The spatial modification effect of predictors on household level food insecurity in Ethiopia

Zelalem G. Dessie¹,², Temesgen Zewotir¹ & Delia North¹

Household food insecurity remains highly prevalent in developing countries (including in Ethiopia) and it has been recognized as a serious public health problem. Several factors such as demographic, economic, social, and clinical factors influence household food insecurity, and these vary geographically. In this work, we investigate the geographical modification of the effect of several factors on chronic food insecurity. The data is from the Ethiopia socioeconomic survey conducted by the Ethiopia Central Statistics Agency (ECSA) in collaboration with the World Bank. Ethiopia socioeconomic survey is a long-term project to collect nationally representative panel survey of over 6500 households. A geo-additive model which accounts the structured and unstructured special effect was adopted to estimate household food insecurity risk factors. The study also revealed significant spatial variations on household food insecurity among administrative zones. Mainly, household living in the Sidama, Gamo Gofa, Shinille, Basketo, Wolyita, Wag Hemira, Liben, Awi, Eastern Tigray and West Harerghé zones, having higher food insecurity than the other zones in Ethiopia. Moreover, the analysis also showed that availability of credit services, proximity to service centers, average years of schooling of members of the household, and household assets are negatively associated with household food insecurity, whereas shocks, age, and dependency ratio increase the odds of a household to be food insecure. The generalized geo-additive mixed-effects model enables simultaneous modeling of spatial correlation, heterogeneity and possible nonlinear effects of covariates. Our study investigated the spatial heterogeneity of household level food insecurity, and its association with shocks, age, dependency ratio, availability of credit services, average years of schooling, and household assets. Our findings have also an important implication for planning as well as in the search for the variables that might account for the residual spatial patterns.

Adequate quality and quantity of food are required for the optimal health, growth and development of humans. Hence, the concern of food security for mankind has continued to be the priority agendas of leaders around the world. According to World Bank and the United Nations⁴, food security is a concept that existed when all people at all times have social, physical, and economic access to safe, sufficient, and nutritious food that meets their dietary needs for an healthy and active life⁵.

Despite significant global progress have been made over the last two decades, severe food insecurity and undernourishment are still increasing in almost all regions of Africa⁶. According to the latest estimates of the State of Food Insecurity in the World 2021⁷, an estimated 720 to 811 million people faced hunger in 2020. The report also documents that more than one-third of the world’s undernourished are found in in Africa (282 million)⁸.

Hunger and food insecurity are major concerns in Ethiopia. The country began with food deficiency in the early 1970s. According to the Global Hunger Index⁹, Ethiopia ranks 90th out of 116 countries and ranks among the world’s hungriest. The latest update of the 2022 Global Report on Food Crises says⁴, Ethiopia is projected to face one of the world’s most severe food crises in 2022, resulting from the combined effects of escalating violence, prolonged drought and macroeconomic instability. The Productive Safety Net Program (PSNP), World Food Program (WFP) and government are struggling to alleviate the hunger crisis in Ethiopia, however, the combined effects of the COVID19 pandemic, locust invasions, floods, drought, market disruptions, and high food prices have left about 13.6 million people food insecure⁹.

The lack of progress towards the WHO global nutrition targets and the increase of severe food insecurity prevalence were major challenges for countries to create a world without hunger and malnutrition by 2030⁸.

¹School of Mathematics, Statistics and Computer Science, University of KwaZulu-Natal, Durban, South Africa. ²College of Science, Bahir Dar University, Bahir Dar, Ethiopia. *email: DessieZ@ukzn.ac.za
Identifying the possible factors that may affect severe food insecurity, is key to achieving the targets of Sustainable Development Goals (SDGs).

Findings from previous studies, highlight a number of factors that may affect the household food insecurity includes credit services9–11, age of the household10,11, gender of household head12–14, education of the household head15–17, family size18,19, household assets20,21 and dependency ratio22,23. Furthermore, severe food insecurity consequences may arise from uneven exposure burdens and differential susceptibility to exposure spatially21–24. These special factors have been shown to have a significant association with household food insecurity. However, studies from Africa designed to adjust for these covariates are limited and there is no study that has assessed effect modification or interaction by these factors.

Mathematical models have been extensively used in research into household severe food insecurity dynamics because they play an important role in improving our understanding of major factors contributing to the household severe food insecurity dynamics. These models range from logistic regression25–28, linear regression model29,30, generalized linear mixed-effects model31,32, generalized estimating Equations33,34, to additive model35. However, these classical modelling approach, without considering spatial effect, affects statistical inference in many ways. Firstly, the classical model have deflated estimates of residual and variance36. This leads to higher type I error rates and loss of model precision37. Secondly, when predictor variables exhibit different degrees of autocorrelation and spatial patterns, the classical models produce overestimated statistical significance of the autocorrelated variables38. Lastly, failure to consider spatial autocorrelation may result in over-optimistic estimates of the model’s predictive power and inappropriate model choice39. In addition, no previous study has directly analyzed the nonlinear effects of the covariates (i.e. age, family size, household assets and dependency ratio) on household severe food insecurity dynamics. Thus, the current study, using latest cohort big dataset, attempts to address these limitations and expands our understanding of the dynamics of household food insecurity in Ethiopia using the geo-additive model. The model assists to investigate factors that affect the severe household food insecurity by accounting for the spatial as well as the linear and the non-linear effects of demographic, economic and clinical factors.

Methods

Data description. The data is from the Ethiopia Socioeconomic Survey (ESS) conducted by the ECSA (Ethiopian Central Statistics Agency) in collaboration with the World Bank. ESS is a long-term project to collect nationally representative panel survey of over 6500 households. The ESS collects information on economic activities along with other information on household agricultural activities, households like human capital, access to services and resources. The 1st wave was carried out in 2011/12, the 2nd wave in 2013/14, the 3rd wave in 2015/16 and the 4th wave was effected in 2018/19. The ESS sample is a two-stage probability sample. It employs a stratified, two-stage design where the regions of Ethiopia serve as the strata. The samples are regionally representative for the major regions of the country (Southern Nations & Nationalities Peoples (SNNP), Tigray, Amhara, Oromia, Afar and Somali) as well as Addis Ababa. For the purpose of this study, five thousand two hundred sixty-two (5262) households were included from 72 Ethiopian administrative zones over 8 years. The GPS coordinates for clusters were obtained from Ethiopian Demographic and Health Survey (EDHS) and those clusters were linked with the corresponding administrative zones for spatial analysis. The shapefiles for administrative zones were freely available on DIVA-GIS project website41. The map of the study sites was displayed in Fig. 1.

Variables and measurements. For this study, the unit of analysis is households. Self-reported food insecurity status is used by recalling a situation of "household was worried that there would not be enough food in the past 7 days" and "food unavailability over the last 12 months", prior to the interview. These outcome variables can reasonably address the four components of food security (i.e. Availability, Access, Utilization and Stability).

Household asset index is a composite indicator, calculated using PCA. It measures the ownership of a mobile phone, bed, gas cooker, bicycle, radio, motor bike, car, and sewing machine among others. Dependency ratio gives insight into the number of people of non-working age, compared with the number of those of working age. It is calculated as the ratio of non-working age individuals to working age individuals. Working age individuals or producers are often defined as being 15–64 years of age, while those less than 15 years or older than 64 years are considered consumers. Moreover, household shocks measures whether the household had, in the past year, experienced any shocks, such as drought, death, theft, floods, illness, loss of jobs, violence, and local unrest.

Generalized geo-additive mixed model. To assess the effects of factors on the household level food insecurity, we adopted a geo-additive model using Bayesian approach. This approach allows to simultaneously estimate the spatial effects of the geographical locations, unknown nonlinear effect of the covariates, as well as the vectors of the fixed effect parameters. This approach also provides monotonicity constraint estimates and allows to borrow extensions developed for Bayesian mean regression such as multilevel structures and regularization priors without the necessity to re-develop the complete inferential machinery32,43. We first performed bivariate analysis to find out the determinants of household food insecurity. We only included variables significantly associated with severe food insecurity in the bivariate analysis in a multivariable analysis. For continuous variables, we checked for the shape of the relation using graphical smoothing techniques.

Model specification. Let \( y_i \) be the status of food insecurity of household \( i \) (and is recoded as 1 if the household faced food insecurity, or 0 otherwise). The risk of a household food insecurity can be associated with head of household gender, age, average year of schooling in the household, family size, credit service, household assets
and dependency ratio using a GLM model with the appropriate link function. GLM is flexible to allow for non-normal outcome variable. Thus, the probability of food insecurity for a household $i$ in this study is defined as

$$
\eta_i = \log \left( \frac{\pi_i}{1 - \pi_i} \right) = \alpha_0 + \alpha_1 \text{Sex} + \alpha_2 \text{MS} + \alpha_3 \text{CS} + \alpha_4 \text{Age} + \alpha_5 \text{AS} + \alpha_6 \text{DR} + \alpha_7 \text{FS}
$$

(1)

where $\pi_i$ is the probability of food insecurity for a household $i$, MS is household marital status, CS is credit services status (is recoded as 1 if the household uses credit service, or 0 otherwise), S is shock status (is recoded as 1 if the household have experienced any shocks, or 0 otherwise), AS is average years of schooling of all family members, DR is dependency ratio of the household and FS is family size of the household.

However, the standard GLM (Eq. 1) assume independent observations (or at least uncorrelated). But, this assumption is not always satisfied, sometimes observations exhibit temporal or/and spatial dependence. This variability has to be incorporated in the model. The predictors modified by taking into accounts the spatial auto-correlation and the non-linear effects of continuous covariates in the current study, can be given as follow

$$
\eta_i = \log \left( \frac{\pi_i}{1 - \pi_i} \right) = \alpha_0 + \alpha_1 \text{Sex} + \alpha_2 \text{MS} + \alpha_3 \text{CS} + \alpha_4 \text{Age} + f_1(\text{Age}) + f_2(\text{AS}) + f_3(\text{DR}) + f_4(\text{Asset}) + f_5(\text{FS}) + f_6(\text{uns}_\text{spacial}) + f_7(\text{str}_\text{spacial})
$$

(2)

where $f(.)$ for $i=1,\ldots,5$ are the smooth functions expressing the unknown nonlinear effects of the covariates. $f_6(\text{uns}_\text{spacial})$ is spatially unstructured random effects to capture the over dispersion at each location (i.e. regions in Ethiopia). $f_7(\text{str}_\text{spacial})$ is structured correlated spatial effect to capture the unobserved spatial heterogeneity and to account the spatial autocorrelations. Equation (2) provides a class of models known as geo-additive model which is a more flexible semiparametric geo-additive regression model.
Prior assumptions and inference. For implementation of our model (i.e. semiparametric geo-additive regression model), a Bayesian approaches which needs priors assumption have to be used. In Bayesian approach, all the smooth functions and the coefficients are assigned prior distributions. In the absence of any prior knowledge, diffuse prior (i.e. $p(\beta | \text{const})$) is the appropriate choice for fixed effect parameters\(^{45,46}\). For the smooth functions $f_i(\cdot)$ for $i = 1, 2, 3, 4, 5$, a 2nd order random walk prior was considered. Let $x$ is covariate with equally spaced observations $x_i$. Suppose that an ordered distinct values for a covariate are $x(1) < \cdots < x(t) < \cdots < x(m)$ and define $f(t) = f(x(t))$. Therefore, the 2nd order random walk is given by $f(t) = f(t-1) + u(t)$ with are Gaussian errors (i.e. $u(t)$) and diffuse priors for initial values. For the spatially correlated effects, the nearest neighbor Gaussian Markov model was chosen\(^7\). For unstructured spatial effects, the parameters were assumed to be i.i.d. Gaussian with unknown variance\(^{48}\) (i.e. $f_2(\text{uns spatial}) \sim N(0, \tau^2)$). Therefore, highly dispersed inverse Gamma distributions are chosen.

For the analysis, we used the Markov Chine Monte Carlo algorithm to sample from the posterior conditional distributions. For each posterior distribution, we report the mean of the 1000 values as the parameter estimate, the SD as the measure of parameter variability, and the 2.5 and 97.5 quantiles, as the 95% credible interval. Model diagnosis was performed based on Markov Chine Monte Carlo postestimation diagnosis, besides the samples of the parameters, autocorrelation plots and implemented trace and, were also extracted using function sample. All of the analyses were implemented using R, version 4.0.5 and in order to map spatial effects, ArcGIS 10.6 was used.

Results

The distribution of economic, demographic and clinical variables at baseline is presented in Table 1. The prevalence of food insecurity for female household in the sample was larger 29.8\% compared to male household (26.3\%). The prevalence of food insecurity was much higher among rural population, at 34.4\%, compared with 15.2\% among urban population. A similar difference was noted for food insecurity in the past 12 months, at 46.5\% among household who have encountered shocks (natural or social) compared with 16.5\% among household who haven’t encountered shocks. The prevalence of food insecurity for Somalia region (39.0\%), Benshagul-Gumuz (35.2) and SNNP (35.2\%) has accounted for relatively higher portion compared to other regions in Ethiopia. Chi-square test indicated that there is a significant association among geographic variables; residence, region and food insecurity in the past 12 months was found ($p$-value < 0.0001). Furthermore, chi-square test also indicated that household food insecurity was significantly associated with sex, marital status, shocks and availability of credit services ($p$-value < 0.05).

Figure 1 shows the prevalence of household level food insecurity across all zones in Ethiopia. It clearly demonstrated that the Wag Hemira, East Harergerhe, Liben, Gamo Gofa, Sidama and Wolayta zones registered higher prevalence of household level food insecurity than the other zones in Ethiopia. Though the prevalence of household level food insecurity is more pronounced in rural populations, the months of August, July, June, and September are identified as slack periods for many households (Fig. 2).

The overall mean household size was $4.36 \pm 2.35$ with a higher mean household size for those who are food insecure ($4.59 \pm 2.43$) compared to those who are not food insecure ($4.32 \pm 2.33$). Similarly, among the household who are food insecure, the average years of schooling in the household, dependency ratio, asset and age were $4.89 \pm 3.20$, $1.14 \pm 1.01$, $2.31 \pm 1.18$ and $44.44 \pm 15.51$ years, respectively while the average years of schooling in the household, dependency ratio, asset and age of household who are not food insecure were $7.27 \pm 4.47$, $0.84 \pm 0.87$, $3.11 \pm 1.42$ and $41.85 \pm 15.03$ years, respectively. The mean difference was also statistically significant at 5\% significance level.

Predictors of household level food insecurity. Assessment of the fitted model. All the goodness of fit assessment results showed that the final model fitted the data adequately. Between the two models above (Eqs. 1 and 2), the generalized geo-additive mixed model given in Eq. (2) resulted in the lowest DIC, which confirms the appropriateness of the model. In the selected model, predictor variables that was significant at a 10\% level in the single covariate analysis were included in the multivariable model\(^{49}\). Furthermore, the range of the estimated structured spatial effect was much higher than the range of random spatial effect, indicating that model fit improvement by including structured spatial effects, is relatively greater.

Spatial effects. The spatial effects presented in Fig. 3 is based on generalized geo-additive mixed model. Our model results showed both negative and positive spatial effects on food insecurity among the households in Ethiopia. The variance estimates for the cluster-level spatial effects (which account for the spatial autocorrelation) and the zone-level random effect were nonzero and significant (Table 2).

The colors on the maps (Fig. 3B) ranged from yellow to dark red such that the dark red and brown colors denoting a positive effect which are associated with an increased risk of severe food insecurity (i.e.,), while the yellow and orange color show the negative effects on household level food insecurity. Moreover, the map showed that the presence of variation in household level food insecurity in Ethiopian clusters. Mainly, household living in the Sidama, Gamo Gofa, Shinille, Basketo, Wolyita, Wag Hemira, Liben, Awi, Eastern Tigray and West Harergerhe zones, showed higher food insecurity than the other zones in Ethiopia (Fig. 3B). Geographically, these areas are generally characterized cash crop producers, densely populated, high climate vulnerability and undulating hills limited agricultural production potential that barely produced enough food to meet the food demands of households.

Fixed effects. Analysis results for modeling the dynamics of household level food insecurity using generalized geo-additive mixed model are presented in Figs. 4 and 5. The residuals plots of the geo-additive model also showed no discernible patterns. Based on the results, we observed that the female-headed households...
Table 1. Association between household level food insecurity and geographic, demographic and socio-economic variables.

| Variables                  | Food insecurity for the last 12 months | Chi-square/Independent t-test P-value |
|----------------------------|---------------------------------------|---------------------------------------|
|                            | No (%)  | Yes (%)  | Total (%) |                                       |
| Gender, n (%)              |         |         |           |                                       |
| Male                       | 2690 (73.7%) | 955 (69.6%) | 3662 (69.6%) | 0.009**                              |
| Female                     | 1120 (70.2%) | 475 (29.8%) | 1599 (30.4%) |                                       |
| Marital status, n (%)      |         |         |           |                                       |
| Never Married              | 363 (87.5%) | 52 (12.5%)  | 416 (8.0%)        | 0.000***                             |
| Married                    | 2601 (73.2%) | 953 (26.8%) | 3568 (68.2%) |                                       |
| Divorced/ Separated        | 339 (67.4%) | 164 (32.6%) | 504 (9.6%)        |                                       |
| Widowed                    | 488 (65.9%) | 253 (34.1%) | 743 (14.2%)        |                                       |
| Region, n (%)              |         |         |           |                                       |
| Tigray                     | 490 (79.9%) | 123 (20.1%) | 613 (11.6%) | 0.000***                             |
| Afar                       | 106 (78.5%) | 29 (21.5%) | 136 (2.6%)        |                                       |
| Amhara                     | 727 (70.6%) | 303 (29.4%) | 1034 (19.7%) |                                       |
| Oromia                     | 779 (74.1%) | 272 (25.9%) | 1051 (20.1%) |                                       |
| Somalia                    | 177 (61.0%) | 113 (39.0%) | 290 (5.5%)        |                                       |
| Benishagul-Gumuz           | 81 (61.4%) | 44 (35.2%) | 125 (2.4%)        | 0.000***                             |
| SNPP                       | 772 (64.8%) | 419 (35.2%) | 1194 (22.7%) |                                       |
| Gambelia                   | 110 (86.6%) | 17 (13.4%) | 127 (2.4%)        |                                       |
| Harer                      | 143 (87.2%) | 21 (12.8%) | 165 (3.1%)        |                                       |
| Addis Ababa                | 275 (92.6%) | 22 (7.4%) | 297 (5.6%)        |                                       |
| Direwda                    | 150 (67.9%) | 71 (32.1%) | 222 (4.2%)        |                                       |
| Residence, n (%)           |         |         |           |                                       |
| Rural                      | 2168 (65.6%) | 1139 (34.4%) | 3323 (63.2%) | 0.000***                             |
| Urban                      | 1642 (84.8%) | 295 (15.2%) | 1939 (36.8%) |                                       |
| Shocks, n(%)               |         |         |           |                                       |
| Yes                        | 1014 (53.5%) | 882 (46.5%) | 1906 (36.2%) | 0.000***                             |
| No                         | 2796 (83.5%) | 552 (16.5%) | 3356 (63.8%) |                                       |
| HH with access to credit, n (%) |       |         |           |                                       |
| Yes                        | 2975 (73.9%) | 484 (36.9%) | 1321 (25.2%) | 0.000***                             |
| No                         | 2690 (73.7%) | 944 (24.1%) | 3929 (74.8%) |                                       |
| Household size, mean(± SD) | 4.32 (2.33) | 4.59 (2.43) | 4.36 (2.35) | 0.000***                             |
| Average years of schooling in the HH, mean(± SD) | 7.27 (4.47) | 4.89 (3.20) | 6.99 (4.41) | 0.000***                             |
| Dependency ratio, mean(± SD) | 0.84 (0.87) | 1.14 (1.01) | 0.88 (0.90) | 0.000***                             |
| Asset, mean(± SD)          | 3.11 (1.42) | 2.31 (1.18) | 3.80 (1.41) | 0.000***                             |
| Age, mean(± SD)            | 41.85 (15.03) | 44.44 (15.51) | 42.19 (15.12) | 0.000***                             |

Figure 2. Dynamics of household level food insecurity over the months.
(aOR = 1.60, 95%CI: 1.44–1.78) tend to have a higher probability of being food-insecured, compared to male-headed households. Households living in small town and large town have 22% (aOR = 0.78, 95%CI: 0.64–0.97) and 24% (aOR = 0.76, 95%CI: 0.65–0.87) lower probability of being food-insecured, respectively than households living in rural areas. Furthermore, households who reported married are significantly associated with a lower probability of being food-insecured (aOR = 0.41, 95%CI: 0.34–0.50), compared to single-headed households. Households who did not face any shocks (natural or social) in the last 12 months periods, have 77% lower probability of being food-insecure (aOR = 0.23, 95%CI: 0.21–0.25) than those who have encountered any such shocks. Households with access to credit service have 42% (aOR = 0.58, 95%CI: 0.51–0.64) lower probability of being food-insecure compared to those without the services. Considering time effects of food insecurity, a decreased likelihood of being food-insecure in 2015/16 (aOR = 0.64, 95%CI: 0.58–0.71) and 2017/18 (aOR = 0.42, 95%CI: 0.38–0.47), compared to 2012/13.

**Non-linear effects.** The non-linear effect of continuous variables on household level food insecurity is given in Fig. 5 and Table 2. Based on the findings, we noted that age of the household had a significant non-linear effect on food insecurity (Fig. 5A). The lowest food insecurity is observed at age below 40 years. Thereafter, an increasing risk of food insecurity for age greater than 40 years. On the other hand, household asset index in Fig. 5C, illustrates an association with the risk of food insecurity. The Figure further suggested that a minimal effect with household asset index less than 4 and subsequently a decreasing risk of food insecurity for household asset index greater than 4. Figure 5B shows a decrease with the risk of food insecurity as the number of family size increases in the household. Figure 5E demonstrates a steady drop in the risk of food insecurity with increasing average year of schooling of all family members. Furthermore, the lowest food insecurity is observed for dependency ratio less than 3. Thereafter, a minimal positive effect with dependency ratio greater than 3 (Fig. 5D).

**Discussion**

The current study investigated the spatial heterogeneity of household level food insecurity, and its association with head of household gender, age, average year of schooling in the household, family size, credit service, household assets and dependency ratio. Several researchers have studied the determinants of household level food insecurity in Africa and their findings supports the factors obtained in this study. However, the
Figure 4. Estimated parameters (with 95% CI) of geo-additive model for linear effects on the household level food insecurity.

Figure 5. Non-linear effects of continuous predictors (with 95% CI) of geo-additive model: (A) Age of the household; (B) Household size; (C) Household assets index; (D) dependency ratio; (E) Average years of schooling of all family members.
extra regional and possible intra-regional spatially modified effect of predictors of household level food insecurity has not been previously described. For this reason, the geoadditive model that includes the structured and unstructured special effects have been used in the current study. A model that allows unknown non-linear relationship b/n the response variable and continuous variables is very important. In addition to the non-linear effect, predictors modified by taking into accounts the spatial auto-correlation, leads to more accurate estimates of the determinants of household level food insecurity. Consequently, the findings of the current study are expected to lead to better estimates of the factors. To our knowledge, no other African study has investigated these spatial effects on of household level food insecurity.

Some of the results of the current study supported the previous literature, whilst some of the results provided new insights. The findings of the current study revealed that the highest prevalence of household food insecurity was observed from the lowland, hilly and mountainous highlands, which is household living in the Eastern Tigray, Sidama, Wag Hemira, Liben, Shinille, Gamo Gofa, Basketo, Wolyita, Awí, and West Harerenge zones. A plausible reason for the high food insecurity Eastern Tigray, Wag Hemira and Awí zones lower crop production potential due to its lower temperature, unfavorable agroecologic conditions, limited access to infrastructure and low natural resource endowments59. The high rates of food insecurity in Shinille, Liben and Western Hararhge which are in Somali region may be attributed because 2015 El-Nino drought that affected food securities in the Somali because of significant rainfall decrement and many livestock deaths in pastoralists80. The three study zones, Sidama, Wolyata and Gamo Gofa were in the SNNP region where Sidama well known for its coffee produccion, grown as a cash crop. Wolyata and its neighbor Gamo Gofa are densely populated zone where land shortage is a major problem77. Therefore, giving special attention for these areas while designing interventions are required.

Female-headed households were also more likely prone to food insecurity compared to male-headed households. This was supported by previous studies Sisha33, Agidew and Singh81, Jung, et al.14, and Negesse, et al.72. This could be possibly explained by the fact that female-headed households especially from the rural areas cannot adopt new agricultural technologies80 and also faced multiple challenges such as lack of agriculture extension services and limited access to land ownership81. Old household heads were significantly associated with an increased likelihood of experiencing household level food insecurity. This was supported by previous findings54,60,61. They found that an increase age of household head decreases the probability of being food-secure.

Schooling of members of the household negatively affects household food insecurity. This is consistent with other research papers that demonstrated food insecurity to be significantly correlated with education33,62,69. This could be possibly explained by the facts that educational attainment by the household members largely contributed on working competency, diversify income, efficiency, and adopting technologies with long term target to ensure better living condition. A study conducted in Ethiopia64,65, Kenya63 and Bangladesh66 also supported the above conclusion. Furthermore, education is associated with better job opportunities and provides households with the knowledge of how to meet nutritional needs and health of their families.

Households with access to credit services in the current study were associated with reduced probability of food insecurity. Evidence has shown that access to credit had a positive influence on a household’s food security54,67–69. This could be due to the facts that, particularly rural area, access to credit enables households to make timely purchase of inputs (agricultural), such as improved seeds, fertilizer, herbicides, and pesticides, which in turn enhances farm productivity and increases consumption expenditure and future food availability. Therefore, access to credit services supports households to put themselves at a better status of food security. In addition, it is an essential component of development in any economy. On the other hand, households with higher wealth are associated with reduced probability of food insecurity, a result consistent with earlier studies78,79. Our analysis also showed that having a high dependency ratio was significantly associated with an increased likelihood of food insecurity. This is consistent with other findings which argue that households having old age groups and many children may lack sufficient manpower, which eventually results in overdependence on limited family resources hence food insecurity33,54,61,73. Thus, promoting family planning helps women limit the number of their children and hence reduces the probability of household level food insecurity.

Shocks coming from various causes are expected to affect vulnerable population. Our analysis also showed that the presence of shock was an independent predictor of food insecurity among households across all rural, semi-urban and urban residences. A study carried out by Sisha33, Owoo73 and Gupta, et al.74 also came up with similar findings. They found that presence of economic shocks such as droughts, floods, or changes in incomes and price, among others, households have worse food security outcome.

Conclusions
Overall, from a methodological perspective, our ability to include extra and intra-regional spatially modified effects on household level food insecurity, adjust for several household-level factors known to be associated with food insecurity, and incorporate these into semi-parametric geo-additive model, strengthened our findings over previous studies. Our analysis lay the foundation for future work to identify specific directions for intervention. Identifying regions that are likely to have chronic food insecurity helps to take measures in those regions that require special attention. This study also proved that food insecurity continued to be a problem for the Ethiopian population. The findings of this study contribute to a better understanding of the spatial distribution of chronic food insecurity and together with possible factors that affect chronic food insecurity among adolescents.

Data availability
The dataset used and analyzed during the current study is available from the corresponding author on reasonable request.
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Author contributions
Z.G.D. designed the study, collected the data, analyzed the data and wrote the article. T.Z. designed the study, advised on analysis and edited the manuscript. D.N. reviewed the study designed and critically edited the manuscript. All authors read and approved the final manuscript.

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Competing interests
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Additional information
Correspondence and requests for materials should be addressed to Z.G.D.

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