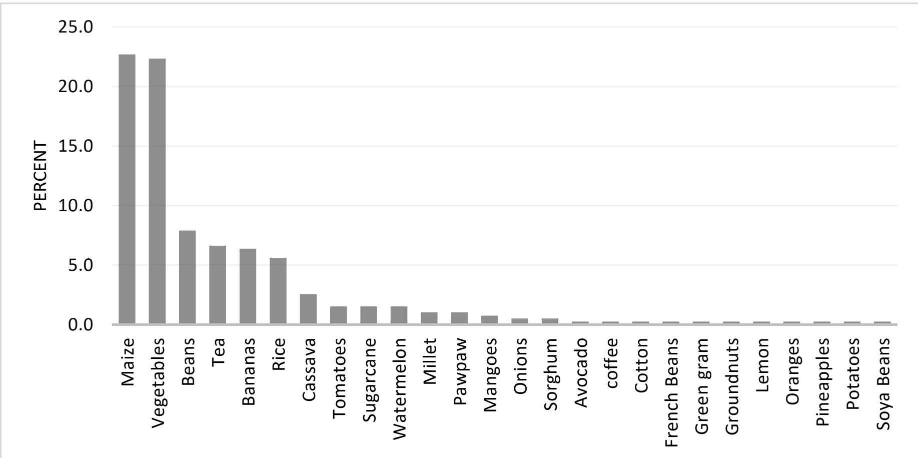

Figure 5:2. Types of crops grown by households in the study areas

Based on the subjective perception of households' food insecurity, results show there is a higher prevalence of food insecurity in the Vihiga and Nyando areas. 49% of households in Nyando and 36% in Vihiga indicated they experienced food insecurity incidences in the last year preceding this survey. Among the surveyed households, livelihood diversification was found to be minimal, with the majority 79% engaged in farming, 12% informal employment, and 9% in informal employment.

The result of the Multinomial logistic regression model (Table 5:3) revealed a mixed influence of various variables on household decision choices. Nine of the hypothesized predictor variables were found to be statistically significant. They positively and negatively influenced smallholders' decisions to participate in agribusiness farming production at different significant levels.

Table 5:3. Result of the multinomial logistic regression model

Dependent variable: Household farming choices adopted by sample households in Vihiga and Nyando area												
Independent variables	**Mixed Subsistence choice**				**Commercial farming choice**				**Horticulture farming choice**			
	Coef.	**SE**	**OR**	**p**	**Coef.**	**SE**	**OR**	**p**	**Coef.**	**SE**	**OR**	**p**
Intercept	8.043	1.767		.000	4.529	2.350		*.054*	6.810	2.532		*.007*
LVTKASST	-2.327	.296	*.098*	*.000*	-1.700	.352	.183	*.000*	-1.986	.383	.137	*.000*
DISMKT	.000	.000	1.000	.971	.000	.001	1.000	.400	-.002	.001	.998	*.066*
INPUT	-.297	.212	.743	.161	-.658	.261	.518	.012	-.284	.336	.753	.397
GENDER	.383	.375	1.466	.308	.082	.464	1.086	.859	1.517	.613	4.558	.013
EDU	1.975	1.197	7.208	.099	2.497	1.277	12.152.	.050	1.114	1.417	3.045	.432
SVNG	-1.099	.446	.333	*.014*	-.162	.522	.850	.756	-.429	.652	.651	.511
AGRIEXT	-1.025	.507	.359	*.043*	.196	.581	1.216	.736	-.175	.776	.840	.822
CLIM	1.624	.567	5.071	.004	2.009	.683	7.453	.003	-.579	1.045	.307	.580
LSZE	-.290	.814	.748	.722	-1.233	1.053	.291	.241	1.280	.764	3.597	.094

The reference category:	Pure subsistence
Maximum likelihood estimates	
Dependent variable:	Farming system orientation
Number of observations	392
− 2 Log likelihood fitting	Intercept only: 885.406, Final: 576.459
Chi-square test	308.947
Degrees of freedom	111
P-value	The significant level at less than 1, 5, and 10% probability levels

Chapter 5

In interpreting Table 5.3, the pure subsistence farming option is made as to the reference category on which the regression model calculations are based. It was the widely practiced farming option by the majority of households in the study areas. The table is interpreted by taking the statistically significant (*p* column) independent variables and reading their corresponding Log odds ratio (OR column). An assumption is made that if all factors are kept constant (i.e., c*eteris paribus)*, the probability of a household in the reference category shifting to other agribusiness farming choices (mixed, commercial, or horticulture) would need *x* number of times (*x* = value of OR column) of the predicted estimate value of the odds ratio of each variable, at a statistically significant level (p column). The positive or negative sign that precedes the value in the coefficient (coef. column) is reported concurrently with the odds ratio and denotes either an increase or decrease of the predicted probability value (odds ratio). For example, the highly significant (p= .000) LVTKASST variable has an odds ratio of 0.098, and a negative sign of the coefficient. This means that if all other factors are kept constant, the likelihood of a household practicing pure subsistence category to shift to the other farming choices would degree by a factor of 0.098 as livestock unit increases by one unit.

Results of the predictive accuracy of the regression model using 10-fold cross-validation

We used the 10-fold cross-validation method to estimate the predictive performance of our logistic regression model. We randomly partitioned our sample size into 10 folds, with a training data set to train the model and a testing data set to validate it, and performed 10 rounds of cross-validation using different partitions. The results (Figures 5.3 to 5.5) show our regression model's predictive performance for commercial, horticulture, and mixed subsistence farming choices. The figures demonstrate that our logistic regression model is very robust and able to estimate the predictive accuracy of the determinants of the adoption of the three farming choices, irrespective of the resampled data sets used for the estimation.

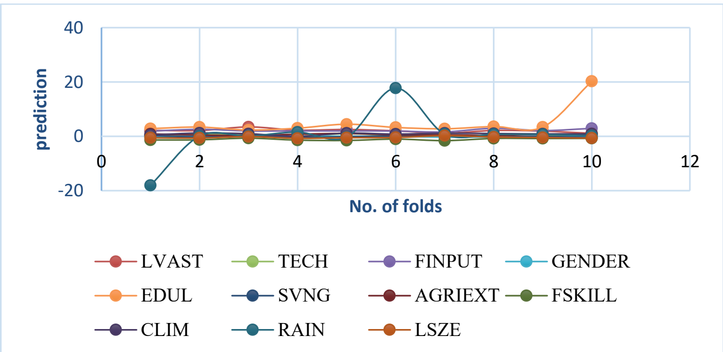

Figure 5.3: Result of 10-fold cross-validation for commercial farming choice

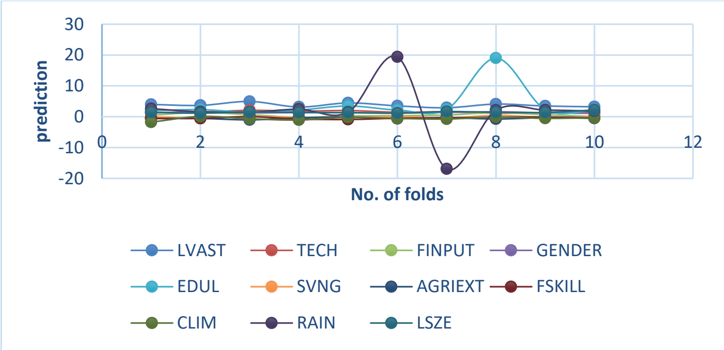

Figure 5.4: Result of 10-fold cross-validation for horticulture farming choice

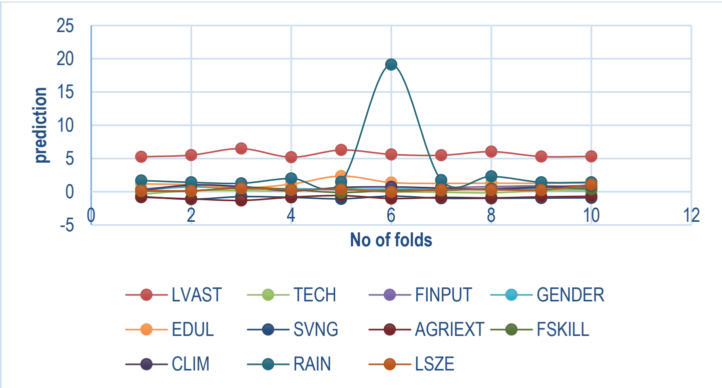

Figure 5.5: Result of 10-fold cross-validation for mixed subsistence choice

Reliability and predictive accuracy of the regression model using the hit ratio analysis

Subsequently, we assessed the reliability and predictive accuracy of the model using the *hit ratio analysis* by cross-tabulating the actual observed data against predicted probability data from the regression model (Table 5.4).

Table 5:4: Results of the Hit ratio analysis on the predictive accuracy of the logistic regression model

		Predicted probabilities category				Actual Observations
Farming categories		Horticulture	Commercial	Mixed Sub	Pure sub	
Horticulture	Count	**1 (6%)**	0 (0%)	8 (50%)	7 (44%)	16
Commercial	Count	0 (0%)	**4 (24%)**	3 (18%)	10 (59%)	17
Mixed subsistence	Count	0 (0%)	1 (0.7%)	**109 (75%)**	36 (25%)	146
Pure subsistence	Count	0 (0%)	2 (1.3%)	50 (34%)	**97 (65%)**	149

The overall performance of our logistic regression model shows it correctly reproduced 65% of pure subsistence observations, 75% of mixed subsistence 24% of commercial, and 6% of horticulture farming observations. The results show that our regression model correctly predicted and classified 109 (75%) of the total 146 actual observations of the mixed subsistence category, under-prediction occurred in 36 (25%) cases wrongly categorizing into pure subsistence and 1 (0.7%) into the commercial category. Additionally, the model was able to correctly predict more than half 97 (65%) of the total 149 actual observations of the pure subsistence farming category, and only underpredicted 50 (34%) which were categorized as mixed subsistence and 2 (1.3%) as a commercial category.

However, the model underpredicted horticulture by only 1 (6%) observation and instead wrongly placed horticulture predictions into 8(50%) mixed subsistence categories and 7(44%) into pure subsistence. Likewise, it also underpredicted 4 (24%) of the 17 observations of commercial farming. Instead, it wrongly classified commercial farming observation into 10 (50%) pure subsistence categories and 3(18%) into mixed subsistence. The reason for the model underestimation for the horticulture and commercial categories can be explained by the small marginal percent (refer to Table 2) of the actual observations of commercial and horticulture farming choices in the study areas.

5.4 Discussion

Overall, livelihood capitals acted in parallel and jointly to influence the decision choices of smallholders to participate in agribusiness. As expected, households with higher livelihood capital accumulation resulted in a higher probability of participating in agribusiness while those with limited livelihood capital ownership resulted in a lower probability to participate in agribusiness. A detailed analysis of the results is provided below.

The ***gender*** of the household head had a positive and significant influence on smallholders' decision to participate in horticulture farming options at a 5% probability level. The odds ratio indicates that the probability of a male household head participating in horticulture farming is 4.6 times more likely than would female household head if all factors are kept constant. Results of cross-tabulation of gender and farming type (Table 5.5) shows a higher percentage of male engaged in horticulture (72.7%) and commercial (62.5%) farming. More females (53.5%) than males (46.5%) were confined to the subsistence production category.

Lack of participation by women in agribusiness activities could be explained by several factors observed in the study area; our findings show that more males than females had a higher literacy level, owned more assets, and had higher technical skills in agribusiness (horticulture farming is presumed to require a higher level of agribusiness skills and investment). Supportive evidence from empirical studies [186] suggests that women are significantly more likely to engage in low-productivity and low-return agricultural activities in rural areas. For example, Abimbola [187] argues that male-headed households are more likely to participate in agribusiness activities that fetch higher returns since they possess high technical knowledge of doing business. Policy and development interventions aimed at promoting gender mainstreaming in agribusiness development should be prioritized if women are to have more opportunities in participating in agribusiness. These should especially target the issue of women's land rights and tenure security, which has been attributed to affect the investment confidence of women-headed households who would want to venture into higher income-generating agribusiness opportunities.

Table 5.5: Crosstabulation of farming type vs Gender of the household head

			Gender		
			Male	Female	Total
Farming types practiced by household	Pure & mixed subsistence	Count	148	170	318
		Percent	(46.5%)	(53.5%)	(100%)
	Commercial	Count	20	12	32)
		Percent	(62.5%)	(37.5%)	(100%)
	Horticulture	Count	24	9	33
		Percent	(72.7%)	(27.3%)	(100%)

The ***education level*** (EDULVL) of the household head positively and significantly influenced smallholders' decision in diversifying into a commercial and mixed farming option, the results were significant at 99% and 95% confidence levels, respectively. Interpretation of the odds ratio shows that *ceteris paribus*, the odds of the likelihood of households in the reference category to participate in commercial and mixed farming options would be 12.1 and 7.2 times if the household head possessed a higher level of education. There is a widely shared perception that smallholder household heads with a higher level of education are more likely to engage in agribusiness. However, basic education training did not seem to contribute to the adoption of modern farming practices in the study area. Our survey findings revealed that half (50%) of all sampled household heads with higher education qualifications (college level and above) were in Formal (salaried) employment. Only 30% of the household heads with college education practiced farming, and none with a university education had their main occupation in farming. This supports the argument that highly educated persons tend to diversify their livelihood options in off-farm and non-farm activities. Possible reasons could be that at higher education levels, people tend to specialize in certain skills other than agribusiness or venture into formal employment which is presumed to have a higher income than farming. The result of this finding contradicts the findings obtained by several other studies [168,187–189] that reported that a higher level of educational attainment had a positive impact on household choices in diversifying their livelihood strategies.

Consistent with this finding, but contradictory to a widely held perception of higher education bequeathing more agribusiness skills, the survey results revealed that household heads' possession of agribusiness skills declined as the level of education increased. The crosstabulation results of agribusiness skills possession vs education level (Figure 5.6) revealed that household head agribusiness technical skills declined as the level of education increased. None of the household heads with higher education levels (college and university education) had farming as their main occupation, as most were found to be informal (salaried) employment.

Generally, in the entire dataset of Nyando, the education levels of sampled participants were low, with more than half (66%) of interviewed households responding to having only completed primary-level education. Our findings show that none of the household heads with higher education levels (college and university education) had farming as their main occupation, as most were found to be informal (salaried) employment. There is a need for tailor-made training interventions in agribusiness skills necessary to empower smallholders to exploit the increasing opportunities of agribusiness markets.

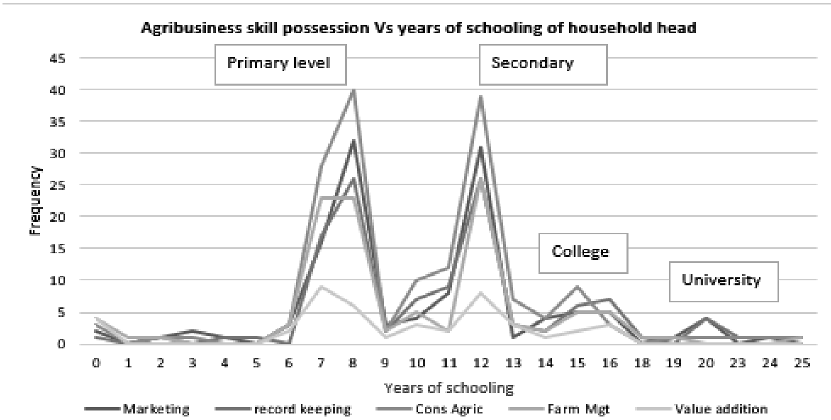

Figure 5.6: Household head education level vs agribusiness skills possession.

In figure 5.6, the sharp spikes of skills agribusiness possessions at 8 years of schooling indicate (primary level education), at 12 years indicate (secondary level), at 15 years indicate (college level) and at 20 years indicate (university-level education). The small spikes at 0 years indicate that there were quite several households who never went to school but possessed some level of agribusiness skills.

Agriculture extension services (AGRIEXT) were found to significantly ($p<0.05$) and negatively influence smallholders' decisions in choosing mixed farming. In interpreting the odds ratio, keeping all other covariates constant, households in the reference category with limited or no access to extension services were .35 times less likely to diversify their farming to agribusiness. There was a low level of provision of agriculture extension services in the two study areas despite the high demands for agronomic skills by households. For example, a high percentage (83.8%) of households practicing mixed farming did not have access to agriculture extension services. Likewise, 80.6% of households practicing horticulture and 60.7% of those practicing commercial farming activities said they lacked access to extension services in the last year. Overall, only a marginal percent (14.3%) of respondents indicated to have either received or attended agriculture training organized by the county government and other agencies in the last year. This may explain why the majority of households had low agribusiness technical skills and knowledge. This in turn affected their agricultural productivity and market participation; both of which were found to be very low among households in the study area. Agriculture extension services are a decisive component in supporting small-scale agribusiness adoption especially in impacting agronomic skills and agronomic information provision. For example, in the study of Birhanu, Girma, and Puskur [190], the provision of agricultural extension services significantly impacted the intensity of input use, agricultural productivity, technology adoption, and market participation of smallholders in Ethiopia. There is a need for the government and other stakeholders to collaborate in imparting agronomic skills and dissemination of relevant agribusiness information to poor smallholder farmers including crop husbandry, use, and application of herbicide, pesticides, and fertilizers usage. Other studies consistent with our findings include that of [191]. In increasing poor smallholder's participation in agribusiness, there is a need for the government to design effective agriculture extension services that target household skills deficiencies. For example, in the study of Birhanu et al., (2017), the authors found that the provision of agricultural services significantly impacted the intensity of input use, agricultural productivity, technology adoption, and market participation of smallholders in Ethiopia.

Livestock assets (LVTASST) had a negative and significant ($p<.01$) influence on smallholder choices in diversifying agribusiness farming choices. *Ceteris paribus*, the odds ratio in favor of the likelihood of smallholders to choose commercial and horticulture farming choices decreased by a factor of .18 and .13, respectively, per unit ownership of livestock. Households with livestock assets were more likely to rely on supplementary income from livestock products (e.g., additional income from selling their products) than they would on income from farming activities. Our study findings also revealed unequal livelihood asset ownership within the households, with women owning more low-value assets (chickens and birds) while men had higher ownership of high-value assets (cows and goats). The results of these findings concur with those of several other studies [168,190,192].

Landholding size (LANDSIZE) positively and significantly ($p<.01$) influenced the likelihood for smallholders in the reference category to participate in horticulture farming but also had a negative influence on mixed and commercial farming. Interpreting the odds ratio, a unit increment in landholding size could increase the probability of smallholder farmers' practicing pure subsistence to shifting to horticulture farming by 3.5 times, if all other factors were held constant. However, small land sizes diminished the odds of households diversifying into other farming types. In interpreting the odds ratio, c*eteris paribus*, there is a low chance of .74 and .29 odds of a household owning a small land size to diversify in mixed and commercial farming, respectively. The majority of smallholders owned very small uneconomical land sizes, a factor that jeopardized their choices of diversifying in agribusiness. Households with small land sizes barely produced enough food to support their household food demands. About 58% of sampled households reported their farms produced barely enough food to sustain them till the next harvest. High population growth is resulting in high land fragmentation and small land sizes, which is a big threat to food security for smallholder households in the two study areas. For example, Vihiga county had one of the highest population densities in Kenya in the 2019 census (1,117 persons per km2) against the nation's average of 92 persons per km^2 [185]. As a consequence, the region grapples with high food insecurity incidences (Vihiga County development Plan 2018-2022). Promoting pro-poor agriculture development strategies and policies among smallholder farmers is seen as an alternate strategy for increasing aggregate-level food availability for smallholder households. Such strategies have been viewed as very promising pathways to accelerate poverty reduction in rural areas of developing countries [167,193]. The result of this finding is consistent with the findings of other studies [168,191,194].

Distant to markets (DISMKT) was found to exert a negative influence on smallholders from participating in horticulture farming at a 0.01 level of significance. The negative sign of the coefficient indicates that the probability of a household participating in horticulture farming will diminish with an increase in distance from the input source. In interpreting the odd ratio, if all factors are kept constant, there is a .99 likelihood for a household in the reference category to engage in horticulture if it is located farther away from the market center. Nyando and Vihiga are highly productive areas for horticulture production, yet the deplorable state of dirt roads makes market accessibility difficult. Poor infrastructure has been observed to increase transaction costs and distances have been observed to confine rural smallholders to the production of low-value and non-perishable commodities, thereby diminishing the prospects of adoption of agribusiness. As distances from the main road increased, so does the transport costs, which in turn affected the profits margins. This ultimately diminishes the allure of market-oriented farming among rural smallholders. Small-scale agribusiness ventures are most susceptible to food price and transport cost shocks, especially horticulture farming, which places a high demand for efficient infrastructure connectivity [195]. Since agriculture policies are rarely geared towards the improvement of road infrastructure, a multisectoral collaboration with sectors such as spatial planning and transport and infrastructure is needed to address infrastructural needs and deficits in rural and peri-urban areas. This study's finding concurs with that of [196].

***Weather* variability** (CLIM), especially drought and famine were identified to be positive and highly significant, (at 99% confidence level) decisive factors influencing households wishing to participate in commercial and mixed subsistence farming. In interpreting the odds ratio, the are 7.4 and 5.1 odds of a smallholder subsistence-oriented household to diversify into commercial and mixed farming, respectively, if it is vulnerable to climate change. In the study area, about 67.8% of households responded to experiencing the negative effects of climate change which had high influences on their farming activities. Yet, government responses to addressing the vulnerability of smallholder households to climate change were found to be minimal, and rather reactive than proactive. For example, in the Nyando area which experiences a high risk of flooding, the government responded by dredging the river. However, the ripple effect of this was felt by many farmers who reported that their soil fertility has significantly lowered since the fertile silt brought by floodwater was cut off. This, they reported, reduced their farm productivity. As a consequence, production costs increased as they spent more on buying fertilizers and pesticides compared to before the dredging was done. Climate variability in Kenya and sub-Saharan Africa continues to aggravate smallholders' productivity, causing severe food shortages [197–199]. Overarching strategies, both mitigative and adoptive are required to effectively strengthen the resilience and coping strategies of resource-poor smallholders to climate change effect [198]. These would include promoting farmer-led technological innovations which have been reported to significantly reduce the severity of hunger and food shortages [179,180], harnessing local knowledge to improve agronomic skills [200], promoting agricultural intensification, and inclusive monitoring systems. Besides, Chriest & Niles [201] empirical research found that rural households with high levels of social capital enabled them to build a higher resilience and adaptation to climate change and food insecurity. This study's finding concurs with that of other studies [191,202].

Farm inputs (INPUT) including fertilizers, hybrid seeds, and other farm implements were found to significantly and negatively influence commercial farming adoption at a 90% confidence level. In interpreting the odd ratio, if all other factors are kept constant, the likelihood of pure subsistence households participating in commercial farming would decrease by .51 times if they have no farm inputs. The result of this finding is consistent with the findings of [191].

Household savings (SVNG) was found to significantly ($p<.05$) and negatively influence farmers' decisions in choosing mixed subsistence. Ceteris paribus, the odds ratio in favor of the probability of households choosing mixed farming decreased by a factor of .33 times as savings of the household decreased by one unit. This means that poor households with little or no savings have a lower probability of engaging in mixed subsistence farming. It has been found that if households do not have access to credit, farm inputs, and other productive capital resources, they are likely to be more vulnerable to food insecurity than those who have access [83]. The results of this study are consistent with the findings of [201]. There is a need for policymakers to design and implement pro-poor policy and development interventions including improving access to banking services, and lowering collateral, and interest rates for the poor and marginalized households. Besides, a saving culture among poor households should be promoted.

Level of influence of predictor variables on smallholder choices

We also wanted to find out the level of influence each predictor variable has on smallholders' choices in diversifying in agribusiness. We used the coefficient of the statistically significant variables to report the degree of influence. According to Tabachnick and Fidell [184], variables that tend to change the odds of the outcomes have the most influence. Thus, the coefficient was sorted from very low (negative) to very high (positive) in classifying the extent of influence of the variables on the three farming choices.

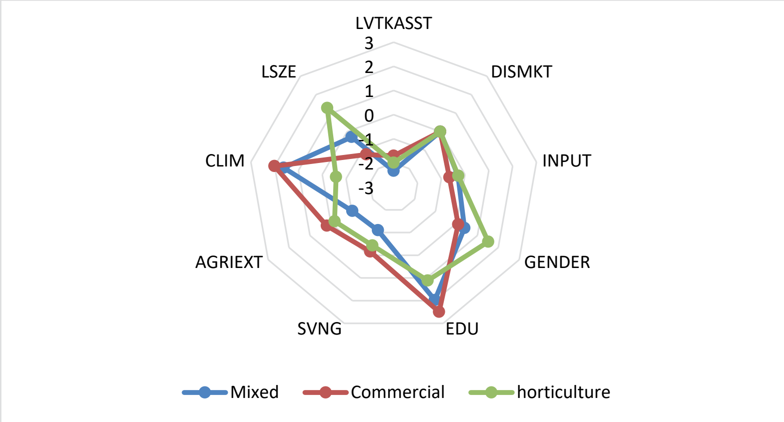

Figure 5.7: The extent of influence of predictor variables of smallholder farming choices

The results (Figure 5.7) indicate that household choice of the commercial farming option was positively influenced by EDULVL, CLIM, and INPUT, while LVSTCK had a negative and low influence. Household choice in horticulture option was highly influenced by GENDER, LANDSIZE, DISMK, and AGRIEXT while LVSTCK exerted very low influence. Likewise, EDULVL, AGRIEXT, and CLIM exerted a positive influence on mixed farming choices. From the analysis findings, we report that higher human, economic, and financial capital endowments could result in higher participation in agribusiness. In effect, strategies aimed at promoting and integrating smallholder farmers in agribusiness would require a targeted improvement of households' livelihood capital base. As Wagah and Mwehe [83] note, households with greater access to a variety of resources arising from linkages, partnerships, and capital asset endowments are expected to be more effective in achieving improved livelihoods and food security than those with low resource access.

Chapter 5

Policy implication

Results from investigations on the role of livelihood capitals in stimulating smallholder participation in contemporary agribusiness are of great importance since this would lead to poverty reduction, food and nutrition security, and diversification of rural economies in sub-Saharan Africa. This study has shown that amongst the barriers to smallholder participation in agribusiness is their high poverty levels, that manifest in lack of or insufficient access to productive livelihood capitals, which significantly jeopardize their ability to pull themselves out of the vicious cycle of poverty and food insecurity. However, the challenge for many rural smallholders in Sub-Sahara Africa is that they are peculiarly and tragically the most asset-poor and food-insecure demographic group. Nonetheless, as Donovan & Poole [37] note, the stronger a household's asset base, the greater its ability to expand and intensify livelihood activities, with those highly endowed having a higher probability to be food secure and participating in agribusiness than others. Policymakers should recognize the critical role livelihood capitals play when designing pro-poor agriculture diversification strategies aimed at improving the food security, of poverty-stricken rural households in LMICs [163,171,203]. Livelihood capital improvement would not only complement poor households' efforts in meeting food and nutrition security but also rejuvenate their livelihood diversification efforts. As Abraham & Pingali, [160] emphasizes, "increased market participation also marks the transition from subsistence-based agriculture to commercialized agriculture" (pg. 192), targeting livelihood capitals would also stimulate poor smallholders' interest in participation in agribusiness activities.

5.5 Conclusion

The catalytic role livelihood capitals have on smallholder decision-making and choices to diversify in agribusiness activities cannot be downplayed. As the results from the logistic regression model have shown, higher livelihood capital ownership resulted in a higher probability of households diversifying in agribusiness activities while lower livelihood capital ownership resulted in a lower probability. All livelihood capitals acted in parallel and jointly to influence the decisions of smallholders. Smallholders' decision to participate in agribusiness was positively and significantly determined by livelihood capitals such as education level, gender, landholding size, savings, access to agriculture extension services, livestock ownership, input access, and proximity to markets. Exogenous variables like climate variability also had a higher influence. The study highlights the need for policymakers to formulate and prioritize the implementation of inclusive pro-poor agriculture policies and interventions that mainly target the improvement of smallholders' livelihood capitals and their proper utilization. Such strategies have been taunted as the most promising pathways to accelerate poverty reduction in rural areas of developing countries [167,193,204] and could enable smallholders to shift from subsistence-oriented production to market-oriented agribusiness.

Limitation of the study

The limitation of this study emanates from the complex nature of factor interactions that influence smallholder farming decisions daily. The possibility of unintended interactions emanating from confounding stressors and complex 'wicked' problems cannot be ruled out. These problems include climate change, poverty, demographic shifts, and social-spatial inequality, which are overrunning poor smallholder farmers coping capacity and resilience.

Chapter 6

A GIS-based Spatially Explicit Approach for Targeting Resource-Poor Smallholders to Improve their Participation in Agribusiness: A Case of Nyando and Vihiga Counties in Western Kenya

Picture: A semi-mechanized potato harvesting in a small-scale farm in Timau, Kenya.
Source: Author

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Abstract

The majority of smallholder farmers in Sub-Saharan Africa face myriad challenges in participating in agribusiness markets. However, how the spatially explicit factors interact to influence household decision choices at the local level is not well understood. This paper's objective is to identify, map, and analyze spatial dependency and heterogeneity in factors that impede poor smallholders from participating in agribusiness markets. Using the researcher-administered survey questionnaires, we collected geo-referenced data from 392 households in Western Kenya. We used three spatial geostatistics methods in Geographic Information System to analyze data—Global Moran's I, Cluster and Outliers Analysis, and geographically weighted regression. Results show that factors impeding smallholder farmers exhibited local spatial autocorrelation that was linked to the local context. We identified distinct local spatial clusters (hot spots and cold spots clusters) that were spatially and statistically significant. Results affirm that spatially explicit factors play a crucial role in influencing the farming decisions of smallholder households. The paper has demonstrated that geospatial analysis using geographically disaggregated data and methods could help in the identification of resource-poor households and neighborhoods. To improve poor smallholders' participation in agribusiness, we recommend policymakers design spatially targeted interventions that are embedded in the local context and informed by locally expressed needs.

Keywords: smallholder farmers; agribusiness; market participation; spatially explicit; GIS; spatial autocorrelation; cluster and outlier analysis; spatial dependency; spatial interventions

6.1 Introduction

Smallholder farmers are important drivers of food security, poverty reduction, and livelihoods in rural and peri-urban areas in developing countries. They produce up to 80% of the food consumed in Sub-Saharan Africa [85,161]. In Kenya for instance, 75% of rural inhabitants are smallholder households that practice smallholder agriculture [205]. However, the majority of smallholder households are disadvantaged in effectively participating in agribusiness activities. Many factors interact to impede their access to and participation in agribusiness markets, including high poverty levels, lack of access to productive resources, and low endowment of human, financial, physical, and socio-economic livelihood capitals, among others[38,51,53,206–208].

The outcome of these factor interactions within individual households is most pronounced at the local level (i.e., farms and neighborhoods). Their spatial manifestation can be observed from the resulting diverse smallholder farming typologies across rural landscapes [47]. However, how these factors interact spatially to influence smallholder farming decisions is little understood. Deconstructing the local spatial complexity of factors and processes affecting agricultural production could provide a deeper insight into how spatially explicit determinants promote or impede poor smallholder farmers' participation in agribusiness.

The spatial heterogeneity of household livelihood capital endowments has often been used to explain the diversity of smallholder farming typologies and choices across and within geographic locations [32,37,79,80]. The different typologies of smallholder farming systems in a given territory can thus be conceptualized as spatial manifestations of individual households' farm management decisions and actions arising from diverse interactions of household livelihood capitals and complex geographic environments [30–33,43,47]. For example, household everyday farming decisions are influenced by the interactions of variabilities of socio-economic, agroecological, biophysical, and institutional variables [48–51]. At the lowest spatial unit (farm level), varying biophysical and agroecological constraints (soil variability, water scarcity, topography, pests and diseases, climatic variability, etc.) act as primary determinants of smallholder households' agricultural productivity [52]. At a higher spatial unit (territory level), exogenous variables like market structures, transport, technology, off-farm employment, market regulations, etc. interact to influence smallholders' market participation decisions. When socio-economic variables are included in the system (e.g., family size, landholding size, labor, skills, education, and training), a clear spatial variation in the characterization of smallholder farming typologies emerge, adopted to, and distinct from one farm to another and across geographic localities. Hence, the geographic (spatially explicit) variables at the local level, if properly interrogated, could be indispensable in explaining the smallholder farmers' choices to participate, or not, in the higher agribusiness value chains.

According to Głębocki, Kacprzak, and Kossowski [47], spatial dependence is considered a leading effect that influences agriculture practices and the decision choices of households. In their study, Głębocki et al.

(ibid) were able to map and geo-visualize the spatial distribution of smallholder farming typologies by analyzing their spatial dependence characteristics. In the literature, spatial dependence is described as a condition where attribute values are observed at one location depending on the values of neighboring observations at nearby locations [47,86,96]. The assumption taken is that relationships between neighboring spatial units are much stronger than between distant ones [47]. Spatial dependence can be captured and geo-visualized as spatial varying patterns across the landscape. Methods that can analyze spatial dependence can then be able to calculate how spatially explicit attributes existing in one household or a neighborhood influence or are influenced by those in the neighboring spatial units. However, most empirical studies do not account for the spatial dependency of spatially explicit factors that play an important role in shaping smallholder decision-making processes. The inherent difficulty emanates from the lack of a clear, spatially explicit methodology that can detect and map location-specific spatial dependence. Besides, Wiggins [85] says that comprehensive spatial data disaggregated at the local level to support localized spatial analysis hardly exists. The risk of relying on aggregated spatial data to detect local spatial dependence, according to Nthiwa [54] and Głębocki et al. [47], is that aggregated data masks important underlying local factors and obscure emergent local spatial patterns. The lack of a method to analyze local spatial dependence makes many existing empirical approaches turn a blind eye to the geographical reality of the spatial context of determinants that influences agricultural production [47,49]. As a consequence, it is difficult for policymakers to design spatially targeted interventions for addressing local-level challenges that hinder many resource-poor smallholders, particularly in marginalized rural areas, from participating in the agribusiness market.

In Geographic Information Systems (GIS), spatial dependency is measured using spatial autocorrelation. In essence, Fotheringham [65], notes that the construction of spatial autocorrelation depends on spatial dependency. He describes spatial autocorrelation as a measure of the strength and direction of spatial dependency, whereby observations at locations closer to each other in geographic space are also more likely to be similar in attribute (positive spatial autocorrelation) than observations farther apart that tend to have dissimilar attributes (negative spatial autocorrelation).

The continued development of GIS has led to the development of advanced local spatial geostatistical methods that analyze and model local spatial autocorrelation [81]. For example, Global Moran's I spatial geostatistics is commonly used. The method identifies the presence of autocorrelation (homogeneous and heterogeneous patterns) in variables at a global 'entire dataset' level. However, according to Ord and Getis [88], the shortcoming of Global Moran's I method only detects spatial autocorrelation at global (entire dataset) and not for disaggregated local-level data. Thus, an additional analysis is required to calculate spatial autocorrelation for local-level disaggregated data. The cluster and Outlier Analysis (Anselin Local Moran's I) method is a spatial geostatistics method that has been developed to detect the presence of local-level spatial autocorrelation and to map spatial clusters [95]. The method classifies statistically significant p-values into Hot spots (High–High clusters, High–Low clusters), Cold spots (Low–High clusters, Low–Low clusters), and non-significant areas. To identify spatially explicit factors causing these spatial clusters, Geographically Weighted Regression (GWR) is used. The GWR identifies statistically significant spatial factors behind the local spatial autocorrelation [95]. In this study, by combining the three methods above, we identified specific localities with a statistically significant concentration of high values (hot spots) and concentrations of low values (cold spots), and the factors causing these spatial clusters [86,87]. Mapping such localities is important because it would allow policymakers to make evidence-based decisions and also enable them to design appropriate spatially targeted interventions tailored to local contexts. The aim of this paper was thus to map, analyze and geo-visualize spatially explicit determinants, in detecting the presence of statistically significant local spatial patterns in Nyando and Vihiga study areas. This was done to unearth local spatial factors that influence smallholder households' decisions to participate (or not) in agribusiness in the two study areas.

6.2 Materials and Methods

Study area

Two distinct study areas (Figure 6.1), Nyando, and Vihiga sub-counties located in Western Kenya were selected for this study.

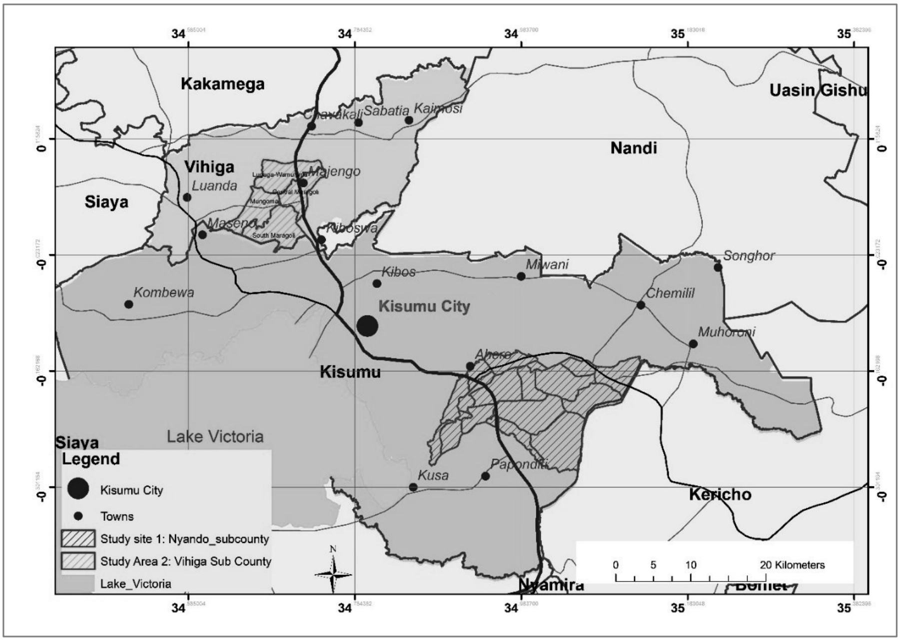


Figure 6.1: Geographical location of Nyando and Vihiga study areas.

The justification for using two geographically distinct study areas in our analysis was to allow for the cross-validation mechanism of our results, and by extension, as a test of the robustness of our spatial analytic method developed. We assumed that the results of local spatial dependence and heterogeneity for one study area could only be considered conclusively robust and reliable if a second study area with distinct characteristics was included in this study. Thus, the results of the two study areas provide a critical reflection on the usability of the method developed in this paper.

The selection of the two study areas was based on several factors, including their high population density, high prevalence of food insecurity, and their agroclimatic and agroecological potential for agricultural production. According to the Kenya National Bureau of Statistics census report, in 2019, Vihiga county has the highest population density in Kenya at 1300 persons per Km^2 against the nation's 92 persons per Km^2 [185]. The Nyando population density is lower at 400 persons per Km^2. In terms of land use, both areas are characterized by heterogeneous land-use systems with farming typologies ranging from pure subsistence, and mixed subsistence, to cash crop-oriented farming. The main cash crop grown by households, at relatively small farms, includes tea and coffee production in Vihiga and sugarcane and rice production in Nyando. Both areas are predominated by smallholder households whose average farm sizes range from 0.1 to 2.0 acres. The two study areas exhibit spatial and biophysical variability in terms of topography, soil types, altitude, and rainfall. They also receive bimodal rainfall, with Vihiga receiving higher amounts than Nyando. The topography of Nyando is predominantly flat while Vihiga's is undulating in the east and gently flat in the west.

Data collection methods

A geocoded household survey, using face-to-face interviews and questionnaires was conducted from June to November 2018. We used households as our sampling units and a total of 392 households were interviewed in the two study areas. A questionnaire with closed and open-ended questions was our main survey instrument and was administered to the households with the help of 10 research assistants from Maseno University. The research assistants were selected based on familiarity with the study area, and the ability to speak the local dialect(s). Before fieldwork, the assistants were trained and incorporated from the initial designing of the questionnaire, translating it to local dialects and pretesting it. The questionnaire covered diverse topics and captured data on biophysical, socio-economic, and agroecological aspects of each household.

Given population distribution characteristics and accuracy, we used Cochran [209] formula to calculate the desired sample size as follows:

$$n_0 = \frac{\mathrm{z}^2\mathrm{pq}}{\mathrm{e}^2} \tag{1}$$

where,

n_0 = desired sample size if the population is greater than 10,000.

z^2 = standard normal deviation at required confidence level (95% or 1.96).

p = the degree of variability 'heterogeneity' of the population (p = 0.5)

q = 1 − p (proportion in the target population)

e^2 = the desired level of precision

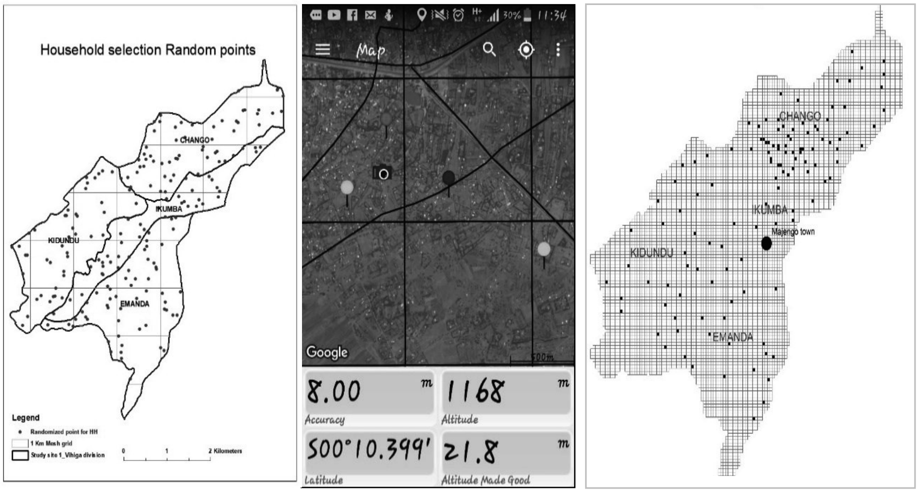
therefore,

$$n_0 = \frac{(1.96)^2(0.5)(0.5)}{(0.07)^2} = 196 \text{ sample households } (for\ one\ study\ area) \quad (2)$$

The study was conducted per the Declaration of Helsinki, and the protocol was approved by Maseno University Ethical Review Committee, (reference number: MSU/DRPI/MUERC/00633/18). All subjects gave their informed consent for inclusion before they participated in the study.

A geocoded sampling design for household interviews

In this study, a well-articulated geocoded data collection strategy was designed for guiding the household survey. In step one, we superimposed the administrative polygon of each study area with a grid cell of 100 by 100 m using the create Fishnet grid function of the ArcGIS software. Secondly, we used ArcGIS software to randomly distribute our predetermined household sample size in the gridded study area polygon. In ensuring a spatially distributed data collection will be achieved, we used a rule-based algorithm to distribute the random sample where a minimum distance between any two random sample points was restricted to 50 m. In step two, the randomized household sample points and the study grids were then converted into Keyhole Markup Language (KML) layers in ArcGIS and then superimposed on the Google Earth browser's high-resolution satellite image. In the last step, we copied these Google Earth KML layers into Geographic Positioning Systems' "GPS Essential App" preloaded on the Android-enabled phones of each research assistant. In the last step, during the fieldwork household survey, we then used the android phones to easily and accurately geolocate the randomized household points for interviews in the study area. The actual household on which each randomized sample point fell on Google's high-resolution satellite image was prioritized for interviewing. Simple random sampling was used to select any household amongst those enclosed by the 100 by 100 m square grid. These steps are illustrated in Figure 6.2.



(**a**) Distribution of GIS randomized sample points on gridded study area polygon to aid fieldwork data collection.

(**b**) Fieldwork data collection: Phone screenshot of Keyhole Markup Language layers with random points.

(**c**) Final output: Spatially joined actual surveyed points on rasterized polygon of study area.

Figure 6.2: Steps applied in geocoded household survey design.

(a) distribution of randomized GIS points; (b) uploaded KML layers on 'GPS Essential App' in Android phone, and (c) Actual surveyed household GPS points.

The quality of data is influenced by the validity and reliability of the method and instruments used to collect data [210]. During fieldwork data collection, data quality management was addressed in various ways. Before and after each day of data collection, the principal researcher and the research assistants discussed the data collection formalities, etiquette, emerging issues, and proposed solutions. Additionally, every day we projected and mapped the GPS coordinates points of the administered household questionnaires and uploaded the projected layers to the android phones of the research assistants. This enabled us to identify interview gaps by identifying areas covered and not covered by research assistants.

Before performing spatial geostatistical analysis, the household data were tested for normality, multicollinearity, and goodness of fit using Statistical Package for the Social Sciences (SPSS) software. Subsequently, we used the Exploratory Regression Statistics tool in ArcGIS software to test these variables for residual spatial autocorrelation, residual normality, and global multicollinearity (of less than VIF < 7.5). Table 6.1 provides a summary of the descriptive statistics of the variables used in this study.

Table 6.1. Description of data variables used in the analysis.

Explanatory Variables	Unit of Measure	Variable Description
Market Participation (Dependent variable)	Binary	1 if the household participates in markets and 0 otherwise
Independent variables		
Socio-economic and welfare		
Gender	Binary	1 if the household head is male and 0 otherwise.
Education level	Categorical	House head level of education (Primary, Secondary, Tertiary).
Family labor availability	Binary	1 if the head has enough family labor, and 0 otherwise.
Family savings	Binary	1 if the head saves money, and 0 otherwise.
Association membership	Binary	1 if the head belongs to a social network and 0 otherwise.
Agriculture training	Binary	1 if the head had training in the last year, 0 otherwise.
Natural and financial factors		
Access to agriculture credit	Binary	1 if the head has access to agric. credit and 0 otherwise.
Household assets (USD)	Continuous	The total monetary value of household assets.
Livestock assets (USD)	Continuous	Natural Log, the value of livestock assets.
Landholding size (acres)	Continuous	Natural Log, landholding size of a household.
Land tenure system	Binary	1 if the head has a title deed and 0 otherwise.
Hybrid seeds use and access	Binary	1 if the head use or has access to hybrid seeds and 0 otherwise.
Agriculture extension	Binary	1 if the head has access to extension services and 0 otherwise.
Biophysical and agroecological		
Soil fertility level	Categorical	Perceived level of soil fertility (low, medium, high).
Slope (derived from altitude)	Ordinal	Household land gradient (flat, gentle, steeply).
Impact of pests and diseases	Ordinal	Level of the impact of pests and diseases on crops. (Little or no impact, medium impact, high impact).
Impact of climate variability	Ordinal	Effect of drought and famine (low, medium, high)
Rainfall adequacy	Ordinal	Level of rainfall (little, medium, high).
Infrastructure and market access		
Travel time to the market center (Mins)	Categorical	0-10 min, 11-20 min, 21-30 min, 31 min and above.
Travel time to Agrovet shop (Mins)	Categorical	0-10 min, 11-20 min, 21-30 min, 31 min and above.
Distance to the tarmac road (Meters)	Categorical	Proximity to tarmac road by a household.
Institutional factors		
Market regulations Influence	Ordinal	Perceived level of influence, (little, medium, high).
Government policy (subsidy) influences farming	Ordinal	Perceived level of influence, (little, medium, high).

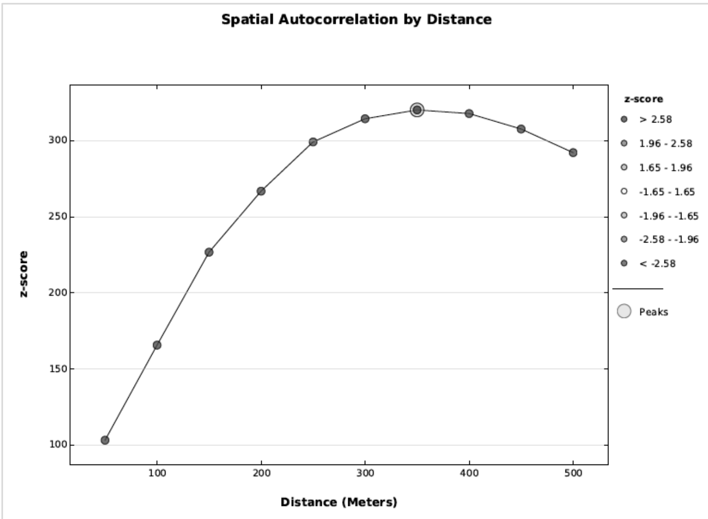
Chapter 6

Modeling Local Spatial Relationships

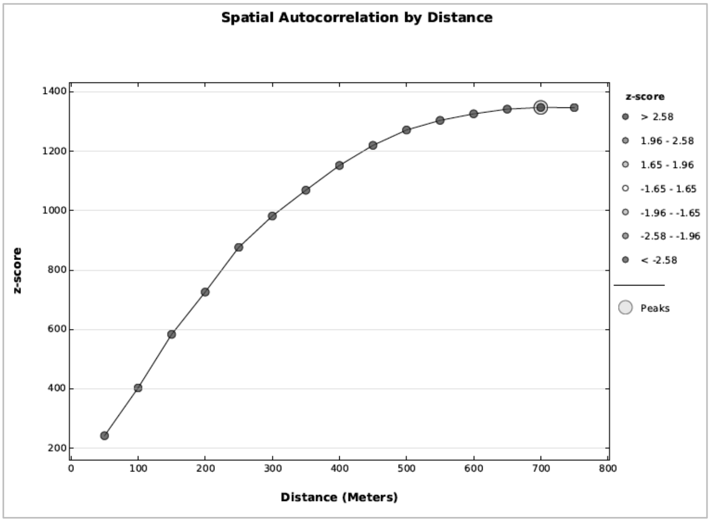
In modeling spatial relationships, and in calculating spatial autocorrelation, there are two crucial factors: (1) spatial unit of analysis and (2) territorial distance or spatial unit of analysis [97] that should explicitly be determined before spatial analysis can be carried out. According to Arsenault, Michel, Berke, Ravel, and Gosselin, [97], choosing the appropriate geographical unit of analysis emanates from the Modifiable Areal

Unit Problem (MAUP). Principally, MAUP emanates from, (1) a lack of adequate conceptualization, (2) a lack of consideration of the scale of measurement, and (3) how spatial data are aggregated or disaggregated [54,97]. The geographical unit of analysis is the extent of a geographic area to which a phenomenon or underlying spatial process occurs [98]. For this study, we used cell grids of 50 by 50 m as our disaggregated geographic unit of analysis. This was achieved by rasterizing the administrative polygon of the study areas by using ArcGIS "create fishnet grid" tool. We then transposed the sampled households' GPS points and their associated attribute data into the rasterized layer to allow cell-by-cell analysis.

The territorial distance value defines the appropriate spatial unit of analysis. The assumption is that the optimal territorial distance value will be where the underlying processes promoting spatial clustering are most pronounced. According to Getis and Aldstadt, [99], the intensity of spatial clustering is determined by the z-score returned, with the most optimal territorial distance symbolized graphically as the peak z-score value. In our analysis, we used the "Incremental Spatial Autocorrelation tool" in ArcGIS to calculate the most optimal statistically significant peak z-scores (Figure 6.3).



(**a**) Nyando



(**b**) Vihiga

Figure 6.3. Graph showing the most optimal statistically significant peak z-scores of spatial clustering.

Our calculations returned an optimal territorial distance of 350 m for Nyando and 700 m for Vihiga study areas. Subsequently, we used these territorial distances as our input value in Cluster and Outlier Analysis in calculating local spatial autocorrelation and geographically weighted spatial regression analysis in ArcGIS. Spatial analysis was based on rasterized cell grids with their associated attribute data.

To improve the accuracy of spatial regression results and interpretability of the output statistics, two problems associated with modeling spatial relationships should be addressed beforehand. First, Głębocki et al. [47] note that, in reality, the spatial relationships are not homogeneous, meaning that factors promoting spatial autocorrelation have different potentials for interactions. In accounting for this shortcoming, we used a row-standardized spatial weight matrix [88]. The spatial weights matrix quantifies the spatial relationships that exist among the features in the dataset and row standardization creates proportional weights to account for where certain features may have an unequal number of neighbors [66,99]. It is noted by Getis and Aldstadt [99] that this method is popularly used by different authors as it is effective. The second problem as highlighted by Castro and Singer [211] is that the spatial data from local features can artificially inflate the spatial statistical significance (i.e., type 1 error where one may incorrectly reject the null hypothesis). To account for this shortcoming, we applied a False Discovery Rate (FDR) correction that adjusts the critical p-value thresholds [211] in our Cluster and Outlier Analysis calculations.

Analyzing local spatial autocorrelation

Our null hypothesis was that there is complete spatial randomness of data on households not participating in markets across the two study areas; that is, no spatial pattern of factors that impede smallholders' participation in agribusiness in both study areas. We used three methods to test our hypothesis. In the first step, we used Global Moran's I spatial autocorrelation method to assess the presence or absence of spatial patterns in our dataset. According to Zhang, Atkinson, and Goodchild [98], the method calculates the z-score and p-values which indicate whether to reject or accept the null hypothesis. However, Global Moran's I result only reveals spatial autocorrelation's 'spatial patterns' for the entire dataset but not at the local level 'households and their neighbors'. Accordingly, in step 2, we used Cluster and Outliers Analysis (Anselin Local Moran's I) method to detect the presence of local-level spatial patterns and clusters and to determine if these spatial clusters are statistically significant or are resultant of complete spatial randomness of data in the study area. This method categorizes spatial units to have either positive or negative spatial patterns at significance ($p < 0.05$). The output of this method is standard deviations (LMi index, LMiZ score, LMip values) for statistical analysis and geo-visualized map (Gi Bin/CO-Type column) statistics that classify all the statistically significant p-values into three types; Hot spots (High–High clusters, High–Low clusters), Cold spots (Low–High clusters, Low–Low clusters) and non-significant areas [86]. The justification for using the Cluster and Outliers Analysis method in our study is that it supports local-level spatial analysis and interpretation of results and also supports the use of a spatial weight matrix [87,88].

In the last step, we used Geographically Weighted Regression (GWR) to examine geographically significant local factors that explain households' non-market participation; in other words, factors behind the observed spatial patterns identified in step 2. According to Fotheringham, Brunsdon, and Charlton [95], the GWR model is a non-stationary technique that measures spatially varying inherent relationships for a set of coefficients. Since the variables being estimated vary continuously over the study area, their "surface can be geo-visualized and interrogated for relationship heterogeneity" [95]. In geo-visualizing localities and households where the concentration of spatial factors hindering market participation was most pronounced, we used the predicted probability score of household market participation and geo-visualized standardized residuals from non-market participants' households. The findings are presented as inferential spatial statistics and geo-visualized as GIS output maps in the results and discussion section below.

6.3 Results and Discussion

Characteristics of sampled Household

A total of 392 sample household heads were interviewed comprising 21% aged between 18 and 35 years, 55% aged between 36 and 60 years, and 24% aged 61 years and above. The sample size was comprised of an almost equal number of male-headed (49.7%) and female-headed (50.3%) households. The average household size was 6.9 persons, which was considerably higher than the national average of 3.9 persons per household as per the latest Kenya census report (Kenya Bureau of Statistics, 2019). We observed large family sizes, with households having 5 persons and above comprising 85% of the total sample. This is quite significant in our study as it is a factor that exerts a huge demand for both household food demands and pressure on cultivable land, especially for the next generation. The average landholding size was found to be 2.12 acres though a larger percent (62%) of sampled households' landholding sizes were below 2 acres. Subsequently, all these factors could have contributed to higher food insecurity incidences observed. About 49% and 36% of sampled households in Nyando and Vihiga, respectively, reported having experienced a food shortage in the last year. The findings correlate with the average food insecurity of 40% for both counties reported in the Kisumu and Vihiga County Integrated Development Plans (2018–2022).

For the context of our study, we considered agribusiness market participants as those households, regardless of farming production typology and the scale of production, which sell certain quantities of either crops or livestock products, personally or through intermediaries to either informal or formal markets. Non-market participant households were categorized as those who do not sell any farm or animal produce to the markets. The results (Table 2) show that, overall, household market participation is low (31%) in both areas, with a higher percentage (69%) of households in both Nyando and Vihiga not participating in markets.

Different farming production orientations were observed in the study areas (Table 6.2). Overall, a high percentage of households' food production in both the study areas is oriented towards subsistence farming, while only a marginal 14% and 8% were oriented towards semi-commercial and horticulture farming, respectively. The main food crops grown both for food crops and for selling included maize, beans, bananas, vegetables, mangoes, avocados, and pawpaws. Cash crops included coffee and tea in Vihiga and sugarcane and rice in Nyando.

Table 6.2: Cross-tabulation of (a) households' non-market participation, and (b) household farming production type.

(a) Household Market (non)Participation				**(b) Farming Production Type**			
	Nyando	Vihiga	Overall	**type**	Nyando	Vihiga	Overall
	Percent	*Percent*	*Percent*		*Percent*	*Percent*	*Percent*
No	75% (147)	62% (122)	69% (269)	Pure subsistence	20% (40)	22% (43)	21% (83)
Yes	25% (49)	38% (74)	31% (123)	Mixed subsistence	66% (129)	47% (93)	57% (222)
	100%	100%	100%	Semi-commercial	2% (3)	27% (53)	14% (56)
				Horticulture	12% (24)	4% (7)	8% (31)

Results of local spatial autocorrelation

The Global Moran's I statistics results (Table 6.3) revealed the presence of spatial autocorrelation in our data set, with a global Moran's index = 0.713, z-score = 242.3, (p < 0.000) for Vihiga and global Moran's index = 0.903, z-score = 383.86 (p < 0.000) for Nyando dataset.

Table 6.3: Global Moran's I result indicating the presence of spatial autocorrelation.

Study Area	***Global Moran's Index***	***Expected Index***	***Variance***	***z-Score ****	**p-*Value***
Vihiga	0.713	−0.000135	−0.000	242.34	0.000
Nyando	0.903	−0.000029	0.000	383.86	0.000

* The high z-score reflects the high intensity of spatial clustering.

Given the statistically significant z-score, there is a less than 1% likelihood that this clustered pattern could be the result of random chance. Thus, we reject our null hypothesis. This confirms that in both study areas, there is a presence of spatial clustering and patterns that could not be the result of complete spatial randomness of data.

Results of Cluster and Outliers Analysis (Anselin Local Moran's I) for the study areas show the presence of local spatial autocorrelation. This is presented as statistically significant (>+1.96>+3.4, $p < 0.05$) local spatial clusters of high values (Hot spots) and clusters of low values (cold spots) geo-visualized in Figures 5.4 and 5.5.

In the maps (Figures 6.4 and 6.5), the local Moran's I p-value, significant at 0.05 using False Discovery Rate (FDR) correction is symbolized as hot spots and cold spot areas in the legend. In both maps, the hot spots and cold spots areas are statistically significant local spatial clusters of high values and low values, respectively. These spatial clusters are surrounded by non-significant areas (white patches). We superimposed the spatial clusters with GPS points of households that did not participate in markets, with red dots being non-market participants' households in hot spots areas and blue dots showing non-market participants' households in cold spots areas.

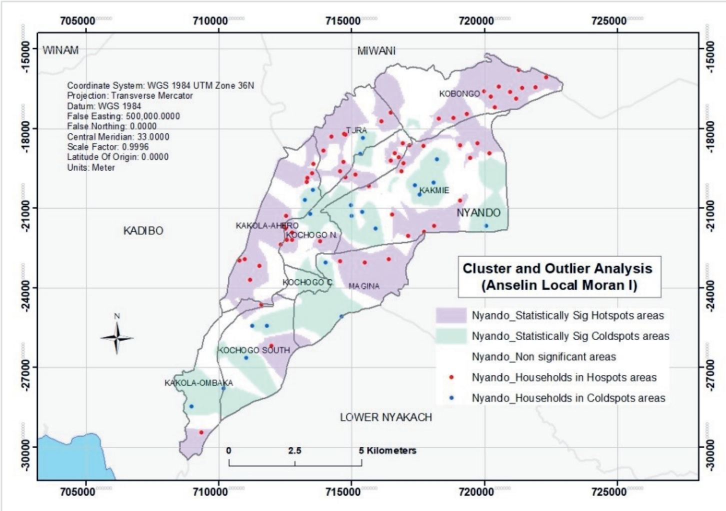


Figure 6.4: Map of Nyando showing local spatial clusters with a higher concentration of poorer households (hot spots) and richer households (cold spots).

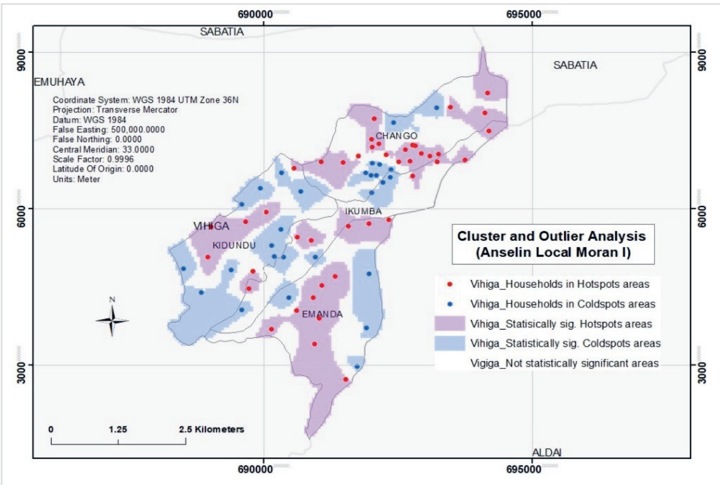


Figure 6.5. Map of Vihiga shows local spatial clusters with a higher concentration of poorer households (hot spots) and richer households (cold spots).

An important observation from the two maps is that factors impeding market participation have several distinct local spatial clustering across the two study areas. The difference in spatial clustering could be explained by the dissimilar social-spatial resources existing in the study areas, and the capability of each household to maximize its livelihood assets to exploit those resources. These maps provide for easier visual interpretation by policymakers for spatial targeting of interventions. The observed spatial patterns are not a result of complete spatial randomness, which means that underlying spatially explicit factors are causing these spatial clusters. These factors are explained in detail in Section 6.4.

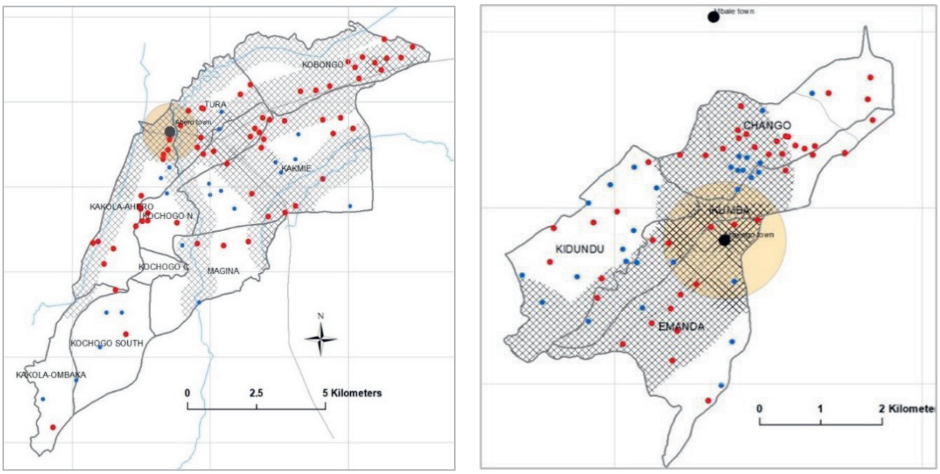
Mapping local spatial complexity of causative factors of non-market participation

The results of spatial proximity to supportive infrastructure (Table 6.4) show that closeness to road, town, and water sources had minimal influence on non-market participant households' decisions to participate in agribusiness.

Table 6.4: Results of spatial proximity analysis of non-market participants' households.

Euclidean Distance	Non-Market Participating Households			
	Nyando		Vihiga	
	In Hot Spot (n = 63)	In Cold Spot (n = 21)	In Hot Spot (n = 43)	In Cold Spot (n = 28)
1 KM buffer from a tarmac road	38 (68%)	4 (19%)	26 (65%)	16 (57%)
1 KM buffer from the main town	6 (10%)	0 (0%)	5 (12%)	3 (11%)
500 M buffer from the river	38 (22%)	4 (19%)	0	0

Contrary to our expectation, in both Nyando and Vihiga, the majority of poorer households in hot spots areas were close to tarmac roads, town centers, and water sources (rivers). Yet, these factors are often viewed as positive drivers of agribusiness and market participation. For example, 68% and 65% of poor households in Nyando and Vihiga, respectively, were located within a radius of 1 km from the main tarmac road. Equally, the spatial proximity maps (Figure 6.6) revealed a high concentration of non-market participants' households (both red and blue dots) within a 1 km buffer of towns, tarmac roads, and a 500-m buffer from rivers.



(**a**) Nyando (**b**) Vihiga

Figure 6.6: The two maps reveal that, in both Nyando and Vihiga areas, there were poorer households (red dots) than richer households (blue dots) located within a Kilometre buffer (crosshatched areas) from the tarmac road, main town, and rivers.

Such high percentages of poorer people staying close to basic services would imply that these services had little influence on their decisions to participate in markets. Several studies [212,213] postulate that the ability (or inability thereof) of poor households to exploit the opportunities for improving their livelihoods is influenced by their level of poverty and multiple deprivation status (figure 6.7). This has a consequence on policy in that improving one aspect of factors that impede agribusiness development cannot produce intended consequences, and hence a holistic approach is needed. Pro-poor agricultural development proponents advocate for smallholder agriculture diversification in both farm and non-farm activities as the most promising pathways to accelerate poverty and income inequality reduction [214]. However, these approaches should be accompanied by integrated and multidisciplinary interventions, where spatial targeting can improve the process.

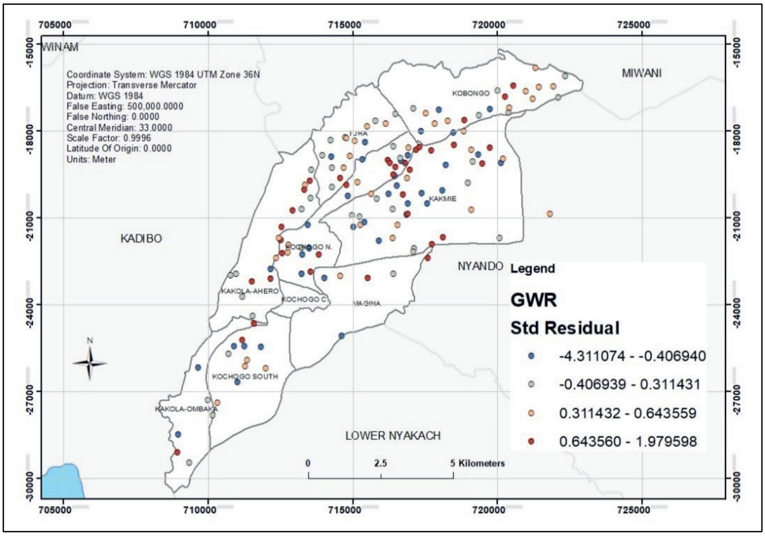


Figure 6.7: Spatial manifestation of multiple deprivations in Nyando geo-visualized from the standardized residual of predicted probability of households not participating in markets. The higher the standard residual (red-doted households), the higher their likelihood of being deprived of the explanatory factors, and the higher the probability of not participating in markets.

Comparing the market participation odds for both richer and poorer households in hot and cold spots in Nyando and Vihiga

The regression results (Table 6.5) show spatially explicit factors that influence market participation decisions of poor smallholder households in the two study areas. These factors are associated with the spatial clusters of hot spots and cold spots geo-visualized by Nyando and Vihiga maps. The two study areas exhibited both similarities and dissimilarities of spatially explicit factors impeding market participation.

Table 6.5: Spatially significant factors influencing smallholder participation in agribusiness

Vihiga Sub-County					
Predictor Variable	**B.**	**S.E.**	**Wald X^2**	***p*-Value**	**Odds Ratio**
Education Level	−2.034	1.124	3.278	0.070	0.131
Savings	−1.348	0.428	9.927	0.002	0.260
Land size	−1.160	0.547	4.496	0.034	0.313
Training	−0.850	0.516	2.718	0.099	0.427
Travel time to markets	−1.751	0.870	4.052	0.044	0.174
Constant	3.740	1.181	10.021	0.002	42.101
Nagelkerke R^2	0.33				
−2 Log-likelihood	205.51				
Nyando Sub-County					
Predictor Variable	**B.**	**S.E.**	**Wald X^2**	***p*-Value**	**Odds Ratio**
Occupation	−1.662	0.784	4.495	0.034	0.190
Education level	−5.515	1.686	10.701	0.001	0.004
Household assets	2.215	1.327	2.789	0.095	9.165
Livestock assets	−1.286	0.748	2.958	0.085	0.276
Savings	0.916	0.561	2.665	0.103	2.499
Landholding size	−1.537	0.702	4.794	0.029	0.215
Social group member	−1.296	0.488	7.037	0.008	0.274
Travel time to market	−2.337	0.828	7.966	0.005	0.097
Travel time to Agrovets	2.119	0.846	6.280	0.012	8.323
Constant	5.037	1.227	16.850	0.000	154.080
Nagelkerke R^2	0.421				
−2 Log-likelihood	154.82				

In Nyando, the results show that occupation, education level, household and livestock assets, savings, landholding size, membership to a social group, and travel time to the output market were spatially and statistically significant factors impeding poor smallholder participation in agribusiness markets. In Vihiga, the regression results revealed that education level, savings, land size, training, and travel time to markets were statistically significant factors that impeded household market participation.

Landholding size negatively and significantly ($p < 0.05$) influenced the decision of households to participate in markets. *Ceteris paribus,* the odds ratio of the likelihood for smallholders to choose to participate in agribusiness markets decreased by a factor of −1.160 for Vihiga and −1.537 for Nyando, with a unit decrease in land size, at a 95 % confidence level. Supportive evidence from the study findings shows that the majority of smallholders owned very small land sizes that were uneconomical to support surplus production for selling to the markets. Again, they barely produced enough to support their household food demands. The majority of households (58%) said that the food they produced was not enough to sustain them till the next harvest. There is a need for local governments to adopt spatially based integrated planning that promotes pre-emptive coordination of different land-use functions and activities as efficiently as possible to maximize the 'benefits' of a given locality [215]. This can be achieved through the adoption of spatially dependent studies that model and predict different spatial scenarios based on optimized resource (re)allocation according to their suitability and availability.

A low level of education has often been reported among the key barriers to market participation of poor households [216]. Our findings corroborate this, as we found education to be statistically significant ($p < 0.01$) in influencing household market participation in both study areas. In interpreting the odd ratio, households with low education levels were 0.004 less likely to participate in markets than those with one level higher of education, all other factors kept constant. From a local-scale perspective, non-market participant households with a low level of education (primary school education and below) were significantly higher (51%) in the high-cluster hot spot areas, than those in cold cluster zones (15%). The same scenario was found in Vihiga, where a relatively high percentage (45%) of non-market participants' households in hot spot areas had a primary level of education as compared to only 21% of respondents in cold spot areas. This would mean that spatially targeted interventions in terms of education and training in hots spot areas would lead to a relatively higher probability of improving the market participation of those households. Even though education level was found to be a positive determinant of market participation, our household survey findings revealed that the agribusiness skills of household heads declined as the level of education increased (Figure 6.8).

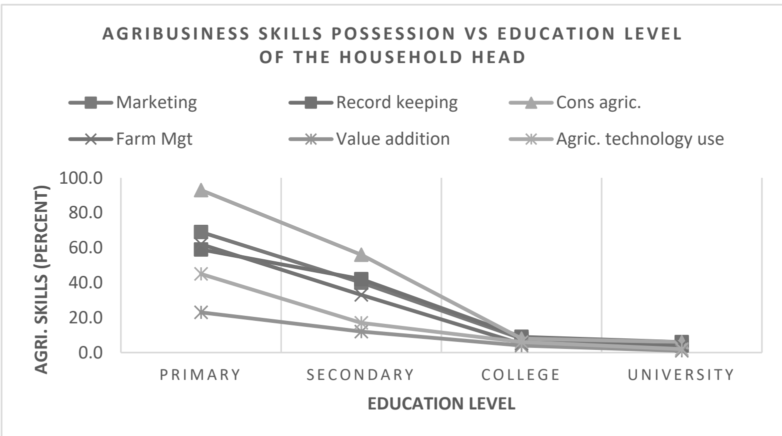


Figure 6.8. Survey results showing households' head education level vs agribusiness skills possession.

This implies that in the study area, a higher level of education of the household head did not translate to more agribusiness skills as often presumed. Additionally, our survey results found half (50%) of the household heads with college and university education were in formal (salaried) employment and were not engaged in farming. This raises an important question on whether general education improvement among poor households would be an effective strategy that can improve their farming livelihoods. We argue that rather than spatially blind policy interventions that often advocate for the blanket improvement of general education among poor smallholders, a spatially explicit methodology could be a useful alternative for identifying specific hot spots localities where households have a deficiency in relevant agribusiness skills for spatially targeted interventions.

Household savings was a statistically significant factor that influenced a household's agribusiness market participation. *Ceteris paribus*, there is 0.266 odds of a household participating in the market in Nyando if it does not have savings while in Vihiga there are 2.49 odds of a household with savings participating in the market. From inferential statistics, the majority of households in hot spot areas in both study areas had little savings. In Nyando, 73% of sampled households in hot spots had no savings, while in Vihiga, not a single household in hot spot areas had any savings. Likewise, lack of savings was also higher in households located in cold spot areas, with 67% and 50% of households in cold spot areas in Nyando and Vihiga, respectively, indicating not to have any savings. Lack of monetary savings among poor households coupled with lack of access to alternative credit sources has been identified in many works of literature as a formidable barrier to poor smallholder's market participation. A pro-poor agricultural policy that promotes a saving culture while enhancing access to affordable credit amongst poor households could empower them to increase their wealth and savings. This in turn would enhance their participation in agribusiness. Spatially targeted analysis for identifying poverty-stricken neighborhoods, locations served and not served by small and microfinance institutions and identification of the most suitable areas for locating these services could generally promote smallholders' credit access and savings culture, factors which are key in promoting agribusiness adoption.

Travel time to output markets was found to be a statistically significant factor that influenced market participation in both study areas. The negative influence indicates that households located farther away from the markets had a higher probability of not participating in markets. All factors kept constant, the odds of a household farther away from the output market participating is 0.097 in Nyando and 0.174 in Vihiga, as would those near market centers. Of the total households in hot spot areas, 67% in Vihiga and 49% in Nyando indicated they took 30 minutes and above to access the nearest output market. In the cold spots' areas, 33% of sampled households in Nyando and 36% in Vihiga took 30 minutes and above to access the nearest markets. Spatial targeting could inform policymakers on resource (re)allocation for market infrastructure provision in areas not served by markets to improve poor smallholder market access and participation.

Livestock and household assets ownership were found to significantly influence market participation in Nyando. Low livestock asset endowment was associated with significantly lower probabilities of households participating in markets. In interpreting the odds ratio, if all factors are kept constant, there are 0.276 odds in the likelihood of a household not participating in the markets if it is lacking livestock assets. In both study areas, results indicate unequal asset ownership between men and women; with women owning more low-value assets (poultry) and men owning more higher-value assets (cattle and goats). Whereas gender-differentiated assets ownership may emanate from a multitude of reasons including inherent repressive culture and traditions, women's assets ownership was found to influence household food production. Half

(49.7 %) of interviewed respondents indicated that women's asset ownership in both the study areas had a medium to high influence on household production practices. In some empirical studies [217], livestock assets have often been viewed as liquid assets for poor households in not only reducing risks but also as a buffer to food security, in addition to increasing household well-being.

Lack of training in modern agribusiness practices was found to be spatially significant ($p < 0.01$) in limiting smallholder market participation in Vihiga. Only a marginal (17%) of the total sampled households indicated they had received training in the last year. For households located in hot spot areas, only 4% indicated having received training. There is 0.427 odds of a household with no training participating in markets as would be a household with relevant agribusiness training skills. In improving access to agriculture extension services, local government officials could benefit from spatially dependent study outputs that spatially identify localities with higher clusters of smallholders deficient in certain agribusiness skills.

Accessibility of input sources (agro vet stores) was found to positively influence market participation in Nyando. In interpreting the odds ratio, *ceteris paribus*, there is 8.323 odds of a household located farther away from an agro vet store participating in the market than it would be for the same household if it is near the input market. In Vihiga, 67% of households in hot spot areas took 20 minutes and above to walk to the nearest agro vet store, while 71% of those in cold spots took 20 minutes and above to walk to the nearest agro vet store. Ease of access to supportive agriculture infrastructure and services has been shown to improve farmers' market participation [218], especially in rural areas. While it is difficult to map and geo-visualize the location of these services using theoretical studies, spatially dependent analytic approaches, and outputs become indispensable.

Relevance of the spatially explicit research outputs in improving spatial targeting of intervention and policy

A common concern for empirical studies is the generalizability and replicability of their study findings to a broader context in informing public policy. Principally, spatially explicit studies highly depend on the quality of spatial data and the clarity of methods used in their analysis. The axiom "garbage in garbage out", is also applicable in GIS-based spatial data analysis. This implies that the quality of spatial data used, and by extension, the study design used to collect it, should be among the most important considerations for researchers if the study outputs are to be relied upon in informing policy and being able to be reproducible elsewhere. We postulate that spatially dependent empirical studies should address these concerns by designing a well-articulated geocoded data collection strategy. For our study, the design and application of the geocoded household survey strategy enabled us to collect quality geocoded data and the application of local spatial analytic methods addressed the concern of relevancy and informative output. Equally, the quality of our household survey was enhanced by incorporating web-based geospatial tools that helped us to easily and accurately geolocate sample households in collecting georeferenced data. The spatially explicit methodological approach provided in this study could enable other researchers to replicate the study elsewhere.

Another concern for empirical studies is the generalizability of the study findings. It can be argued that empirical findings may only be valid for a narrow time scope. This argument emanates from the fact that geocoded surveys capture point data for that particular moment in time, thus localizing the findings and interpretations thereof by binding them in both space and time. However, in principle, territories exhibit spatially heterogeneous characteristics due to the diversity of local geographic specificities and levels of a territorial capital endowment. Even though these territorial characteristics are dynamic, they rarely change rapidly, enabling the projection of study findings even when such studies are based on local geographic parameters. Thus, the correct choice of spatially explicit variables and their analysis can be used to inform decisions in both short- and long-term planning scenarios. While recognizing the multiplicity of parameter variables that can be used to capture local spatial autocorrelation, the spatial unit of analysis used, and the level of disaggregation of spatial data used should be key considerations in studies that analyze local spatial relationships. As such, the broader relevance of this study would be pegged on the applicability of all these factors discussed, as well as the ability of other researchers, and local governments to apply them in modeling complex local problems.

The application of studies designed to provide local solutions to socio-spatial problems using GIS-based approaches [89,90,219,220] has increasingly gained prominence in the recent past. While the capability of local authorities, especially in Sub-Saharan Africa, to apply spatially explicit methodologies in decision-making processes has been questioned, recent developments could promote their relevance and adoption. First, most of the policy directives in Kenya, and Sub-Saharan Africa in general, are often formulated at the national level, but their implementation is carried out at the grassroots level by relevant local authorities. Secondly, social problems have increasing become interwoven in socio-spatial complexity and their manifestation is most evident at the local level, rather than a regional or national level. In light of this, local governments are embracing Geographic Information and Communication Technologies (or "Geo-ICT") and Spatial Decision Support Systems (SDSS) in their day-to-day problem-solving and decision-making processes to address complex social-spatial problems.

The use and adoption of spatially explicit methodologies, like the one espoused in this study, for analyzing geographically referenced data are bound to increase in the future due to the increasing accessibility and affordability of Geo-ICT and SDSS tools and methods. Buoyed by the easily accessible and web-based geographic data and information, a plethora of Geo-ICT tools, and SDSS analytic techniques continue to be developed and embraced for deconstructing geographic complexity. Additionally, a multiplicity of geospatial-based courses and open-source software have also been developed by higher learning institutions to build the capacity of both local government staff and new students. In Kenya for example, the use of GIS as an SDSS for spatial thinking and planning in County governments has been anchored in law through the County Governments Act (No. 17 of 2012) and the Urban Areas and Cities Act (No. 13 of 2011). These Acts provide both legal and policy frameworks for the institutionalization and adoption of GIS in County governments. Under these Acts, County governments, including Vihiga and Kisumu counties used in this study, are mandated to develop County Integrated Development Plan (CIDP) and establish GIS databases to support County spatial planning. All these developments have increased the demand for GIS courses and professionals, and several universities in Kenya and elsewhere have rolled out courses in this domain to bridge the demand gap.

6.4 Conclusion

Studies that use spatially explicit decision support systems in analyzing socio-spatial complexity provide a better-contextualized understanding of local-level interactions of variables that influence smallholder agriculture systems. This paper underscores the importance of designing spatially targeted interventions that are embedded in the local reality and informed by the locally expressed needs of smallholder households. Geospatial analysis using disaggregated local-level data is likely to unearth spatially explicit local factors that impede smallholders from participation in agribusiness markets than would spatially aggregated data analyzed at a higher spatial level.

Using Global Moran's I, results have revealed the presence of spatial patterns in our dataset that was not caused by spatial randomness of data. Furthermore, the Anselin Local Moran's I, identified statistically significant local spatial clusters of factors that hinder smallholder participation. Finally, the geographically weighted regression identified spatially significant causative factors impeding market participation in the study areas. The results show that occupation, education level, livestock assets, savings, landholding size, membership in social groups, training, and travel time to output markets were spatially and statistically significant factors impeding smallholder market participation. Non-market participation was found to result from multifactorial causation linked to the local context. The results have shown that factors hindering market participation were heterogeneous within and across farms and neighborhoods in the study areas. We also found that spatially explicit factors causing non-market participation differ between the two study areas. The geo-visualized regression probability maps are important decision-making visual tools for policymakers to easily identify localities with a high probability of spatial clustering of social-spatial problems of deprivation and inequality. The study has demonstrated how spatially explicit analysis conducted at the local level could help in identifying deprived areas where the most vulnerable, most impoverished and resource-poor households reside.

In designing spatially targeted interventions, policymakers should take cognizance of complex interactions of socio-spatial processes in the local landscape and interrogate how they interact to influence smallholders' decision-making and choices. For spatial interventions to be successful, all the factors behind the spatial clustering observed in a locality should be addressed concurrently at the design stage of spatially targeted intervention. Targeting a single factor may fail to enhance smallholder's market participation, since lack of market participation emanates from the complex interaction of multiple factors, as the study has shown. A further study could use a similar approach but carry out analysis at higher spatial units to test explicitly the effect of spatial scale on the patterns of spatial associations which can further help to unearth socio-spatial clustering households' multiple deprivations.

Chapter 7

Mapping the Spatial Dimension of Food Insecurity Using GIS-based Indicators and a Place-based Approach: A Case of Western Kenya

Picture: Farmers sorting and grading potatoes after harvesting in Timau, Kenya. Source: Author

Mathenge, M., Sonneveld, B. G. J. ., & Broerse, J. E. (2022). Mapping the spatial dimension of food insecurity using GIS-based indicators: A case of Western Kenya. *Food Security*. https://doi.org/10.1007/s12571-022-01308-6

Abstract

Food insecurity elimination is a major focus of the Sustainable Development Goals and addresses one of the most pressing needs in developing countries. With an increasing incidence of food insecurity, poverty, and inequalities, there is a need for realignment of agriculture that aims to empower especially the rural poor smallholders by increasing productivity to improving the food security conditions. Repositioning the agricultural sector should avoid general statements about production improvement, instead, it should tailor to location-specific recommendations that fully acknowledge the local spatial diversity of the natural resource base that largely determines production potentials under current low-input agriculture. This paper aims to deconstruct the complex and multidimensional aspect of food insecurity and provides policymakers with an approach for mapping the spatial dimension of food insecurity. Using a set of GIS-based indicators, and a small-area approach, we combine Principal Component Analysis and GIS spatial analysis to construct one composite index and four individual indices based on the four dimensions of food insecurity to map the spatial dimension of food insecurity in Vihiga County, Kenya. Data were collected by the use of a geocoded household survey questionnaire. The results reveal the existence of a clear and profound spatial disparity of food insecurity. Mapping food insecurity using individual dimension indices provides a more detailed picture of food insecurity as compared to the single composite index. Spatially disaggregated data, a small area approach, and GIS-based indicators prove valuable for mapping local-level causative factors of household food insecurity. Effective policy approaches to combat food insecurity inequalities should integrate spatial targeted intervention of each dimension of food insecurity.

Keywords: food insecurity, GIS-based indicators, smallholders agriculture, spatial planning, small-area approach.

7.1 Background

Hunger and food insecurity are global social problems that present formidable challenges to policymakers and local governments mandated to provide solutions [17]. Globally, approaches for providing sustainable food security for smallholder households have increasingly gained priority in agriculture planning and policy agendas. However, chronic hunger, poverty, and multiple deprivations have become critical in the last decade, particularly in rural and peri-urban areas of Low-and Middle-Income Countries (LMICs) [27,221,222]. In addressing food insecurity, governments and relevant stakeholders continue to formulate and implement various agricultural and development planning policies aimed at improving food security, agriculture productivity, land use sustainability, and agribusiness markets [223–225]. Despite these interventions, higher concentrations of food insecurity and socioeconomic deprivation have been recorded in LMICs, especially among poor smallholder farmers [5,27], who constitute the majority of the rural population [160].

Previous studies have brought to the fore the socio-spatial inequality of food insecurity, its multifactorial causation, and the complexity associated with addressing this critical societal problem [226,227]. However, in many of these studies, little focus has been devoted to mapping the resultant spatial patterns and disparities of food insecurity at the local level. Importantly, the prominence of spatially explicit factors as a possible contextual explanation of the spatial patterns of food insecurity has received little attention. Yet, agriculture productivity and food insecurity cannot be delinked from the influence exerted by local geographic specificities existing at smallholder households' places of residence. At a lower spatial scale (local level), many of the factors that influence smallholders' everyday farming activities emanate from the households' interaction with geographic specificities, including biophysical, agroecological, and socio-economic factors, among others [31,51]. These factors impact a household's access to livelihood capital and income, which are paramount indicators of wealth, inequality, and, by extension, food insecurity. At a higher spatial scale (macro-level), inequalities in food insecurity could result from the variability of geographic or territorial specificities, including territorial capitals, territorial policies, infrastructure availability, demographic characteristics, and institutional development policies [68,72].

In contemporary times, composite indicators have been constructed to measure various aspects of complex social problems like food insecurity that are usually embedded in local socio-spatial complexity [228]. According to OECD (2008), composite indicators are constructed by aggregating several individual dimensions that represent different aspects into a single index, based on an underlying model of the multi-dimensional concept of the phenomenon being measured. These composite indicators (e.g., the index of multiple deprivations) are presumed to adequately capture all aspects of the phenomenon being measured. Several studies provide useful insights on the application of Geographic Information Systems (GIS) based indicators in spatial targeting of interventions including mapping the spatial dimension of poverty hotspots [230,231], mapping physical deprivation [232], mapping the spatial dimension of income inequality [233], and mapping the spatial dimension of food access [234]. Marivoet, Ulimwengu, & Sedano [235] present a good case on how to improve spatial targeting of food and nutrition security intervention. The authors designed a typology based on four key food and nutrition security indicators that enabled a broad identification and mapping of major food security bottlenecks in the rural territories of the Democratic Republic of Congo. Two programs implemented by international organizations offer useful insight into the spatial mapping of food insecurity. The first program, the World Food Program's Vulnerability Analysis and Mapping (VAM) uses food security data, and GIS spatial analysis methods to map geographic patterns of food insecurity and identify the locations with the most food-insecure households. In Kenya, the VAM database (dataviz.vam.wfp.org) uses 'County level' as its spatial unit of analysis to geo-visualize various food security indicators. At this higher spatial level of analysis, capturing micro (local-level) indicators of food insecurity becomes a challenge. The second program is the USAID pioneered 'Demographic and Health Surveys' (DHS) that combines geographic data with publicly available nationally representative household survey data in GIS to spatially characterize various indicators of health, nutrition, and population. Though the maps produced in these two programs are good for informing food security policies at a territorial level, they may be insufficient for local-level spatial targeting of food insecurity. Thus, this study details the spatially explicit methodologies for developing local-level GIS indicators for mapping spatial patterns of food insecurity at lower spatial levels (i.e., Ward or a neighborhood). The output thus provides extra insights to spatial targeting of interventions and add knowledge on how local governments, planners and practitioners can use GIS and disaggregated spatial data to design spatially integrated food policies that could improve local food planning and interventions.

The spatial varying relationship between factors that cause food insecurity and local geographic specificities often lacks adequate consideration in composite indicators designed to measure food insecurity. Many of the methodological approaches used to construct composite indicators fail to integrate and analyze the spatial dimension of the hypothesized indicators. In recent times, GIS-based methods have been developed that can map and analyze the spatial varying relationships of indicators at a lower spatial level [77,78]. One such method combines a small area approach with GIS to construct spatially relevant indicators (GIS-based indicators). On the one hand, GIS-based indicators use georeferenced data that allow local-level spatial analysis, depending on the constructed indicator and the level of aggregation or disaggregation of the spatial data used [73,77,78]. On the other hand, the small-area approach uses a geographically defined area as a primary entry point to build a deeper, contextualized understanding of the socio-spatial complexity of a decision problem in that locality [73]. The use of a small area approach and disaggregated spatial data diminishes the extent of the measurement error of the GIS-based composite indicators to reveal accurate spatial patterns of the issues under investigation [73–76].

This paper combines geocoded survey data disaggregated at a household level, and a small area approach to construct GIS-based indicators in mapping the spatial patterns of food insecurity in central Maragoli, of Vihiga County in western Kenya. Using principal component analysis (PCA), we first construct one composite indicator of food insecurity - The food Insecurity Multidimensional Indicator (FIMI). Then, we construct four composite indicators of food insecurity based on the four dimensions of food security (availability, stability, access, and utilization). Using the GIS, we perform spatial analysis to map the spatial patterns of food insecurity in the case study area. By comparing the resultant spatial patterns of food insecurity from FIMI and the four indicators, we deduce important insights as to which indices are more effective in revealing local spatial patterns of food insecurity. Gaining a contextualized understanding of how geographic specificities at the local level influence food insecurity is crucial for the spatial targeting of interventions. In addition, the knowledge is useful for designing place-based interventions that are aligned to specific challenges and opportunities of a defined geographic area. Similarly, a deeper understanding of the spatial dimension of food insecurity can contribute to the development of sustainable territorial-based agriculture and food security policies, that could result in increased smallholder agriculture productivity, and, by extension, food security.

7.2 Methodology and Data

According to OECD "Handbook on Constructing Composite Indicators", the construction of a small-area composite index for measuring the spatial dimension of food insecurity involves several stages: (1) selection of appropriate data and geographic area, (2) selection of indicators, (3) construction of the index by combining and weighting indicators, (4) validation of the resultant index, and (5) dealing with uncertainty. This section describes these procedures.

Selection of the study area

Central Maragoli ward was selected for this study. The ward is located within Vihiga County, in the western part of Kenya. The choice for selecting this area was motivated by key socio-spatial characteristics including very high population densities, high prevalence of food insecurity, favorable agro-climatic conditions and agro-ecological potential for agricultural production, and a high level of absolute poverty (40%). In Vihiga County, agriculture contributes to about 62% of employment. In terms of land use, the area is characterized by heterogeneous land use patterns. Farming systems practiced include pure subsistence, mixed subsistence, and cash-crop-oriented farming. Smallholder farming is the predominant agricultural activity and constitutes about 70% of agricultural production. The landholding sizes for the majority of households are very small, ranging between 0.1 to 2.0 acres. Vihiga's topography is undulating rocky hills in the East and gently flat in the West, with red loamy soil, high bimodal rainfall (1900 mm/year), and a favorable equatorial climate. Table 7.1 shows salient territorial characteristics of the study area deduced from the reconnaissance visits and secondary data sources.

Table 7.1: Salient socio-spatial heterogeneity of Central Maragoli, Vihiga County

Attribute	Characteristic
Physical and Agroecological	
Altitude	1,600 m.a.s.l
Average precipitation	1,900 mm per year
Dominant soil	Red loamy and sand soil
Rainfall type	Bimodal pattern
Climate type	Equatorial
Annual temperature	18-21 degrees centigrade
Topography	Undulating
Agro-ecological zones	Upper midlands
Socio-economic attribute	
Population density	1,046 per km^2
Agricultural production	70% (small scale)
Average farm sizes	0.1–2 acres
Agriculture employment	62%
Absolute Poverty	40%
Land use attribute	
Main food crops grown	Maize, beans
Main cash crops grown	Tea, coffee
Main Livestock system	Tethered, zero grazing

*Rainfall exhibits a bimodal pattern of long and short rainy seasons.
**Lowest monthly temperature and warmest monthly temperature.
Data source: Kenya National Bureau of Statistics, Vihiga County Development Plans (2018-2022), and fieldwork reconnaissance.

Collection of georeferenced household data

We conducted a geocoded household survey to collect data on different aspects of food insecurity from 196 sampled households. During the survey, households were used as the sampling units and the main survey instrument was a questionnaire that had both closed and open-ended questions. The researcher (first author), together with ten research assistants from Maseno University administered the questionnaire through face-to-face interviews of the sampled households. Data quality including accuracy, completeness, and consistency was checked before, during, and after fieldwork. The research assistants were selected based on familiarity with the study area, and ability to speak the local dialects and were engaged in translating the questionnaire into local dialects, and in its pretesting. Ethical approval for the study was granted by Maseno University Ethical Review Committee (reference number: MSU/DRPI/ MUERC/00633/18). Informed consent was sought from every participant before the interviews commenced.

The sample size was computed based on the population of Central Maragoli, which stood at 24,345 persons as of the 2019 population census [185]. We used Cochran's [209] formula to calculate the desired sample size as follows:

$$n_0 = \frac{Z^2 pq}{e^2}$$

where

n_0 = desired sample size if the population is greater than 10,000.

Z^2 = standard normal deviation at required confidence level (95% or 1.96).

p= the degree of variability 'heterogeneity' of the population (p=0.5)

q = 1-p (proportion in the target population)

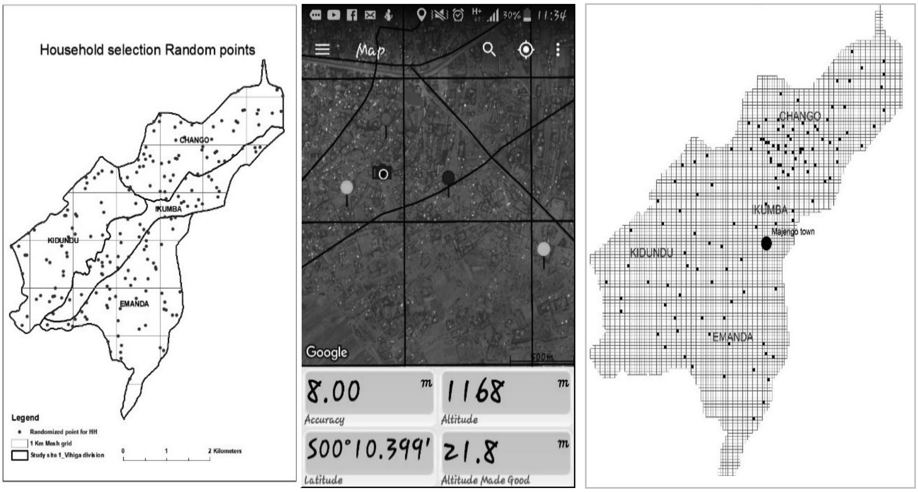
e^2 = the desired level of precision

therefore**,**

$$n_0 = \;= \frac{(1.96)^2(0.5)\,(0.5)}{(0.07)^2} = 196 \text{ sample households}$$

Using the ArcGIS software, we randomly distributed the calculated sample size as point data, in the study area polygon. In distributing these random points, a rule-based algorithm was used that restricted the minimum distance between any two random points to 50 meters. The minimum range between the point data was imposed to prevent spatial clustering of point data and by extension the collected data during fieldwork. During fieldwork, we were guided by the randomly distributed point data to interview households and to achieve a uniformly distributed data collection. We converted these randomized points to a GIS spatial data layer and then superimposed the layer on a high-resolution satellite image of the study area. We then inputted these layers into the 'GPS Essentials App' on the Android phones of the research assistants. During field data collection we used the GPS Essentials App and Google Earth App to geolocate the randomized points. The household upon which the random point fell was selected for interview. To improve data collection accuracy, we partitioned the study area image into a grid of 25 by 25 meters. One household within the enclosed grid where the random point fell was randomly selected for interview. Geographic coordinates from every household that was interviewed were recorded using GPS. These steps are summarized and illustrated in Figure 7.1.

To facilitate the smallest possible spatial unit of analysis that would possibly reveal spatial varying relationships at a local (neighborhood), the sampled households' data were transferred to the raster grids using the 'spatial join analysis' in ArcGIS. Spatial analysis was based on this rasterized layer.



(**a**) Distribution of GIS randomized sample points on gridded study area polygon to aid fieldwork data collection.

(**b**) Fieldwork data collection: Phone screenshot of Keyhole Markup Language layers with the random points.

(**c**) Final output: Surveyed household points spatially joined with rasterized polygon of the study area.

Figure 7.1. Steps applied in the design of geocoded household survey; (**a**) distribution of randomized GIS points; (**b**) uploading of KML layers on 'GPS Essential App' in Android phone, and (**c**) Actual surveyed household GPS points superimposed on the rasterized polygon of the study area.

Selection of indicators for constructing indices

A composite index consists of a set of indicators that are compiled to produce a composite measure [236]. An indicator is designed to describe a particular aspect of the latent phenomenon, and thus it is anticipated that each indicator ideally has a high level of correlation. The reason behind this is that each indicator of the composite index is used to hypothetically describe a unique single aspect of the latent phenomenon, which is viewed as a 'combination' of related different aspects. Principal Component Analysis (PCA) method enables the researchers to choose those indicators 'components' that have a higher probability of conceptualizing reality without the removal of important information before analysis [237]. PCA starts by specifying the indicator, normalized by its mean and standard deviation to calculate the factor weights of each indicator [238,239]. The advantage of PCA, as espoused by Knox (2000), is that it uncovers significant statistical relationships among the independent variables. The method is popular in dimensionality reduction because it attempts to capture the maximum information present in the original data, at the same time minimizing the error between the original data and the new lower-dimensional representation [229,237]. Other methods like stepwise regression do not correctly identify the best variable of a given size and thus may not produce the best model if there are redundant predictors [240]. The authors (ibid) also notes that stepwise regression models sometimes have an inflated risk of capitalizing on chance features of the data, but when applied to new dataset often fail. Whichever the choice of method, Judd et al., [240] stress the importance of researchers being guided by substantive judgment in understanding their data rather than relying on computer models.

For this study, a set of 25 potential explanatory indicators of food insecurity were chosen from the collected household survey data (Table 7.2).

Table 7.2: Selected indicators hypothesized to affect food security in the study area

Food Security dimensions and indicators	Data type	Level of food insecurity (Q1= Worst to Q4 = Least) Quartiles Categories Q1	**Q2**	**Q3**	**Q4**
Availability dimension indicators	*Data type*				
Modern agriculture technology	Ordinal	Low	Medium	High	Very high
Agriculture information	Ordinal	Low	Medium	High	Very high
Agriculture extension services	Binary	No	*n/a*	*n/a*	Yes
Farm inputs and tools	Ordinal	Low	Medium	High	Very high
Land ownership and tenure	Binary	No title deed	*n/a*	*n/a*	Title deed
Possession of agronomic skills	Binary	No	*n/a*	*n/a*	Yes
Land tenure security	Binary	Low	Medium	High	Very high
Utilization dimension indicators					
Tradition and customs	Ordinal	Low	Medium	High	Very high
Gender roles and division of work.	Ordinal	Low	Medium	High	Very high
Women asset ownership	Ordinal	Low	Medium	High	Very high
Women land inheritance	Ordinal	Low	Medium	High	Very high
Eat a balanced diet at least once a day	Binary	No	*n/a*	*n/a*	Yes
Sanitation (toilet) ownership	Binary	No	*n/a*	*n/a*	Yes
Travel time to the nearest water source (mins)	Continuous	>30 min	21-30min	11-20min	0-10min
Piped water in the compound	Binary	No	*n/a*	*n/a*	Yes
The main cooking fuel type used	Categorical	Firewood	Paraffin	LPG gas	Biogas
Stability dimension indicators					
Financial risk	Ordinal	Very high	High	Medium	Low
Pest and disease	Ordinal	Very high	High	Medium	Low
Climate variability	Ordinal	Very high	High	Medium	Low
Personal health risk	Ordinal	Very high	High	Medium	Low
Access dimension indicators					
Travel time to market (mins)	Categorical	>30 min	21-30min	11-20min	0-10min
Travel time to Agrovet shops (mins)	Categorical	>30 min	21-30min	11-20min	0-10min
Access to agriculture credit	Binary	No	*n/a*	*n/a*	Yes
Household income (Kshs)	Continuous	< 1000	1001-10000	10001-20000	>20001
Household savings	Binary	No	*n/a*	*n/a*	Yes
Households' assets (USD)	Continuous	< 500	501-1000	1001-5000	>5000
		Cut-off points	*Households falling in the cutoff category (Q1) are assumed to be most food insecure (poorest)*		

Source: Author.

As illustrated in Table 7.2, each of the four dimensions of food security (availability, utilization, stability, and access) is explicitly defined by several hypothesized indicators conceptualized by the researcher. To establish a multidimensional index that can comprehensively measure food insecurity in the study area, the multiple indicators selected for each dimension were informed by an extensive literature review and informed by the assessment of contextual factors during reconnaissance visits in the study area. we used exploratory factor analysis to select the optimal and representative combination of factors for measuring food insecurity from the household data. The method also enabled the identification of principal indicators with the highest probability of capturing the multifaceted aspects of household food insecurity in the study area. Exploratory PCA was used to reduce the dimensionality of our indicators whereby 16 significant variables were selected as final explanatory indicators for constructing the four composite indices of the dimensions of food security. Likewise, 17 indicators (out of the 41 initially selected) were selected for constructing the composite Food Insecurity Multidimensional Index (FIMI).

Combining and weighting indicators

In this study, we performed PCA using two different sets of indices. The first PCA was performed by merging all the hypothesized indicators of food insecurity to construct FIMI. The FIMI index was constructed by independently combining the weighted combination of the transformed and standardized scores of all sub-indicators of food security. The second PCA was performed using the indices of the four dimensions of food security. We then used GIS to analyze and map geographic patterns of food insecurity using the two sets of indices.

PCA was used to calculate the weights of the indicators, whereby the factor scores of the first principal component were used as weights. This is a standard procedure widely adopted in many studies where the first principle components' factor loadings, that is normally expressed in terms of the original indicator, serve as the composite indicator [184,228,229,236]. The rationale for using the first principal component weight is that, since PCA is based on statistical variance, the first factor accounts for most of the variance in the data, as it has the indicators strongly loaded on the first factor. The variance or the weights for each principal component is given by the eigenvectors of the covariance matrix of the standardized data, which indicates the percentage of variation in the total data explained [241,242] Subsequently, the components are then ordered so that the first component explains the largest possible variation in the original data (ibid.).

Validity and suitability of the constructed indices

As espoused by the Organization for Economic Co-operation and Development [229], the standard practice when selecting the indicators is to extract and retain only those factors that meet the following criteria; eigenvalues values greater than one, total variance more than 10%, cumulative variance greater than 60%, Kaiser-Meyer-Olkin (KMO) coefficient greater than 0.5 and with a statistically significant Bartlett test of sphericity. As explained by Vyas & Kumaranayake [242], "The eigenvalue (variance) for each principal component indicates the percentage of variation in the total data explained" (pg. 463). The KMO normalization coefficient determines the sampling adequacy by measuring the proportion of variance among variables that might be caused by underlying factors (ibid). This ensures the validity and suitability of the constructed indices [104]. High values above 0.5 generally indicate that factor analysis may be useful with the data. The Bartlett Test of Sphericity tests the null hypothesis that the observed individual indicators in the correlation matrix are an identity matrix [104]. In other words, the null hypothesis is not correlated with variances between the groups. This test eradicates redundancy between the variables.

After assessing the extracted principal components' suitability using the above-espoused criteria, our results (Table 7.3) show that all the extracted components meet these criteria, which suggests our data are suited for PCA [243]. The results of the first principal component for the four dimensions indices show the cumulative eigenvalues for the stability dimension is 60.3%, availability dimension (60.1%), access dimension (73.4%), utilization dimension (65.8%), and FIMI (72%). The KMO and Bartlett's Test of sphericity for the four food insecurity dimension indices were all statistically significant. We thus picked the first principal component of each indicator as our composite indicator of household food insecurity.

Table 7.3: PCA results showing the number of principal components extracted per each dimension with their optimal statistical cut-off criteria

Dimension of food security	No. of principal components extracted	% Total variance of components	KMO and Bartlett's Test of sphericity			
		(Eigenvalues) Cumulative %	KMO	*df*	χ	Sig.
Stability	2	60.3%	0.58	21	133.4	.000
Availability	2	60.1%	0.72	15	250.4	.000
Access	3	73.4%	0.52	15	103.2	.000
Utilization	4	65.8%	0.57	28	140.4	.000
FIMI	7	72.1%	0.58	136	614.8	.000

Extraction method: Principal component analysis, rotation method: Varimax with Kaizer normalization. Component loadings with an absolute value of ≥0.50 we retained.

In table 7.3, each of the dimensions of food security is explicitly defined by the hypothesized parameters presented in the previous table (Table 2). To facilitate results interpretation, we categorized households' food insecurity status in four quintiles as follows: Q1=Worst off 25% (assumed to be most food insecure), Q2=Next worst off 25%, Q3=Next best 25%, and Q4=Best off 25% (assumed to be food secure). The cut-off points of these categories were informed by the pre-defined structure of the sampled household data and deduction from the literature review [242].

Mapping the spatial dimension of food insecurity using GIS Hot spot analysis

The spatial patterns of food insecurity can be revealed by analyzing the local spatial autocorrelation in the dataset [237], using ArcGIS software. Spatial autocorrelation is a condition where attribute values closer together in geographic space are assumed to be more likely to share similar attributes (positive spatial autocorrelation) than observations farther apart which tend to have dissimilar attributes (negative spatial autocorrelation) [47,86,96]. The assumption taken when calculating spatial autocorrelation is that relationships between neighboring spatial units are much stronger than between distant ones [47,65]

Getis-Ord GI* Hot spot analysis in ArcGIS is one of the commonly used methods to calculate local spatial autocorrelation [86,91,93]. The method uses spatial statistics to calculate statistically significant spatial clusters of high values (hot spots) and low values (cold spots) (ibid.). In calculating spatial autocorrelation, the geographical unit of analysis and territorial distance should explicitly be determined before performing Hot Spot Analysis [97]. The geographical unit of analysis is the extent of a geographic area to which the underlying spatial process of a phenomenon occurs [98]. The territorial distance is the optimal territorial distance value where the underlying processes promoting spatial clustering in a geographic area are assumed to be most pronounced (i.e., where peak intensity of spatial clustering occurs). Thus, it determines the appropriate spatial unit of analysis [99]. We used the "Incremental Spatial Autocorrelation tool" in ArcGIS to calculate the most optimal (statistically significant) territorial distance value (Figure 7.2). We then used this value as our input value in calculating local spatial autocorrelation.

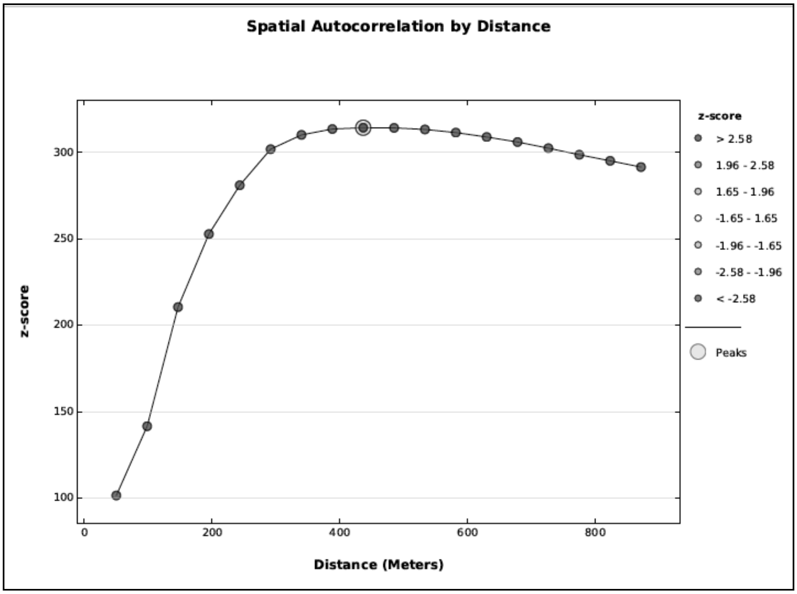


Figure 7.2: Graph showing the optimal territorial distance value (400 meters) where spatial clustering would be most pronounced in central Maragoli.

One challenge that arises in calculating spatial autocorrelation is that in reality, factors promoting spatial autocorrelation tend to be spatially heterogeneous and thus have different potential ways for interactions [88]. To solve this challenge, we calculated the Spatial Weight Matrix (SWM) using a row-standardized matrix for our dataset in ArcGIS to quantify the many spatial relationships that exist among the features. Row standardization creates proportional weights to account where certain features may have an unequal number of neighbors [66,99].

The input data for hot spot analysis was the indices weights of the first principal components of the food insecurity dimension computed from PCA, and the SWM table or the territorial distance value. In the conceptualization of spatial relationships, we used inverse distance parameters and Natural Breaks (Jenks) classification. Before performing spatial analysis, exploratory spatial data analysis was conducted to address the problem of data outliers.

7.3 Results

Household's food security situation

A total of 196 sample household heads, 25% aged 18–35 years, 53% aged 36–60 years, and 22% aged 61 years and above were interviewed. In terms of gender distribution, the interviewed sample size was equally representative, comprising 49% males, and 51% females. Overall, agriculture was the main source of food and livelihood, with the large majority (86%) of interviewed households dependent on subsistence agriculture as their main livelihood activity. Only a small percentage (12%) of the households were engaged in market-oriented farming. The main food crops grown included maize, beans, bananas, vegetables, mangoes, avocados, and pawpaw. A marginal share (2%) of sampled households grew cash crops (sugarcane and rice), albeit in small quantities. The majority (62%) of households had small landholdings of less than 2 acres. Overall, and based on self-assessment, 36% of sampled households reported having experienced food insecurity in the last 12 months (Table 6.4). A crosstabulation between household food insecurity status and household types revealed that there were more male-headed households (38%) that were reported to be food insecure than female-headed households (30%). This underscores the important role women play in ensuring the household's food security.

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Table 7.4: Crosstabulation of frequency (percentage of total) for household food insecurity vs. household type in Central Maragoli

	Experiencing food insecurity		Total
	Yes	No	
Male-headed household	56(38%)	90(62%)	146(100%)
Female-headed household	15(30%)	35(70%)	50(100%)
Total food (*in*)secure	71(36%)	125(64%)	196(100%)

The spatial dimension of food insecurity as mapped using FIMI

From a conceptual perspective, the FIMI incorporates multifactorial indicators to cover all aspects of food insecurity and reveal the main hotspots of food insecurity in central Maragoli. The spatial analysis output (figure 7.3) shows the spatial dimension of food insecurity in central Maragoli, as mapped using FIMI. The FIMI index produces a more distinct spatial pattern, revealing a significant spatial difference in food insecurity levels in the study area.

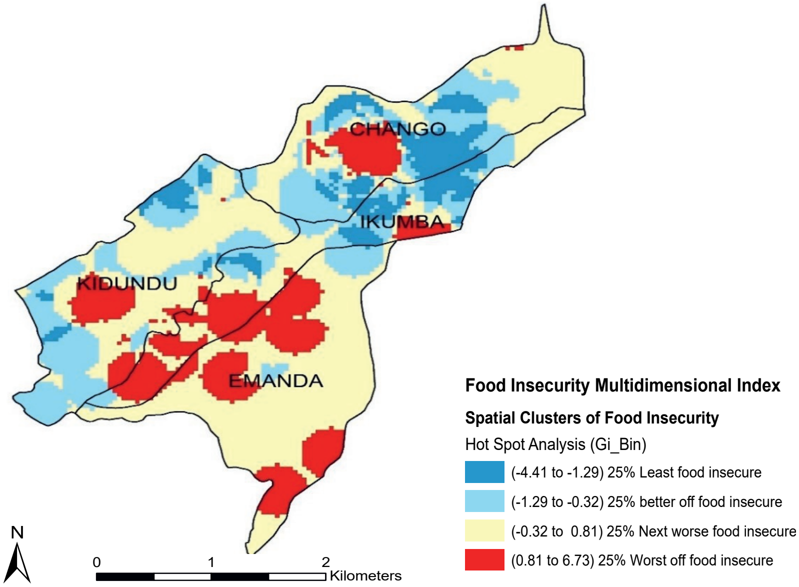

Figure 7.3: Spatial patterns of food insecurity in Central Maragoli as geo-visualized using FIMI.

Spatially, the majority of households experienced food insecurity (areas in yellow color). There were a few cold spot clusters (areas in blue color). Households in cold clusters were categorized as food secure. The larger cold cluster in the northern part of the study area is located on the outskirt of Mbaale town, the main urban center of Vihiga county. The households' food security in this area may be associated with the access dimensions (map 7.4 a) and availability dimensions (map 7.4 b). However, the same area, when mapped using the disaggregated indices, turns out to be food insecure, especially in access dimensions (map 7.4 a) and utilization dimensions (map 7.4 c).

In figure 7.3, there are several spatially concentrated 'hot spots' of households experiencing high levels of food insecurity in the study area. These food insecurity hot spots (areas in red color) are more pronounced in the lower southern area in Emanda and Kidundu wards. Geographically, we found these areas to be characterized by many rock outcrops and undulating hills, and, hence, had a limited agricultural production potential. The second hot spot cluster is in the upper northern parts of the study area, in Chango ward. Several reasons could be attributed to the occurrence of this hot spot. First, the hot spot is located on the immediate outskirts of the main urban center (Mbaale town) of Vihiga County. The town outskirts have a higher concentration of deprived population, some of them who had very small land sizes. While proximity to town improves access and availability dimensions of food security, it was not a guarantee of stability and utilization (see maps in figure 7.3a-d). Secondly, the area had a higher level of land fragmentation due to a higher rate of conversion of agricultural land to residential and commercial development. This resulted in small uneconomical land sizes that barely produced enough food to meet the food demands of households.

The occurrence of food insecurity hot spot clusters means that factors causing food insecurity were more pronounced in some areas than others. In addition, it implies that the causal factors of food insecurity had spatial autocorrelation that is linked to local geographic specificities predominant in the place of residence of those households. The combination of all these factors decreased poor smallholders' resilience in responding to food insecurity problems.

The spatial dimension of food insecurity as mapped using disaggregated dimensions of food security

In the preceding section, the examination of the geographic patterns of food insecurity has focused on the overall FIMI, but it is important to remember that food insecurity emanates from multiple and complex factors. This section deconstructs this complexity by mapping the spatial dimension of food insecurity using the four dimensions of food security. The maps of individual indices (see figures 7.4a to d) reveal a spatially disaggregated patterning of food insecurity across the study areas. Each dimension reveals a geographical variation of food insecurity that is unique to specific areas, with some areas having hot spots of food insecurity and others being relatively food secure. Some localities identified as food secure on the FIMI map are shown to be food insecure based on disaggregated indices. In one locality, high food insecurity may be related to a low level of access or availability indicators, while in another, food insecurity may be due to utilization or stability factors. This shows that causes of food insecurity are complex and multidimensional and thus the need for location-specific and spatially targeted interventions.

Generally, as shown by the four maps (see figure 7.4), central Maragoli experiences a high level of food insecurity (25% next worse food insecurity). This is shown by the prevalence of yellow color in most parts of the study area. The maps depict several pockets of food insecurity hot spots (25% worst off food insecure), geo-visualized by the red color. In addition, there are relatively food secure areas (25% better off food secure) that are geo-visualized in light blue color and also food secure areas (25% best food secure) in dark blue color.

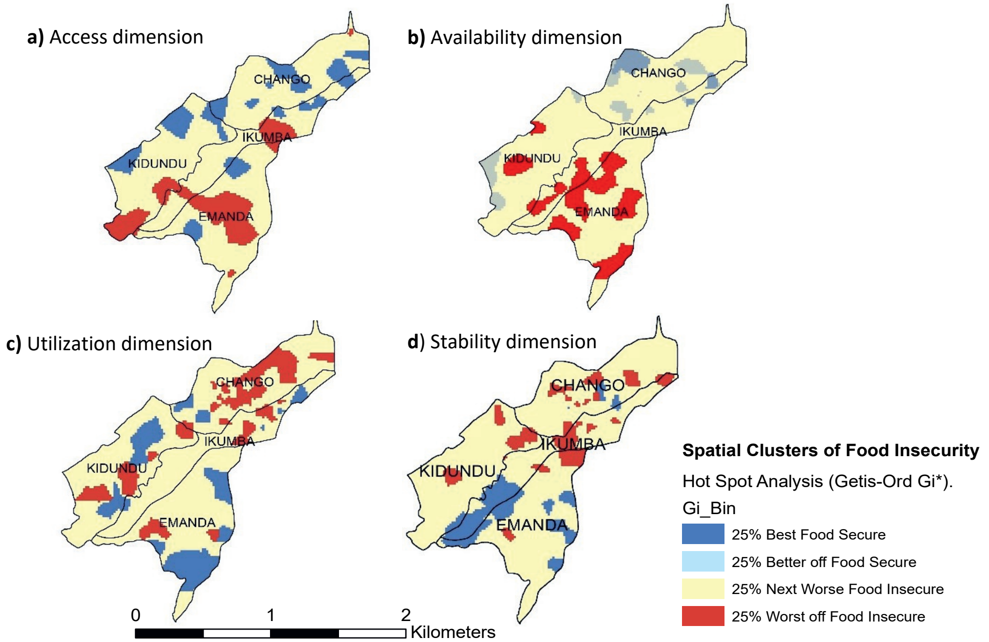

Figure 7.4: Maps showing spatial patterns of food insecurity for the individual dimensions of food insecurity in Central Maragoli.

The access dimension map (*map 7.4a*), depicts a higher level of food insecurity spread across the study area (yellow areas), with a few spatial clusters of food insecurity hot spots (red areas) mostly located in the southern area of Kidundu and Emanda Wards. Explanatory causes of food insecurity based on the access dimension include; low level of access to agriculture credit, low level of household savings, low level of household assets ownership and low level of household income (average household income was USD 160), and longer distances (average distance was 2.2 Kms) to input and output markets by households in the study area.

In the availability dimension map (*map 7.4b*), there is a higher spatial clustering of food-insecure households (red areas) in the southern parts of the study area, in Kidundu and Emanda Wards. From our analysis, the explanatory factors causing food insecurity based on the availability dimension include; a low level of farming skills, a low level of access to farming technology, a low level of agriculture information, and a low level of farm inputs.

In the utilization dimension map (*map 7.4c*), hot spots of food insecurity are mostly concentrated in the northern area of Chango Ward, with small pockets of hot spots also scattered across the study area. The results show that food insecurity attributable to the utilization dimension is caused by several factors; low level of women's asset ownership, and low level of access to clean water in the compound. In addition, there was low land ownership by women that emanated from customary land inheritance practices that bequeathed men with higher custodial rights to land ownership than women.

In the stability dimension map (*map 7.4d*), pockets of hot spots of food insecurity are more pronounced in Chango and Ikumba Wards. Results show that stability dimension factors causing food insecurity include; the unpredictability of weather, the prevalence of pests and diseases, low levels of access to capital, and personal risks (i.e., impact on human health).

A comparison between the output maps of FIMI and the four dimensions indicators (Figures 7.3 and 7.4) shows a significant geographic difference in the spatial patterns of food insecurity. For example, the FIMI tends to mask significant hotspots clusters of food insecurity that are revealed by the other four maps. This may be attributed to the aggregation of data, a problem called the modifiable areal unit problem. Consequently, this implies that FIMI, and by extension, indicators developed by highly aggregated data may not be very effective in unearthing local-level determinants of food insecurity.

Disaggregating the root causes of household food insecurity

The results of the PCA analysis characterize the multifarious determinants of food insecurity. Table 7.5 presents the results of PCA for the FIMI index, revealing how various socioeconomic characteristics of the households contributed to food insecurity.

Table 7.5: Rotated Component Matrix from Principal components analysis of FIMI

	Extracted components and loading weights							
FIMI indicators	1	2	3	4	5	6	7	Communality (h^2)
Farming skills	.867							0.80
Farming technology availability	.817							0.74
Agriculture info. Availability	.804							0.67
Farm inputs availability	.568							0.58
Women's roles/division of work		.768						0.65
Traditions and norms influence		.800						0.74
Weather variability			.851					0.79
Pest and diseases impact			.825					0.73
Distance to markets				.914				0.85
Distance to Agrovet shops				.907				0.85
Household assets ownership					.768			0.75
Household income					.726			0.77
Land tenure security					-.608			0.51
Women asset ownership						.781		0.68
Women land inheritance						.641		0.69
Personal risks (health) effect							.830	0.78
Financial risks effect							.764	0.67

Extraction method: Principal component analysis, rotation method: Varimax with Kaizer normalization. Loadings with an absolute value of ≥0.50 are displayed

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In the table, the last column shows the results of communalities (denoted by h^2). A communality is an extent to which an indicator correlates with all other indicators. The common variance ranges between 0 and 1. Values with a score closer to 1 suggest that the extracted factors explain more of the variance of an individual item, while factors with lower communalities (i.e., less than 0.4) imply that they may struggle to load significantly on any factor. In our results, most factors have a communality of greater than 0.5, meaning they all have a higher significant influence on household food insecurity. Seven principal components were extracted in the FIMI that accounted for a total cumulative variance of 72%, an eigenvalue greater than one, and the Bartlett test of sphericity of 614.8 ($p < 0.001$). Only the factors with a KMO coefficient greater than 0.50 were extracted. Generally, a variable with a positive factor score is associated with a higher FIMI, and conversely, a variable with a negative factor score is associated with a lower FIMI. Most of the extracted factors had a positive score apart from land tenure security, meaning it had a lower influence on household food insecurity.

Overall, factors with the highest factor loading and highest communalities included distance to markets, (0.914, $h^2 = 0.85$) and distance to Agrovet shops (0.907, $h^2 = 0.85$), meaning they exerted the highest influence or were the highest contributors to household food insecurity in the study area. The first group of factor components, explaining 16% of the total variance, with the highest influence on household food insecurity include; low level of farming skills, with factor loading and communalities of (0.867, $h^2 = 0.80$), farming technology availability (0.817, $h^2 = 0.74$), agriculture information availability (0.804, $h^2 = 0.67$), and farm inputs availability (0.568, $h^2 = 0.58$). Among these indicators, farming skills were strongly correlated ($r = 0.68$) with the composite indicator, while farming technology availability was moderately correlated ($r = 0.59$) with agriculture information availability. These characteristics are evidence of multiple deprivations status of a household, a situation that traps many resource-poor households in the vicious cycle of poverty and by extension food insecurity.

For the availability dimension (Table 7.6), the PCA extracted two components that have total cumulative Eigenvalues that explain 60% of the total variance. The factor I indicators accounted for 41% while factor II indicators accounted for 19% of the total variance.

Table 7.6: Rotated Component Matrix from principal components analysis of **Availability Dimension** indicators

Indicators	Factor I	Factor II	h^2
Farming skills	0.84		0.76
Farming technology	0.81		0.66
Agriculture information	0.78		0.62
Farm inputs access	0.68		0.52
Land tenure security		0.73	0.54
Agricultural extension services		0.72	0.52

Extraction method: Principal component analysis, rotation method: Varimax with Kaizer normalization. Loadings with an absolute value of ≥0.60 are displayed

Farming skills had both the highest factor loading and highest communality (0.84, $h^2 = 0.76$). This means low farming skills exerted the highest influence within the availability dimension in causing food insecurity in the study area. Other factors which contributed to food insecurity included; low level of farm technology (0.81, $h^2 = 0.66$), low level of agriculture information (0.78, $h^2 = 0.62$) and low level of access to farm inputs (0.68, $h^2 = 0.52$). Results of bivariate correlation between availability dimension indicators reveal that a low level of farming skills had a higher positive correlation with agriculture information availability (0.625, $p<0.05$). Farm input access moderately correlated with farm technology access (0.440, $p<0.05$). The close similarity of spatial patterns of food insecurity between FIMI and availability dimension indicators implies that factors causing food insecurity are strongly related to each other and could be among the main causes of food insecurity in the case study.

In the stability dimension (Table 7.7), PCA extracted two components that cumulatively accounted for 60% of the total variance.

Table 7.7: Rotated Component Matrix from Principal components analysis of **Stability dimension** indicators

Indicators	Factor I	Factor II	h^2
Weather variability	0.84		0.71
Pest and diseases influence	0.83		0.68
Financial risks (capital)		0.86	0.75
Personal risks (human health)		0.80	0.70

Extraction method: Principal component analysis, rotation method: Varimax with Kaizer normalization. Loadings with an absolute value of ≥0.60 are displayed

The first group of indicators accounted for 34% of the variation in the original data. These included the weather variability (0.84, h^2=0.71) and pests and diseases (0.83, h^2= 0.68) that adversely affected the food security level of the households. The second factors loadings, accounting for 26% data variance included financial risks (0.86, h^2=0.75) and personal risks (0.80, h^2=0.70). This indicates they also exerted a higher influence on smallholder households' food security status. Bivariate correlation results show that pests and diseases influence had a higher positive correlation with weather variability influence (0.503, $p< 0.05$, 1-tailed). Equally, financial risks had a moderate correlation with personal risks (0.386, $p<0.05$, 1-tailed).

In the utilization dimension, the results (Table 7.8) show that two factors, women's land inheritance (0.85, h^2=0.75) and women's asset ownership (0.81, h^2=0.73), exerted the highest influence on household food insecurity, while gender roles and division of work (0.69, h^2=0.52) had a lower influence.

Table 7.8: Rotated Component Matrix from Principal components analysis of **Utilization dimension** indicators

Indicators	Factor I	Factor II	Factor III	Factor IV	h^2
Women land inheritance	0.85				0.75
Women asset ownership	0.81				0.73
Gender roles and division of work	0.69				0.52
Distance to the nearest water source		-0.76			0.63
Eat a balanced diet at least once a day		0.65			0.66
Sanitation (toilet ownership)			-0.77		0.66
Piped water in the compound			0.71		0.58
The main cooking fuel type used				0.86	0.74

Extraction method: Principal component analysis, rotation method: Varimax with Kaizer normalization. Loadings with an absolute value of ≥0.50 are displayed

In the access dimension, PCA resulted in three principal components cumulatively explaining 73% of the total variance in data (table 7.9).

Table 7.9: Rotated Component Matrix from Principal components analysis of **Access dimension** indicators

Indicator	Factor I	Factor II	Factor III	h^2
Distance to Agrovet store	0.91			0.83
Distance to markets	0.91			0.83
Access to agric. credit		0.89		0.79
Household savings		0.73		0.60
Household assets			0.89	0.80
Household income			0.68	0.56

Extraction method: Principal component analysis, rotation method: Varimax with Kaizer normalization. Loadings with an absolute value of ≥0.60 are displayed

The first principal component, having the highest factor loading and accounting for 29% of variance includes distance to Agrovet stores (0.91, h^2= 0.83) and distance to output markets (0.91, h^2= 0.83). These are identified to have exerted the highest influence on household food insecurity in the study area. The second set of factors exerting high influence in the access dimension, with a variance of 22%, included; low access to agriculture credit (0.89, h^2= 0.79) and low household savings (0.73, h^2= 0.60). Equally, the third principal factors included low household assets (0.89, h^2= 0.80) and household income (0.68, h^2= 0.56).

The correlation analysis of the indicators found that a household suffering from food insecurity is more likely to be deprived of income, savings, and assets and tended to be located farther away from input markets (agro vet stores). the results also revealed a positive correlation between household assets and household income (0.32, $p < 0.05$), and between household savings and access to credit (0.38, $p<0.05$).

Comparing the results of FIMI and the four-dimension indices of food security

Table 7.10 shows the bivariate correlation matrix results between FIMI and the four dimensions of food insecurity.

Table 7.10: Bivariate correlations between FIMI and the four dimensions of food insecurity

Dimension	Stability	Availability	Access	Utilization	FIMI
Stability	1				
Availability	-.028	1			
Access	-.051	.048	1		
Utilization	.311**	-.136	-.024	1	
FIMI	-.072	**.982****	.068	-.147*	1

**. Correlation is significant at the 0.01 level (1-tailed): *. Correlation is significant at the 0.05 level (1-tailed).

The highest strong positive correlation (r=0.982) was observed between FIMI and the availability dimension index. This indicates that a low level of availability dimension factors among households accounts for the highest causes of food insecurity in the study area. These factors include; a low level of farming skills, (which has the highest loading), meaning it accounts for the highest influence, a low level of access to farming technology, a low level of agriculture information, a low level of farm inputs, low level of land tenure security and low level of agricultural training services. This implies that if these factors were addressed concurrently and comprehensively, there would be a very significant reduction in food insecurity in the majority of households in the study area. Results also show there is a small negative correlation (r=-0.147) between FIMI and the utilization dimension, which indicates that, generally, utilization dimension indicators have a lesser influence when computed and compared with FIMI.

7.4 Discussion and policy implications

Mapping the spatial dimension of agriculture and food insecurity is important for several reasons. There is an increasing recognition that place-specific features and geographic specificities strongly influence food security outcomes. An investigation of local spatial patterns of food insecurity thus offers important insights into the spatial disparities of the territorial dimension of food security and poverty. The traditionally "top-down" and sector-specific food security policies, often formulated at the national levels, without sufficiently taking into account the local socio-spatial heterogeneity, would not be sufficient conditions to address the multi-dimensional aspects of food security at the local level. This informs policymakers of the need for formulation of bottom-up, and context-specific policies and interventions to address the complex causation of low agriculture productivity and food insecurity.

The causes of food insecurity among resource-poor households are deeply rooted in their multiple deprivation status. Multiple deprivations are a consequence of spatial inequalities, socioeconomic exclusion, and segregation of rural areas where the majority of poor smallholders reside. All of these act as a barrier to poor smallholders in productively exploiting the resources at their disposal. As such, research to improve the understanding of the spatial dimension of food insecurity and its causative factors ought to deconstruct the spatial complexity and processes operating in the local environment. This can be achieved by spatially modeling the local geographic factors operating within the environments within which smallholder production systems operate [31,32]. The outputs could be useful to policymakers and food planners in generating spatially relevant policy information for diagnosing food insecurity at a local level and in food security planning [33]. As the study has shown, composite indicators like FIMI could be useful in mapping the spatial manifestation of food insecurity and can reveal hotspots of food insecurity. However, it may also conceal intricate details of food insecurity due to several parameters including the level of aggregation of data and indicators and the spatial level 'unit' of analysis. Lack of a clear articulation of these factors before constructing the indicators would make it difficult for policymakers to diagnose local-level determinants of food insecurity and unearth local spatial clusters of food insecurity and deprived households. Spatial targeting of interventions could be more effective if informed by disaggregated indicators because spatial interactions between factors influencing households' farming activities and local environments are more evident at the lowest spatial level. This is a result of the geographical coalescing (or spatial autocorrelation) of attributes with similar values [47,64].

In many LMICs, sectoral policies and interventions for tackling food insecurity and disparities across geographic areas have traditionally narrowed their scope by prioritizing agriculture productivity, without sufficiently taking into account other multidimensional aspects of food security. Typically, food security policies often formulated at the national level, and implemented through a top-down approach tend to ignore the geographic variability of food insecurity. If policies to address food insecurity are to be effective, they should recognize that food (in)security spatially differs and that the nature and magnitude of food (in)security also vary within and across local, rural, regional, and urban territories. Crescenzi and Rodríguez-Pose [244] postulate that policies formulated from the bottom-up are seen to be more spatially sensitive to the spatial heterogeneity of localities than those formulated from the top down.

In like manner, the adoption of agriculture policies that integrate local territorial specificities could be more responsive in addressing local spatial inequalities of food insecurity and local constraints of agricultural production [57]. Labidi [245] posits that spatial inequalities of food insecurity and development emanate from the weak integration of spatial development policies at the national, regional, and local levels. As such, food security experts, spatial planners, and local governments need to go beyond agriculture by taking a territorial approach that fosters the integration of the geographic dimension of food insecurity and the multi-dimensional perspective of territorial development planning [68,246]. This would give more prominence to territorial-explicit factors affecting smallholder agriculture productivity and food security. Addressing this would also require a multisectoral and multilevel integration of macro enabling policies, sectoral policies, and spatial planning policies to comprehensively address the broader context of territorial development inequalities, poverty, and spatial disparities of food insecurity. This would also require the strengthening of sectoral and institutional and policy frameworks and collaboration at local, regional, and national planning levels. We posit that a holistic approach to territorial agricultural development could achieve desirable spatial equity, thus enhancing agricultural sustainability, equitable resource distribution, and equitable territorial development. [68,159].

With the current challenges affecting global agri-food supply chains and the inherent inability of many rural smallholders to access emerging agri-food value chains, there is a need for a paradigm shift in policy development towards the strengthening and supporting of local agribusiness food supply chains. Localized food systems would greatly benefit from spatially explicit studies that bring clarity to local spatial processes that impact agricultural production and food security. The development of local food systems would be premised on leveraging poor smallholders' inclusive growth whilst transitioning their fragmented subsistence-centered production and spot-market transactions to more agribusiness-oriented production and direct-market networks [11]. A territorial, place-based approach, that recognizes the diversity of food security would provide an integrated framework for the integration of local, regional, and national food policies. Such a framework and approach would allow for the formulation and implementation of integrated and place-based policies [247] that tap into the resource heterogeneity of territories and would create the prerequisites required to develop localized food systems while enhancing their sustainability. This would also facilitate the development of rural-urban market interlinkages and the removal of physical, and institutional barriers that prevent local food systems from being integrated with regional, national, and global agrifood value chains and markets [248,249].

7.5 Conclusion

This study has used georeferenced households' socio-economic data, and combined PCA and GIS analytic tools to explicitly integrate the different dimensions of food insecurity to arrive at a multidimensional characterization of the households suffering from food insecurity. By constructing GIS-based indices and using a small area approach, the paper mapped and geo-visualized the spatial dimension of food insecurity, thus providing a better-contextualized understanding of the local-level spatial patterns of food insecurity. The results have shown that several factors interact concurrently to cause food insecurity. Overall, the main determinants of food insecurity were in the availability dimension, specifically the low level of farming skills, farming technology, agriculture information, and farm inputs. In the stability dimension, climate variability, pests, and diseases adversely affected the level of food security of the households. In the utilization dimension, low levels of women's land ownership and low asset endowment exerted the highest influence on household food insecurity. In the access dimension, access to inputs (agro vets) and output markets adversely contributed to food insecurity. In formulating place-based policy interventions adapted to local needs, composite indicators, constructed using aggregated indicators, may not fully diagnose locally expressed needs. An alternative approach would be to disaggregate the FIMI into the four dimensions of food security. This would enable diagnosis and spatial targeting of localities and multi-deprived households experiencing food insecurity.

The use of GIS-based indicators in conjunction with a small area approach could provide policymakers and government with better methods for mapping and geo-visualizing the multidimensional characterization of food insecurity at the local level, thereby improving the spatial targeting of food insecurity. According to Martinez [73], the combination of GIS-based indicators and spatially explicit methodologies presents a more viable diagnostic tool for mapping local spatial interactions and increases the effectiveness of unearthing deep-rooted causes of social problems. The identification of geographically deprived areas and clusters with higher concentrations of hotspots of food insecurity is particularly useful in identifying the most vulnerable households. This knowledge would provide policymakers and local governments with an evidence-based approach in the application of remedy policies for prioritization of resources, spatial targeting of resources, and the design of location-specific interventions to improve poor household livelihoods and welfare [69].

Consequently, the multidimensional nature of food insecurity and its causal factors underscore the need for integrated agriculture policies that are spatially sensitive to the spatial variation of food insecurity and spatial heterogeneity of territorial resources. With the increasing embedding of agricultural production and food insecurity problems in local spatial complexity, and, given the multidisciplinary nature of food security, spatially targeted policies are needed to address hunger, food insecurity, and spatial inequality. By analyzing and mapping the spatial distribution of households' inequalities and factors causing food insecurities, policy planners can better target deprived areas and develop appropriate, location-specific intervention strategies. Equally, spatially explicit analytical outputs would provide policymakers with comparative information on the spatial patterns of food insecurity, and decision-making outcomes of households at both the neighborhood level and across territories. This would enable policymakers to draw important inferences on the underlying spatial variations between local geography and agriculture productivity, and how these influence households' food security statuses. We recommend that multidimensional factors of food insecurity be addressed comprehensively and concurrently, starting at the local level, with more emphasis on the poorest and most vulnerable households, to enhance smallholder agriculture and food security. This would require policymakers to adopt a territorial approach to food security planning and designing spatially integrated food security policies that are multisectoral, and multidisciplinary.

Limitations of the study

This study relied on self-reporting of food insecurity statutes by households. However, data based on self-reporting measures may have potential limitations related to validity and accuracy. For example, during interviews, households may over/underestimate their status of food insecurity. We addressed this shortcoming by cross-validating the collected data and triangulation of data. We also designed the questionnaire with several open and closed-ended questions to collate the same information. Another limitation is that, often, composite indicators used to monitor spatially linked problems, frequently apply aggregated data collected at national, subnational, or regional levels. A criticism of using indicators generated at a higher spatial level of aggregation is that they can produce a misleading output and representation of the problem they address and quantify [73]. This emanates from the problem of ecological fallacy – a situation whereby inferences made from geographically aggregated data e.g., indicators constructed exclusively from census data, can produce misleading outcomes. It can also result in a modifiable areal unit problem, in which aggregation of data may mask important spatial differences when mapped at different spatial levels. This often hides the stark contrast between better-off and poor households in a locality, since not every person living in a better-off area is necessarily well-off and vice versa. We overcame this problem by designing a geocoded household survey that collected georeferenced spatial data at the household level and then used GIS-based local spatial autocorrelation methods to map spatial patterns at the neighborhood level. We rasterized our study area administrative polygon into small equal-sized grid cells to lower our spatial unit of analysis. This diminishes the extent of measurement error and improves the measurement of local spatial heterogeneity of problems under investigation [74,76]. Another limitation associated with spatial autocorrelation analysis is that if the data collected is not uniformly distributed across the study areas, the subsequent analysis may produce false hotspots from the areas the data collection was concentrated. To overcome this problem, after calculating our sample size, we used ArcGIS functionalities to evenly distribute the sample point in the study area and partitioned our study area into small grids. Then we used GPS-enabled android phones during fieldwork to geolocate the randomized sampled points falling in these grids, and the household into which the random point fell was earmarked for interview.

Chapter 8

Integration of the Spatial Dimension of Agriculture and Spatial Planning in Policy Frameworks for Improving the Sustainability of Smallholder Agri-food Systems. A case study of Kenya

***Picture**:* A green house at Bezoek Agriport excursies, Amsterdan. Source: Author

Mathenge, M., Sonneveld, B. G. J. ., & Broerse, J. E. (2022). Integration of the spatial dimension of agriculture and spatial planning in policy frameworks for improving the sustainability of smallholder agri-food systems. A case study of Kenya (*submitted to land use policy*)

Abstract

Smallholder agriculture sustainability and food security is a multicausal and multidisciplinary challenge that requires integrated public policy responses at different spatial scales and across policy domains. However, albeit many Low and Middle-Income Countries (LMICs) advocate for a multifaceted policy approach in addressing smallholders' sustainability issues, the majority of agriculture and spatial policies are not usually sufficiently integrated. Rather, many of the agriculture policies in LMICs are sector-specific and lack multi-level, multi-sectoral, and multi-actor policy integration. This study aims to assess the effectiveness of agriculture and spatial "agri-spatial" policy integration in improving the sustainability of smallholder farmers. This is achieved by conducting an in-depth analysis of the structural and practical inhibitors and facilitators for policy integration. We used Kenya as a case and focused on the County government of Vihiga in Western Kenya. We employed a mixed-method approach, combining key expert interviews, desktop policy analysis, and semi-structured interviews to collect and synthesize data. The study findings reveal that decentralization of agriculture and spatial planning governance frameworks from national to County governments provided an expanded opportunity for agri-spatial policy integration. However, several factors impeded agri-spatial policy integration including fragmented policy instruments, weak legal and institutional frameworks, and a lack of synchronization of the many disjointed sectoral policies and plans. There is a need for governments in LMICs to adopt more pragmatic approaches for multi-level, multi-sectoral, and multi-actor policy integration. In addition, there is a need for strengthening institutional and policy frameworks to support agri-spatial policy integration in achieving agriculture sustainability and food security.

Keywords: policy integration, spatial planning, agriculture planning, smallholder agriculture, food security, agriculture sustainability. Agri-spatial integration

8.1 Background

Many governments in Low and Middle-Income Countries (LMICs) have endeavored to formulate and implement agriculture policies and institutionalize reforms in the agricultural sector aiming at revitalizing smallholder agricultural productivity, food security, and agribusiness development [56,212,221,222,250]. Despite these efforts, various studies observed persistent food insecurity inequalities, poverty, and socio-spatial exclusion of smallholder agriculture systems in the mainstream spatial and development planning [58,221]. Agriculture policies and food security interventions have been criticized for lack of spatial explicitness, especially when addressing those factors of spatial nature or those which can be directly linked to certain local geography like poor roads, pest and disease infestations, poor agronomic practices, lack of access to credit, among others. Several empirical studies [57,64,244] show that problems affecting smallholders' productivity tend to share intrinsic spatial characteristics of the local geographic specificities. This implies that policy proposals to address these problems should encompass spatially targeted interventions and possibly be formulated at the local level, rather than at the higher echelon of government, as has been the case in many LMICs. Addressing the placed-based and multidimensional nature of these challenges requires the integration of physical, social, economic, political, environmental, and spatial aspects of agricultural production and a spatial 'territorial' approach. This requires not only multisector coordination but also multilevel (territorial) and multi-actor pragmatic approaches.

Although the need for integrated agri-spatial policy responses is increasingly acknowledged [57,250], many agriculture policies and interventions are still sector-specific oriented, devoid of multi-level, multi-sectoral, and multi-actor coordination and cooperation across policy domains. The lack of vertical and horizontal policy integration can be attributed to a myriad of factors. On the one hand, the traditionally strong focus of agriculture policies on improving agricultural productivity at the expense of other dimensions of agriculture (i.e., social, economic, cultural, environmental, and spatial aspects), narrows the scope of the highly context-specific and place-based nature of agriculture and food security. On the other hand, food insecurity reduction per se has not been a priority of spatial planning policies [251]. At any rate, spatial planning policies have not adequately addressed agriculture productivity and related food insecurity inequalities. Traditionally, the top-down spatial planning policies widely adopted by many LMICs are overly biased towards promoting the economic side of land-use planning, while giving little emphasis on agri-food systems planning [56,62,246,251]. This is despite the popular assertion that rural agricultural lands of many LMICs act as the 'bread baskets' for feeding the growing urban population [7]. This continuous 'agri-spatial' policy disconnect and the dichotomous rural-urban divide have been blamed for perpetuating food insecurity, poverty, and marginalization of rural areas by various scholars and international organizations [57,58,63]. The spatial and development policy disconnect often presents major impediments not only to effective policy integration but to practical policy implementation at the grass-root level.

This study aims to expand the current knowledge of policy integration and assesses the effectiveness of agri-spatial policy integration for a project geared toward improving the sustainability of smallholder farmers. To this end, we conducted an in-depth case analysis to understand the structural and practical inhibitors and facilitators of policy integration in Kenya at the national and local levels. Based on these, we make practical recommendations for implementing policy integration, especially on integrated agri-spatial projects to address the multidimensional challenges that hinder the sustainability of small-scale agriculture. Before going into the case study, we first further conceptualize policy integration in the context of spatial planning.

Policy integration in spatial planning

Broadly speaking, spatial planning sits at the nexus of integration between different spatial 'territorial' scales and across sectoral policy domains [252,253]. As Borisov [254] notes, spatial planning is an important policy instrument for "coordination or integration of the spatial dimensions of the sectoral policies through territorial-based strategies, complex regulations on land use and the contradictions between sectoral policies" (p.1142). To achieve sustainability, policies and plans should integrate the intertwined complexities of social, economic, cultural, and environmental dimensions of development planning. Spatial planning provides an overarching framework and the means for integrating the spatial aspects of these dimensions in policies and plans geared towards addressing the sustainability of agriculture and food security.

Ran & Nedovic-Budic [255] define "integration" as an approach to strengthen linkages, cooperation, and interconnections between spatial, sectors, and policies. Sue Kidd & Kidd [256] view integration as a strategic approach that can aid to structure solutions to complex multidimensional societal problems that cannot be addressed by a single jurisdiction or from one perspective. In literature, several synonymous terms have been applied to refer to policy integration including policy coordination, cooperation, cross-cutting policy-making, joined-up government, policy coherence, and holistic government [257]. Stead, Domonic, and Jong [258] view policy integration as the management of cross-cutting issues in policy-making and implementation that transcends the boundaries of responsibilities of established institutions, sectors, and individual departments.

Spatial plans and interrelated sectoral policies are formulated at different spatial scales and across policy domains and are often characterized by the complexity of conflicting and divergent goals, objectives, intertwined challenges, different visions, expectations, etc. In achieving coherence, policy integration can be used to harmonize and synchronize policy issues that straddle sectors and those with conflicting goals. Integrated policies ensure that envisioned development goals and solutions proposed in the plans are holistic and sustainable in supporting social, economic, political, and environmental aspects. Policy integration thus serves as an important mechanism for contributing to sustainable development, promoting synergies and consistency between sectoral policies, reducing duplication in the policy-making process, promoting innovation in policy formulation and implementation, and can help in addressing trade-offs and improving the achievement of cross-cutting issues [253,254,259].

The literature identifies different dimensions and types of policy integration in spatial planning [260–262]. These are presented in Table 8.1 and include sectoral integration (cross-sectoral and inter-sectoral), territorial integration (vertical and horizontal), organizational integration (strategic, and operational), and disciplinary and stakeholder involvements (professional domains and actors).

Table 8.1: Dimensions and types of policy integration in the spatial planning domain

Dimension of integration	Type of policy integration	Description
Sectoral	Cross-sectoral integration	• Integration (collaboration) between different sector's policy domains within a territory.
	Inter-sectoral integration	• Integration of several sectors including public, private, and other sector activities within a territory.
Territorial (multi-level)	Vertical integration	• Integration between actors and spatial policies across spatial scales of government (national, regional, county, or local levels)
	Horizontal integration	• Integration between sectoral policies in ministries, and departments, and between professions and staff working in these sectors
Organizational	Strategic integration	• Integrating spatial planning policies with other strategies within a territory.
	Disciplinary / stakeholder integration	• Integration of different disciplines and stakeholders within a territory.
	Operational Integration	• Integration of spatial planning with the delivery mechanisms in all relevant agencies within a territory

Sources: [255,260–262]

In the spatial planning context, various policy instruments and integration mechanisms are used in promoting policy integration including policies, and legal and institutional mechanisms [259,263]. These instruments provide departments with mandates and responsibilities in addition to dictating formal rules, procedures, processes, and channels of policy integration. They also help policymakers in government and relevant stakeholders at different territorial levels to synchronize cross-cutting and often divergent goals, build consensus, harmonize competing goals, and coordinate wider policy-making and implementation activities [256]. According to Stead and Meijers [259], policy integration mechanisms can be formalized in terms of intergovernmental and interdepartmental committees or specially purposed institutions that can coordinate multi-sectoral policies, define priorities, and integrate the spatial aspects of multi-sectoral policy with the spatial development frameworks. In the absence of formal rules and procedures, policy integration and coordination across policy domains may also be facilitated through informal arrangements, where interactions and arrangements that emerge between individuals and organizations within the same policy level and across departments can be used as a vehicle to promote integration [264].

8.2 Data and methods

In this section, we detail the case study and methods used to collect and analyze data.

Case description and research setting

Since Kenya provides the setting of our case study, we describe Kenya's spatial planning system and identify the inbuilt instruments and mechanisms of policy integration. Post-independent Kenya has been shaped by an intertwined spatial planning and development planning discourse that is deeply rooted in rational planning theories [265] and rational decision-making models [266]. These models heavily rely on a centralized system of planning which is tightly connected with state interventions [267] where a command-and-control kind of governance [268] is executed. In these models, the government is viewed as the overall, powerful 'mono actor' that has hierarchical 'top-down' and bureaucratic structures which anchor spatial and development planning. Often, such spatial governance arrangements provide for a weak multisectoral 'horizontal' and multilevel 'vertical' policy integration.

In the year 2010, Kenya promulgated a new constitutional dispensation, that created a new devolved system of governance that has two distinct, but interrelated, levels of government – one national government and 48 devolved county governments that are semi-autonomous and interdependent. This was meant to address the weakness and bottlenecks created by centralized government systems and brought a new paradigm shift in spatial and development planning. The previously hierarchical and bureaucratic system was replaced with a decentralized 'bottom up' spatial governance system. In the established devolved governance system, various functions were transferred to the newly created county governments. While some functions were retained in the national government, others are concurrently implemented by the two-tier governments. The decentralization of power, resources, responsibilities, and tasks from the national to county level has substantially increased the role of county government in policy-making and the implementation of development interventions. In addition, the devolved county governments now play the role of mediators between national policy design and county-level policy implementation. The decentralized spatial planning system is seen as a positive endeavor of abandoning the rigid and overriding centralized planning frameworks that have been perceived to perpetuate the underdevelopment and marginalization of the grassroots citizens, especially those residing in the rural areas of Kenya. Overall, Kenya's spatial planning framework has two-tier systems of governance (i.e., national and county governments). Within this, several spatial planning instruments, for various spatial territorial levels and with different planning periods are prepared (Table 8.2).

Table 8.2: Hierarchy of spatial planning instruments in Kenya.

Spatial levels of planning	Spatial planning instruments	Preparatory authority	Spatial Plan focus	Plan period
National government level	1. National Spatial Plan (NSP)	National Government	Strategic spatial vision for the Nation	20 years
	2. Regional/ metropolitan physical development plan (RPDP)	National Government (coordination) County government (implementation)	Spatial framework to address issues that transcend more than one County	20 years
County government Level	3. County spatial plan (CSP)	County Government	Spatial development for the whole County	10 years
	4. Integrated Urban development plan (IUDP)	County Government	Spatial plan for city, municipality, or town	10-15 years
	5. Local Physical Development Plan (LPDP)	County Government	Development plan for city, municipality, town, market, or local center	Long term (10-20 years) Short term (5-10 years)

The hierarchy of the spatial planning instruments in the devolved system constitutes the primary mechanism for promoting policy integration in development and spatial planning. Each planning level is guided by one or several spatial planning instruments and is often treated as a separate planning entity. The planning levels assume five levels: 1) National planning, 2) Regional/Metropolitan planning, 3) County planning, 4) Urban planning and 5) City/Municipal planning. Additionally, the spatial planning instruments are often interlinked with development planning instruments that include Kenya's Vision 2030 (addressing social, economic, and political development goals), the Big Four agenda (covering food security, affordable housing, manufacturing, and affordable healthcare development goals), and several other ministerial and departmental policies and strategies which all have a spatial dimension. Several key legislations including the Constitution of Kenya (2010), the County Government Act, (2012), the Urban Areas and Cities Act (2011), and the Physical Planning Act (2019) provide the necessary frameworks, mechanisms, and channels for policy integration at both the national and county governments levels and across sectors. They also establish structures, processes, and procedures that facilitate effective public participation in the spatial planning and budgetary preparation process in county governments. With all these multitudinous spatial and development planning policy instruments arise the practical challenge of synchronizing and harmonizing their policy goals, visions, and strategies. This necessitates policy integration across sectors, spatial levels, and policy domains as a means of avoiding policy conflicts, fragmented decision-making, contradictions, and redundancy.

Vihiga County is selected as an embedded case. It is one of the 48 devolved county governments located in Western Kenya, a few kilometers from Lake Victoria and the main city of Kisumu. The county was selected because of several reasons. First, the county has made significant strides in terms of establishing various governance and institutional frameworks to support the implementation of the devolved government system. Second, since the devolution of agriculture and spatial planning functions from national to county government in the year 2010, the county is listed among those that have formulated and implemented several legislations, policies, spatial plans, and supportive institutional mechanisms to anchor and guide the two sectors. Third, in Vihiga County relevant information is easily accessible. The high adoption of information technology and e-government in the county enables it to publish all its policies, legislation, fiscal strategies, and other relevant information on its website (https://vihiga.go.ke/downloads.html). Fourth, the county has high agroecological potential for agricultural production. In terms of land use, the county is characterized by heterogeneous land-use systems with farming typologies ranging from pure subsistence, and mixed subsistence, to cash-crop-oriented farming. Agriculture activities in the county are predominated by small-scale agriculture with the majority of households average farm sizes ranging between 0.1 to 2.0 ha. However, the county experiences a high prevalence of food insecurity and high population pressure, and agricultural production faces several challenges that require a pragmatic and multifaceted approach to addressing them.

Data collection

The study used a mixed-methods approach to collect data: semi-structured key informant interviews, observations, and desk research. These methods are described below. Ethical approval to conduct the study was granted by Maseno University Ethical Review Committee, reference number (MSU/DRPI/ MUERC/00633/18).

Semi-structured key informant interviews (KIIs) with 23 experts, guided by open-ended questions were conducted by the researcher using face-to-face interviews. The key informants were strategically selected using snowballing, which enabled the researcher (the first author) to quickly get in contact with persons with in-depth knowledge to give insights into the topic of the study. The experts were chosen from national and county government staff, the private sector, and relevant institutions in the agriculture, spatial planning, and research and development sectors. Table 8.3 presents the list of experts interviewed. Interviews were either digitally recorded, or the researcher transcribed notes during the interview sessions. The transcribed interview information was exported to excel and Microsoft word. Permission to interview was sought from every respondent before the interview commenced.

Observations were made by the researcher during the entire fieldwork period detailing how the staff of different departments executed their daily work, and how they collaborated (or not) on various policy issues. These observations were written down in a logbook.

Desk research entailed careful selection and analysis of relevant legislation, policy documents, and project implementation reports (Table 8.4).

Table 8.3: List of interviewed experts (N=23) with their main characteristics

Coding	categorization		characteristics
NG-MAL	*National government* ***(N=4)*** Representatives at the Ministry of Agriculture, Livestock, Fisheries, and Cooperatives at the county level		1. Director of Agriculture 2. ASDSP national project coordinator of Vihiga county 3. ASDSP program officer 4. The chief officer, of the Ministry of Lands
CG-DAG	*County government:* ***(N=7)***	*Department of Agriculture, Livestock, Fisheries, and Cooperative Development*	5. County agriculture minister (County Executive Committee Member- CECM), 6. Chief Officer, Agriculture Department, 7. Crop officer 8. Agribusiness value chain officer
CG-DPP		*Department of Physical Planning, Land, and housing.*	9. Chief officer, Department of Physical Planning, Land, and Housing 10. Directorate of Geospatial Technologies Services lab (GTS/GIS), Vihiga
RI-MU	*Research Institution:* Maseno University **(N=2)**		11. Physical planning expert/ lecturer 12. Land use planning expert/senior lecturer
PO-KIP	*Professional organization:* Kenya Institute of Planners (KIP) **(N=10)**		13. Urban and regional planners registered with the KIP

Table 8.4: List of documents used in the desktop study.

Document coding	Categorization of data	Document categorization
DocKL	**a. Kenya Laws** (only those relevant to this research)	1. Constitution of Kenya, 2010 2. Kenya's vision 2030 3. National Government Co-ordination Act, No. 1 of 2013 4. Intergovernmental Relations Act, No. 2 of 2012 5. Transition to Devolved Government Act, No. 7 of 2013 6. County Governments Act, No. 17 of 2012 7. Physical And Land Use Planning Act (No. 13 Of 2019) 8. Urban Areas and Cities Act, No. 13 of 2011 9. Public Finance Management Act, No. 18 of 2012
DocSDP	**b. Spatial Development Plans**	1. National Spatial Plan 2015-2045 (NSP) 2. Vihiga county integrated development plan (CIDP), 2018-2022. 3. Vihiga county annual development plan (ADP), 2018-2019, 2020-2021.
DocASPD	**c. Agriculture Sector Policy Documents**	1. Agricultural Sector Development Strategy 2010-2020 (ASDS) 2. National Agricultural and Rural Inclusive Growth Project (NARIGP). 3. Vihiga county Agricultural Sector Development Support Programme (ASDSP) report.
DocPIR	**d. Project Implementation Reports for Vihiga County**	1. Vihiga "Governor's annual State of the County address", 2019 and 2020. 2. Vihiga County Fiscal Strategy Paper, 2019, 2020, 2021 3. Vihiga county budget implementation reports, 2018, 2019 and 2020 4. Vihiga County government project implementation report during the financial year 2018-2019 5. Handbook of county reporting indicators for the CIDP 2018-2022.

Data analysis

The thematic content analysis was used to analyze the data. Coding was done using Microsoft Excel and was based on deductive and thematic analysis from topics used to guide the KIIs. This was followed by inductive coding based on the emerging thematic topics from the desk research. The data analysis highlighted several factors that influence policy integration; five broad categories (see Box 8.1) were identified, including institutional and organizational factors, economic and financial factors, management and instrumental factors, political factors, and behavioral, cultural, and personal factors. The emerging codes were used by the researcher to elicit in-depth knowledge on the issue of agri-spatial policy integration. The findings were then qualitatively synthesized in explaining the factors influencing policy integration and are discussed in the next section.

Box 8.1. Factors affecting policy integration as synthesized from the literature [253,259,260]

- **Institutional and organizational factors:** These entail institutions established to manage and support coordination and cooperation of spatial planning activities between and among sectors and various levels of government. Some authors [255,258,262] identify several institutional and organizational tools for supporting policy integration including departmental and interdepartmental committees and steering groups, commissions, and joint working groups.
- **Economic and financial factors**: According to Stead & Jong [258], the process of policy integration is costly and requires a commitment of resources. Promoting cross-cutting working arrangements would also require the government to establish incentive structures and appraisal systems to reward and promote intersectoral policy integration. Other factors include a joint budget allocation for policy activities that cut across ministries.
- **Process management and instrumental factors:** These promote communication instruments to allow systematic dialogues and collaboration between individuals and actors involved in policy integration. In addition, a monitoring mechanism would allow for flexibility in the implementation process in case of the need to reconcile conflicting priorities or changes in circumstances.
- **Political factors** influence policy integration in that policies and plans must have political goodwill and backing to sail through state and county legislative councils. As such factors like political commitment, allocation of resources, and priorities and ideologies of political leadership are identified as imperative in achieving integrated policies in spatial planning [259].
- **Behavioral, cultural, and personal factors:** Meijers and stead [263] list positive attitude of staff, professional defensiveness, personal relations, the organizational culture of working with others, willingness to cooperate, and a shared framework of understanding as some of the important factors to policy integration.

Applying these factors in the embedded case study allowed us to examine how policy instruments and mechanisms inbuilt in Kenya's spatial planning system influenced policy integration. Additionally, the use of these factors enabled us to perform an in-depth interrogation of the unique mix of policy instruments, mechanisms, structures, and institutional arrangements that can support policy integration. The output of this analysis was a synthesis of facilitators and barriers influencing policy integration in Vihiga county.

8.3 Results

This section provides the results of the study by first presenting the spatial development framework used in Vihiga county, then we detail the policy instruments embedded in the framework. We conclude the section by presenting a detailed synthesis of the facilitators and barriers to policy integration.

Integrated spatial framework for agri-spatial policy integration

We found that the hierarchy of multi-layered and interlinked spatial planning instruments formulated and implemented by both national and county governments, and operationalized at different spatial levels, constituted the primary mechanisms for both vertical and horizontal policy integration in the case study. The planning framework has an institutionalized structure where the higher-level (national government) plans inform and guide the preparation of the lower-level (county government) plans, and the lower-level plans implement the higher-level plans. Figure 8.1 conceptualizes the two-tier spatial and development planning frameworks showing how agri-spatial policies and plans are interlinked.

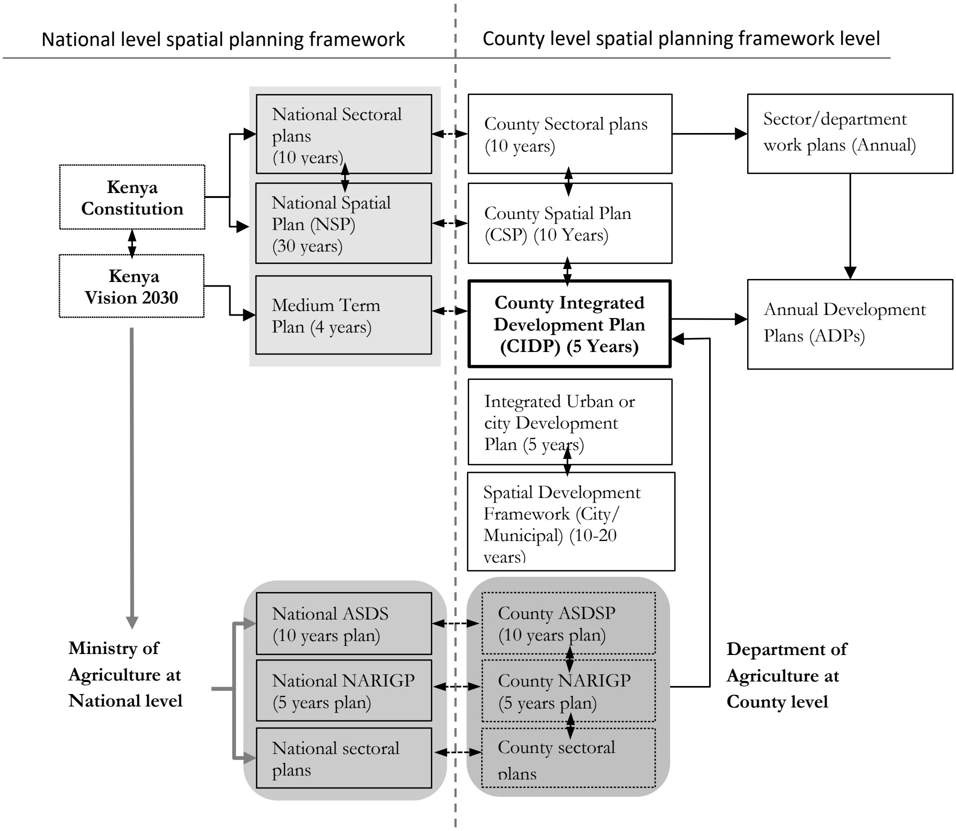

Figure 8.1: The agri-spatial policy integration framework used in Kenya and Vihiga County. Source: Author.

Chapter 8

Policy instruments and mechanisms for agri-spatial integration inbuilt into Kenya's spatial framework

From the document analysis, we identified various policy, legal, and institutional mechanisms embedded in both the national and county government spatial planning frameworks that supported policy integration. The constitution of Kenya provided the overarching structure of development and prescribes legislations that guide planning. Kenya's Vision 2030 is the national blueprint that forms the national development agenda and is implemented through a series of Medium-Term Plans (MTP). At the national government level, the National Spatial Plan (NSP) forms the basis of spatial planning that gives a broad framework for policies, principles, and standards for guiding spatial planning in the country. It provides a vertical integration mechanism through its linkage with the County Spatial Plan (CSP) and forms the basis upon which all lower-level spatial plans – regional plans, county spatial plans, urban plans, and local physical development plans – are prepared. At the county government level, the main spatial plan guiding spatial development is the 5-year County Integrated Development Plan (CIDP) and CSP. The CIDP is aligned with Vision 2030 through the MTPS. The CIDP is the overall policy integration mechanism at the county level that integrates all department strategies, and plans of the lowest planning levels (municipal, town, or local area). Subsequently, the Annual Development Plans (ADP) are formulated to implement projects and programs identified in the CIDP. As per the Public Finance Management Act, 2012 the CIDP form the "basis for all the budgeting and planning in the County" and states that "no public funds shall be appropriated outside a County's planning framework". At the lowest planning levels, urban and city planning is guided by the Integrated Urban Development Plan (IUDP), while municipal and local area spatial development is guided by Local Physical Development Plans (LPDP). Sector ministries at the national level were guided by the National Sectoral Plan (NSP) and County Sectoral Plan (CSP) at the county level, with these two being interlinked with other spatial and sectoral plans by CIDP.

Factors influencing agri-spatial policy integration in Vihiga County

In this section, we present the results of various key expert interviews and document analyses. The results (Table 8.5) show the synthesis of factors that interacted to facilitate and or inhibit policy integration in Vihiga County. An in-depth explanation of how these factors influenced agri-spatial policy integration is presented below, following the five main categorizations identified in the methodology section.

Table 8.5: Facilitators and inhibitors of agri-spatial policy integration in Vihiga county

Categorized factors of policy integration	**Facilitators of policy integration**	**Barriers to policy integration**
Institutional and organizational factors	• Devolved structure of governance • Devolved agri-spatial policies and functions • Existence of coordination capacity for managing multilevel and multisectoral integration • Presence of inter-governmental relations and structures for dialogue	• Hierarchical, and bureaucratic structures. • Fragmented and conflicting policy instruments at various levels of planning • Inadequate staff and lack of technical capacity • Weak legal and institutional frameworks • Lack of harmonized approach and common reference frame to guide agri-spatial planning • Duplication of sectoral functions
Management and instrumental factors	• Availability of legal and institutional Instruments • An available mechanism for consultation and communication • Existence of an integrated policy mechanism supporting sectoral and national plans linkages • Attempt to involve all actors in the planning process	• Weak management mechanism for sorting inconsistencies and reconciling conflicting priorities between policy instruments • Compartmentalization of departments • Ineffective monitoring and evaluation framework • Inconsistent linkages between development and spatial planning policies • Weak coordination between sectoral and multilevel policy integration • Narrow policy perspectives due to sectoral centered approach to policymaking and problem-solving
Behavioral, cultural, and personal factors	• The willingness of staff to cooperate and work with others • Presence of informal networks for collaboration	• Professional defensiveness reinforcing sectoral/department domain • Lack of sector culture towards working with others • Lack of effective collaborative structures
Economic and financial factors	• Availability of data and indicators • Available integrated spatial development plans	• Insufficient finance, and over-reliance on donor funding • Budget allocation to sectoral rather than cross-cutting policy issues • Lack of incentive and appraisal system for collaborative efforts
Political factors	• Political will and commitment by the political leadership to support policy and plan integration	• Divergent priorities and goals • Short-term political aspiration as compared to the time frame for integration • Prioritization of sectoral goals over cross-cutting issues

Institutional and organizational factors

Several institutional and organizational mechanisms were found to facilitate policy integration between the county and national government and across the sectors. At the national level, an inter-ministerial committee spearheaded the overall coordination and implementation of NSP. As stated in the NSP "the committee ensures that the NSP development objectives are mainstreamed in the county and sectoral plans in achieving integrated development" (DocSDP). The National and County Government Coordinating Summit and Intergovernmental Relation Forum (IRF), established by the Intergovernmental Relations Act, 2012, and the National Government Co-ordination Act, (2013) are formal, centralized institutions that provide a framework for intergovernmental consultation and cooperation. Specifically, these forums "facilitate the harmonization of national and sectoral plans by providing support in the plan formulation and implementation process" (DocKL). Their mandate and responsibilities, as itemized in the Act include the harmonization of policies of ministries and departments, coordination of development planning activities, coordination of intergovernmental functions, and resolution of intergovernmental disputes (DocKL).

At the county level, the County Planning Unit (CPU), established by County Government Act, (2012), provided the linkages between national and County levels planning frameworks. Its function, as enumerated in the Act, is to coordinate integrated development planning by ensuring national-level plans, programs, policies, and strategies are integrated into the county-level plans. Another institutional arrangement that facilitates policy integration was the County Executive Committee (CEC). According to a key informant, the CEC and CPU mandate are to:

> "*Facilitate the coordination and alignment of county spatial planning with the national government's strategies and plans*" (KII: PO-KIP).

However, in Vihiga, the major challenge was how to effectively operationalize and harmonize these loosely coordinated institutional instruments in clear legal and concrete strategies, as noted by a key expert from the Kenya Institute of planners:

> "*Though many new institutional setups have been established by the devolved spatial development framework, the majority of them are primarily advisory. I see that policy and mechanism for coordinating multi-level policies are essentially weak, and hence the weak implementation outcomes of some of the development plans."* (KII: PO-KIP).

From the document synthesis, we noted a lack of clear coherence between various layers of spatial plans and agriculture policies. This presented a substantial challenge to both national and county governments' intergovernmental coordination efforts. This view was echoed by several of the interviewed experts, saying,

> *"The major challenge for achieving policy integration in agri-spatial planning at both the national and county level was the inconsistent linkages between the many spatial plans objectives and their targeted priorities" (KII: PO-KIP).*
>
> *"It is clear that we have multiple laws operating within the same space and thus the need for their harmonization. As an institution, I would like to hear the next steps KIP is planning in regards to the harmonization." (KII: PO-KIP).*
>
> *There are indeed so many laws leading to confusion in land use planning, approval, and development control in general. Each sector is bent on having its laws. There is a need to harmonize and merge some of the sectoral laws" (KII: PO-KIP).*

The policy integration challenges were also highlighted by the governor of Vihiga county, in his year 2019 state of County address, "*the inconsistent linkages between the CIDP priorities and actual implementation"*. He gave an example of this where *"the formulation of the CIDP (2017-2018) was not guided by the CSP as mandated by the law"* (DocPIR).

The County had not formulated the CSP when the CIDP was developed. Since CIDP implements CSP plans in the county, this meant that the national and county development plan objective had considerable discrepancies, which affected their concretization and realization. Several key informants concurred on the existence of these bottlenecks of policy integration:

"*In Vihiga, and Kenya in general, the need for policy integration is espoused in principle, but little significant progress to true integration has been realized in practice during the implementation of plans.*" (KII: RI-MU).

"*The existing planning legislation scenario in Vihiga is complicated by the multiplicity of laws and development plans with often overlapping mandates, characterized by duplicity and functional jurisdiction.*" (KII: PO-KIP).

To support integrated policies, an expert proposed:

"*I see a need for these policies and laws to be critically and objectively looked into and appropriately modified to make the entire process of planning, development, and management more effective and efficient.*" (KII: PO-KIP).

Another professional planner noted:

"*In the absence of a well-coordinated policy framework and an integrated implementation plan, formulation of the many plans could just remain an academic exercise rather than being measured by their effectuation.*" (KII: PO-KIP)

Management and instrumental factors

From the results of the document analysis, we found that in Kenya, and Vihiga in particular, the existence of multi-level spatial planning frameworks (see figure 8.1), which anchor spatial planning of both county and national government. The framework encompasses several embedded policy instruments and mechanisms that facilitated multilevel and multisectoral policy integration. For instance, the results of the document analysis showed that the CIDP provided an integrated framework that interlinked county agriculture department strategies with the national-level spatial policies. At the national level, we observed that the Agricultural Sector Development Strategy (ASDS) provided the overall framework for integrating the national policy into the county spatial development frameworks. The county agriculture minister indicated that the National Programme Secretariat (NPS) is the institutional framework that is used in the coordination of the implementation of the ASDS program at the national level, while at the county level, the County Coordination Unit (CCC) is bestowed with responsibilities for coordination of the projects prioritized by the program. At the county level, the project coordinator indicated that the ASDS program is implemented at the county level by a program called Agricultural Sector Development Support Programme (ASDSP). As articulated by the ASDSP national program coordinator for Vihiga,

"This multilevel framework, where national structures of the program are not wholly imposed at the counties, but new structure aligned to the county governance structure established to anchor the program, provides an ideal impetus for policy integration, especially in supporting vertical and horizontal coordination and collaboration on pertinent cross-cutting agriculture problems" (CG-DAG).

However, from our observation, the lack of coherence between various layers of agri-spatial policies presented a substantial challenge to the intergovernmental coordination and integration efforts. For instance, the national government agriculture sectoral plans were implemented at the county level by the National Agricultural and Rural Inclusive Growth Programme (NARIGP). However, there was a lack of clear coordination and collaboration between national NARIGP and county ASDSP. This meant that the two programs were running concurrently while focusing on almost the same local problems facing agriculture. For example, we found that both ASDSP and NARIGP in Vihiga focused on increasing market access of smallholders through the commercialization of the same agricultural value chains (dairy, fish farming, indigenous chicken, local vegetables, and bananas). This not only provided resource wastage but also duplicity of activities and efforts that could have been used to address other pertinent issues affecting smallholder farmers in Vihiga.

Based on the analysis of documents, we found that public participation in Kenya is embedded in spatial planning frameworks by several policies and legislations[1]. These laws espouse that public participation should be a fundamental legal requirement in the County's integrated planning process. To implement citizen participation requirements at both levels of government, several institutional mechanisms were established, including joint committees between the county and national government, an Inter-governmental budget council, a sectoral inter-governmental consultative forum, and a joint inter-governmental technical committee. In Vihiga, we observed several channels and platforms for citizen involvement in policymaking and information exchange instituted. These included citizen forums, town hall meetings, budget preparation, validation workshops, and county agribusiness investment forums. Echoing this in his state of county address for the year 2020, the Vihiga governor noted,

> *"Citizen engagement was relatively high on the plan preparation process, but insufficient on project implementation and in the identification of local-based projects" (*DocPIR*)*

Additionally, we observed that Vihiga county employed information and communication technology to promote public participation and dialogue. For instance, the Vihiga county government extensively used web-based platforms in sharing all the policies, legislation, budget expenditures, project implementation reports, and newsletters with the general public. For ease of access, these documents were provided in downloadable formats on its government website. A key informant concurred with our observation,

> *"Making public government policy documents and reports increases the accountability and transparency, which are necessary preconditions for promoting effective policy integration" (KII, PO-KIP)*

However, even with the availability of these public participation structures, we noted several bottlenecks that hindered effective citizen engagement, especially at the grassroots level, including poor intersectoral communication and a lack of effective collaborative structures. These bottlenecks hampered multi-actor engagements and policy harmonization across sectors and ministries.

Another inhibitor of policy integration was the departmentalization of policymaking. The researcher observed that plan formulation and implementation were largely carried out in respective departments and the sectoral ministries, which were treated as though they were separate planning entities. This, according to views shared by several key informants, not only hindered effective intersectoral policy integration but

[1] Legislations that anchor public participation in Kenya includes, Article 10 of the Kenya constitution, the County Governments Act, (2012), Urban Areas and Cities Act, (2011), and Public Financial Management Act, (2012).

creates professional defensiveness that reinforces the department domain. This leads policymakers to have a narrow perspective on the policy formulation process, focusing more on departmental objectives rather than holistic development goals.

Another inhibitor of policy integration identified was the partial devolution of functions of the agriculture sector to the counties. As spelled out in the County Governments Act, (2012), the agricultural sector at the County level is only mandated to address the four devolved functions of the agriculture sector. Other agriculture issues falling outside of this scope were left to the national government. This raises several challenges, according to several experts:

> *"This partial decentralization of functions hampers a holistic approach to policy integration and provides a major setback in addressing cross-cutting policy issues that transcended territorial boundaries (KII: RI-MU).*
>
> *"When you devolve only certain functions of the agriculture sector and leave the rest to the national government, and fail to create appropriate interlinkages for cross-cutting issues, this creates a disconnect in both policy formulation and implementation processes between the two levels of government* (KII: PO-KIP).
>
> *"Agricultural services that are not devolved are equally important and are needed in addressing the sustainability challenges facing smallholder farmers at the grassroots level."* (KII: CG-DAG)

Economic and financial factors

The issue of the lack of enough funds for plan preparation and implementation was highlighted by several interviewed county government officials and reiterated in several project implementation reports as one of the prominent factors hampering effective agri-spatial policy integration at Vihiga county. Despite agriculture forming the backbone of the Vihiga county economy, where 70% of the population were engaged in smallholder agriculture, and 62% employed by the agriculture sector (CIDP, 2018-2022), the sector was allocated inadequate funds to effectively execute the project and programs identified in the Development Plans. Information synthesized from document analysis (Table 8.6) shows that the percentage of the development budget for the agriculture department was below 10% of the total development expenditure budget for Vihiga county for four consecutive years.

Table 8.6: Development budget allocation for the agriculture sector in Vihiga.

Financial year (FY)	Approved development budget for the agriculture sector (Ksh. millions)	As a % of the total development expenditure budget for Vihiga county	Absorption rate (% of actual expenditure on agric. development
FY 2017-2018	48.3	10.5%	17%
FY 2018-2019	150	9.6%	40%
FY 2019-2020	196	6.3%	-
FY 2021-2022	53.3	5.4%	-

Source: Vihiga County fiscal strategy paper and budget implementation reports (2018 to 2021)

Ensuring intersectoral plans and policies were successfully implemented was a big challenge. From our synthesis of fiscal strategy papers and budget implementation reports, we found that there was no budgetary allocation for joint policymaking and crosscutting issues. Additionally, many of the prioritized agricultural projects and programs in the CIDP, ASDSP, and NARIGP overly relied on the national government funds or external donors' funding for their implementation. We observed that the national government budgetary allocation to counties was often marred with delays in the disbursement of allocated funds from the national treasury. Due to insufficient funding, several proposed projects under various development plans could not be implemented within the stipulated planning timelines. Others were only partially implemented, while yet others stalled. This made it difficult to achieve development plan goals, at the same time constraining policy integration efforts.

Behavioral, cultural, and personal factors

The result of document analysis (DocPIR) for Vihiga revealed that lack of sector culture towards working with others, professional defensiveness especially in departments, lack of effective collaborative structures, and professional staff shortage affected policy integration. For example, according to the Vihiga County Governor, *"poor work ethics and attitude for work by County government staff affected the performance of plan implementation"* (CG-PIR). In addition, the governor also stated that *"the county faces a shortage of staff with enough technical capacity and experience for implementing integrated policies, especially those that straddle departments"* (CG-PIR). This was not only a challenge for the case study but for other counties as observed by a professional planner,

> "A *key challenge that some counties are grappling with is inadequate manpower. Even where a county has prepared a really good plan (mostly from consultants and donors), implementation remains difficult without qualified physical planners (KII: PO-KIP).*

In bridging the staff deficit, and poor works ethics, the county identified capacity building and continuous professional development as a strategic priority in the ADP of 2019-2020. Policy integration was also affected by performance contracting, as noted by a key expert;

> *"The County government staff at managerial positions operates on performance contracting. This tends to create competition and individualistic mindsets since each staff strives to achieve his/her set performance targets, often at the detriment of the shared intersectoral goals" (KII: CG-DAG).*

Political factors

In Vihiga, the researcher observed that the political will for policy integration by the county political leadership was present. However, we observed that matching political will with financial commitment was problematic due to among others, insufficient budgeting, budgeting being done on a departmental basis rather than on policy goals, and lack of budgetary commitment to intersectoral issues. In addition, short-term political aspiration affected policy integration since county government political leadership is selected after every 5-year cycle. Thus, politics in planning affected both policy integration and agri-spatial planning in Kenya as one expert wondered;

> *"We as a country are not short of laws, policies, and institutions. What is eating us? Why is planning not being felt and or seen in this country?" "The planning process is both technical and political, could it be that our plans aren't implemented because one cannot legislate political issues affecting planning" (KII: PO-KIP).*

There is a need therefore for integrating political aspects into agri-spatial policy planning and implementation if they are to be successful.

8.4 Discussion

Several supportive policy instruments and institutional arrangements embedded in the spatial planning frameworks promoted policy integration efforts in the case study. In particular, the devolution of the spatial governance structures and the agri-spatial planning functions created favorable conditions for supporting policy integration at the county level. Nevertheless, though Kenya has made good progress in promoting agri-spatial policy integration, several considerable challenges exist that hamper effective agri-spatial policy integration. The existence of numerous legislations and policy instruments creates a practical challenge in their implementation, particularly in synchronizing their visions, goals, and strategies, across policy domains and spatial scales. In addition, the multi-layered spatial and sectoral policies and plans, often with conflicting implementation time frames, and anchored on disjointed legal and institutional frameworks become a major bottleneck to effective policy integration. There is a need for both national and local governments in LMICs to adopt pragmatic approaches for coordinating the often-fragmented agriculture policies and strengthening their integration in achieving sustainable agriculture and food security.

Whilst a range of policy instruments and institutional arrangements can help promote policy coherence, strengthening their integration is considered crucial in creating the fundamental conditions for effective multi-level, multi-sectoral, and multi-actor policy integration., Achieving effective agri-spatial policy integration would thus require the strengthening of the weak institutional and-organizational structures that inhibit policy integration [263]. In addition, there is a need for the replacement of bureaucratic structures of decision-making with more participative and networked spatial governance structures [259,268]. This can be achieved by adopting strong collaborative governance structures that support spatially coordinated policy implementation [269], and the interconnectedness of institutional frameworks between different sectoral policies [265]. Nonetheless, as noted by Klijn & Koppenjan [268], decentralized governance structures are often espoused in principle, but are usually undermined by the perpetuation of rigid 'top-down' institutional structures that fail to allow lower-cadre staff to articulate problems and prioritize policies. Addressing this weakness would require policymakers in LMICs to dismantle the boundaries created by silo-based governance structures [270]. Formally established rules and legislation, according to Leiren & Jacobsen [270], may be used to reduce silo-based tendencies in spatial planning and can be enjoined to corroborate a more integrated approach to policy-making.

Addressing the management and instrumental barriers of policy integration would call for a strengthening of the tools and mechanisms to facilitate active citizen and stakeholders' engagement, consultation, and communication [260,269]. As was noted by several authors, the involvement of the public and stakeholders, in policy formulation, implementation, monitoring, and evaluation processes are important ingredients for effective policy integration. To overcome the bureaucratic structure of decision-making, there is a need for greater emphasis on decentralizing the decision-making framework, as well as strengthening the legislation for public participation, and the establishment of effective structures and avenues for participative governance [260,266]. This would help shift the focus from the government being the only actor involved in formulating policies and delivering services to many interdependent actors with divergent interests and perceptions to find and implement solutions. As espoused by Rao et al., [271], the guiding principles for multilevel and multisectoral policy integration ought to be informed by collaboration and participation throughout the agri-spatial planning process. This should be a public sector-led process where all actors are provided with an equal platform to fully communicate and articulate their values, visions, and ideas within the spatial planning process [164,272,273].

Several strategies can be used to overcome behavioral, cultural, and personal barriers. Stead and Jong [258] note that the lack of a departmental and professional culture of strategic partnerships among sectors becomes a barrier to effective multilevel and multisector integration. Professional defensives tend to reinforce the bureaucratic structure of communication by centralizing the decision-making process to the intellectuals and public servants [259]. This limits the meaningful participation of the common citizen at the grassroots level. Entrenching an administrative and professional culture that promotes good work relations, and cross-sectoral professional cooperation and dialogue is crucial for strengthening policy integration [259,263]. This can be achieved through continuous professional training that in turn promotes a positive attitude of sectoral staff and teamwork [258]. It can also be used as a channel for exchanging information and experiences between and among multilevel and multisectoral staff. This would not only aid in dismantling professional defensiveness but also in creating mutual understanding in cross-cutting policy issues between county staff and national government staff.

In addressing economic, financial, and political inhibitors of policy integration, systems to strengthen the weak structures of revenue collection and allocation need to be put in place [274]. Enhancing participatory budget-making promotes transparency and accountability which are important preconditions for positive policy integration [253]. Local governments also need to expand their tax collection base to locally finance agri-spatial plan making. This can be achieved by expanding various economic activities for taxation and by the digitization of tax collection to avoid embezzlement. This could help diminish the donor dependency syndrome and influence, thus establishing local ownership of policies and spatial plans. Additionally, political will and commitment toward policy integration are necessary preconditions for promoting policy integration at all spatial levels (Stead & Meijers, 2017). Lack of ownership and responsibility for cross-cutting issues and those transcending departmental boundaries is a setback to integrated policies since it may lead to a lack of commitment and accountability by those staff implementing the projects [274].

8.5 Conclusion

This paper has presented a synthesis of policy instruments and mechanisms for policy integration inbuilt in Kenya planning frameworks, in expanding the current knowledge of policy integration in improving agriculture sustainability. We conclude that a devolved and integrated spatial development framework, with its several embedded policy instruments aided multilevel and multisectoral agri-spatial policy integration. However, the results have shown that poor coherence and weak synchronization between various layers of agri-spatial policies, and plans present a considerable challenge to policy integration efforts. Supportive institutional and organizational instruments including joint inter-ministerial committees, and intergovernmental coordination forums facilitated agri-spatial policy integration between national and County governments. However, how to effectively operationalize and harmonize these loosely coordinated institutional instruments in clear legal and concrete strategies was a challenge. Lack of enough funds for joint policymaking and implementation and lack of budgetary commitment to intersectoral policy issues hampered integration efforts. Information and communication technology was an efficient platform used by the county government to promote public participation and dialogue through sharing of plans, policies, and plan implementation progress reports on online platforms. Several channels including citizen forums, town hall meetings, budget preparation, validation workshops, and county agribusiness investment forums were used as channels for promoting agri-spatial policy integration. However, poor intersectoral communication and a lack of effective collaborative structures hampered these efforts. Other issues that affected policy integration included a lack of sector culture towards working with others, professional defensiveness especially in departments, and a shortage of qualified staff affected policy integration. Whilst a range of policy instruments and institutional arrangements can help promote policy coherence, strengthening their integration is considered crucial in creating the fundamental conditions for effective multi-level, multi-sectoral, and multi-actor policy integration.

Chapter 9

Discussion and Conclusions

9.1 Introduction

This concluding chapter provides the discussion of the main research findings according to the five study questions formulated in chapter 3. In this chapter, we reflect upon the results presented in chapters 4 to 8, upon which we draw conclusions for this research. We also present policy and practical recommendations for decision-makers in improving spatially targeted policy interventions. Finally, the chapter reflects on the limitation of the thesis and ends with recommendations for further research.

In this thesis, we aimed at mapping, analyzing, and geo-visualizing the spatially explicit factors that influence smallholders' agricultural production, food security, and decision to participate in the agribusiness value chains and markets. This was aimed at seeking a deeper and localized understanding of the underlying causes of food insecurity and impediments to market participation amongst poor smallholder households. The main research question was split into five sub-questions presented in chapter 3. These questions formed the basis for five studies, which resulted in:

- A systematic review of GIS applications in agriculture to identify recent trends and future perspectives on how GIS can be used in informing evidence-based policymaking to improve agriculture sustainability.
- Assessment of the catalytic role household livelihood capitals played in influencing poor smallholders' decisions and choices to diversify their farming activities in agribusiness.
- Development of a GIS methodology for mapping and analyzing spatially explicit factors that hindered smallholders from participating in agribusiness markets.
- Development of a GIS-based approach for deconstructing the multidimensional aspect of food insecurity and mapping and geo-visualizing the spatial patterns of food insecurity. This helped us to identify the local causative factors of food insecurity among smallholder households in the study area.
- A case study analysis to identify the structural and practical inhibitors of agriculture and spatial policy integration and developed an integrated conceptual framework for the integration of agri-spatial policies.

Both spatial and non-spatial data were elicited, collected, and analyzed from two selected study sites located in Kisumu and Vihiga counties in Western Kenya. In total, 392 smallholder households were surveyed, and 28 small-scale agribusiness owners and informal market traders were interviewed. In addition to 13 key informants being interviewed, two focus group discussions were conducted.

9.2 The main research findings of the thesis

In this section, we discuss the main findings according to the five study questions of this thesis.

Use of GIS technology in agriculture to promote spatially integrated agriculture policies

The extent to which smallholder farming decisions are influenced by endogenous factors can better be understood by mapping and analyzing the spatially varying relationships between geographic-explicit factors and smallholder households' production practices. As such, insights into the analysis of the spatial dimension of agriculture can provide farmers with practicable information for improving their agricultural production practices and at the same time provide policymakers with evidence-informed decisions that could improve the formulation of spatially integrated agriculture policies. For this very reason GIS, RS, and GPS technologies can assist in improving the understanding of this spatial dimension and make it actionable as they provide users with a mixture of geospatial data management tools and methods that collect, store, integrate, query, analyze and display processed data at various scales [92,107]. In understanding how GIS has been used in the agriculture sector, we conducted a systematic literature review to synthesize existing evidence on its application in improving agriculture sustainability. We synthesized a decade of literature starting from the year 2010 up to 2021 in the databases SCOPUS, Web of Science/Clarivate, Bielefeld Academic Search Engine (BASE), COnnecting REpositories (CORE), and google scholar. The results show that the main GIS technology applications in agriculture include: crop yield estimation/forecasting (26% of the articles), soil fertility assessment (18%), cropping patterns and agricultural monitoring (13%), drought assessment (16%), pest and crop disease detection and management (11%), precision agriculture (8%) and fertilizer and weed management (8%). Hence, GIS applications in agriculture have recently received more attention and concentrated on practical solutions to address the challenges facing agribusiness value chains.

Integrated GIS, RS, and GPS technologies provide a powerful spatial decision support system that has the potential to improve evidence-based agricultural practice and policies in several ways. The opportunities provided by GIS technology in predicting potential crop yields before harvest are important in food security planning, especially in regions characterized by climatic uncertainties, drought, famines, and water shortages. The capability of GIS in monitoring agricultural crop growth conditions and the prediction of potential crop yield could assist policymakers in LMICs in developing spatially integrated agriculture policies for improving agronomic practices that boost productivity and sustainability [122,124,127]. This could potentially address the food production yield gaps, especially for smallholder farmers who heavily rely on rainfed subsistence farming. GIS and RS provide new opportunities for assessing soil quality at different spatial scales, This enables decision-makers, policy formulators, land-use planners, and agriculturalists to efficiently manage soil resources according to their potential, and in developing sustainable agricultural practices [130,132,133].

In an era of unpredictable climate changes, erratic rainfall patterns, and intensifying droughts, GIS-based agricultural crop monitoring systems could help governments, policymakers and farmers plan and design cropping patterns that adapt to changing weather patterns and water availability [136,141,142]. It can also have a wider application in improving crop production and management decisions including optimizing land and labor productivities, enhancing higher cropping intensities, and producing better crop yield [136]. GIS and RS-based real-time monitoring of crops have the potential to increase crop production and ensure better crop management decisions at the farm level. Another advantage of the adoption of RS and GIS technology is that it provides evidence-based data and methods for developing spatial drought risk inventory. The inventory can be used in the assessment of agricultural drought risk patterns and the development of agricultural drought vulnerability maps. These can proactively inform policymakers in formulating spatially explicit drought mitigation policies. These policies would have a wide application including improving farmers' and government preparedness in case of drought, mitigation-oriented management of droughts, helping in identifying the drought-prone areas to reduce the risk of crop yield loss, and aid in the suggestion of alternative drought-tolerant crops [141,142]. In addition, drought vulnerability maps would be used to indicate where socioeconomic development policy programs should be given priority [143].

The development of precision agriculture practices using integrated GIS, RS, and GPS technologies have enabled farmers to optimize crop production and facilitated site-specific crop management. In addition, the adoption of precision agriculture has provided several opportunities [151,154–156] including, (1) increasing the capabilities for agricultural monitoring and crop management, (2) abiotic and biotic stresses detection, (3), improving the estimation of crop yields, and (4) enhanced crop type classifications. Furthermore, precision agriculture has improved the detection and monitoring of pests and crop diseases consequently reducing the application and effect of pesticides and herbicide chemicals on the environment [145–148]. All of these opportunities have led to the development of sustainable agriculture management and enhanced environmental sustainability. The application of GIS in accurately mapping weed distribution greatly enhances efficiency in weed management and efficiency of input application. Accurate spatial information on weed distribution and composition reduces weed damage and provides smallholders with added benefits in terms of reduction of overhead costs of crop production accrued from herbicide and fungicides application and consumption of fertilizers [117,152,153].

Though GIS technology provides a promising pathway for improving agronomic practices, it remains underexploited in many sub-Saharan countries where a dire need for enhancing agriculture and food production practices is most needed. The result of our review showed that only 1 out of 40 papers reviewed originated from sub-Saharan Africa (that is, Ethiopia). The lack of evidence-based agriculture data that could support decision-making and action seriously impedes spatially integrated policy formulation and implementation in the agricultural sector. Several other constraining factors towards the adoption and use of GIS technology include low awareness of the potential of GIS technology, low adoption of GIS by government and public institutions, low technical skills among government staff, and low access to affordable spatial data. We posit that the adoption of GIS in the agriculture sector would not only help to improve efficiency in policy formulation but effectiveness in policy implementation, monitoring, and evaluation processes.

Influence of livelihood capitals on poor smallholder's decisions to participate (or not) in agribusiness markets

Even though several works of literature show livelihood capitals influence smallholders' choices in different ways, it is rarely understood what combination of livelihood capitals could result in a higher probability of smallholders diversifying their subsistence production into more income-generating agribusiness. We sought to understand the extent to which livelihood capitals catalyze smallholders' participation in agribusiness.

As chapter 5 shows, higher livelihood capitals endowment in a household (e.g., education level, gender, landholding size, savings, access to agriculture extension services, livestock ownership, input access, and proximity to markets) resulted in a higher probability of diversifying agribusiness activities, while lower livelihood capitals ownership resulted in a lower probability of a household to participate in agribusiness. Our study findings further revealed that the education level of the household head positively and significantly influenced smallholders' decision in diversifying into commercial and mixed farming options. The likelihood of households in the reference category participating in commercial and mixed farming options would be 12.1 and 7.2 times if the household head possessed a higher level of education. The gender of the household head had a positive and significant influence on smallholders' decision to participate in horticulture farming options at a 5% probability level. The odds ratio indicates that the probability of male household heads participating in horticulture farming are 4.6 times more likely as would female household head if all factors are kept constant. Our findings show that more males than females had a higher literacy level, owned more assets, and had higher technical skills in agribusiness. Policy interventions aimed at promoting women's participation in agribusiness should be prioritized if women were to be active players in agribusiness opportunities.

In addition, the study findings show that households with limited or no access to agriculture extension services were .35 times less likely to diversify their farming to agribusiness. This in turn affected their agricultural productivity and market participation; both of which were found to be very low among households in the study area. Agriculture extension services are a decisive component in supporting small-scale agribusiness adoption especially in impacting agronomic skills and agronomic information provision. Results indicate that landholding size positively and significantly influenced the likelihood for smallholders in the reference category to participate in horticulture farming. A unit increment in landholding size could increase the probability of smallholder farmers' practicing pure subsistence to shifting to horticulture farming by 3.5 times if all other factors were held constant. However, small land sizes diminished the odds of households diversifying into mixed and commercial farming types. Distant to markets was found to exert a negative influence on smallholders from participating in horticulture farming. The probability of a household participating in horticulture farming diminished with an increase in distance from the input source. Small-scale agribusiness ventures are most susceptible to food price and transport cost shocks, especially horticulture farming, which places a high demand for efficient infrastructure connectivity. Since agricultural policies are rarely geared towards the improvement of road infrastructure, a multisectoral collaboration with sectors such as spatial planning is needed to address infrastructural deficits in rural and peri-urban areas. Climate change's impact on smallholder productivity in Kenya and sub-Saharan Africa continues to aggravate smallholder productivity, causing severe food shortages.

The findings also revealed that climate variability especially drought and famine were highly significant in influencing households to participate in commercial and mixed subsistence farming. There were 7.4 and 5.1 odds of a subsistence-oriented household diversifying into commercial and mixed farming, respectively, due to vulnerability to climate change. The promotion of climate-smart agriculture and integration of climate issues in agriculture policies would help address the interlinked challenges of agricultural production and climate change. Household savings play an important factor in participating in agribusiness. In our case study, household savings were found to significantly and negatively influence farmers' decisions in choosing mixed subsistence. The odds ratio in favor of a household choosing mixed farming decreased by a factor of .33 times as savings of the household decreased by one unit. This means that poor households with little or no savings had a lower probability of engaging in agribusiness farming. Improving access to banking services, and lowering collaterals, and interest rates for poor households would be positive in promoting a saving culture among smallholders.

In conclusion, livelihood capital improvement would not only complement poor households' efforts in meeting food and nutrition security but also catalyze their transition from subsistence-based agriculture to commercialized agriculture. As corroborated by other studies [51], resource-poor households tend to be impacted more negatively, as insufficiency in livelihood capital perpetuates poverty, jeopardizing poor households' ability to pull themselves out of a vicious cycle of poverty and food insecurity. This is because the way poor households utilize their livelihood capitals could potentially promote or limit their capability to diversify their farming strategies into productive farming activities leading to low-income earners. Policymakers must recognize the critical role livelihood capitals play when designing pro-poor agriculture diversification strategies aimed at improving food security. In the context of severe resource constraints resulting from poverty, participation in agribusiness by poor smallholders could be enhanced by sustained pro-poor poverty reduction interventions that target livelihood capital improvement, especially in marginalized rural areas. We conclude that differentiated livelihood capital endowments could create different outcomes necessary for the transition of poor subsistence smallholders into market-oriented agribusiness. As such, there is a need for more attention to the role livelihood capitals play in livelihood diversification strategies employed by poor smallholders to achieve food security [37].

Influence of spatially 'geographically' explicit factors at the local level on poor smallholder farmers' decisions and choices to participate in the agribusiness markets

The spatial interactions between local geographic specificities and smallholder farming decisions and choices adopted by households are manifested by the resulting spatial typologies of farming systems in a given locality [47,51,64]. This emanates from the spatial dependence (spatial autocorrelation) that influences the spatial organization of different farming decisions and choices [47]. However, how to map and analyze spatial autocorrelation in factors that influence poor smallholder agriculture productivity and decisions to participate in agribusiness is little understood. The major challenge is the lack of a spatially explicit methodology that can map and analyze spatial autocorrelation. Another challenge is the lack of comprehensive spatial data disaggregated at the local level that can support localized spatial analysis. Additionally, existing empirical approaches mostly used in agriculture research rarely integrate the spatial dimension of agriculture in their analysis. This leads many policymakers in the agriculture sector to turn a blind eye to the spatially explicit determinants that influence agricultural production and market participation at the local level [47,49]. As a consequence, it has been difficult for policymakers in the agriculture sector to design spatially targeted interventions that address local-level challenges that hinder many resource-poor smallholders, particularly in marginalized rural areas, from participating in the agribusiness market.

In the study presented in chapter 6, we first designed a GIS-based spatially explicit methodology (illustrated in figure 9.1) that can detect and map local-level spatial autocorrelation in our dataset. We used spatial geostatistics to measure and map the level of geographic factors' influence on the household decision process, which is explained in detail as follows. In GIS, spatial dependency is measured using spatial autocorrelation. Thus, we used three spatial autocorrelation methods (Global Moran's I method, Cluster and Anselin Local Moran's I method, and Geographically Weighted Regression) to unearth spatially explicit factors that impede smallholders from participation in agribusiness markets. By combining the three methods above, we identified specific localities with a statistically significant concentration of high values (hotspots) and concentrations of low values (cold spots), and the factors causing these spatial clusters [86,87]. Since factors affecting smallholder farmers are more manifest at the farm and neighborhood level, GIS could support policymakers in mapping the spatial dimension of agriculture and food insecurity and factors impeding agriculture productivity and visualize them in maps. This would provide a better conceptualization of the reality of these problems thus effectively improving their identification (through mapping), diagnosis (through spatial analysis), and designing of spatial-targeted interventions.

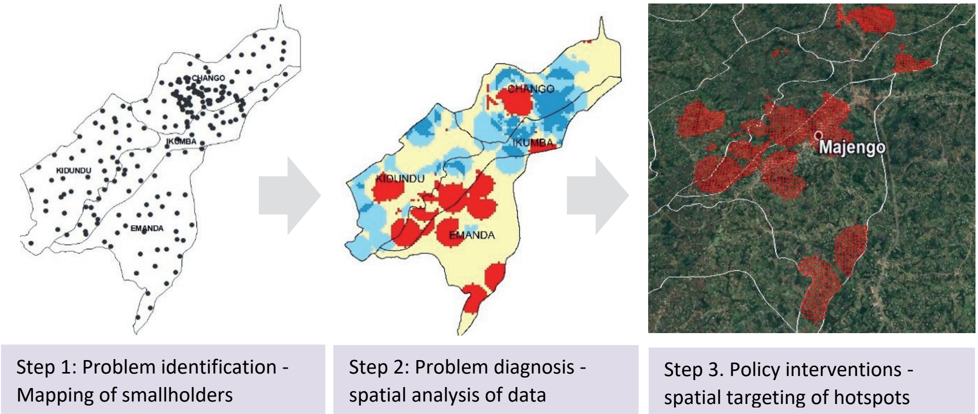

Figure 9.1: A GIS-based spatially explicit methodology to detect, map, and measure coalescing of local geographic factors that impede smallholders from participation in agribusiness markets.

Based on our findings, the inability of poor smallholders to effectively participate in the market emanates from their inability to exploit local resources, which undermines their collective problem-solving ability in responding to the opportunities provided by the emerging agribusiness markets. For example, in the Nyando study area, we mapped the spatial distribution of deprivations using the GWR standard residual and visualized it using quartile classification. As the results have shown (see Figures 6.4, 6.5, and 6.6), there is a widespread spatial manifestation of food insecurity inequalities in the study area. Food insecurity is seen as emanating from a lack of multiple deprivations, which acts as a barrier to poor households' market participation.

Mapping the spatial dependence of local factors provided a deeper insight into how spatially explicit determinants promoted or impeded poor smallholder farmers' participation in agribusiness. This knowledge would allow policymakers to make evidence-based decisions and also enable them to design appropriate spatially targeted interventions tailored to local contexts. We suggest that causative factors of socio-spatial inequality should be addressed comprehensively and concurrently, starting at the local level, to enhance resource-poor smallholders' integration in agribusiness markets.

Mapping and geo-visualization of the spatial dimension of food insecurity in providing a contextualized understanding of local-level causative factors of food insecurity

Although many studies have shown the multifactorial causation of food insecurity [181,221,225,275,276], little attention has been focused on mapping the spatial patterns 'manifestation' of food insecurity at the local level, in diagnosing local causative factors of food insecurity. Local governments and policymakers must have a better understanding of the causes of food insecurity at the local level to design appropriate local-based interventions. However, due to the complex and multidimensional nature of food insecurity, it has become nearly impossible to measure food insecurity in totality using the commonly used composite indicators. In chapter 7, we explored the spatially varying relationship between local geographic context and agriculture productivity in mapping the spatial patterns of food insecurity. This was meant to elicit a deeper understanding of the underlying causes of food insecurity amongst poor smallholder households. Several studies have shown that the spatially heterogeneous food insecurity patterns can be mapped and analyzed using GIS-based spatially explicit methodologies [47,65,66]. We combined two methodologies to map and geo-visualize the spatial patterns of food insecurity and to identify local causative factors of food insecurity among smallholder households in the study area: GIS-based indicators and a place-based approach.

Our results revealed that food insecurity has a spatial pattern that is inherently linked to the local geographic factors existing at the smallholder's place of residence. By separating the index into the four-food security dimensions and mapping each dimension separately using spatially disaggregated GIS-based indicators, we provided a more accurate conceptualization and spatial manifestation of the geographic patterns of food insecurity at the local level. The disaggregated index was able to reveal localities and deprived neighborhoods' where poverty-stricken households experiencing worst food insecurity resided than the aggregated single index. The results showed that food-insecure households formed spatial clusters in several areas across the study area. This would mean that factors causing food insecurity were more pronounced (with spatial clusters) in some areas than others (figures 7.3 and 7.4). This proves that causal factors of food insecurity can be linked to the local geography.

However, the inherent difficulty in adopting spatially explicit methodologies in the agriculture sector remains a serious caveat in understanding the spatial patterns of food insecurity, but also in identifying and mapping its local causative. The spatially explicit approach developed in this study presents a viable diagnostic tool for identifying food security hotspots and locations where the most vulnerable, impoverished, and resource-poor households reside. If the spatial dimension of agriculture and food insecurity can be accurately mapped and geo-visualized, it can provide policymakers with a contextualized understanding of local-level causative factors of food insecurity. This would particularly be useful for policymakers, local government, and development practitioners in generating spatially relevant information for diagnosing local-level food insecurity, setting policy priorities, better resource allocation, and better-targeted interventions.

Factors enabling or constraining integration of agriculture and spatial policies

In addressing persistent food insecurity inequalities, poverty, and socio-spatial exclusion of smallholder agriculture systems in the mainstream spatial and development planning, many governments in LMICs have endeavored to formulate and implement integrated agriculture policies. However, many agriculture policies and interventions formulated are usually sector-specific, devoid of multi-level, multi-sectoral, and multi-actor integration. Most importantly, they rarely consider and integrate the spatial dimension of agricultural production in their formulation and implementation. On the one hand, the traditionally strong focus of agriculture policies on improving agricultural productivity at the expense of other dimensions of agricultural (i.e., social, economic, cultural, environmental, and spatial aspects), narrows the scope of the highly context-specific and place-based nature of agriculture and food security. On the other hand, the top-down spatial development policies widely adopted by many LMICs are overly biased toward promoting the economic side of land-use planning, while giving little emphasis on the spatial aspect of agricultural production and planning [56,62,246,251]. This agri-spatial policy disconnect and the dichotomous rural-urban divide have been blamed for perpetuating food insecurity inequalities, poverty, and marginalization of agricultural development in the rural areas [57,58,63,277]. In chapter 8, we examined existing agriculture and spatial planning policy frameworks and the extent they support multisectoral, multilevel, and multi-actor integration in agriculture development. In achieving so, we conducted an in-depth analysis to identify the structural and practical inhibitors and facilitators for agri-spatial policy integration, using an embedded case study of Kenya, specifically focusing on the County government of Vihiga in Western Kenya.

Our study findings revealed that agriculture sector policies in Kenya were not sufficiently integrated to effectively address the multidimensional challenges facing smallholder farmers. Several factors hindered agri-spatial policy integration including weak institutional frameworks and a lack of coordination of the sectoral policies with development plans. In addition, the fragmented policy instruments, weak legal and institutional frameworks, and a lack of synchronization of the many disjointed sectoral policies and plans impeded agri-spatial policy integration. Decentralization of agriculture and spatial planning systems played a pivotal role in promoting policy integration. For example, Kenya's decentralization strategy has given the county government the autonomy to make its own decisions. Since the year 2010, Kenya created a new devolved system of governance that has two distinct, but interrelated, levels of government – one national government and 48 devolved county governments that are semi-autonomous and interdependent. This was meant to address the weakness and bottlenecks created by centralized government systems and brought a new paradigm shift in spatial and development planning. The previously hierarchical and bureaucratic system was replaced with a decentralized 'bottom up' spatial governance system. In the established devolved governance system, various functions were transferred to the newly created county governments. While some functions were retained in the national government, others are concurrently implemented by the two-tier governments.

The decentralization of power, resources, responsibilities, and tasks from the national to county level has substantially increased the role of county government in agri-spatial policy-making and the implementation of development interventions. The decentralized spatial planning system is seen as a positive endeavor of abandoning the rigid and overriding centralized planning frameworks that have been perceived to perpetuate the underdevelopment and marginalization of the grassroots citizens, especially those residing in the rural areas of Kenya. In the newly created county government, the planning framework has an institutionalized structure where the higher-level (national government) plans inform and guide the preparation of the lower-level (county government) plans, and the lower-level plans implement the higher-level plans. The decentralization spatial development framework had several embedded policy and legal instruments, institutional frameworks, and mechanisms that facilitated multilevel and multisectoral policy integration.

Despite the decentralized agriculture and spatial framework, several considerable challenges were found to hamper effective agri-spatial policy integration. The numerous legislations and policy instruments created a practical challenge in synchronizing their visions, goals, and strategies, across policy domains and spatial scales. In addition, the multi-layered spatial and sectoral policies and plans – often with conflicting implementation time frames, and anchored on disjointed legal and institutional frameworks – were a major bottleneck to effective policy integration and implementation. Also, poor coherence and weak synchronization between various layers of agri-spatial policies and plans present a considerable challenge to policy integration efforts. Whilst a range of policy instruments and institutional arrangements can help promote effective agri-spatial policy integration, strengthening their integration is considered crucial in creating the fundamental conditions for effective multi-level, multi-sectoral, and multi-actor policy integration. This would require the strengthening of the weak institutional and organizational structures that inhibit policy integration [263]. This can be achieved by adopting strong collaborative governance structures that support spatially coordinated policy implementation [269], and the interconnectedness of institutional and sectoral frameworks between different sectoral policies [265]. Based on the results of this study, we developed an integrated agri-spatial framework (figure 9.2) for improving the sustainability of smallholder agrifood systems.

The guiding principles for the integration of multilevel and multisectoral policy and plans ought to be informed by collaboration and participation throughout the policy formulation process [271]. This should be a public sector-led process where all actors are provided with an equal platform to fully communicate and articulate their values, visions, and ideas within the plan-making arena [164,272,273]. Adoption of integrated agri-spatial policy and planning frameworks in the public sector would contribute to the success of this participatory process by creating a more holistic understanding of barriers and facilitators of smallholder value chains which would, in turn, improve the sustainability of smallholder agri-food systems in the LMICs. It has been argued that well-articulated and integrated agri-spatial planning strategies [247] that tap into the resource heterogeneity of rural and peri-urban areas while enhancing the diversity are seen as an alternative to redress rural underdevelopment thereby enhancing rural agricultural production and food security.

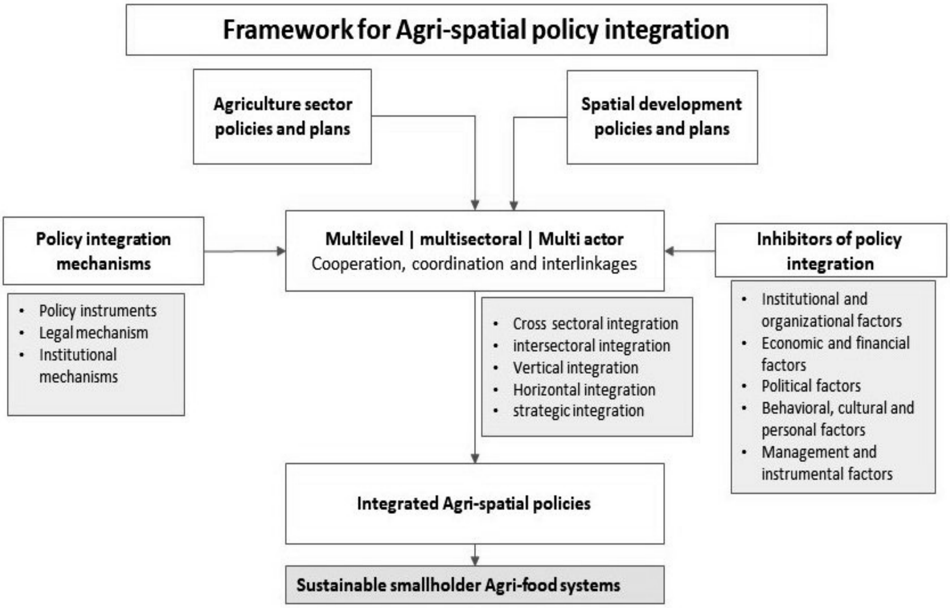

Figure 9.2: A conceptual framework to support multilevel, multisectoral, and multi-actor agri-spatial policy integration.

9.3 Overall conclusion and recommendations for policy and practice

The tremendous challenge of providing a rapidly increasing population with affordable, safe, and nutritious food is both urgent and complex. Challenges facing smallholder agricultural productivity are multidimensional in scope, and span across many government sectors, ministries and departments. This makes it difficult for agriculture sector policies alone to provide effective solutions. Based on our findings, the inability of poor rural smallholders to effectively exploit resources at their disposal in improving agricultural productivity, food security, and market participation emanates from their multiple deprivation status, socio-spatial inequality, economic exclusion, and rural segregation. This undermines their collective problem-solving ability in responding to the challenges of agribusiness production. The complex, multidimensional nature of poverty has been pursued in many works of literature, as a possible root cause of multiple deprivation and inequality, which hinders many resource-poor households from productively exploiting resources at their disposal. This leads to our conclusion that non-market participation is deeply rooted within the multiple deprivations, which breed inequality between the poor and rich in the echelons of society.

We, therefore, recommend policymakers formulate and prioritize the implementation of inclusive pro-poor agriculture policies and strategies that mainly target the improvement of poor smallholders' livelihood capitals and their proper utilization. These intervention strategies have been taunted as the most promising pathways to accelerate poverty reduction in rural areas of developing countries [167,193,204], which could rejuvenate smallholders to diversify their farming activities into market-oriented agribusiness. Pro-poor agribusiness policies should focus on transitioning smallholder agriculture value chains from the 'traditional' subsistence-oriented value chains and spot-market commodity transactions to more direct-market 'agribusiness' value chains. These policy interventions could include initiatives like inclusive market development, rejuvenating producer organizations, reorganizing cooperative movements, contract farming, and improving value chain financing and governance [159,213,214,278,279].

This thesis provides a better-contextualized understanding of the local level spatial patterns of food insecurity, which then inform us how place-based policies and spatially targeted interventions can be informed from such an analysis. The use of spatially explicit methodologies can be used as a diagnostic tool for analyzing locally expressed needs in understanding complex socio-spatial inequality of food insecurity. Studies that employ methods that deconstruct the spatially explicit environments may provide a deeper understanding of the localized variables that influence smallholders. In this thesis, by combining GIS, disaggregated spatial data, and spatial geostatistics analysis, we developed a spatially explicit methodology that can be used to detect, map, and analyze local spatial factors that hinder or foster smallholder agriculture from participating in agribusiness. Deconstructing the spatially explicit environments at the micro-level within which smallholders operate revealed the social-spatial inequality of food insecurity, agricultural productivity, and impediments to market participation. This would provide an evidence-based approach for identifying resource-poor smallholder farmers in implementing targeted policies to support them in participating in agri-business markets. The produced spatial distribution of non-market participation and food insecurity presented in the geo-visualized output maps can aid decision-making efforts, especially when designing spatially targeted interventions. We suggest that causative factors of social-spatial inequality should be addressed comprehensively and concurrently, starting at the local level, to enhance resource-poor smallholders' integration in agribusiness markets.

To address the ambiguity associated with complex persistent problems, a spatially integrated transdisciplinary approach is best placed to produce knowledge of immediate relevance for solving complex societal problems. In addition, there is a need for strengthening multisectoral and multilevel collaborative structures and frameworks for agri-spatial policy formulation, implementation, monitoring, and evaluation. The creation of multidisciplinary interlinkages would facilitate collaboration and integrated decision-making. As such, improving smallholder farmers' sustainability requires collective public policy responses from various sectors of the economy. This would require the integration of physical, social, cultural, economic, institutional, and environmental aspects in agri-spatial policy planning and implementation. We posit that approaches for achieving food security sustainability ought to be supported by a holistic and coordinated multisectoral approach, and integrated agricultural and spatial planning policies where smallholders play a crucial role. The need for holistic, inter-, and transdisciplinary solutions is deemed important because of the complexity and interconnectedness of economic, social, and environmental processes that affect agricultural production. Integration of the spatial dimension into agriculture policy could be seen as more responsive to addressing local problems that impede smallholder agriculture development [244].

GIS adoption would support the creation of geographically referenced agricultural information management systems and establish policy frameworks to facilitate data sharing, data integration, and quality control across the sectors. Adoption of the GIS would provide the capabilities for county Governments to establish comprehensive agriculture information databases that can continuously be populated in providing up-to-date information to support integrated spatial policy-making and spatially targeted interventions. Since factors affecting smallholder farmers are more manifest at the farm and neighborhood level, GIS would support policymakers in mapping the spatial dimension of agriculture and food insecurity and factors impeding agriculture productivity and visualize them in maps. This would provide policymakers with a better conceptualization of the reality of these problems thus effectively improving their identification (through mapping), diagnosis (through spatial analysis), and designing of spatial-targeted interventions. The effectiveness of policy implementation depends on the availability of well-trained staff. However, our study findings revealed that county governments lack staff with sufficient technical capacity and experience for implementing GIS-based spatial analysis in supporting integrated policy implementation, monitoring, and evaluation. Continuous staff training and development should be a strategic priority.

Rather than formulating agriculture policies that advocate for the blanket improvement of smallholder agricultural production, policymakers should spatially target territories with geographic specificities and hot spots of food insecurities. After all, the more food insecure a household is, the less likely it is to produce a surplus to sell in agribusiness markets. As such, integrated policies that focus on the multidimensional aspect of agricultural production and food security, and are formulated from the bottom-up, are more likely to be spatially sensitive to the spatial heterogeneity of localities. This would require policymakers to adopt place-based policy interventions and integrate local territorial specificities since this could be more responsive in addressing local constraints and opportunities for agribusiness market participation.

9.4 Limitation of the study

This study relied on self-reporting of food insecurity from households. However, data based on self-report measures may have potential limitations related to accuracy. For example, during fieldwork interviews, households may have over or underestimated their food insecurity situation. We addressed this limitation by cross-validating the collected data. The household questionnaire was also designed by combining several open and closed-ended questions to collate the same information.

The study area transcended two regions with two different ethnic tribes (Luhya and Luo) whose language the author could not speak or understand. The non-familiarity with the local dialect and culture may have limited an in-depth interrogation and a contextualized understanding of local issues. To overcome the language barrier, research assistants were engaged who could speak the local dialect to interview households.

In the middle of the data collection phase, the Covid-19 global pandemic broke out and severely disrupted research undertakings. The foreboding and uncertainties brought by the strict Covid-19 lockdowns enforced in Kenya curtailed my fieldwork data collection excursions for several months. After the lockdowns were lifted, most people were anxious to engage in face-to-face meetings and interviews. Also, the personal health and safety of the researcher and the respondents became a matter of grave concern.

A common limitation of empirical studies in a specific locality is the generalizability of the study findings. It can be argued that spatially explicit findings may only be valid for a narrow time scope. This argument emanates from the fact that geocoded household surveys capture point data georeferenced for that particular moment in time, binding them in both space and time. This localizes the findings and interpretations thereof. However, in principle, different territories across LMICs exhibit spatially heterogeneous characteristics due to the diversity of local geographic specificities and levels of a territorial capital endowment. Even though these territorial characteristics could be perceived as dynamic, they rarely change rapidly and tend to exhibit similar characteristics across LMICs, enabling the generalizability of study findings even when such studies are based on specific local geographic parameters. Thus, for spatially explicit studies to be generalizable, four important aspects must be considered to produce accurate spatial models that inform decisions in both short- and long-term planning scenarios. These considerations include (1), the choice of spatially explicit variables, (2), the conceptualization of the spatial varying relationships, (3), the geocoded study design to collect data, and (4), the correct choice of spatial analysis methods. While recognizing the multiplicity of parameter variables to model local spatial autocorrelation, the spatial unit of analysis used, and the level of disaggregation of spatial data should be a key consideration in studies that analyze local spatial relationships. As such, the broader relevance of this study would be pegged on how accurate other researchers integrate these factors, as well as their ability to apply them in modeling the complexity of spatially linked problems.

For this study, we designed a well-articulated spatially explicit methodology for the collection of quality household survey data that was enhanced by incorporating web-based geospatial tools that helped us to accurately collect quality georeferenced data. The step-by-step description of the process of designing a spatially explicit methodology and articulate description of the spatial analysis methods used in chapters 6 and 7 of this study could easily enable other researchers to replicate this study or design similar studies elsewhere. Kenya is unique in Africa in that it is the only country that has implemented devolved systems of governance (with two distinct, but interdependent, levels of government – one national government and 48 semi-autonomous devolved county governments) and has decentralized agriculture and spatial planning to the county level. Thus, the agri-spatial policy integration framework developed in this study can inform LMICs, especially those with bureaucratic and centralized systems of governance or those in transition how to decentralize and integrate agriculture policies in local development planning frameworks.

9.5 Recommendations for future research plans

The output of this study demonstrates the importance of developing spatially targeted policies and interventions that are embedded in the local context and informed by the locally expressed needs of smallholders. However, it is not exhaustive in itself, and further research to ground the spatially explicit methods and frameworks developed in this thesis into policy and practice are proposed.

Further studies can interrogate exhaustively, all the possible combinations of productive livelihood capitals, taking into consideration the effect of confounding stressors and other exogenous factors in understanding smallholder agribusiness adoption and practices.

Given that GIS technology provides promising new ways to enhance agricultural production, future studies could study the specific role the integrated GIS, RS, and GPS technologies could play in improving local agri-food supply chains and their integration into regional or national agribusiness and food value chains. In addition, a detailed analysis of how GIS and RS technology can be applied in developing resilient smallholder agri-food systems would constitute an interesting research undertaking.

From the research findings, GIS use and adoption in the agriculture sector in LMICs were found to be very low (with systematic review results showing only one publication done in sub-Saharan Africa in the last decade). Yet, from our study findings, GIS and RS provide practically-oriented and solution-focused agriculture knowledge that has been applied to support better innovations that address challenges facing the agriculture sector. Future studies could investigate the enablers and barriers of GIS technology adoption and the ways its adoption might be accelerated.

For spatial interventions of food insecurity to be successful, all the factors behind the spatial patterns observed in a locality should be addressed concurrently at the design stage of spatially targeted interventions. Likewise, lack of market participation emanates from the complex interaction of multiple factors; targeting a single factor will most likely fail to enhance smallholder's market participation. Further research could expand on this by including both endogenous and exogenous variables in GIS models in mapping market participation determinants. In addition, given that the spatially explicit methodology developed in chapter 7 to map the spatial dimension of food insecurity was applied in a small study area, future studies could apply the same methodology but use both two spatial scales; in a small area (e.g., neighborhood) and a larger study area (e.g., a county) to map and analyze the spatial heterogeneity of food insecurities and the causes of food disparities. Furthermore, such a study could shed more light on the effect of spatial scale and the influence of modifiable area unit problem on the spatial patterns of food security, which can further help to unearth the causes of territorial food inequality

Anchoring agribusiness development in spatial policy frameworks constitutes a very promising pathway to improve the development of sustainable smallholder systems. However, the multi-dimensional and multifaceted nature of problems facing poor smallholder systems makes agri-spatial policy integration a complex endeavor. To address this complexity a transdisciplinary approach that encompasses multiple actors in co-creating innovative knowledge in agribusiness planning and policy formulation and implementation is needed. Since agri-spatial policy integration crosses several disciplines and policy domains, future research can employ a transdisciplinary approach in investigating the extent to which agri-spatial policy integration could work in LMICs where spatial planning and participatory governance frameworks are either weak, vaguely defined, or non-existent.

Finally, with increasing global food insecurity, poverty, climate change, and global food supply chains crisis brought about by the covid-19 pandemic, and the Russia-Ukraine war and resulting geopolitics, there is a need for LMICs to shift their dependency on globalized agri-food value chains and instead focus more on the development of localized agribusiness value chains. The development of smallholder agribusiness should become an urgent priority, especially in LMICs that suffer from a perpetual food crisis. Addressing complex food security problems will call for the adoption of transdisciplinary, farmers-led, and spatially-explicit approaches that integrate a diversity of factors, societal actors, and institutions in knowledge co-sharing and co-creation to find solutions to complex food production problems. Now and in the future, GIS and RS technologies will even become more important in the development of local sustainable agricultural practices and in supporting spatially integrated solutions to complex problems facing smallholder agricultural systems.

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SUMMARY

Background

The tremendous challenge of providing a rapidly increasing population with affordable, safe, and nutritious food is both urgent and complex. Today, more than 100 million households in Sub Sahara Africa experience varying levels of food insecurity and chronic poverty. The majority of these households are rural smallholder farmers, who heavily rely on subsistence agriculture as their main livelihood and account for the largest segment of agricultural food production globally. These poor smallholders are often characterized by marginal agriculture productivity, rudimentary production methods, and little or no commercialization and thus unable to effectively participate in contemporary agribusiness markets. The causes of these problems can be attributable to a multiplicity of factors that can be linked to an interplay of dynamic socio-economic, biophysical, and political variables, both at the household and societal level. In recent times, approaches for addressing the sustainability of smallholder farming have increasingly gained priority in LMICs. Although various efforts have been made to improve smallholder livelihoods and in boosting their agricultural production and market participation, limited success has been achieved in transitioning poor smallholders from 'traditional' subsistence-centered production to 'modern' agribusiness-oriented value chains.

The complexity and multifaceted nature of problems facing smallholders present formidable challenges for policymakers in the agriculture sector. to a larger extent, smallholder agricultural production decisions are influenced and compounded by the complex interactions emanating from variabilities of socio-economic, cultural, agroecological, biophysical, institutional, and spatial environmental dynamics. The impact of these variable interactions on smallholder households at a local level creates diverse, spatially heterogenous farming patterns and production systems adopted to, and distinct to the local context. These resulting spatial patterns can be conceptualized as spatial manifestations of individual household decisions that respond to actions resulting from the interaction between household livelihood capitals and local geographic factors and constraints. Understanding how these dynamics impact smallholders would require policymakers to have a localized understanding of the geographic specificities of various localities, in determining the best location-specific interventions for each locality. However, many agriculture policies and interventions rarely have a clear consideration for local geographic specificities in their formulation and implementation. they tend to follow the generic recommendations that miss the spatially explicit determinants of agricultural productivity at the local level. The lack of spatial contextual awareness of agriculture policies narrows the highly context-specific and place-based nature of agricultural production. As a consequence, it has been difficult for policymakers in the agriculture sector to design spatially targeted interventions for addressing local-level challenges that hinder many resource-poor smallholders, particularly in the marginalized rural areas, from participating in the agribusiness market.

However, the prominence of spatially explicit factors as a possible contextual explanation of the spatial pattern of food insecurity has received little attention. Yet, agriculture productivity and food insecurity cannot be delinked from the influence exerted by local geographic specificities existing at smallholder households' places of residence. The spatially explicit determinants of agricultural productivity, at the local level, if properly interrogated, and analyzed could be indispensable in explaining the spatial disparities of food insecurity at the local level, and spatial impediments that hinder smallholders to participate in agribusiness value chains. In addition, mapping the spatial dimension of agriculture and food insecurity can provide a contextualized understanding of local-level causative factors of food insecurity.

In this thesis, we aimed at mapping, analyzing, and geo-visualizing the spatially explicit factors that influence smallholders' agricultural production, food security, and decision to participate in the agribusiness value chains and markets. The central research question of this thesis was formulated as follows:

> How do spatially explicit factors influence smallholders' agricultural productivity, food security, and decisions to participate (or not) in agribusiness, and how can these factors be mapped, analyzed, and integrated into the agriculture and spatial planning policies in improving smallholder sustainability and their participation in agribusiness?

Methodology

We first designed a spatially explicit methodology to identify, map, and analyze (1), the spatial dimension of agriculture, that is, spatially explicit factors that contribute to low agriculture productivity and those that impede smallholder farmers to participate in agribusiness (2), the spatial dimension, that is, spatial patterns of food insecurity, (3) local causative factors of food insecurity. Developing a spatially explicit methodology entailed combining both normal statistics and GIS spatial statistics methods and processes to enable mapping and modeling of the local spatial relationships resulting from households' livelihood capital interactions with spatially explicit factors. The aim was to uncover spatial relationships and detect spatial patterns, and spatial impediments from hitherto unknown local spatial processes. We used two geographically defined study areas (Kisumu and Vihiga County), to collect both spatial and non-spatial data. We used a mixed-method approach to collect both spatial and non-spatial data. We combined geocoded household interviews, semi-structured key informant interviews, focused group discussions, document analysis, systematic review, and GPS mapping.

Data analysis entailed the use of several analytic techniques and methods to analyze both spatial and nonspatial data, of which a summary is presented below.

In chapter 4, we conducted a systematic literature review, by synthesizing 10 years of selected publications (from 2010 to 2020) in the databases of SCOPUS, Web of Science, BASE, CORE, and google scholar. The synthesized literature provided insights into the recent trends and future perspectives on GIS application in agriculture. The review enabled us to deduce important insights on how GIS and RS technology can be applied to enhance evidence-based policymaking to improve agriculture sustainability. **In chapter 5**, we used, Multinomial logistic regression analysis using SPSS software to identify how livelihood capitals 'asset base' influenced poor smallholders' farming activities. The aim was to measure, using the odds ratio, the extent to which each household capital influenced smallholders' decisions to participate in agribusiness in the selected study areas. **In chapter 6**, we combined three GIS spatial statistics analysis methods in ArcGIS to map the poor smallholder households and identify the local spatial factors that impede their market participation. In step one, we used Global Moran's I spatial autocorrelation method to assess the presence or absence of spatial patterns in our dataset. In step 2, we used Cluster and Outliers Analysis (Anselin Local Moran's I) method to detect the presence of local-level spatial patterns and clusters and to determine if these spatial clusters are statistically significant or are the resultant of complete spatial randomness of data in the study area. In the last step, we used Geographically Weighted Regression (GWR) to examine geographically significant local factors that explain households' non-market participation; in other words, factors behind the observed spatial patterns identified in step 2 above. **In chapter 7,** we used geocoded household survey data, to develop GIS-based indicators to map the spatial patterns of food insecurity in the study area. By first using Principal Component Analysis (PCA) method, we constructed one composite indicator of food insecurity (Food Insecurity Multidimensional Index), and then used the four dimensions of food security (availability, stability, access, and utilization,) to construct four distinct composite indicators. PCA method was then used to measure the level of each indicator's influence on household food insecurity. Then, using the GIS Hot spot analysis method, we performed spatial analysis to map the spatial manifestation of food insecurity based on the developed indicators. By comparing the resultant spatial patterns of food insecurity from these two sets of indicators, we deduced an important conclusion as to which set of indices was more effective in revealing local spatial patterns of food insecurity. Finally, **in chapter 8,** we employed an embedded case study, and used a mixed-method approach, combining document analysis, FGD, and KII method to conduct an in-depth analysis in identifying structural and practical inhibitors and facilitators of agri-spatial policy integration.

Results

In Chapter 4, the results of a systematic literature review show that GIS technology application in agriculture has gained prominence in the last decade. GIS technology provides practically-oriented and solution-focused knowledge that enhances spatially-based decision support systems for improving agriculture sustainability. The results show that areas the GIS technology has been applied to improve agriculture sustainability are expanding, including crop yield estimation/forecasting (30% of the reviewed papers), soil fertility assessment (22.5%), cropping patterns, and agricultural monitoring (10%), drought risk assessment (10%), pest and crop disease detection and management (7.5%), precision agriculture (7.5%) and fertilizer and weed management (5%). However, the lack of quality spatial data to support policy and decision-making has continued to undermine evidence-based policy formulation and effectiveness in their implementation. Achieving better policies demands comprehensive, up-to-date datasets and better methods that combine and analyze complex data sources from various sources to produce useful information. This would necessitate governments to adopt methods, strategies, and techniques that facilitate the collection of diverse spatial and non-spatial agricultural datasets in providing comprehensive insights to policymakers, planners, farmers, and a broad spectrum of stakeholders in the agriculture sector. GIS provides a promising pathway for supporting spatially integrated agriculture policies and for the acquisition of comprehensive, up-to-date spatial data. In addition, it provides better spatial analysis methods for analyzing complex spatial and non-spatial data from various sources to produce useful information. If properly adopted and implemented, it will enhance the spatial decision support system in empowering the County government to improve efficiency and effectiveness in agriculture policy and planning through the collection and analysis of up-to-date spatial data that inform better decision-making.

In Chapter 5, the results from the multinomial logistic regression analysis revealed that all livelihood capitals acted in parallel and jointly to influence the decisions of smallholders. Higher livelihood capital endowment resulted in a higher probability of a household participating in agribusiness activities, while lower livelihood capital ownership resulted in a lower probability to participate in agribusiness. Smallholders' decision to participate in agribusiness was positively and significantly determined by livelihood capitals such as education level, gender, landholding size, savings, distance to markets access to agriculture extension services and farm input, and livestock ownership. The study contributes to the knowledge gap by bringing a better understanding of the causative relationships between livelihood capital assets and their influence on smallholders to participate in agribusiness. The spatial heterogeneity of households' livelihood capital endowments (human, financial, physical, natural, economic, and social assets) can be used to explain the diversity of choices adopted by smallholders within a geographic territory. The study highlights the need for policymakers to formulate and prioritize the implementation of inclusive pro-poor agriculture policies and interventions that mainly target the improvement of smallholders' livelihood capitals and their proper utilization. Implementation of pro-poor policies and tailor-made interventions that target the improvement of specific livelihood capitals that are deficient in a household or a locality could be an alternate strategy for increasing aggregate-level food availability for smallholder households in marginalized areas or food insecurity hot spots. Promoting pro-poor policies in agriculture could also enable smallholders to shift from subsistence-oriented production to market-oriented agribusiness.

The results of **Chapter 6** shows that spatially explicit factors hindering market participation exhibited local spatial autocorrelation that was linked to the local context. Using GIS spatial analysis, we identified and mapped distinct local spatial clusters (hot spots and cold spots clusters) that were spatially and statistically significant. Specifically, Global Moran's I, results revealed the presence of spatial patterns in our dataset that was not caused by spatial randomness of data. Secondly, the Anselin Local Moran's I, identified statistically significant local spatial clusters of factors that hinder smallholder participation. Finally, the geographically weighted regression identified spatially significant causative factors impeding market participation in the study areas. The results show that occupation, education level, livestock assets, savings, landholding size, membership in social groups, training, and travel time to output markets were spatially and statistically significant factors impeding smallholder market participation. Non-market participation was found to result from multifactorial causation that was linked to the local context. Spatially explicit factors hindering market participation varied between the two study areas. Results affirm that spatially explicit factors play a crucial role in influencing the farming decisions of smallholder households. Social problems have increasing become interwoven in socio-spatial complexity and their manifestation is most evident at the local level, rather than a regional or national level. In designing spatially targeted interventions, policymakers should take cognizance of complex interactions of socio-spatial processes in the local landscape. The conclusion of this study underscores the importance of designing spatially targeted policies and interventions that are embedded in the local context and informed by the locally expressed needs of households.

In Chapter 7, the GIS Hot Spot Analysis revealed significant spatial differentiation in food insecurity in the study area. The FIMI index produced a more distinct spatial pattern of food insecurity than the other four-dimension indices that revealed a spatially disaggregated patterning of food insecurity across the study areas. Each dimension revealed a geographical variation of food insecurity that was unique to specific areas, with some areas having hot spots of food insecurity and others being relatively food secure. The results also showed that several food-insecure households formed spatial clusters in several areas across the study area. This would mean that factors causing food insecurity were more pronounced in some areas than others. The FIMI Indicator showed the following factors contribute very highly to food insecurity; Distance to markets, Distance to Agrovet shops, low level of farming skills, low level of farming technology lack of agriculture information, weather variability, and pest and disease infestation. comparing this to the four disaggregated food security dimensions, in the food availability dimension index, low level of farming skills and low level of farming technology contributed the highest to food insecurity. In the food stability dimension index, weather variability, pest and disease influence, and lack of capital contributed the highest to food insecurity. In the food utilization dimension index, women's land inheritance and women's asset ownership exerted the highest influence on household food insecurity. In the access dimension index, distance to agro vet store, distance to markets, Access to agriculture credit, and household assets ownership contributed the highest influence to food insecurity. Overall, the availability dimension indicators were the greatest contributors to food insecurity in the study area. Mapping the local spatial patterns of food insecurity offers important insights into the spatial disparities of food insecurity. If policies to address food insecurity are to be effective, they should recognize the spatial inequality of food insecurity within and across regions, and that the nature and magnitude of food security also vary within and across local, rural, regional, and urban territories. As such, policies formulated from the bottom-up could be more spatially sensitive to the spatial heterogeneity of food insecurity in different localities than those formulated from the top down. The use and adoption of GIS-based indicators in conjunction with a small area approach could provide policymakers with better methods for mapping and geo-visualizing food insecurity at the local level thereby improving the spatial targeting of food insecurity. Gaining a contextualized understanding of how geographic specificities at the local level influence agricultural production and by extension, food insecurity could help in the spatial targeting of interventions, and for designing place-based policies that are aligned to specific challenges and opportunities of a defined geographic area. In addition, developing a deeper understanding of the spatial dimension of food insecurity can contribute to more sustainable local food systems, resulting in increased smallholder agriculture productivity, and, by extension, food security.

In Chapter 8, we conducted an in-depth analysis to identify the structural and practical inhibitors and facilitators of agriculture and spatial policy integration. This was premised on the fact that problems affecting smallholder farming tend to share intrinsic spatial characteristics of the local geographic specificities. However, agriculture policies and food security interventions have been criticized for lack of spatial explicitness, especially when addressing those factors of spatial nature or those which can be directly linked to a certain local geography. Addressing the placed-based and multidimensional nature of these challenges requires the integration of physical, social, economic, political, environmental, and spatial aspects of agricultural production and a spatial 'territorial' approach. The results of the case study revealed that the hierarchy of multi-layered and interlinked spatial planning instruments formulated and implemented by both national and county governments, and operationalized at different spatial levels, constituted the primary mechanisms for both vertical and horizontal policy integration in the case study. Several supportive policies and legal and institutional mechanisms embedded in the national and county government spatial planning frameworks promoted policy integration efforts in the case study. In particular, the devolution of the spatial governance structures and the agri-spatial planning functions created favorable conditions for supporting policy integration at the county level. Nevertheless, the multi-layered spatial and sectoral policies and plans, often with conflicting implementation time frames, and anchored on disjointed legal and institutional frameworks become a major bottleneck to effective policy integration. In addition, the many legislations and policy instruments created a practical challenge for agri-spatial policy integration, especially in their implementation, synchronizing their visions, goals, and strategies, across policy domains and spatial scales. As an output of this chapter, we developed an integrated multilevel and multisectoral framework for the integration of agri-spatial in policies for improving the sustainability of smallholder food agriculture systems. However, whilst a range of policy instruments and institutional arrangements can help promote policy integration, strengthening their integration is considered crucial in creating the fundamental conditions for effective multi-level, multi-sectoral, and multi-actor policy integration. Achieving effective agri-spatial policy integration would thus require the strengthening of the weak institutional and-organizational structures that inhibit policy integration. This can be achieved by adopting strong collaborative governance structures that support spatially coordinated policy implementation and the interconnectedness of institutional frameworks between different sectoral policies.

Conclusion

Addressing the intertwined challenges of low agricultural productivity, food insecurity and non-market participation by poor smallholder households is a complex undertaking that would require an integrated multidisciplinary approach and spatially integrated agriculture policies. However, many of the agricultural policies in LMICs are not usually sufficiently spatially integrated and are deficient in multi-level, multi-sectoral, and multi-actor integration. With the increasing embedding of agricultural production and food insecurity challenges in local spatial complexity, and, given the multidimensional nature of food security, agriculture policies should be spatially sensitive to the spatial variation of food insecurity and spatial heterogeneity of territorial resources. By mapping the spatial patterns of households' food inequalities, policy planners can better understand the local causation of low agriculture productivity and food insecurity. This can enable policymakers and relevant stakeholders to spatially target deprived areas and develop appropriate, place-based intervention strategies and policies.

Mapping local spatial patterns of food insecurity offers important insights into the spatial disparities of the territorial dimension of food security and causes of agriculture productivity poverty. With increasing recognition that place-specific features and territorial specificities strongly influence agriculture activities and food security outcomes, there is a need for place-specific policies and spatial-based interventions that are grounded in the local reality and informed by the local needs of smallholders. However, traditionally based "top-down" and sector-specific agriculture policies often designed at the national level, do not sufficiently take into account the spatial heterogeneity of territories. Thus, they would not offer sufficient conditions to address the multi-dimensional causes of low agriculture productivity and food insecurity.

The combination of GIS-based indicators and spatially explicit methodologies presents a more viable diagnostic tool for mapping local spatial interactions and increases the effectiveness of unearthing deep-rooted causes of social problems. This provides policymakers and local governments with an evidence-based approach in the application of remedy policies for prioritization of resources, spatial targeting of resources, and the design of location-specific interventions in improving the sustainability of smallholder systems. Well-articulated and coordinated spatial targeted development policies that tap into the resource heterogeneity of territories with geographic specificities while enhancing the diversity of particular regions would create the prerequisites required to develop local and sustainable smallholder systems while enhancing their sustainability.

With increasing global food insecurity, poverty, climate change, and global food supply chains crisis brought about by the covid-19 pandemic, and the Russia-Ukraine war, there is a need for LMICs to shift their dependency on globalized agri-food value chains and instead focus more on the development of localized agribusiness value chains. In this regard, the development of local smallholder agribusiness value chains should become an urgent public policy priority, especially in LMICs that suffer from a perpetual food crisis.

Addressing complex food security problems will call for the adoption of transdisciplinary, farmers-led, and spatially-explicit approaches that integrate a diversity of local factors, societal actors, and institutions in knowledge co-sharing and co-creation to find lasting solutions to complex food production problems. Now and in the future, GIS and RS technologies will even become more important in the development of spatially integrated agriculture policies to improve sustainable agricultural practices. In addition, the spatialization of agriculture policies will go a long way in supporting spatially integrated solutions to complex problems facing smallholder agricultural systems.

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AMEN.

PUBLICATIONS

ARTICLES INCLUDED IN THE THESIS

Mathenge, M., Sonneveld, B. G. J., & Broerse, J. E., (2022). Application of GIS in agriculture in enhancing evidence-informed policies for improving agriculture sustainability. A Systematic Review. *Sustainability* , Vol. 14. https://doi.org/10.3390/su14169974

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George G Wagah, and **Mathenge Mwehe** (2019). Harnessing Social Capital to Improve Food Security of Peri-Urban Households. Experiences from Kisumu City, Kenya. Journal of Food Security, 2019, Vol. 7, No. 6, 196-205. Available online at http://pubs.sciepub.com/jfs/7/6/2. DOI:10.12691/jfs-7-6-2

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ABOUT THE AUTHOR

Mathenge Mwehe was born in 1982 in Nyeri, Kenya. He studied for his undergraduate in Maseno university Kenya, graduating with a degree in Urban and Regional Planning (*1st class honors*) in the year 2007. He then pursued a Master's of science in 'Geo-Information Science for Earth Observation' at the University of Twente, the Netherlands in the year 2011. In the year 2014, he pursued a postgraduate diploma in urban development *(attaining a distinction)* at Erasmus University, Rotterdam. In the year 2018, he started his doctorate at the faculty of science (Athena) of the Vrije University Amsterdam, the Netherlands. His Ph.D. research focus is on the multidisciplinary integration of spatial planning, and agriculture policy (using GIS technology) in addressing the sustainability of smallholder agriculture, especially in sub-Saharan Africa. Mathenge has been a Lecturer and researcher at the School of Planning and Architecture, Maseno University since the year 2011 where he teaches various undergraduate and graduate programs. His research interest is in the field of spatial planning, urban development, project planning and management, Geographic Information Systems, Remote Sensing, agriculture and agribusiness development, food security and agri-spatial policy integration.

Addressing the intertwined challenges of low agricultural productivity, food insecurity and non-market participation facing poor smallholders is a complex undertaking that would require spatially integrated agricultural policies, and a multidisciplinary approach. With increasing recognition that spatially explicit factors and territorial capitals strongly influence agriculture activities and food security outcomes, there is a need for devising agriculture policies that are grounded in the local reality and informed by the local needs of smallholders. As such, agriculture and food security policies and interventions should be place-specific and spatially sensitive to the spatial heterogeneity of territorial capital and resources. This thesis combines GIS and RS technologies, to develop a spatially explicit methodology for mapping local spatial patterns of food insecurity and spatial impediments that hinder smallholders to participate in agribusiness market. The thesis offers important insights into the causative factors of local spatial disparities of the food insecurities, and low agriculture productivity. The outputs provide policymakers and local governments with an evidence-informed approach in the application of remedy policies for spatial targeting of food insecurity and poor smallholder households. The outputs also provide insights in the design of place-based policy interventions in improving the sustainability of poor smallholder systems. The spatialization of agriculture policies can go a long way in developing spatially integrated agriculture (agri-spatial) policies in improving the sustainability of smallholder agricultural systems in sub–Saharan Africa