



Mapping the spatial dimension of food insecurity using GIS-based indicators: A case of Western Kenya

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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 the 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 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 security (access, availability, stability, and utilization) 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 spatially targeted interventions for each dimension of food insecurity.

Keywords Food insecurity · Food security dimension · GIS · Indicators · Smallholder farmers · Small-area approach · Indices

1 Introduction

Hunger and food insecurity are global social problems that present formidable challenges to policymakers and local governments mandated to provide solutions (FAO et al., 2019).

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) (Conceição et al., 2016; Fawole et al., 2015; Sasson, 2012). 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 (Foran et al., 2014; Sabi et al., 2018; Swavely et al., 2019). Despite these interventions, higher concentrations of food insecurity and socioeconomic deprivation have been recorded in LMICs, especially among poor smallholder farmers (Collier & Dercon, 2009; Conceição et al.,

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2016), who constitute the majority of the rural population (Abraham & Pingali, 2020).

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 (Kanbur & Venables, 2005; Venables, 2005). 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 geographic 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, agro-ecological, and socio-economic factors, among others (Archer et al., 2008; Tittonell et al., 2011). 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 (Camagni, 2009; Perucca, 2014).

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 (Greco et al., 2019). 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 (Cohen et al., 2019; Li et al., 2020), mapping physical deprivation (Khadr et al., 2010), mapping the spatial dimension of income inequality (Mastronardi & Cavallo, 2020), and mapping the spatial dimension of food access (Yenerall et al., 2017). Marivoet et al. (2019) 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 spatially 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 spatially varying relationships of indicators at a lower spatial level (Keenan & Jankowski, 2019; Sui, 2004). 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 (Keenan & Jankowski, 2019; Martinez, 2019; Sui, 2004). 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 (Martinez, 2019). 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 (Baud et al., 2009; Chen, 1990; Li & Fang, 2014; Martinez, 2019).

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.

2 Materials and methods

According to Organization for Economic Co-operation and Development (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.

2.1 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 agriculture 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 1 shows salient territorial characteristics of the study area deduced from the reconnaissance visits and secondary data sources.

2.2 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

Table 1 Salient socio-spatial heterogeneity of 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 C
Topography	Undulating
Agro-ecological zones	Upper midlands
Socio-economic	
Population density	1,046 per km ²
Agriculture production	70% (small scale)
Average farm sizes	0.1–2 acres
Agriculture employment	62%
Absolute Poverty	40%
Land use	
Main food crops grown	Maize, beans
Main cash crops grown	Tea, coffee
Main Livestock system	Tethered, zero grazing

Data source: Kenya National Bureau of Statistics, Vihiga County Development Plans (2018–2022), and fieldwork reconnaissance

*Rainfall exhibits a bimodal pattern of long and short rainy seasons;

**Lowest monthly temperature and warmest monthly temperature

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 (Government of Kenya, 2019). We used Cochran's (1977) 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 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 (version 10.2.2), 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 m. 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 m. 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 Fig. 1.

To facilitate the smallest possible spatial unit of analysis that would possibly reveal spatially varying relationships in a local level (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.

2.3 Selection of indicators for constructing indices

A composite index consists of a set of indicators that are compiled to produce a composite measure (Greyling & Tregenna, 2017). 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 removal of important information before analysis (Demšar et al., 2013). PCA starts by specifying the indicator, normalized by its mean and standard deviation to calculate the factor weights of each indicator (Pearson, 1901; Spearman, 1904). The advantage of PCA 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 (Demšar et al., 2013; OECD, 2008). 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 (Judd et al., 2017). 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., (2017) 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 household survey data (Table 2).

As illustrated in Table 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

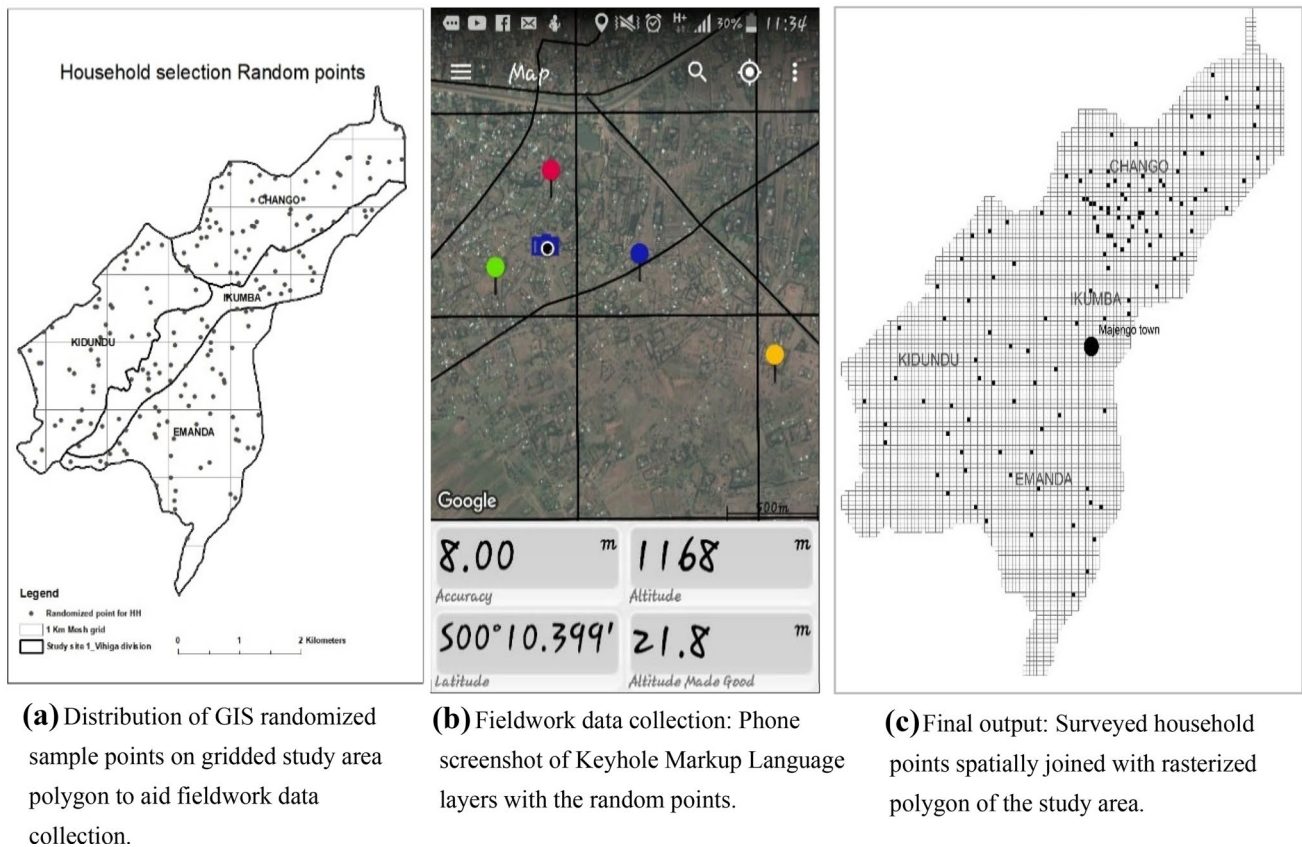


Fig. 1 Steps applied in the design of geocoded household survey; **a** distribution of randomized GIS points **b** uploading of KML layers on 'GPS Essential App' in Android phone, and **c** Actual surveyed household GPS points superimposed on the rasterized polygon of the study area

extensive literature review and contextual factors identified 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).

2.4 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 principal components' factor loadings, that is normally expressed in terms of the original indicator, serve as the composite indicator (Greco et al., 2019; Greyling & Tregenna, 2017; OECD, 2008; Tabachnick & Fidell, 2007). 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 (Braeken & Assen, 2016; Vyas & Kumaranayake, 2006). Subsequently, the components are

Table 2 Selected indicators hypothesized to affect food security in the study area

Food Security dimensions and indicators		Quartiles Categories			
		Q1	Q2	Q3	Q4
Availability dimension indicators	<i>Data type</i>				
Modern agriculture technology	Ordinal	Low	Medium	High	Very high
Agriculture information	Ordinal	Low	Medium	High	Very high
Agriculture extension services	Binary	No	<i>n/a</i>	<i>n/a</i>	Yes
Farm inputs and tools	Ordinal	Low	Medium	High	Very high
Land ownership and tenure	Binary	No title deed	<i>n/a</i>	<i>n/a</i>	Title deed
Possession of agronomic skills	Binary	No	<i>n/a</i>	<i>n/a</i>	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	<i>n/a</i>	<i>n/a</i>	Yes
Sanitation (toilet) ownership	Binary	No	<i>n/a</i>	<i>n/a</i>	Yes
Travel time to nearest water source (mins)	Continuous	> 30 min	21–30 min	11–20 min	0–10 min
Piped water in the compound	Binary	No	<i>n/a</i>	<i>n/a</i>	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	21–30 min	11–20 min	0–10 min
Travel time to Agrovets shops (mins)	Categorical	> 30 min	21–30 min	11–20 min	0–10 min
Access to agriculture credit	Binary	No	<i>n/a</i>	<i>n/a</i>	Yes
Household income (Kshs)	Continuous	< 1000	1001–10000	10001–20000	> 20001
Household savings	Binary	No	<i>n/a</i>	<i>n/a</i>	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

Level of food insecurity (Q1 = Worst to Q4 = Least)

then ordered so that the first component explains the largest possible variation in the original data (ibid.).

2.5 Validity and suitability of the constructed indices

As espoused by the OECD (2008), the standard practice when selecting the 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. As explained by Vyas and Kumaranayake (2006), “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 (Nardo et al., 2005). 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 (Nardo et al., 2005). 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 3) show that all the extracted components meet these criteria, which suggests our data are suited for PCA (Kherallah et al., 2015). 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.

In Table 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 (Vyas & Kumaranayake, 2006).

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

The spatial dimension of food insecurity can be revealed by analyzing the local spatial autocorrelation in the dataset (Demšar et al., 2013), using ArcGIS. Spatial autocorrelation is a condition where attribute values closer together in geographic space are assumed to more likely share similar attributes (positive spatial autocorrelation) than observations farther apart which tend to have dissimilar attributes (negative spatial autocorrelation) (Anselin, 1995; Głębocki

et al., 2019; Lesage, 2008). The assumption taken when calculating spatial autocorrelation is that relationships between neighboring spatial units are much stronger than between distant ones (Fotheringham, 2009; Głębocki et al., 2019).

Getis-Ord GI* hot spot analysis in ArcGIS is one of the commonly used methods to calculate local spatial autocorrelation (Anselin, 2010, 1995; Getis, 2010). 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 (Arsenault et al., 2013). The geographical unit of analysis is the extent of a geographic area to which the underlying spatial process of a phenomenon occurs (Zhang et al., 2014). 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 (Getis & Aldstadt, 2004). We used the "Incremental Spatial Autocorrelation tool" in ArcGIS to calculate the most optimal (statistically significant) territorial distance value (Fig. 2). We then used this value as our input value in calculating local spatial autocorrelation.

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 (Ord & Getis, 1995). 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 spatially varying relationships that exist among the features. Row standardization creates proportional weights to account where certain features may have an unequal number of neighbors (Brunsdon et al., 2002; Getis & Aldstadt, 2004).

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 either the SWM table or the calculated territorial distance value. In the conceptualization

Table 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 (Eigenvalues) Cumulative %	KMO and Bartlett's Test of sphericity			
			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 Kaiser normalization. Component loadings with an absolute value of ≥ 0.50 we retained

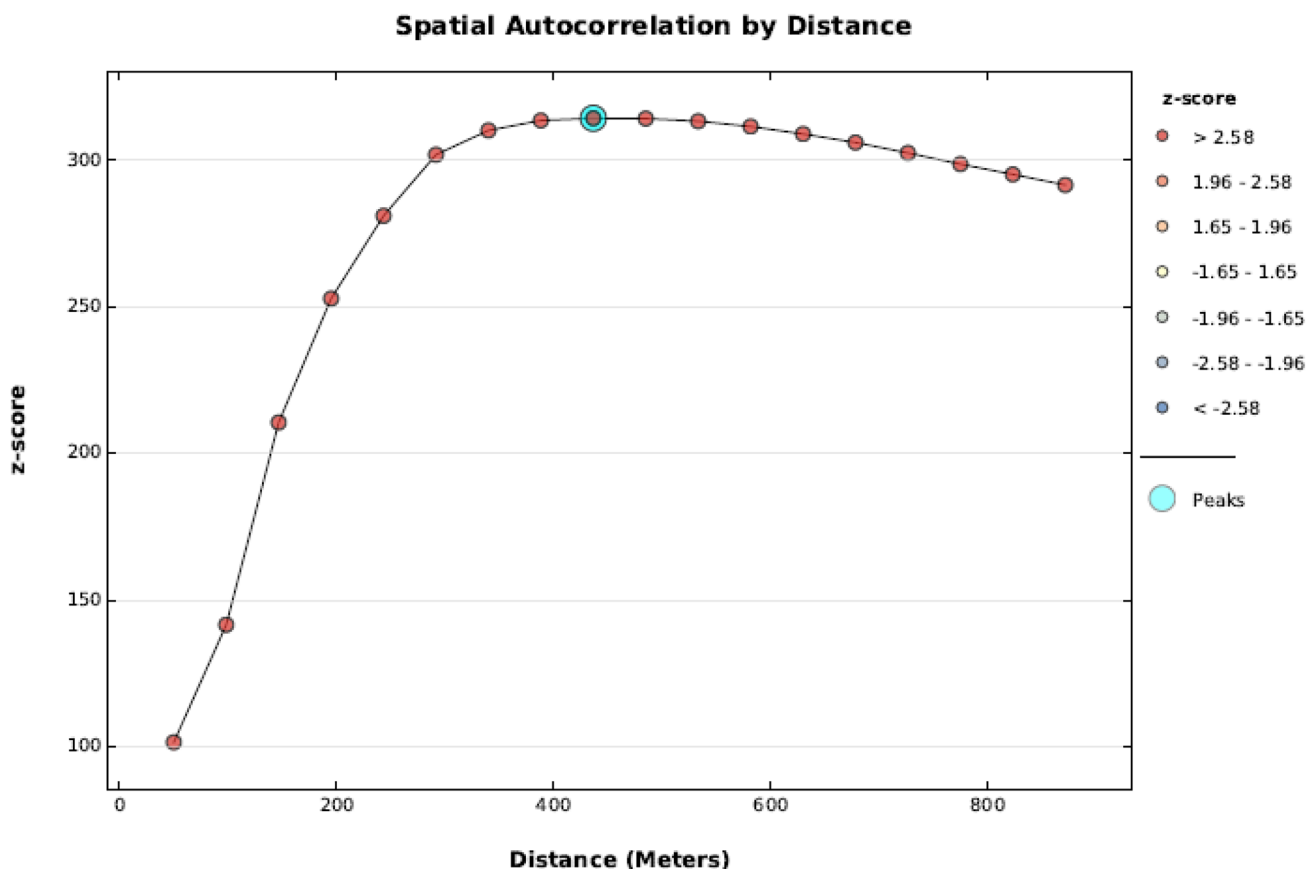


Fig. 2 Graph showing the optimal territorial distance value (400 m) where spatial clustering would be most pronounced in central Maragoli

of spatially varying 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.

3 Results

3.1 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 4). A crosstabulation between household food insecurity status and household types revealed that there were more male-headed households (38%) that reported to be food insecure than female-headed households (30%). This underscores the important role women play in ensuring a household’s food security.

Table 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
Female-headed household	15 (30%)	35 (70%)	50
Total food (in)secure	71 (36%)	125 (64%)	196 (100%)

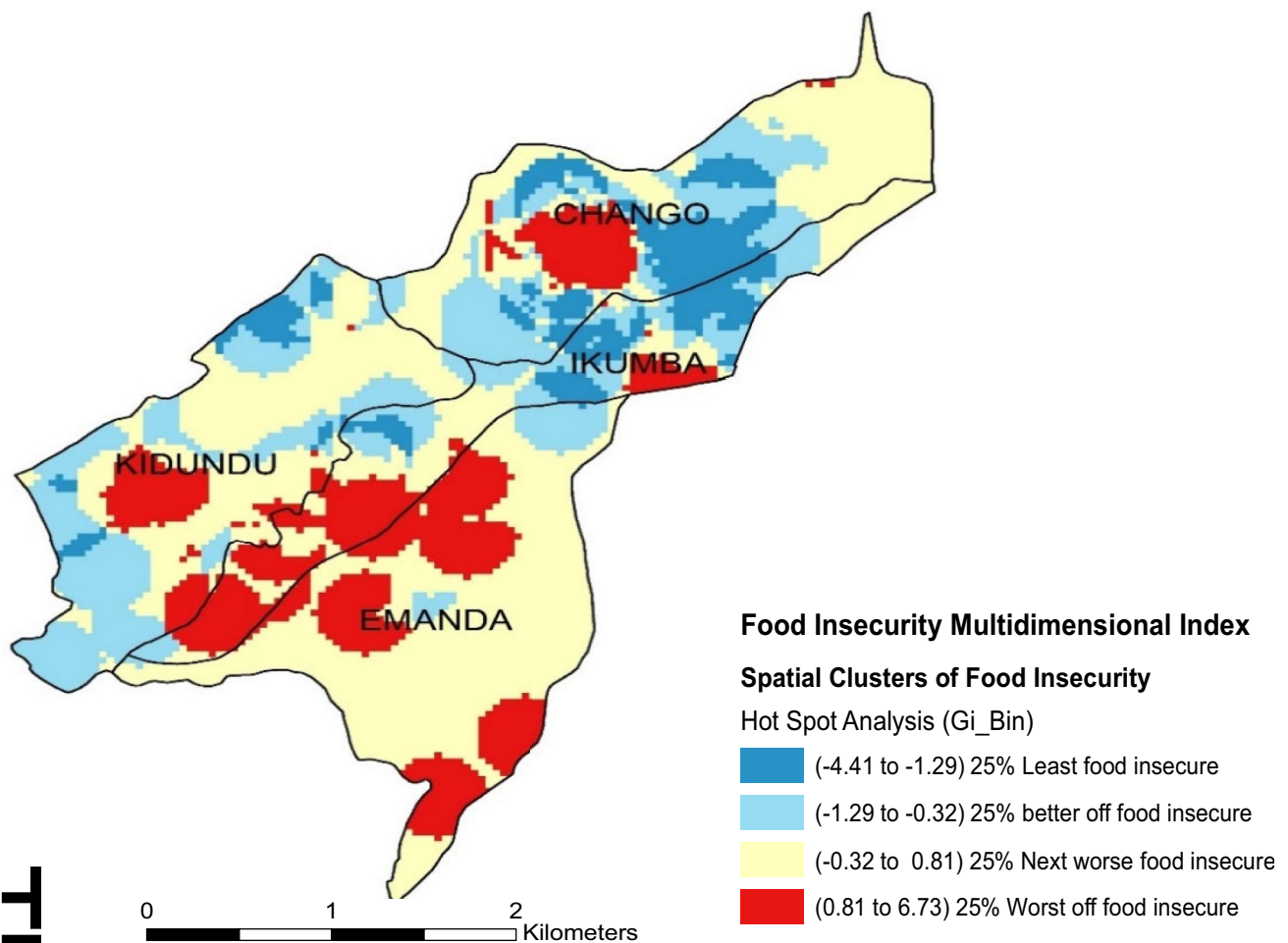
3.2 The spatial dimension of food insecurity as mapped using FIMI

From a conceptual perspective, the FIMI incorporates multifactorial indicators to cover all aspects of food insecurity and reveal the main hot spots of food insecurity in central Maragoli. The spatial analysis output (Map 1) 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.

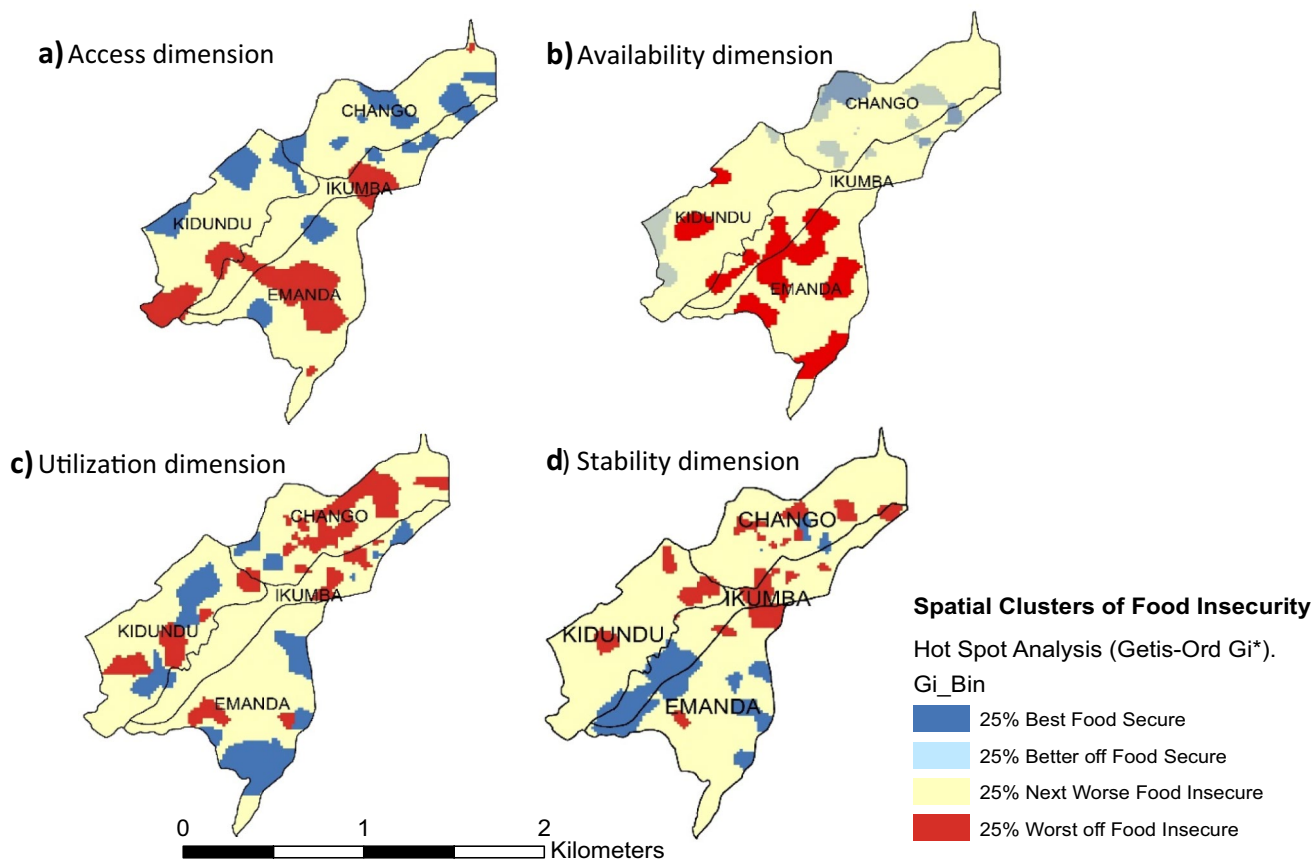
Spatially, the majority of households experienced food insecurity (areas in yellow color). There were few cold spot clusters (areas in blue color). Households in cold spots were categorized as food secure. The large cold spots cluster in the northern part of the study area is located on the outskirts of Mbaale town, the main urban center of Vihiga county. The households' food security status in this area may be associated with the availability and access dimensions (see Map 2a, b.) However, the same area, when mapped using the disaggregated

indices, turns out to be food insecure, especially in utilization and access dimensions, as depicted in Map 2a, d.

In Map 1, 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 in the immediate outskirts of the main urban center (Mbaale town) of Vihiga County. The town outskirts have a higher concentration of deprived population, with some of them having 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 Map 2c, d). Secondly, the area had a higher level of land fragmentation due to a high rate of conversion of agricultural land



Map 1 Spatial patterns of food insecurity in Central Maragoli as geo-visualized using FIMI



Map 2 a–d Maps showing spatial patterns of food insecurity based on the four dimensions of food security in Central Maragoli

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 spots 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.

3.3 The spatial dimension of food insecurity as mapped using four-dimensional indices

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 (Fig. 2a 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 Map 2), central Maragoli experiences a high level of food insecurity (25% next worst food insecurity). This is shown by the prevalence of yellow color in most parts of the study area. In the Map 2a–d, there are several pockets of food insecurity hot spots (25% worst off food insecure), geo-visualized by the red color. The relatively food secure areas (25% better off food secure) are geo-visualized by light blue color and food secure areas (25% best food secure) by dark blue color.

The access dimension map (Map 2a), 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.

In the availability dimension map (Map 2b), 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 2c), 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 was caused by several factors including a low level of women's asset ownership, and a low level of access to clean water in the compound. In addition, there was a low level of land ownership by women that emanated from customary land inheritance practices that bequeathed men higher custodial rights to land ownership than women.

In the stability dimension map (Map 2d), 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 (Figs. 1 and 2a–d) shows a significant geographic difference in the spatial patterns of food insecurity. For example, the FIMI tends to mask significant hot spots clusters of food insecurity that are revealed by the other four maps. This may be attributed to the aggregation of data, a problem called 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.

3.4 Disaggregating the causes of household food insecurity

The results of the PCA analysis characterize the multifarious determinants of food insecurity. Table 5 presents the results of PCA for the FIMI index, revealing how various socioeconomic characteristics of the households contributed to food insecurity.

Table 5 Rotated Component Matrix from Principal components analysis of FIMI

FIMI indicators	Extracted components and loading weights							Communality (h ²)
	1	2	3	4	5	6	7	
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 Agrovets 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 Kaiser normalization. Loadings with an absolute value of ≥ 0.50 are displayed

In the table, the last column shows the results of communalities (denoted by h^2). A communality is the 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%, eigenvalue greater than one, and the Bartlett test of sphericity of 614.8 ($p < 0.001$). Only the factors with a KMO coefficient of greater than 0.50 were extracted. Generally, a variable with a positive factor score is associated with higher FIMI, and conversely, a variable with a negative factor score is associated with 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 Agrovets 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 6), the PCA extracted two components that have a 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.

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

Table 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 Kaiser normalization. Loadings with an absolute value of ≥ 0.60 are displayed

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), PCA extracted two components that cumulatively accounted for 60% of the total variance.

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 8) show that two factors, women's land inheritance (0.85, $h^2 = 0.75$)

Table 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 Kaiser normalization. Loadings with an absolute value of ≥ 0.60 are displayed

Table 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 Kaiser normalization. Loadings with an absolute value of ≥ 0.50 are displayed

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.

In the access dimension, PCA resulted in three principal components cumulatively explaining 73% of the total variance in data (Table 9).

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, $p < 0.05$),

Table 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 Kaiser normalization. Loadings with an absolute value of ≥ 0.60 are displayed

and between household savings and access to credit (0.38, $p < 0.05$).

4 Bivariate correlation between FIMI and the four-dimension indices of food security

The bivariate correlation matrix (Table 10) between FIMI and the four dimensions of food insecurity.

The highest strong positive correlation ($r = .982$) 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,

Table 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 0.05 level (1-tailed); **Correlation is significant at the 0.01 level (1-tailed)

utilization dimension indicators have a lesser influence when computed and compared with FIMI.

4.1 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 in the environments within which smallholder production systems operate (Tittonell et al., 2011; Wittman et al., 2017). 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 (van Mil et al., 2014). As the study has shown, composite indicators like FIMI could be useful in mapping the spatial manifestation of food insecurity and can reveal hot spots 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 (Głębocki et al., 2019; Mathenge et al., 2020).

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 (2011) 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 (OECD et al., 2016). Labidi (2019) posits that spatial inequalities of food insecurity and development emanate from the weak integration of agriculture and 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 (Gennaioli et al., 2014; Perucca, 2014). 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. (Van den Broeck & Maertens, 2017; Perucca, 2014).

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 and 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 (Maertens et al., 2012). 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 that promote the mobilization of the local endogenous potential of places, thus facilitating the development of localized food systems. Well-articulated and coordinated spatially targeted development policies (Allmendinger & Haughton, 2010) that tap into the resource heterogeneity of territories while enhancing the diversity of particular regions 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 integrating with regional, national, and global agrifood value chains and markets (Ebata & Hernandez, 2017; Miyata et al., 2009).

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 has 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 (2019), 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 hot spots 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 (Chambers & Conway, 1992).

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 of spatially integrated food security policies that are multisectoral, and multidisciplinary.

6 Limitations of the study

This study relied on self-reporting of food insecurity statuses 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 (Martinez, 2019). 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 (Chen, 1990; Li & Fang, 2014). Another limitation associated with spatial autocorrelation analysis is that if the data collected is not uniformly distributed across the study area, the subsequent analysis may produce false hot spots 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 points 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.

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Declarations

Ethics approval Ethical approval to conduct the study was granted by Maseno University Ethical Review Committee, reference number (MSU /DRPI/ MUERC/00633/18). The procedures used in this study adhere to the tenets of the Declaration of Helsinki.

Consent to participate Informed consent was obtained from all individual participants included in the study.

Competing interests The authors declare no conflict of interest.

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