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Research article

Spatiotemporal modeling of household's food insecurity levels in Ethiopia

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ABSTRACT

The state of moderate and severe food insecurity in Ethiopia has not been significantly reduced for a long time due to cultural, natural, and manmade shocks, which cover most part of the country with considerable magnitude and have adverse effects on the health and economy. This temporal evolution of the wider geographic distribution of the food insecurity levels has not been investigated for the feeding culture and shocks effect in Ethiopia, though previous studies have indicated significant geographic distribution and related factors. In addition, the longtime zone-specific comprehensive drivers were not assessed. Therefore, this study focused on investigating the feeding culture-adjusted food insecurity levels (FCSL) and their evolutional sustainability across zones by identifying the factors causing each level of household's food insecurity tailored to a specific zone.

In this study, Ethiopian socio-economic longitudinal data from years 2012, 2014, and 2016 with a sample size of 3835 households were analyzed. An ordinal spatiotemporal model with different interactions under empirical Bayes estimation was adopted, and the type III interaction with Markov random field was selected to reveal the evolution of FCSL sustainability across zones and find-out the causing factors of households to each level of food insecurity tailored to zone-level by analyzing the effects of diverse factors and shocks. The result reveals that a greater portion (52.07 %) of households' population is moderately and chronically food insecure. Basically, households living in neighboring zones have significantly similar food insecurity levels, and slight improvements were observed over time. This transition over time within neighboring zones, revealed that chronic food insecurity in neighboring zones has transited to moderate food insecurity, particularly in most of the northern and southwestern areas of Ethiopia. However, the interaction term showed that the change in food insecurity levels for households living in neighboring zones is similar at one time point, but the evolution is not sustainable. Therefore, working on major zone-specific factors, such as enhancing zone-level urbanization through improving market and road linkage to rural areas, education, employment, non-agricultural businesses, and promoting integrated farming by conserving soil with consideration of additional confounding factors, will bring change and can sustainably eradicate moderate and chronic food insecurity in zone households through controlling dependency ratios, shocks, and small land size farming. This study brings resilient, manageable, and zone-specific mitigation for households living in food-insecure and vulnerable zones.

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1. Introduction

Food security is defined as secure access to enough food for all people at all times [1]. Food insecurity got attention after the world food crisis and the 1984-85 African famine and was considered an adequate standard of living to be imposed on the states [1]. Food insecurity negatively impacts mental health [2–4] and results in adverse health outcomes such as increasing obesity, stunting, wasting children [5–7], women with anemia [5], having type 2 diabetes [8,9] and other chronic conditions [10,11]. It is also related to low human development [12].

The major influencing factors affecting food insecurity are the frequently occurring climate change, conflicts, displacement, and desert locust [13–16], for most of the population's livelihood depends on agriculture with an unstable food supply [17,18] and low market integration [19]. The global shocks added 148 million people in 2020 compared to 2019, and in total, 928 million people became food insecure [16]. The evolution of food insecurity has shown a slow rise since 2014 [16]. In recent years, the prevalence of severe global hunger and food insecurity has aggravated mainly after trade wars [16,20–22], the Russian - Ukraine war [23,24], and COVID-19 [5,16,18,20–23,25,26]. Particularly, the higher food insecurity disaster occurred in 2020 [5,16]. Similarly, the problem has continued up to 2022 with a severe adverse effect on child malnutrition [27].

In particular, countries that exhibit conflicts and wars contribute a higher proportion of food insecurity [16] and stunted populations (80 % of global stunting) [16,20]. In developing countries, climate change and the food insecurity of rural areas are deeply intertwined [16] and prone to climate change [16,28], particularly in low Gross Domestic Product (GDP) per capita African countries like Ethiopia [29], Rwanda [30], and other Sub-Saharan countries [31]. Particularly, Africa has faced frequent droughts, which have led to the loss 89 % of crops and livestock [32], which have a larger contribution to severely food-insecure population [20]. In recent years, food insecurity in developing countries has heavily risen due to economic slowdowns and downturns as a result of the Russian - Ukraine war [24], and COVID-19 [18,22,33]. The problem is exacerbated in East Africa, with a prevalence rate of 42 % [34]. In this region, mainly Ethiopia grappled with food insecurity for many years, experiencing notable instances such as the famines of 1979/80 and 1995/96 [35], a food shortage due to the 2015 El-Nino drought [36], and, similarly, more than half (56 %) of the total households' population suffered from moderate or chronic food insecurity in the years 2019–2021 [37].

In recent years, Ethiopia has had one of the fastest-growing populations, reaching over 120 million in 2023 [29,38], of which 68 % are facing severe poverty [39]. From the total population, 78 % live in rural areas, relying on natural rain-dependent farming, which is frequently exposed to drought and desert locust [40]. In addition to, the large and poor population, the influence of global shocks [18,23], internal conflicts [23], displacement [41], and frequent droughts [42] collectively aggravate food insecurity, with over 20 million people facing hunger [43].

Moreover, literature on food insecurity in the country indicated the influence of demographic, social, economic, environmental, and geographic factors [36,44–51]. Literature indicates that the advantage of using the population as human power and productive land with water can be a potential resource for a way out of hunger and food insecurity [52–54].

Despite the numerous investigation results on the prevalence of the country's food insecurity, Ethiopia hosts many cultural and religious ceremonies that introduce different feeding patterns compared to the usual dietary practices. Ceremonies of cultural and religious events bring a different feeding pattern to the usual feeding culture. However, food insecurity has not been assessed to account for these cultural influences, nor have the recommended locally adopted cut-points for the Food Consumption Score (FCS) measure by the World Food Programme (WFP) been applied. The WFP food consumption score is recommended to take into account the local factors that contribute to diverse feeding patterns, such as the exclusion of small amounts of food items from the diet during measurement, in addition to sugar and oil consumption [55,56]. Literature also suggested that, despite the ordinal WFP standard food consumption scale being formulated based on 7-day household food intake with cut points 21 & 35, leveling, which considers society's dieting culture and pattern, is recommended. For example, the WFP recommends 28 and 42 for sugar and oil consumption, which is 5–7 days a week [57], the FAO (2016) study on Jordan household food security used 45 & 61 as cut points [58], and S. Baumann et al. (2013) [59] used new cut points (32 & 43) by excluding small amounts of food items.

In adopting this locally corrected response, for the purpose of a more informative assessment instead of a dichotomized response (which is limited in fitting the non-linear relation) [52,60] and for the practicality and manageability of the study instead of a continuous measure, grouping households' food insecurity by ordinal levels is adopted for this study. While ordinal measures can offer a more informative assessment than binary classification (as insecure & secured), given the ordinal measure's increased number of classes and inherent ordering, it's important to acknowledge that we will lose information when analyzing grouped measures (i.e., which give constant odds to move across all levels) compared to a continuous measure of each household's food insecurity dynamics. Therefore, the food insecurity levels measure (FCSL) is formulated by adjusting the cut points of the FCS for local factors to consider the diversity of feeding culture [56,59,61,62], using an effect-driven quantile clustering approach that groups the food security score into three ordered levels with cut points of 35.5 & 49: severe food insecure, moderate or vulnerable to insecurity, and food secured [60]. Moreover, exploratory analysis indicated that households living in the same administrative zone have similar ethnicity and culture, which have similar effect on feeding patterns and cause the FCSL of households within a zone to be homogeneous but vary between zones (see Fig. S5). Furthermore, the exploratory analysis of covariates' effect on the response is not linear; these suggest or raise the research question, "Observations may have a zone-level spatial and temporal pattern." Therefore, we plan to investigate the evolution of culture-corrected food insecurity levels in households across geographic areas. The response of FCSL has a longitudinal nature in all surveyed administrative zone households; hence, the data consists of multiple scores for levels of food insecurity on each pixel in space $\times$ time, and it may change in space & time [36] due to the diverse effects of covariates in space & time [36,63], which leads the FCSL to have a spatial and temporal pattern. In modeling such phenomena, as literature recommends, for this type of extended mixed model, empirical Bayes with penalized likelihood can bring better convergence than full Bayes [64] and an unbiased variance estimate for the random effect parameter (Harville, 1976) [65] than the maximum likelihood approach) [66]. Therefore, we start with the spatio-temporal additive regression models of Knorr-Held (2000) [67], which fit the covariates linear & non-linear effects on each level of FCSL by considering the geographical and temporal (main) effects [68,69], and extend the space-time interaction based on a suggestion by Clayton [70].

This study found that although the literature deeply points out that the factors associated to household food insecurity and vulnerability are multiple and complex, no previous study directly examined the temporal evolutional sustainability of food insecurity levels constrained to cultural effects on feeding patterns and determined natural and man-made shocks/factors structural and area-specific influence on households in different areas/zones of the country. Therefore, for practical implementation of the household-level study output across the country, we have to design area-specific mitigation that should be manageable in size and easy for admiration and evaluation. Since zones are the most nearer judicial, administrative, large markets, better health (referral hospitals), better education (higher education), media, and other infrastructure centers for rural households, we choose to apply zone-level study. As an advantage to this study's novel perspective, "zone-specific causing factors of households' food insecurity level corrected for culture effect on feeding pattern," zones in Ethiopia are bounded based on community similarity in language and culture, which is a major source for the country's constitution and politics, and a truly implemented administrative area. Hence, this study hypothesizes that the temporal evolution reflects the dynamics and the neighboring/distance between zones reflects the spatial dependency of the food insecurity levels of households living in zones, and it can reflect the presence of spatial, temporal, and space $\times$ time correlation. Therefore, for the corrected-FCSL measure in considering the cultural diversity effect on feeding pattern, "it is a universally accepted community-based measure," we can investigate the zone-level causing factors of households' food insecurity level, which can be structured or/and local (zone-specific) factors to the spatiotemporally clustered zones with the same level across different regions of the country.

The objective of the study is to assess the feeding culture-corrected food insecurity levels evolutional sustainability across administrative zones by investigating the effects of causing factors on each level of households' food insecurity tailored to a specific zone using an ordinal spatiotemporal model with different interactions under empirical Bayes estimation. The findings of this study can inform the development of resilient and manageable interventions tailored to specific zones and address the unique challenges faced by households in different regions of Ethiopia. Additionally, new confounding interventions across each level of the food insecurity-covered region can be considered during the intervention. Furthermore, this comprehensive longitudinal assessment of food insecurity is suggested by Barrett (2010) [71] and can be an input for the literature related to the level of household food insecurity, which considers the diversified feeding culture in assessing over space-time with the impact of comprehensive factors [32,72].

2. Method

2.1. Data and variables

This study analyzed the three-term longitudinal data for the years 2012, 2014, and 2016, covering the whole the country. The data is taken from the Ethiopian Socioeconomic Survey (ESS) of the World Bank data set, representing the first panel data collection effort in Ethiopia conducted jointly by the World Bank and Central Statistical Agency (CSA) of Ethiopia. The aim was to quantify household-level food security and related factors in rural and urban (small & medium town) areas.

The analysis utilized a total sample size of 3835 households, with three replications from 64 administrative zones, collected using two-stage probability sampling (enumeration areas and households). Two instances of longitudinally missed values were excluded after data cleaning. The missing values were treated using the longitudinal mean and mean imputation.

The ESS survey employs a two-stage probability sampling method. Initially, 290 rural and 43 urban enumeration areas (EAs) are selected through simple random sampling from the sampling frame. Subsequently, households are chosen from these EAs via simple random sampling. Data collection is done by interview using paper sheet and computer in Timeframe of three rounds from September to October, November to December, and January to April in all survey years of 2012, 2014, and 2016.

During the sampling process, certain biases are noted, including a high 99.3 % response rate and challenges such as limited electricity availability for recharging the CAPI tablets during fieldwork. These factors contributed to a relatively smaller sample size for sparsely populated regions.

The response of this study is the weekly household's FCSL, categorized into three ordered classes: food insecure, vulnerable to insecurity, and food secured [60]. The explanatory variables selected for analysis, following dimension reduction, variable selection, and exploratory analysis, comprise eight categorical factors and fourteen continuous covariates. It is assumed that these variables have linear & nonlinear effects on food security levels, respectively. The Central Statistical Agency & World Bank manual have classified data into some categories, such as agriculture, household's assets, household's demography, environment and geography, food security, education, health, finance, etc., and carried out the data collection based on the designed questionaries' in each category [73]. Accordingly, the dimension of explanatory variables is reduced by principal component analysis (PCA). Specifically, the decision for the number of components in PCA is made by considering the proportion of variance explained, components with Eigenvalue greater than one, and by observing highly contributing variables to each component to have a subjective meaning [74,75]. Then, the dimension is reduced for geographic variables from 19 to 6 components, explaining 76.12 %; similarly, 12 agricultural variables are reduced into 4 components, explaining 53 %; and 47 asset variables are merged into 12 components, explaining 50.11 % of the total variance. The principal component analysis reduces the dimension of variable space by removing the redundancy through linear combination of correlated features by maximizing variation accounted without much loss of information. Particularly, dimension reduction is helpful for convergence for complex models like spatio-temporal model with space × time interaction.

2.2. Model development

The Food insecurity level $FCSL_{s;t}$ is a categorized version of a latent continuous variable of food consumption score, denoted as $D_{s;t}$ which is truncated normal. Specifically, $D_{s;t} = \eta_{s;t} + \epsilon_{s;t}$ where $\eta_{s;t}$ is a predictor depending on covariates and parameters, and $\epsilon_{s;t}$ is an iid n × t error vector, for n = 3835, s = 1,2,3, …, 64, and t = 2012, 2014, 2016. The two variables $FCSL_{s;t}$ and $D_{s;t}$ are linked by $FCSL_{s;t} = r$ if and only $\theta_{r-1} < D_{s;t} \le \theta_r$, r = 1, 2, 3, with an ordered threshold $-\infty = \theta_0 < \theta_1 < \theta_2 < \theta_3 = \infty$, for $\theta_1 = 35.5$ & $\theta_2 = 49$. The probity link is a preferred link than logit link for continuous latent response, and the modeling is done by proportional-odds cumulative-probit model. Therefore, $FCSL_{s;t}$ can be modeled by threshold model with cumulative probit link for r = 1, 2 as follows,

$$p(FCSL_{s;t} \le r) = \mathrm{P}(D_{s;t} \le \theta_r) = \mathrm{P}(\eta_{s;t} + \epsilon_{s;t} \le \theta_r) = \mathrm{P}(\epsilon_{s;t} \le \theta_r - \eta_{s;t}) = F(\theta_r - \eta_{s;t})$$

$$= > p(FCSL_{s;t} \le r) = \mathrm{P}(\epsilon_{s;t} \le \theta_r - \eta_{s;t}) \text{ or } p(FCSL_{s;t} \le r) = F(\theta_r - \eta_{s;t})$$

where the distribution function of the error variable $\epsilon_{s;t}$ of $D_{s;t}$ is given by F by assuming $\epsilon_{s;t} \sim N(0, 1)$.

Next, we applied a Bayesian perspective for spatiotemporal extensions of the generalized Geoadditive model [69,76,77] to fit the main effect model [67] and extend the space - time interaction based on a suggestion by Clayton [70]. In modeling this longitudinal data with a mixed model, particularly the two-stage model, the random effect parameter estimate has a conditional expectation form, and Bayesian inference is a recommended approach. We applied the empirical Bayes rather than the full Bayes due to a lack of sufficient prior for country-wide panel for households' food insecurity levels, mainly specific to the $FCSL_{s;t}$ measurement, and its convergence advantage [64]. Moreover, empirical Bayes with restricted maximum likelihood (REML) can bring an unbiased variance estimate to the parameters compared to maximum likelihood estimation [66]. Therefore, empirical Bayes with REML for the spatio-temporal model parameter estimation is applied for the inference to be lied majorly on the data by assuming flat prior for parameters.

The estimator for spatiotemporal additive predictor modeled by spatiotemporal main effect formulation as Knorr-Held (2000) [67] is given by:

$$\eta_{s;t} = \boldsymbol{X}^T\boldsymbol{\gamma} + f_1(z_1) + \ldots + f_p(z_p) + f_{str}(s) + f_{str}(s) + f_{str}(t) + f_{unstr}(t)\ldots \tag{1}$$

Where $\mathbf{X} = x_1, \ldots, x_q$ are categorical factors of n × p matrix modeled by a linear function; $\boldsymbol{\gamma} = $ q × 1 vector of linear effects; $\mathbf{Z} = z_1, \ldots, z_p$ are continuous factors of n × p matrix modeled by a non-linear function $f_1, \ldots, f_p$, where $f_j(z_{1j}), \ldots f_j(z_{nj}) = f_j = Z_j\beta_j$; $f_{str}(s)$ & $f_{unstr}(s)$ are spatial and random effects, respectively, which do and do not display spatial structure; and $f_{str}(t)$ & $f_{unstr}(t)$ are structured & unstructured (random) temporal effects, respectively, which do and do not display temporal structure [68].

A function f_j is approximated by a cubic P-spline base function over set of equally spaced 20 knots $x_{j,min} = \zeta_{j,0} < \zeta_{j,1} < \ldots < \zeta_{j,k-1} < \zeta_{j,k} = x_{j,max}$ within the domain of x_j. The P-spline used is a linear combination of the B-spline (i.e., cubic spline) base function $B_j(x_j)$ estimated by $f(x_j) = \sum_{s=1}^{S_j} \beta_{js} B_{js}(x_j)$ [64,68,78].

The parameters of additive predictor $\eta_{s;t}$ is estimated by assigning priors. In this study we have employed diffuse prior $p(\gamma) \propto$ *const* for fixed effect. In modeling the spatial effects, the unstructured or random effect is fitted by Gaussian random effect, and the structured or the spatial is fitted by Markov random field (MRF) priors [79], the MRF a natural choice for district-level [64], and two-dimensional P-splines [80]. Whereas, the first order random walk prior is used to fit structured temporal effect and the unstructured is fitted by the Gaussian random effect. The random walk of order two (RW2) is recommended for larger and unequally spaced time, it tends to be smoother than RW1 [81]. The non-linear effects of continuous covariates are modeled through Bayesian versions of penalized splines (P-splines). **Neighboring matrix:** The Ethiopian shape file map "Eth_Zone_2013" is given for the analysis using BayesX package R version 4.02. For contingency based spatial modeling, the neighborhood matrix is defined by a 64 × 64 square matrix of 0 and -1. It takes the value −1 if zones are defined as neighbors by sharing a common boundary and are assumed to be more likely in food security level than any other zones else it takes the value 0 [64]. On the other hand, for the distance based spatial modeling, four nearest neighbors are taken as a neighbor according to zones longitude-latitude spatial distance. This is fitted by two-dimensional first order random walk prior using a tensor product of zone coordinates, longitude and latitude [82].

2.3. Interaction effects model

The main effect model in equation (1) can be extended to include the space and time interaction effect, which would explain the evolutional sustainability of food insecurity levels across different zones. In this study, we have applied space - time interaction based on a suggestion by Clayton [70], which is a smoothing prior by the Kronecker product of the precision matrix (the product of variance & structure matrix for neighboring structure) of two main effects. Clayton's rule tells us the interaction between space and time effect is incorporated using smoothing prior defied by the penalty matrix K_{SPTM} by taking the Kronecker product of K_{SP} and K_{TM} [67].

In our case, the Kronecker product of the precision matrix of spatial main effect with MRF prior (K_{MRF}) and the temporal main effect with first-order random walk prior (K_{RW1}) is fitted and given by $K_{MRF} \otimes K_{RW1}$ [76]. In space-time interaction modeling tensor product splines are chosen over thin-plate splines, because even if the thin-plate is isotropic it is not invariant to covariate scaling, since units in time & space are different [83]. Therefore, the unknown interaction surface, the space-time interaction, $f(s_{ij}, t_{ij})$ can be approximated by the tensor product of two one dimensional B-splines, given by:

$$f(s_{ij}, t_{ij}) = \sum_{m_1=1}^{M_j} \sum_{m_2=1}^{M_j} \beta_{j,m_1 m_2} B_{j,m_1}(s_{ij}) B_{j,m_2}(t_{ij}); \text{ for i} = 1, 2, .., 64 \text{ and j} = 1, 2, 3.$$

Where the priors for $\beta_j = \left(\beta_{j,11,\ldots,}\ \beta_{j,m_j m_j}\right)'$ are two-dimensional first-order random walks [77,84].

A choice of a suite of prior models for the space-time dependence structure or interaction can be found from the Types I to IV space-time interaction in Knorr-Held (2000) [67]. Specifically, if the space-time residual does not play any role and the interaction parameters are priori independent the interaction is Type I; or if the interaction is temporally smoothed but do not have any structure in neighboring zones or temporal trends are different from zone to zone the it is called Type II; or if the interaction is spatially structured but short-lived model or spatial trends are different from time point to time point it is called Type III; whereas the interaction is Type IV if the estimates of temporal trends borrow strength from trends in adjacent zones, and the interaction parameters are dependent over space and time.

The spatiotemporal interaction model is an extension of the spatiotemporal main effect model (2) by adding the interaction effect of space & time:

$$\eta_{s;t}{}^{*} = \eta_{s;t} + f(s_{ij}, t_{ij}) \quad \ldots \tag{2}$$

Priors for the interaction: In equation (2) the spatial & temporal covariance structure is modeled by Gaussian random effect (re) priors for Type I interaction; the Gaussian random effect (re) and rw1 priors respectively are used for Type II interaction; the MRF and re priors respectively are used for Type III interaction; and the MRF and rw1 priors respectively are used for Type IV interaction [81, 83].

2.4. Inferential method and model selection

The empirical Bayes with restricted maximum likelihood is adopted due to its better convergence than full Bayes and its' an unbiased variance estimate for the random effect parameter comparing to the maximum likelihood approach. Flat priors are given for the regression parameters and the hyper-parameters and estimated in advance from the data [64,68,85,86]. The additive spatiotemporal model with empirical Bayes inference through REML estimation is applied using the R version 4.02 interface for **BayesX,** called the **R2BayesX** package [86–88]. For comprehensive and robust analysis, we have assessed the linear and non-linear comprehensive effects of demographic, agricultural, geographic, environmental, and socio-economic factors by considering the possible space-time dynamic with its' interaction effect in empirical Bayes perspective. Factors are taken as statistically significant determinants of FCSL if their effect is significant at a 0.05 level of significance; for categorical variables (p-value <0.05); and for continuous variables if the 95 % confidence interval plot of the effect is diverged or out from the horizontal line passing through zero. The fitted additive spatiotemporal models were compared and the model having the smallest generalized cross-validation (GCV) is selected to fit the data and make inference [68,76].

Table 1
Summary statistics for the households' levels of food insecurity r baseline characteristics.

State of food security levels		Food insecure (0–35.5)	Moderately food insecure or Vulnerable to food insecurity (35.5–49)	Food secure (>49)
FCS of 2012		28 %	28 %	44 %
FCS of 2014		24 %	27 %	49 %
FCS of 2016		23 %	27 %	50 %
Average FCS		25 %	27.1 %	47.9 %
Residence	Rural	26.1 %	27.7 %	46.2 %
	Urban	16.6 %	22.8 %	60.6 %
Can read & write	No	29.5 %	29.6 %	40.9 %
	Yes	18.6 %	23.4 %	58 %
Household head employed	No	26 %	27.7 %	46.3 %
	Yes	16 %	21.1 %	62.9 %
Small size land owned	No	22.7 %	25.7 %	51.6 %
	Yes	25.3 %	27.3 %	47.4 %
Shock occurred	No	24.9 %	26.6 %	48.5 %
	Yes	25.1 %	27.5 %	47.4 %
Farm types	Cropping	35.6 %	29.1 %	35.3 %
	Livestock	18.6 %	23.8 %	57.6 %
	Both	24.3 %	27.1 %	48.6 %

3. Result

3.1. Baseline characteristics of the study population

The summary statistics for households' food insecurity levels and its factors are presented in Table 1 indicated that the greater portions of the households are moderately and severely food insecure, and the food insecure households' decreased from 28 % to 23 % with a slight decrement in moderately food insecure or vulnerable households (28 %–27 %). The prevalence of moderately and severely food insecure is much higher among rural, female-headed, can't read & write, faced shock/s, small land owned, farming only crops, and unemployed head comparatively.

The food insecurity levels plot in Fig. 1(a, b, & d) depicted that the hot spot areas of higher food insecurity level are located in the northern & southern parts. The closer look at the temporal progress of zones spatial plot in Fig. 1(a, b, & c) reflects that on the early years highly food insecure areas were located by making a pattern from the northern to central (partially) to the southwestern part of Ethiopia zones, then on the earlier years these areas are transferred to vulnerable status; i.e. starting from the 2012 FCSL plot (Fig. 1a) slight changes are observed in 2014 plot (Fig. 1b) and more changes are observed in 2016 plot (Fig. 1c). However, the observed yearly change of FCSL varies across zones, and suggested that the common spatial and temporal main effect cannot capture well the variance

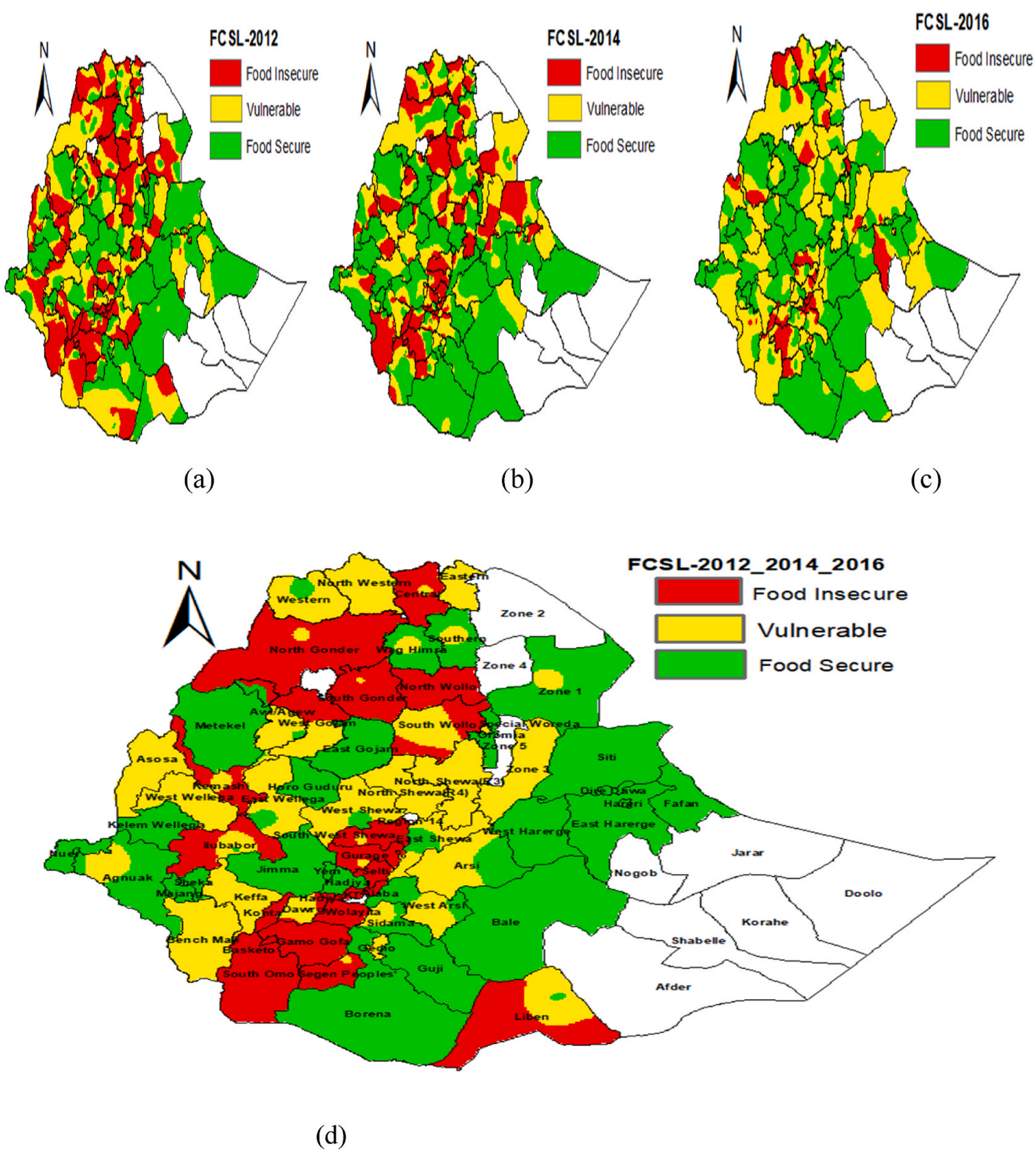


Fig. 1. Observed spatial distribution of FCSL across zones through the years. (a) The 2012 household's FCSL across; (b) The 2014 household's FCSL; (c) The 2014 household's FCSL; (d) The longitudinal household's FCSL from 2012 to 2016. (These plots are obtained using ArcGIS software.)

in the data, and suggested the need for the space-time interaction model.

3.2. Spatiotemporal model results

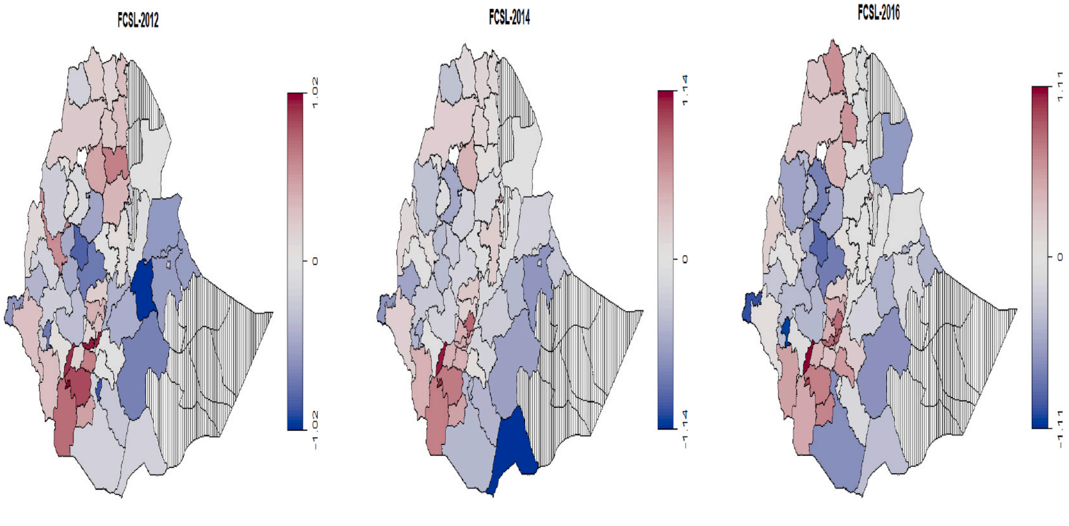
The result of the yearly structured spatial effect modeled by MRF in Fig. 2 (a) for 2012 food insecurity levels, (b) for 2014 food insecurity levels, and (c) for 2016 food insecurity levels showed that the food insecurity levels vary across zones, and yearly improvement is observed in a general sense but it varies from zone to zone. This critically suggested further investigation into space-time interaction, in support of Fig. 1 (a, b, & c) suggestion. Therefore, to add robustness to the findings ten models have been done; one main effect and four space-time interaction effect models based on spatial modeling in two categories; spatial distance (using k-nearest neighbors) and contingency (using MRF); and the result in Table 2 reveals that the Type III interaction effect using MRF (MRF type III) model brings a better fit with smaller GVC of 1.7678. Moreover, the posterior mode indicates that modeling time interaction (rw1) (Figs. S3 and S4) dese not add information to the main effect model (Fig. S1), even though little improvement was seen by Type I interaction (Fig. S2).

A detailed look at the MRF type III model reveals that at a time point neighboring zones have similar level of food insecurity change improvement but the evolution of the change is not sustainable (see, Fig. 7). The food insecurity levels over space-time interaction in Fig. 7 indicated that there is a transition from high level to low level of food insecurity in the front & back sides, moreover, the general progress showed a decline in food insecurity level, which coincide with the result in Fig. 1(a, b, & c). Specifically, the structured spatial pattern fitted by MRF in Fig. 6 (a) showed the most of northern and west-northern parts of Ethiopia faced chronic food insecurity, and the southern and east-southern parts of Ethiopia have better food security, whereas the central part of Ethiopia zones are moderately food insecure or vulnerable (whiten colored) to food insecurity. The random Gaussian fit result in Fig. 6 (b) showed a different result from the MRF fit, except for some central parts of Ethiopia zones. This implies the change in food security levels is not random across zones of Ethiopia.

The posterior mode estimates result in Table 3 for the linear effects revealed that households faced shock ($\beta = 0.07^{**}$) and owned small size land ($\beta = 0.18^{***}$) are significantly increasing the severity of food insecurity levels. Moreover, households live in urban area (β = -0.38), a head who can read & write ($\beta = -0.23^{***}$), employed ($\beta = -0.20^{***}$), use fertilizer ($\beta = -0.13^{***}$) for cropping, and farming livestock ($\beta = -0.33^{***}$) or both livestock & cropping ($\beta = -0.19^{***}$) are significantly decreasing the severity of food insecurity level. The posterior mode estimates of the nonlinear effects in Fig. 3 indicate that the household's dependency ratio and coping strategy index have significant non-linear effects on the household's food insecurity levels (Fig. 3 (a), & (e), respectively).

The non-agricultural business and related factors, sanitation, and drinking water have non-linear significant effects on household's food insecurity levels (Fig. 4 (b), (c), & (d), respectively). Similarly, soil property, a component of agro-ecology, distance from the border and related factors, and a component of rainfall, greenness and related factors have non-linear significant effects on household food insecurity levels (Fig. 5 (a), (b), & (c), respectively). Whereas adult equivalence (Fig. 3 (b)), age of household head (Fig. 3 (c)), household size (Fig. 3 (d)), agricultural packages and related factors Fig. 4 (a), and components of irrigation, mixed crops and related factors (Fig. 5 (d)) have almost constant insignificant effect on food insecurity levels.

In general, households' urbanization, farming livestock, ability to read and write, having more than four non-agricultural businesses, colder areas, being far from the border, and high rainfall have played major roles in decreasing the severity of food insecurity



(a) (b) (c)

Fig. 2. The temporal progress for the zone-level spatial distribution of household's food insecurity levels in Ethiopian. The FCSL of 2012(a), 2014 (b), & 2016(c).

Table 2
Spatiotemporal models result with four possible space-time interaction models.

Model Type	df	AIC	BIC	−2*log-likelihood"	GCV (based on deviance residuals)
Spatial model by MRF using boundary or contingency neighborhood method					
Type III [zone(MRF) & year(re)]	225.52	21611.2	23268.9	21160.2	1.7678
Type I [year(re) & zone(re)]	160.26	21574.7	22752.7	21254.2	1.7962
Type II [year(rw1) & zone(re)]	140.847	21699	22734.3	21417.3	1.8162
Type IV [zone(MRF) & year(rw1)]	133.669	21686.7	22669.2	21419.3	1.8187
Main effect model	129.484	21694.2	22646	21435.3	1.8214
Spatial model by tensor product of Longitude & Latitude using Euclidean distance neighborhood method					
Model Type	df	AIC	BIC	−2*log-likelihood"	GCV (based on deviance residuals)
Type III [zone(MRF) & year(re)]	223.273	21599.4	23240.6	21152.8	1.7679
Type I [year(re) & zone(re)]	180.439	21543	22869.3	21182.1	1.7838
Type II [year(rw1) & zone(re)]	146.128	21656.6	22730.8	21364.4	1.8101
Type IV [zone(MRF) & year(rw1)]	133.39	21685.4	22665.9	21418.6	1.8188
Main effect model	128.907	21693.4	22641	21435.6	1.8216

Remark: The spatiotemporal Interaction term can be obtained by multiplying the space & time components using a tensor product or varying coefficient, here both techniques bring equivalent results. Hence, the varying coefficient model result is presented in this study, but one can use the tensor product.

Table 3
Posterior mode estimates of spatiotemporal model with type III space-time interaction model.

Coefficients of Fixed effects	Estimate	Std. Error	t value	Pr(>|t|)
θ_1	−115.16	9891.38	−0.01	0.990711
θ_2	−114.29	9891.38	−0.01	0.990781
Resident in urban vs. rural	−0.38	0.05	−8.43	3.96E-17 (***)
Can read & write (Yes vs. No)	−0.23	0.03	−8.77	1.98E-18 (***)
Shock occurred (Yes vs. No)	0.07	0.02	2.95	0.0032 (**)
Fertilizer used (Yes vs. No)	−0.13	0.04	−3.59	0.000335 (***)
Household head employed (Yes/vs. No)	−0.20	0.04	−4.67	3.05E-06 (***)
Health problem occurred (Yes vs. No)	0.03	0.03	1.04	0.298835
Small size land owned (Yes vs. No)	0.18	0.05	3.95	7.92E-05 (***)
Farm Type:[Livestock vs. Cropping]	−0.33	0.07	−4.75	2.05E-06 (***)
Farm Type: [Both Livestock & Crop farming vs. Cropping]	−0.19	0.04	−4.61	4.13E-06 (***)
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1				
Main effects				
Structured year by rw1	20.09	0.05	0.84	0
Unstructured year by re	0.80	1.24	0.19	0
Structured spatial (zone) by MRF	25.30	0.04	0.03	0
Unstructured spatial (zone) by re	9057.35	0.00	27.71	0
Interaction effect				
	Variance	Smooth Par.	df	Stopped
Spatial (zone) by MRF & year by re: $K_{SPTM} = K_{MRF} \otimes K_{re}$	0.10	10.00	60.16	0

N = 11505 df = 225.52 AIC = 21611.2 BIC = 23268.9, logLik = −10580.1 GCV = 1.76782 method = REML family = cumprobit

levels, whereas farming on small land and the occurrence of shocks aggravate it.

4. Discussion

This study assessed the evolutional sustainability of the FCSL trend and the change from trend across zones by considering cultural effects, manmade and natural shocks effect on levels of food insecurity of households, and find-out the long-time zone-level causing factors for each level of food insecurity by using spatiotemporal interaction effect models, and add robustness by comparing ten models with Bayesian analysis. This approach is particularly designed to find-out resilient and manageable specific solutions for unique challenges faced by households living under a zone in different regions of the country. The result of the best fitting model "Type III model with MRF" identifies neighboring zones that have similar mean FCSL and showed progress in time, and the change at one time point (year) is similar for neighboring zones but the evolution of this change is not sustainable. In fitting the space × time change of FCSL, the spatial structure is smoothed by MRF (a natural choice for district-level spatial effect [64]) and the temporal dependency is taken as random which add/increases the variance of unstructured spatial effect (9057.35) is comparing to a model fitting it by rw1. The result from the smoothing of temporal change by rw1 in type IV interaction effect model (Table S1) which brings smaller unstructured effect variance with larger GCV is an indication on sustainability problem. Therefore, working on the major causing factors to each level of the clustered zones with confounding factors impact sustainability can sustainably improve the food insecurity of zone households. In doing so, the detail investigation of the study indicated that the transition from higher to lower food insecurity levels

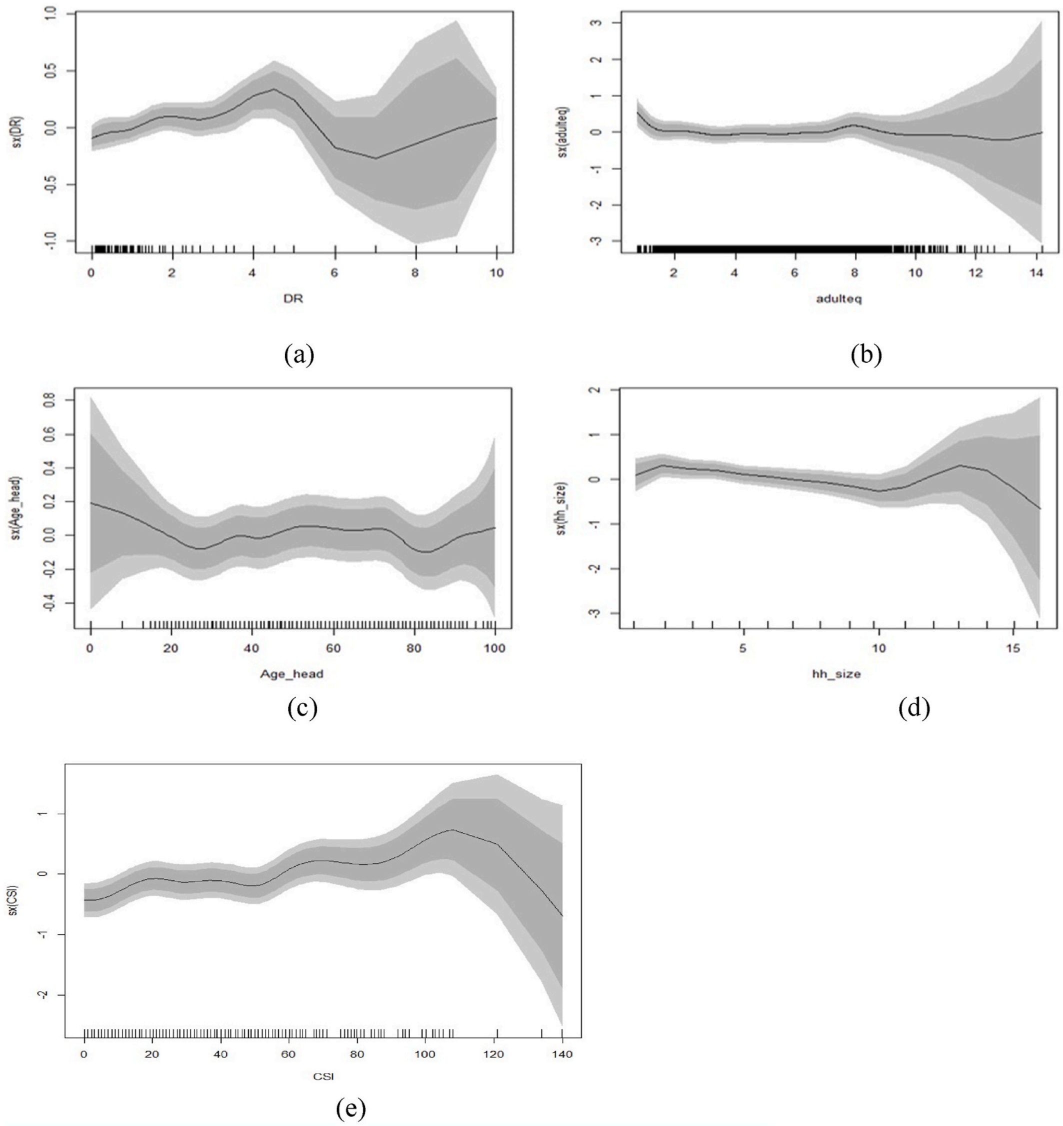


Fig. 3. Plot for the posterior mode estimates: Dependency ratio (a), Adult equivalence (b), Age of household head (c), Household size (d), and Copping Strategy Index (e) (with 95 % CI) on levels of food insecurity.

within neighboring zones from year 2012–2016 was observed. Specially, most of the zones in the northern & southwestern parts (except Eastern & Central Tigray, and Northern Wollo zones continue to face with severe food insecurity) are transferred from food insecure to vulnerable households. Hence, taking the major driving factors of this pattern with additional confounding factors can be an intervention for a sustainably improved change from chronic food insecurity to vulnerable or moderate levels.

Moreover, the space × time change of food security levels fitted by interaction effect using the structured MRF elaborates the change on the northern and northwestern parts is higher and the southern part is lower. As expected, the random Gaussian fit result showed different results from the MRF fit except for some central parts of Ethiopia zones. A supportive result for smoothness due to considering zone level spatial effect is reported by Dessie et al. (2022) [36] & Wubetie et al. (2024) [89] other studies also showed the presence of spatial variation in food insecurity [63,90–92]. The previous studies on spatiotemporal assessment of global food insecurity support the findings of this study and showed the significant internal fluctuations in extremely insecure countries, such as sub-Saharan Africa, and on some part of Asia [93,94], improvement in food insecurity also observed in similar comprehensive studies in china [94,95], and Tanzania [96]. In general, food insecurity is a global urgency, in need of the United Nations (UN), scientific research programs and the government's co-working for a revised working policy, to the failed proposal of UN Millennium Development goals planed in the year 2000 [93] to halve proportion of hunger by the year 2015, and end hunger and food security by 2030 [97].

Despite the presence of numerous study results on poor countries [98–103] including Ethiopia [36,47,50,51,104,105], for the

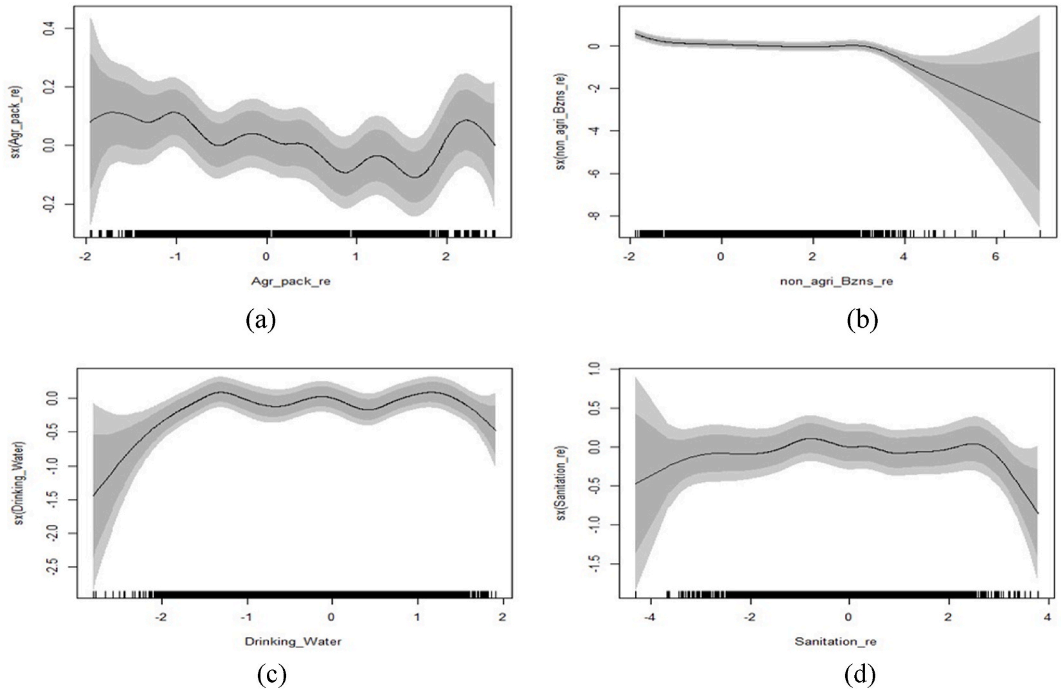


Fig. 4. Plot for the posterior mode estimates: Agricultural package related (a), Non-agricultural Business related (b), Drinking Water (c), and Sanitation related (d) (with 95 % CI) on levels of food insecurity.

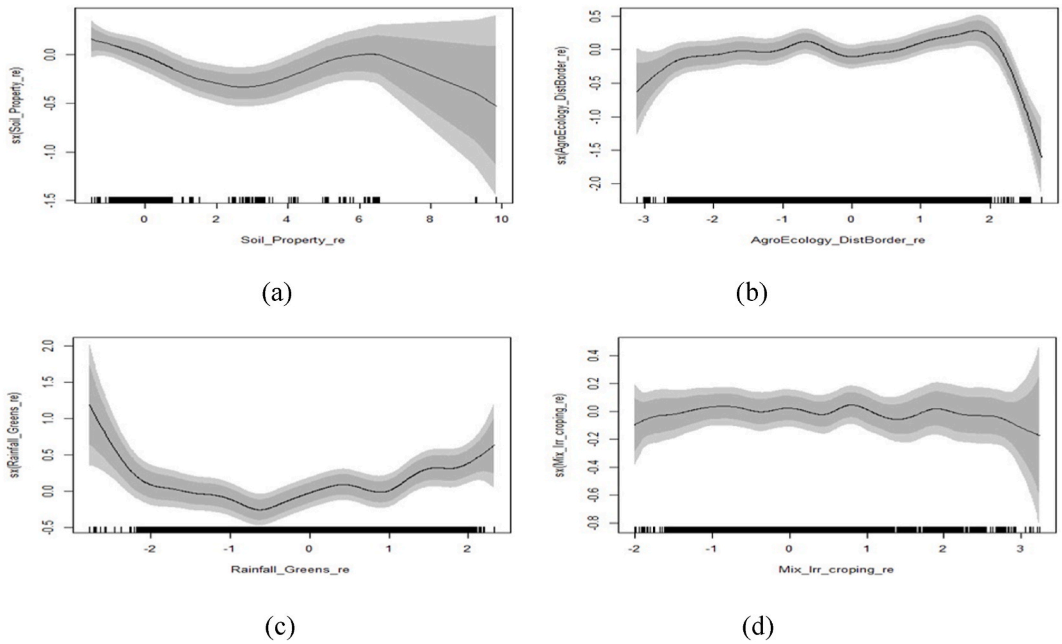
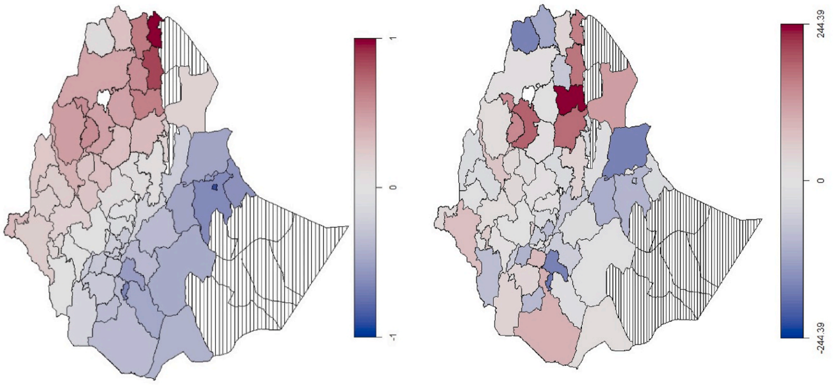


Fig. 5. Plot for the posterior mode estimates: Soil property related (a), Agro-ecological & distance from border-related (b), Rainfall & greens related (c), and Irrigation, Mixed cropping & related (d), (with 95 % CI) on levels of food insecurity.

influence of various factors and spatial dependency [45,106] on household's food insecurity, the space-time effect of factors investigated by this study has not previously been assessed in Ethiopia. Accordingly, the estimate of the linear effect in this study found that the effects of urbanization, education, employment, and farming type have a higher magnitude on the reduction of higher levels of food insecurity (i.e., chronic and moderate food insecurity) compared to other effects. Previous studies have also shown the positive impact



(a) (b)

Fig. 6. Spatial plot for posterior mode of food insecurity levels from type III interaction, for structured spatial effect fitted by MRF prior (a), and unstructured spatial effect fitted by Gaussian prior (b) (zones with vertical lines represent areas with no data).

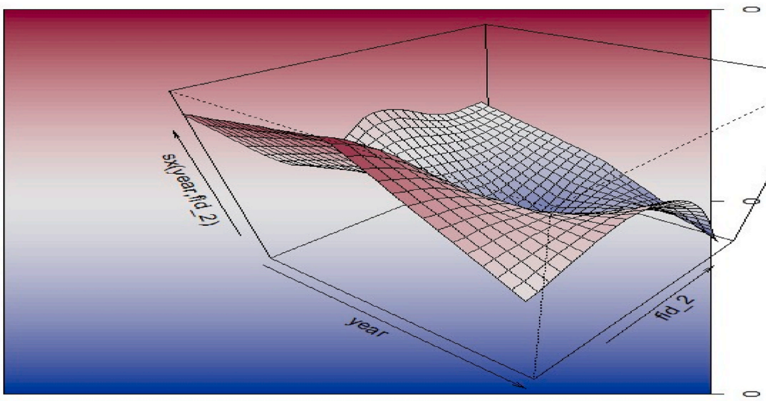


Fig. 7. The posterior mode of food insecurity levels for space-time interaction. Note: The fid_2 represent space/Zone and the year represents time.

of urbanization on reducing food insecurity, particularly in rural households, which are more food insecure compared to urban areas [36,45,54,95,106,107]. The positive effect of education on the reduction of food insecurity is indicated by previous studies [44,47,90, 100,103,104,108–110], and similarly, studies on food insecurity also indicated the contribution of higher employment to the reduction of food insecurity [47,100,107,111]. Moreover, the comparative drought-resistantness of livestock farming to cropping and its higher calorie content are indicated by previous studies [103,104,107,112–114]. Hence, food insecurity is related to national security and human development due to its impact on the health and wellbeing of society [94,95,115,116]. The household's fertilizer usage also reduces food insecurity and vulnerability. The positive impact of fertilizer usage during cropping for better food security is supported by literature [36,110,113,117]. The occurrence of shocks such as drought, illness of a household member, and rising costs of food items and inputs have aggravated the chronic and moderate food in the household. The influence of such shocks on exacerbating food insecurity in households is well documented in the literature [36,45,54,93,114,118–121]. Households owning small land sizes are directly related to higher levels of food insecurity and face moderate and chronic food insecurity. This result supported the Ethiopian government's initiative to focus agriculture on integrated farming rather than small-scale farming. Moreover, the positive impact of integrated farming over small-scale farming on production and food security has been reported in numerous studies [47,107,110,112, 113,120].

The posterior mode estimates of the nonlinear effects reveal that the probability of being in higher levels of food insecure rise with the household's dependency ratio, even if in the middle, from 5 to 7, showing decrement, the effect rises again. Particularly, the food insecurity level increases from a negative to a positive scale when the household dependency ratio increases from 0 to 1. This indicates the household's food security in Ethiopian transit to food insecurity for one more dependent individual in a family. The severity of food insecurity levels due to the loaded dependency ratio in a household is indicated by previous reports [36,45].

The strength of the copping strategy up to 100 has a monotonic direct relation with food insecurity levels, then the food insecurity steps down. Therefore, the coping strategy should depend on the severity of food insecurity, and the food insecurity can decrease with a higher copping strategy such as limiting the food variety, food size, number of meals, and less preferred foods. Literature also the adoption of different coping strategies to control and reduce food insecurity level [45,122].

The posterior mode estimates of the nonlinear components revealed that the probability of a household's being at higher levels of food insecurity declines as the property of soil increases, though the effect showed an insignificant increment at the middle score. The effect of soil having better nutrients and oxygen on higher production of farming crops & livestock for food insecurity was also reported by previous studies [104,107,121,123]. Moreover, the probability of higher food insecurity levels (moderate & chronic food insecurity) declines with a higher score of agro-ecological zone-related factors (>2), though an increment in food insecurity was observed at lower values (−2). This suggested that the central part of Ethiopia, which consists of highland and temperate areas, is less likely to have higher levels of food insecurity. The impacts of residing at low temperatures and the Centre part of the country or far from the border on reducing moderate and severe food insecurity were also reported by many researchers [93,94,121].

An increase in components of rainfall and greenness reduces the chronic and moderate food insecurity at lower values (<0), but it aggravates the food insecurity at higher values from 0 to 2. Therefore, moderate rainfall and precipitation can enhance production and increase food security, whereas too much rainfall aggravates food insecurity. A similar result for the impact of rainfall, greenness on food insecurity is reported by many studies [91,93,94,104,119,124].

The probability of a household facing moderate and chronic food insecurity decreased as the number of non-agricultural businesses increased, mainly because owning more than three non-agricultural businesses led the household to have higher food security. Similar studies have also supported the effect of having more income sources on reducing the level of food insecurity [47,104,109].

A household having at least one (score >1) drinking water source can help to reduce the probability of higher levels of food insecurity, but an unsuitable source of drinking water (score <2) aggravates the food insecurity. Literature also supports the importance of drinking water sources to enhance households' food security [93,120]. The decline in household sanitation (score<0) increases the probability of a household being at a higher food insecurity level, but households having higher sanitation material (score >2) are related to a higher probability of being food secure. This implies a household with higher sanitation, i.e., better solid waste disposal, bathing, and toilet, has a higher probability of having lower levels of food insecurity. The direct relationship between sanitation and food insecurity has been reported in previous studies [45,93,108].

However, even if food insecurity improvement were achieved for neighboring zones located at northern & southwestern parts of Ethiopia, its sustainability needs hard work on the highly influencing zone specific factors of each level. Specially, enhancing zone-level urbanization, education, employment, farming strategy, drinking water and sanitation inputs, non-agricultural business, controlling dependency ratio and shocks, conserving soil and integrated farming, rain fall, distance from market and road/urban, and applying better copping strategy impacts soundly in reducing chronic and moderate food insecurity. The household based result is supported by Maxwell recommendation for policy intervention focused on individual/households rather than centrally-administrated programs [1].

FAO (2023) reported that stunting increases as cities are farther from urban areas and overwight is higher in urban areas [27]. In Ethiopia, the majority of rural areas are not well connected to urban areas due to low road infrastructure; consequently, farmers cannot access modern inputs to produce higher yields and sell their products or buy inputs from the market [27]. Similarly, rural households are apart from accessing hospitals, education, media, and law services. Hence, we recommend policymakers target zone-level urbanization through connecting rural areas and providing sufficient administrative and public services, especially in addressing education for all, farming livestock, and side-to-side creating suitable conditions for the spread of non-agricultural business.

4.1. Strength, limitation and future work

This study has several strengths; one of the strengths of the study is it modifies the covariates' convolutional effect on the evolutional progress and zone-level spatial dependency of food insecurity levels, which was not well studied by previous studies. This indicated zone specific factors to improve households' food insecurity levels, where FCSL is adjusted for cultural effect of feeding pattern. The novelty of this study lied in accounting for community culture effect on feeding patterns, and it coincides with the nature of our zone population which contains similar culture and language households. Moreover, this study enhanced robustness trough comparing the possible alternative ten spatiotemporal models for comprehensive analysis of linear and non-linear factors of the households' food insecurity levels by extending to the Bayesian inference.

This study also used the available three term panel data from year 2012–2016 which covers all regions of the country with large sample size (n = 3835). However, we have analyzed seven-year-old data, as recent data has not yet been collected by the concerned authority due to various issues faced in Ethiopia, including COVID-19 and recent conflicts and displacement. Furthermore, this study has also accounted for survey limitations such as EA's sampling under representation for unpopulous regions. Therefore, without prior information on food security level of not samples zones the projection of this study results to not sampled zones of unpopulous regions may lead to irrelevant inference and may not bring the expected improvement. Moreover, the 7-day food consumption list is collected at the household level rather than at the individual level; hence, the inference may not be applied as an intervention for individual-level challenges. The analysis considers the ordinal scale, and it is limited to analyzing each household's food insecurity dynamics rather than classifying them in one group "for the practicality of the recommended mitigation." Future studies may further include additional confounding factors, which may be new or confounding not included in this study, that can enhance sustainable improvement in reducing food insecurity and vulnerability. Since the survey forms are filled out by data collectors by face-to-face interviewing the head of a household, there may be bias on the response due to social desirability.

Therefore, future researchers can fill in the data limitations and recent food insecurity status by considering the future panel study data set together with recent shocks such as the COVID-19 pandemic, internal conflicts, displacement, and other factors confounding effects to get a more complete and updated understanding of the process.

5. Conclusion

The households living in neighboring zones share a similar food insecurity status, and slight improvements were observed over time. While this change is consistent among neighboring zones at a given time point, the evolution of this improvement is not sustainable. The transition from a higher food insecurity level to low levels has been observed across various zones, especially most of the northern & southwestern parts of Ethiopia, which transit from food insecurity to vulnerability. Nevertheless, the Eastern & Central Tigray, and Northern Wollo zones continue to face severe food insecurity.

The space-time assessment using the measurement corrected for different feeding cultures can make more informative & relevant inferences in designing society-based interventions for the reduction of higher levels of households' food insecurity. Since, in fitting the space × time change of FCSL, the MRF smoothed the spatial effects and the temporal dependency was taken as random, which increases the variance of the unstructured spatial effect (9057.35) compared to type IV interaction, this is an indication of the sustainability problem. Therefore, working on the major determining factors of each food insecurity level in the clustered zones with additional confounding factors can sustainably improve the food insecurity of similar zone households. Hence, targeting major zone-specific factors such as enhancing zone-level urbanization, education, employment, market and road linkage, non-agricultural businesses, controlling dependency ratios and shocks (i.e., drought, illness, and input price rise), improving drinking water & sanitation, working on soil conservation and integrated farming strategies, and applying better copping strategies should get more focus for a sustainably improved change from chronic food insecurity to a vulnerable or moderate level.

In general, we recommend policymakers prioritize zone-level urbanization by connecting rural areas and ensuring the provision of administrative and public services as a key introduction to comprehensive interventions through the design of additional confounding factors that impact the sustainable reduction of food insecurity and the vulnerability of households.

Ethics approval and consent to participate

This study analyzed secondary data collected from years 2012, 2014, and 2016 by the World Bank and CSA of Ethiopia, and we thank the data delivery organizations and the participant households for their positive response to the data collection.

Consent for publication

Not applicable.

Data availability statement

The data source is the Ethiopian Socioeconomic Survey (ESS) of the World Bank data set, which is the first panel data in Ethiopia collected by a project of the World Bank and the CSA of Ethiopia to quantify household-level food security and related factors in rural and urban (small & medium town) areas. Therefore, one can access this open access data from the World Bank data set data set. The ESS 2012–16 data files and documentation are of local use and one can access this open access data from the World Bank data set data set using the link at: https://microdata.worldbank.org/index.php/catalog/2053, https://microdata.worldbank.org/index.php/catalog/2247 and https://microdata.worldbank.org/index.php/catalog/2783. Further inquiries can be directed to the corresponding author (habtamu.tilaye@yahoo.com).

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CRediT authorship contribution statement

Habtamu T. Wubetie: Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Temesgen Zewotir:** Writing – review & editing, Supervision, Conceptualization. **Aweke A. Mitku:** Writing – review & editing, Visualization, Validation, Supervision, Methodology. **Zelalem G. Dessie:** Visualization, Validation, Investigation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Acronym

AgSS	Annual Agricultural Sample Survey
EAs	enumeration areas
CSA	Central Statistical Agency
FAO	Food and Agriculture Organization of the United Nations
FCSL	Levels of Food insecurity
GAMMs	Generalized Additive Mixed model
GRF's	Gaussian random fields
GCV	Generalized cross-validation
GAM	Generalized Additive Model
MCMC	Markov chain Monte Carlo
MRF's	Markov random field
WFP	World Food Program

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e32958.

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