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Spatial location, temperature and rainfall diversity affect the double burden of malnutrition among women in Kenya

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ABSTRACT

Studies have looked into how environmental and climate covariates affect under-and over-nutrition, but little is known about the spatial distribution of different forms of malnutrition in Kenya and whether there are locations that suffer from double-burden of malnutrition. This research quantifies spatial variations and estimates how climatic and environmental factors affect under-and over-nutrition among women in Kenya. This enables us to determine if the patterns in which these factors affect the malnutrition indicators are similar and whether there are overlaps in the spatial distributions. The study used data from the Demographic and Health Survey, which included cross-sectional data on malnutrition indicators as well as some climate and environmental variables. A multicategorical response variable that classified the women into one of four nutritional classes was generated from the body mass index (BMI) of the women, and a Bayesian geoadditive regression model with an estimate based on the Markov chain Monte Carlo simulation technique was adopted. Findings show that women in Turkana, Samburu, Isiolo, Baringo, Garissa, and West Pokot counties are more likely to be underweight than women in other counties while being overweight is prevalent in Kirinyag'a and Kitui counties. Obesity is prevalent in Kirinyag'a, Lamu, Kiambu, Murang'a, and Taita Taveta counties. The study further shows that as mean temperature and precipitation increase, the likelihood of being underweight reduces. The chances of being underweight are lower among literate women [OR: 0.614; 95% CrI: 0.513,0.739], married women [OR: 0.702; 95% CrI: 0.608,0.819] and those from rich households [OR: 0.617; 95% CrI: 0.489,0.772], which is not the case for overweight and obesity. The generated spatial maps identify hot spots of the double burden of malnutrition that can assist the government and donor agencies in channeling resources efficiently.

1. Introduction

The coexistence of malnutrition, such as obesity, overweight, and underweight in the same population across life, referred to as the double burden of malnutrition (DBM), is emerging as a global problem (Shrimpton & Rokx, 2012). DBM can occur at the individual level, such as obesity caused by a lack of one or more minerals and vitamins, or being underweight, especially in adults who were stunted by under-nutrition during childhood (World Health Organization, 2017a). Secondly, DBM can exist at the level of the household; for example, a mother who is overweight or nutritionally anemic, and a grandparent or child who is underweight. Lastly, DBM also exists at a population level where the prevalence of both overweight and under-nutrition, non-communicable diseases (NCDs), or obesity occurs in the same region, nation, and community. In many low- and middle-income countries (LMICs), overweight and under-nutrition, NCDs, or obesity now coexist with women being disproportionately affected at the population level (Agriculture Organization, 2006). Many NCDs such as cancer, stroke, hypertension ischaemic heart diseases, and diabetes are caused by obesity (Delisle, 2005). Up to 80% of deaths in LMICs are deemed to have been caused by these NCDs (Shrimpton & Rokx, 2012). In Africa, an estimation of almost 50% of pregnant women tends to suffer from anemia, which gives rise to the risk of death for both themselves and their unborn babies (Amugsi et al., 2019). Globally, these DBM key indicators are rising, with LMICs bearing the brunt of the burden (Kolčić, 2012). In an analysis of survey data from 24 African countries spanning 25 years, obesity and overweight were found to be on the rise among women (Amugsi, 2017). A comparative study conducted on men and women in LMICs showed that DBM tends to affect women more than men. Women are prone to DBM since they require high nutritional kinds

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of stuff for pregnancy and lactation (Amugsi et al., 2019).

The nutritional status of women of reproductive age requires some attention since it has a crucial influence on the health of women before the pregnancy period and has implications for the health of newborns. It has a close relationship with status throughout pregnancy and nutritional reserves because it forms the foundation for the development of the fetus (Williamson, 2006). Africa has the highest proportion of women suffering from anemia, with approximately 468 million women of childbearing age being the most affected (World Health Organization, 2017b). In Kenya, maternal deaths are mostly caused by anemia, and the most common type is deficiency anemia that is caused by inadequate intake of iron (Brabin et al., 2015). Anemia is primarily a nutritional disorder that affects women and children in LMICs (Reimer-Jaß, 2016). As a result, iron deficiency anemia is highly treatable and preventable (Miller, 2013).

Studies have revealed the increasing speed of the urbanization process in Kenya, raising some concerns about the spread of malnutrition. This is evident given the mushroom slums caused by rapid urban population growth that results from inadequate urban planning. Approximately 56% of residents living in sub-Saharan Africa's urban areas in 2014 lived in shanty overcrowded places with inadequate sanitation and water, poor housing conditions, very poor infrastructure, and deficient health facilities, all of which worsen their nutritional intake (Aerni, 2016). Furthermore, Kimani-Murage et al. (2014) claimed that malnutrition in these slums is associated with frequent lack of food and other deprivation forms. Consequently, in informal settlements, infections and nutrient deficiencies are caused by several factors, and women and children tend to have similar determinants of malnutrition (Fotso et al., 2012). New evidence shows that being underweight is primarily caused by poor hygiene and a lack of access to safe drinking water (Dangour et al., 2013). To curb this, nutritionists are working together with experts in the Water, Sanitation, and Hygiene (WASH) sector to improve sanitary conditions being experienced especially in countries with high urban slum populations. The co-occurring and risk issues for women living in populated urban slums show that malnutrition does not only relate to nutrient intake but also to other factors (De Vita et al., 2019).

Food security and agricultural production in Kenya are threatened by continued population and consumption growth, as well as rising temperatures and changing rainfall patterns. A decrease in agricultural production not only affects food supply but also affects the major sources of income of most households (Schmidhuber & Tubiello, 2007). Many developing countries in sub-Saharan Africa, where food production is frequently influenced by environmental factors (such as rainfall, and temperature), face the risk of declining food availability as warming climates threaten current food systems (Funk & Brown, 2009). Among these countries, Kenya (along with the Horn countries) has a high potential for extreme weather events under scenarios of climate change (Grace et al., 2012). As the land area suitable for planting and agricultural production shrinks, the combined effect of these climate factors puts an increasing strain on food resources (Grace et al., 2012). Kenya is also witnessing rises in average annual temperatures while experiencing a decrease in growing season rainfall, according to climatologists.

Given that malnutrition is closely related to household food security, this issue raises concerns about the impacts of climate change on DBM. Climate variability is likely to exacerbate under-nutrition indirectly through reduced agricultural income and directly through food availability, as per strong evidence of unfavorable effects of climate change on crop yields, such as maize, rice, and beans (Challinor et al., 2014). Small-scale farmers are especially susceptible to rainfall fluctuations because they depend on rain-fed agriculture (Niles & Brown, 2017). Climate change does not only affect under-nutrition. From recent research, climate change is linked to obesity in two vital ways; first, as a result of climate change, over-consumption contributes to the epidemic of obesity, and second, with relation to climate change's obesity-related impacts (An et al., 2018). According to Dinsa et al. (2012), there is little agreement in LMICs about how obesity is related to dietary choices and socioeconomic status.

Kenya suffers from frequent famines and droughts, with millions of people being affected every time a drought occurs. This threatens food security across the country, with counties located in the Northeast, North, and Northwest of the country being affected the most. However, parts of Eastern Kenya, including Kitui and Makueni counties, and Tana River County, in the coastal region, are frequently affected (Lokuruka, 2020). As a result of food insecurity, the cost of nutritious foods like fresh fruits and vegetables has risen, causing households to shift to low-priced, high-calorie items that are associated with obesity and overweight (Popkin et al., 2012). This means that less educated and less fortunate individuals may opt for cheaper, non-nutrient-rich foods since they experience difficulty accessing healthy foods, particularly during income shocks and weather crises (Muttarak, 2019). Food insecurity is highly associated with hunger in households, which promotes maternal underweight.

This study focuses on investigating how climate and spatial factors might have been contributing to a change in the nutritional status, mainly focusing on the shift in BMI of Kenyan women. To simultaneously study the geographical patterns and impact of some climatic conditions on the different forms of malnutrition in Kenya, we created a multi-categorical variable that classifies women into four categories based on their nutritional status and used a geoadditive multicategorical regression model where the response variable was assumed to follow a multinomial distribution (Kneib & Fahrmeir, 2007). This model enabled the smooth effects of continuous covariates and the spatial effects with flexible forms to be incorporated (Kammann & Wand, 2003).

2. Methods

2.1. Data

The study makes use of data from the 2014 Kenya Demographic Health and Surveys (KDHS), with a sample taken from a master sampling frame, the Fifth National Sample Survey and Evaluation Programme (NASSEP V). NASSEP V contains 5360 clusters that are split into 4 equal sub-samples. The NASSEP V frame was sub-sampled twice for the 2014 KDHS. The 2014 KDHS produced representative estimates for survey variables at the national level, for both rural and urban areas, at the regional (former provincial) level, and selected variables at the county level. The 40, 300 household samples were drawn from 1, 612 clusters, with 617 clusters for urban areas and 995 clusters for rural areas. In each sampling stratum, a two-stage sample design was employed to choose samples independently. From the NASSEP V frame, 1, 612 enumeration areas were chosen with equal probability for the first stage. The second stage entailed selecting 25 households from each cluster to serve as a sampling frame. During the data collection, the interviewers only visited pre-selected households, and replacement of pre-selected households was not authorized. In all of the pre-selected households, women's and household questionnaires were administered. Since the allocation to the fixed sample size per cluster and sampling strata was non-proportional, the survey was not self-weighing and the resulting data has been weighted to be representative at national, regional, and county levels. Individual record data for women was extracted from the KDHS to examine the influence of covariates on the response variable. The body mass index (BMI), which was computed based on weight and height indices, was considered to be our response variable of interest and was used to access malnutrition. A woman with a BMI of less than 18.5 kg/m^2 is said to be underweight; a woman whose BMI lies between 18.5 kg/m^2 and 24.9 kg/m^2 is said to be of normal weight; a woman with a BMI that lies between 25 kg/m^2 and 29.9 kg/m^2 is said to be overweight; and a woman with a BMI greater than 30 kg/m^2 is considered to be obese. Thus, a four-category variable was created based on these classifications that serves as the response variable of interest. This data set was perceived to be more suitable for analysis since it is a national representative sample with a significant number of observations on the response variable. It also includes detailed geographical information that enables spatial modeling. The KDHS data set contained various other variables. Only variables that were perceived to be associated with malnutrition among women were considered. The independent variables were selected based on past empirical studies, among other factors. The following variables were included in the study: educational level of the woman, marital and employment statuses, household wealth index, type of place of residence, source of drinking water, type of toilet facility in the household, whether or not the household has electricity, whether or not the woman accesses each of radio, television, and newspaper at least once in a week, whether or not the woman exercises at work, and religious group. Since Kenya is divided into 47 counties that serve as devolved administrative units, the geographic unit of the study was determined by the respondent's home county.

The two climate factors that contribute directly to malnutrition, the mean temperature, and annual precipitation, were also used in the study. The data for the climate variables was obtained from the spatial data repository of The DHS Program, available at https://spatialdata.dhsprogram.com. Both variables were collected within a 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster locations. They were originally derived from the meteorological stations across the world's land areas collected by the Climate Research Unit of the University of East Anglia, UK. The details of these climate variables have been reported in (Mayala et al., 2018). We, therefore, linked the data to the demographic data based on the survey clusters. Missing values and completeness were reviewed after the data was extracted. We discovered that the proportion of missing values was small across the variables, so all missing values were removed.

2.2. Statistical method

2.2.1. Multinomial logistic model

We use a multinomial logistic model to analyze a categorical variable that considers category probability for membership on the response variable based on multiple covariates. In general, multinomial logistic regression is the extension of binary logistic regression with more than 2 categories of the response variable. The categorical response variable $Y_i \in \{1, \ldots, c+1\}$ is estimated on a nominal scale. In addition, we have covariates x_i independent of response variable category. Thus, we define the probability of occurrence of category r as follows;

$$\mathcal{P}(Y_i = r) = P_{ir} = \frac{\exp(x_i'\beta_r)}{1 + \sum_{s=1}^{c}\exp(x_i'\beta_s)} \qquad r = 1, \ldots, c, \tag{1}$$

where x is a vector of covariates and β denotes a vector of regression coefficients. Considering a category as the reference, we have;

$$P_{i,c+1} = 1 - P_{i1} - \ldots - P_{ic} = \frac{1}{1 + \sum_{s=1}^{c}\exp(x_i'\beta_s)}. \tag{2}$$

Then we define equivalent representation as

$$\text{logit}\frac{P_{ir}}{P_{i,c+1}} = x_i'\beta_r \qquad \text{or} \qquad \frac{P_{ir}}{P_{i,c+1}} = \exp(x_i'\beta_r) \qquad r = 1, \ldots, c, \tag{3}$$

where parameter vector $\beta_r = (\beta_{r0}, \beta_{r1}, \ldots, \beta_{rk})'$ is a vector of regression coefficients that corresponds to outcome r and therefore our linear predictor can be defined as

$$\eta_{ir} = x_i'\beta_r = \beta_{r0} + x_{i1}\beta_{r1} + \cdots + x_{ik}\beta_{rk}, \tag{4}$$

with each category $r = 1, \ldots, c$ being specified.

2.2.2. Geoadditive regression model

Suppose we have additional metrical observations $z_{i1}, \ldots, z_{iq}$ for all $i = 1, \ldots, n$ that have to be modelled non-parametrically, and another discrete covariate s_i that describes the geographical location in the form of county where the woman lives.

All these variables can be combined in a regression setting through a geoadditive predictor that extends Equation (4) to include spatial and nonlinear covariates given as:

$$\eta_{ir} = f_{ir}(z_{i1}) + \cdots + f_{qr}(z_{iq}) + f_{geo,r}(s_i) + \beta_0 + \beta_{r1}x_{i1} + \cdots + \beta_{rk}x_{ik} \tag{5}$$

where f_j for $j = 1, 2, \ldots, q$ are smooth functions expressing nonlinear relationship between the continuous covariate and response variable, and $f_{geo,r}$ is the spatial effect for the rth category.

2.2.3. Bayesian inference

Because of the different parameters and functions to be estimated, we considered a Bayesian approach for inference, which entails that prior distributions must be specified. For the smooth functions $f_j, j = 1, 2, \ldots, q$, we specified Bayesian splines prior (Ngwira & Stanley, 2015). By this, the unknown smooth functions f_j are approximated by polynomial spline of degree l defined on equally spaced set of knots $z_j^{min} = \zeta_{j,0} < \zeta_{j,1} < \ldots < \zeta_{j,p-1} < \zeta_{j,p} = z_j^{max}$ that belongs to the domain of z_j. Thus, we can write such splines in linear combination terms of $d = p + l$ as basis functions of B_m that is,

$$f_j(z_j) = \sum_{m=1}^{d} \varepsilon_{jm} B_m(z_j) \tag{6}$$

where ε_j is a vector of unknown regression coefficients. Since we have functions B_m being positive only within the area spanned by $l + 2$ knots, the Bayesian splines create a local basis. We use this important property in the construction of penalized splines smoothness penalty. Then, we reduce the estimation of $f_j(z_j)$ to estimation of unknown regression coefficients $\varepsilon_j = (\varepsilon_{j,1}, \ldots, \varepsilon_{j,d})$ from data (Osei et al., 2012). In the Bayesian context, the smoothness was achieved through a second-order random walk model (7).

$$\varepsilon_j = 2\varepsilon_{j-1} - \varepsilon_{j-2} + u_j, \tag{7}$$

with Gaussian errors i.e., $u_j \sim \mathcal{N}(0, \tau^2)$. The variance τ^2 determines the amount of smoothness (Fahrmeir & Lang, 2001).

We break spatial effects into spatially uncorrelated part (unstructured effect, f_{unstr}) and spatially correlated part (structured effect, f_{str}) considering that spatial data has spatial heterogeneity and correlation due to unobserved varying covariates (Pata et al., 2010). That is

$$f_{geo}(s) = f_{str}(s) + f_{unstr}(s). \tag{8}$$

This representation of spatial effects enables us to distinguish between two kinds of unobserved independent variables, namely, those which are available locally, and those which display a strong spatial structure (Fahrmeir et al., 2003).

A Markov random field prior was chosen for the structured spatial effects $f_{str}(s)$ defined as

$$\{f_{str}(s) | f_{str}(t); t \neq s, \tau^2\} \sim \mathcal{N}\left(\sum_{t \in \delta_s} \frac{f_{str}(t)}{N_s}, \frac{\tau^2}{N_s}\right), \tag{9}$$

where N_s denotes the number of adjacent sites and $t \in \delta_s$ indicates that site t is a neighbor of site s. The conditional mean of $f_{str}(s)$ is the average of the function evaluating $f_{str}(t)$ of the neighboring sites t.

The unstructured spatial effects are assumed to be independently and identically distributed random effects i.e., $f_{unstr}(s) \sim \mathcal{N}(0, \sigma^2)$ (Kneib & Fahrmeir, 2007). Independent diffuse priors $\beta_j \propto const, j = 1, 2, \ldots, q$ was considered for the parameters of the linear fixed effects (Kandala et al., 2009).

Parameter estimation from the posterior distribution was done through the Markov Chain Monte Carlo (MCMC) simulation technique. For all models considered, we performed 30,000 MCMC simulations and discarded the first 5000 as burn-in samples. We fitted four models to determine what can be gained by fitting models with the subset of the covariates and examined model performance through the deviance in-

Table 1
DIC summary and sensitivity analysis of the four models fitted.

Hyper-parameter	Diagnostics	Model 1	Model 2	Model 3	Model 4
$a = 0.001, b = 0.001$	Deviance $(\overline{D})$	27993.526	26028.89231	26253.666	25150.411
	p_D	109.991	137.499	159.564	181.240
	DIC	28213.508	26305.359	26572.794	25512.891
$a = 1, b = 0.005$	Deviance $(\overline{D})$	27994.023	26029.072	26254.215	25151.842
	p_D	109.656	137.929	158.715	180.218
	DIC	28213.620	26305.694	26573.316	21057.278
$a = 0.0001, b = 0.0001$	Deviance $(\overline{D})$	27994.931	26029.735	26265.884	25164.512
	p_D	109.401	138.115	156.908	173.048
	DIC	28213.734	26305.964	26579.700	25510.607

Note: Models 1 to 4 are as described in Section 2.2.3.

Table 2
Posterior odds ratio estimates for linear effects.

	OR	95% CI	OR	95%CI	OR	95% CI
Education level						
Illiterate	1		1		1	
Literate	0.614	0.513,0.739	1.704	1.376,2.104	1.331	0.963,1.838
Currently Married						
No	1		1		1	
Yes	0.702	0.608,0.819	1.299	1.156, 1.465	1.566	1.300,1.885
Employment Status						
Not working	1		1		1	
Working	0.796	0.684,0.912	1.081	0.966, 1.212	1.204	1.010,1.435
Wealth index						
Poor	1		1		1	
Middle	0.666	0.559,0.796	1.385	1.211,1.587	1.749	1.391, 2.220
Rich	0.617	0.489,0.772	1.759	1.516,2.042	2.898	2.287,3.651
Place of Residence						
Urban	1		1		1	
Rural	1.026	0.862,1.189	0.905	0.808,1.017	0.914	0.773,2.284
Source of drinking water						
Protected	1		1		1	
Not Protected	1.162	1.019, 1.322	0.947	0.851,1.056	0.880	0.758,1.037
Type of toilet facility						
Improved	1		1		1	
Non-improved	1.123	0.971,1.300	0.866	0.777,0.962	0.840	0.707,0.981
Electricity						
No	1		1		1	
Yes	0.954	0.726,1.235	1.185	1.017, 1.398	1.299	1.037,1.631
Reads newspaper						
No	1		1		1	
Yes	0.860	0.735,1.004	1.070	0.961, 1.195	1.166	0.993,1.365
Listens to radio						
No	1		1		1	
Yes	0.944	0.810,0.963	1.007	0.880, 1.161	0.946	0.755,1.157
Watches television						
No	1		1		1	
Yes	0.889	0.752,1.035	1.090	0.971,1.223	1.202	1.009,1.446
Exercise at work						
No	1		1		1	
Yes	1.010	0.872, 1.164	0.960	0.860,1.072	0.950	0.809,1.116
Religion						
Roman Catholic	1		1		1	
Protestants	0.974	0.848,1.124	1.026	0.917,1.151	1.226	1.039,1.463
Muslim	1.067	0.817,1.431	1.178	0.908,1.527	1.540	1.076,2.182

formation criterion (DIC) (Spiegelhalter et al., 2002) defined as

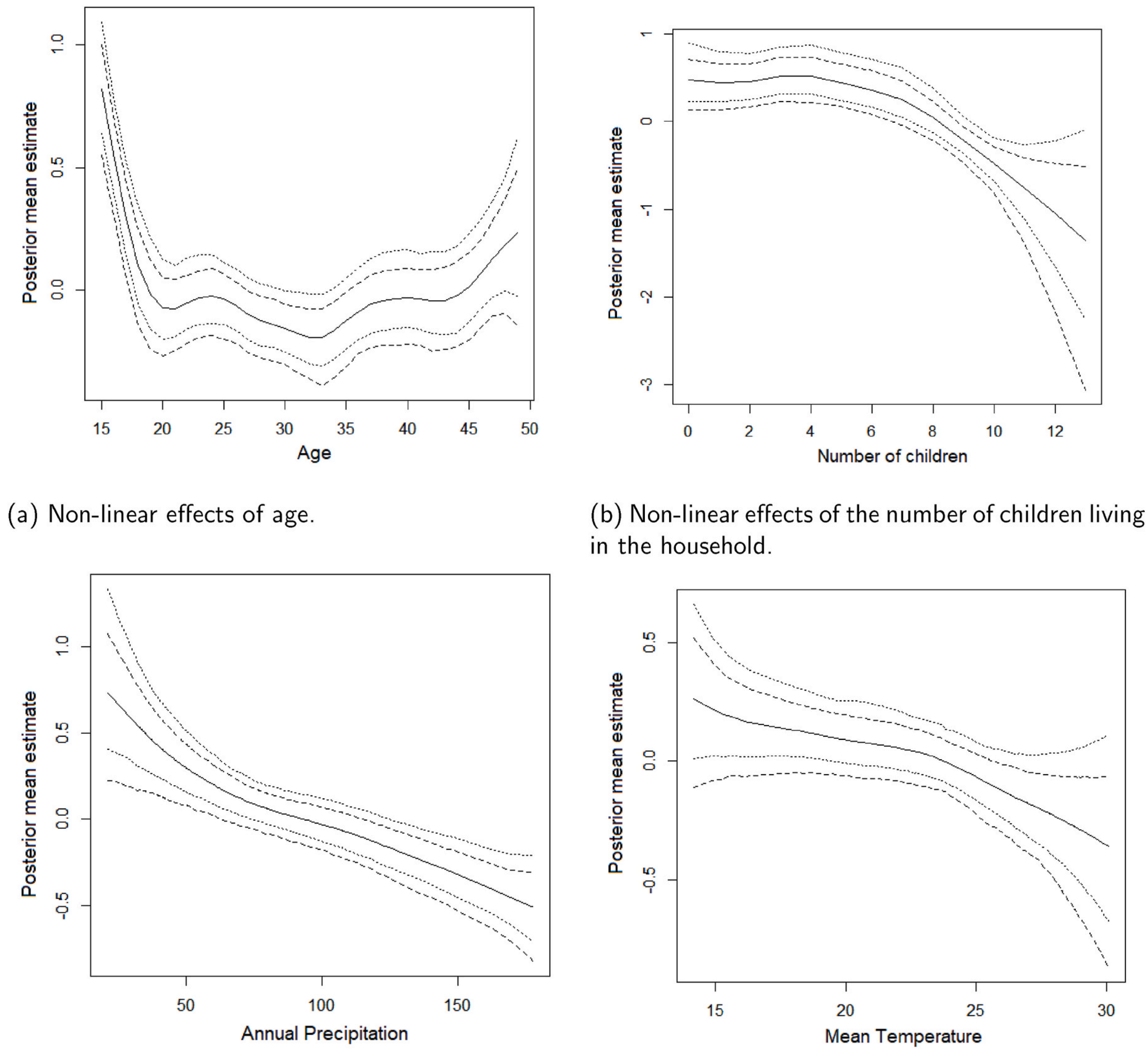
$$DIC = D(\overline{\mu}) + p_D, \tag{10}$$

where $D(\overline{\mu})$ is the deviance posterior expectation, that measures the goodness of fit, and p_D denotes the effective number of parameters while p_D is a metric for model complexity that penalizes over-fitting. Overall, the model with the least DIC value is considered the best. For each of the model, we ran sensitivity analysis to determine how the results were sensitive to the hyperparameters. The following alternatives vales were considered: $a = 0.001$, $b = 0.001$, $a = 1$, $b = 0.005$, or $a = 0.0001$, $b = 0.0001$ as suggested by Belitz et al. (2015).

The following multinomial logit regression models were considered;

- Model 1: $\eta =$ spatial structured effects + unstructured random effects (No covariates)
- Model 2: $\eta =$ Model 1 + linear effects
- Model 3: $\eta =$ Model 1 + non-linear effects (continuous covariates)
- Model 4: $\eta =$ Model 1 + non-linear + linear effects

In implementing the multinomial models, we set women whose BMI was classified as the reference category and estimated parameters for those in other categories (underweight, overweight, and obese).



(a) Non-linear effects of age.

(b) Non-linear effects of the number of children living in the household.

(c) Non-linear effects of annual precipitation.

(d) Non-linear effects of mean temperature.

Fig. 1. Nonlinear estimates for underweight. Shown are the posterior means (represented by the center line) together with 95% and 80% pointwise credible intervals based on fully Bayesian approach estimated with MCMC techniques.

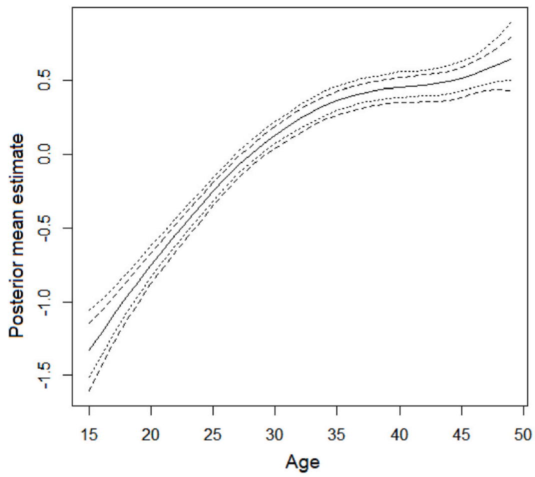
3. Results

Table 1 presents results of the model diagnostics criterion based on the hyperparameters. The results of the DIC show that for all the hyperparameters, model 4 consistently outperformed the other models. Consequently, results presentations and discussions shall be based on those of this model.

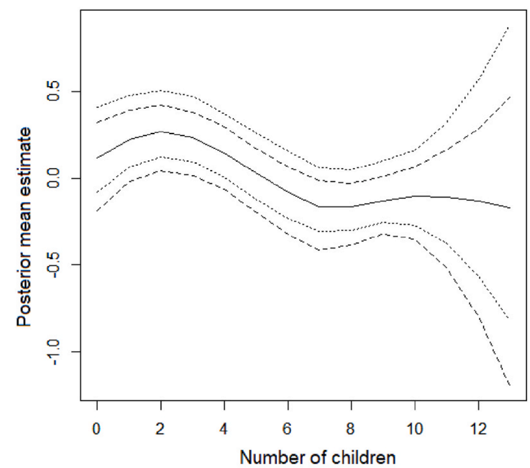
3.1. Linear effects

Table 2 shows the results for the categorical variables indicating the posterior odds ratio estimates and 95% credible intervals for the three levels of malnutrition. The findings indicate that literate women are significantly less likely to be underweight when compared with those who have no formal education, but these women are more likely to be overweight. The estimates for obesity are not significant. Working women are less likely to be underweight but more likely to be obese when compared to non-working women, but estimates of overweight are not statistically significant. Furthermore, compared with women who were not married, currently married women are less likely to be underweight, but more likely to be overweight or obese. Under-nutrition has a positive and statistically significant association with the household wealth index. When compared with women from poor households, those from the middle and rich households are less likely to be underweight, but, as may be expected, they are more likely to be overweight and obese. The estimates for the place of residence are not significant for all the forms of malnutrition. The results show that women who have no access to protected water sources are more likely to be underweight when compared with those who have access to protected water sources, but the estimates for both overweight and obesity are not significant.

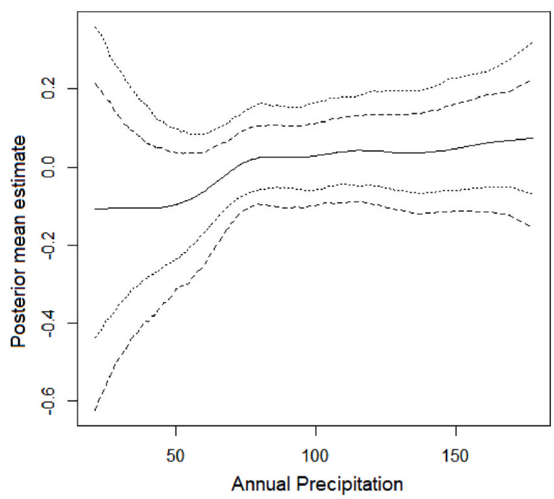
Women from households without enhanced toilet facilities are less likely to be overweight or obese but more prone to being underweight when compared to women from households with improved toilet facilities. Women who have electricity supplied to their households are more likely to be overweight and obese when compared to those without electricity. As for the mass media, women who listen to the radio are less likely to be underweight when compared to those who do not listen to the radio. Women who watch television, on the other hand, are more likely to be obese. Estimates for women who read newspapers and exercise at work are not significant. Further, the results show that women who are either protestants or Muslims are more likely to be obese when compared with those of Roman Catholics, but the estimates for being



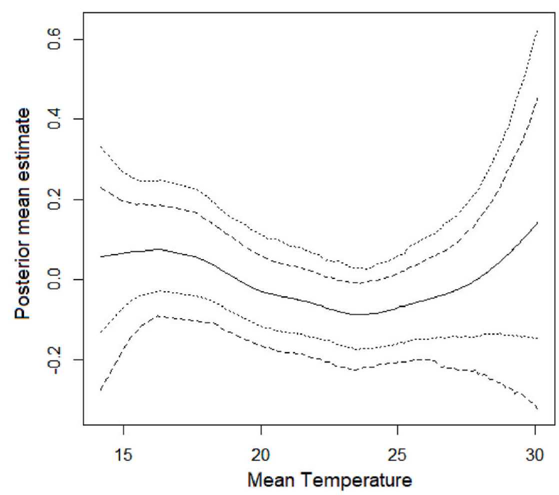
(a) Non-linear effects of age.



(b) Non-linear effects of the number of children living in the household.



(c) Non-linear effects of annual precipitation.



(d) Non-linear effects of mean temperature.

Fig. 2. Nonlinear estimates for overweight. Shown are the posterior means (represented by the center line) together with 95% and 80% pointwise credible intervals based on fully Bayesian approach estimated with MCMC techniques.

underweight and overweight are not significant.

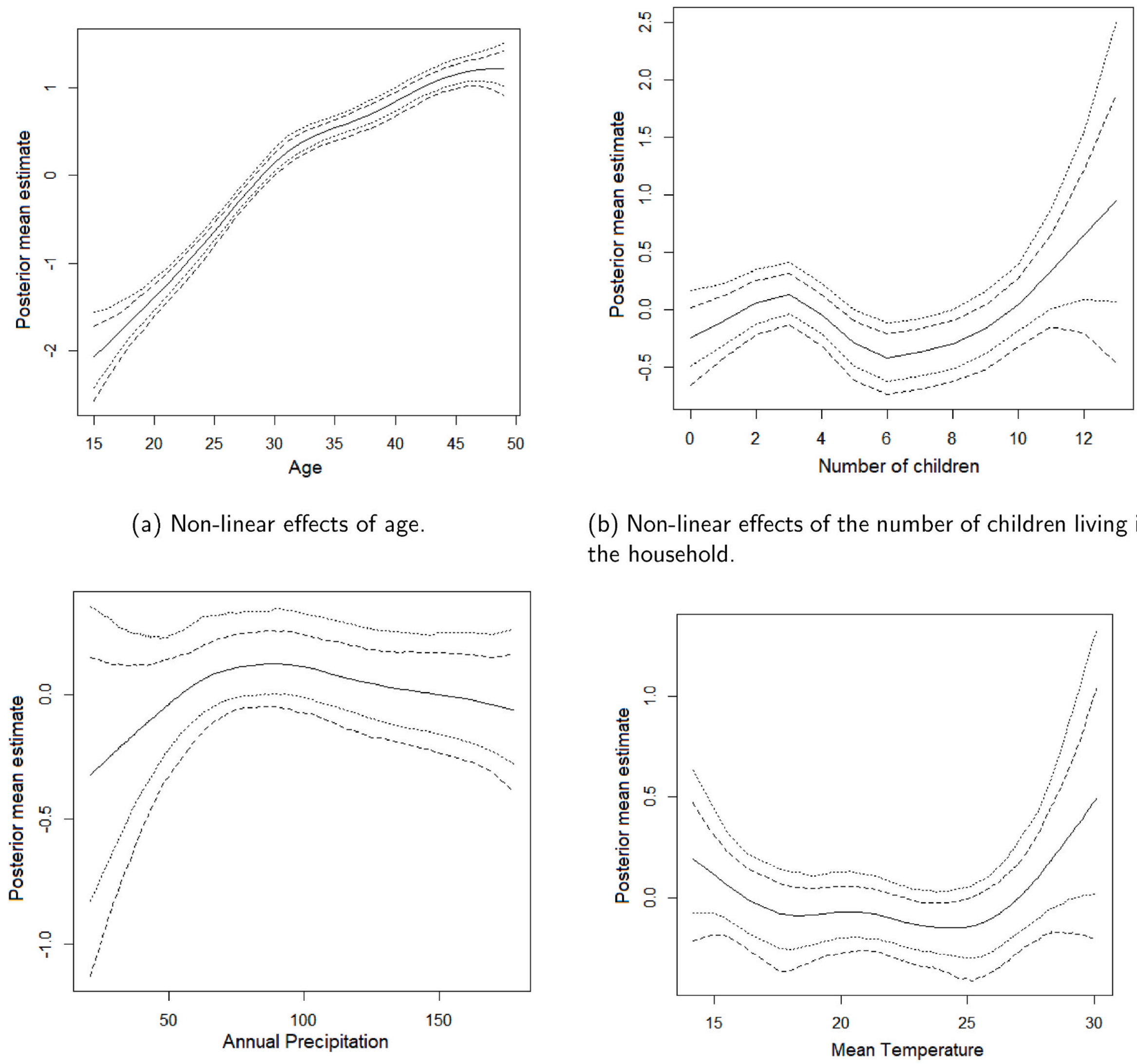
3.2. Non-linear effects

The non-linear effects components of the continuous covariates for underweight, overweight, and obesity categories are displayed in Fig. 1−3 respectively, where each plot indicates the posterior mean (center line) bounded by two inner lines, which are 95% credible intervals and the outer lines are those for 80% credible intervals.

Fig. 1a shows the non-linear effects of women's age for underweight depicting a somewhat U-shaped, indicating that the likelihood of being underweight was highest at age 15 years but reduced with age till around age 20 years. Thereafter, the likelihood of being underweight stabilizes and rises gradually from age 34 years. The estimates for the number of children living in the households show that as the number of children increases, the chances of being underweight reduces (Fig. 1b). The results for annual precipitation (Fig. 1c) and mean temperatures (Fig. 1d) reveal a similar downward pattern, implying that as annual precipitation and mean temperature increase, the chances of being underweight reduce.

Figs. 2a–3a present non-linear effects of woman's age for both overweight and obesity. The results reveal some nonlinear relationships between overweight and obesity levels of malnutrition and the effect of woman's age, indicating that as women advance in age, they are more prone to these forms of malnutrition. An assumption of linear relationships in a modeling approach would have been conservative. As for the number of living children, there appears to be a sigmoid relationship with overweight (Fig. 2b) which indicate that as the number of children increases up to 2, the chances of being overweight increase followed by a decrease to around 7 children before stabilizing. Similarly, as the number of children living in the household increases up to 3, the chances of a woman being obese increases, but reduces thereafter till around 6 before rising again, with a wide credible interval towards the end (Fig. 3b).

Results for the climate variable reveal that as annual precipitation rises, the likelihood of a woman being overweight rises arbitrarily up to around 70 mm and then stabilizes (Fig. 2c). Fig. 3c shows that as precipitation increases, the likelihood of being obese increases up to around 80 mm but reduces thereafter. In the case of temperature, Fig. 2d shows that as temperatures increase up to around 17°C, the likelihood of being overweight stabilizes, and thereafter it reduces up to around 25°C from where it starts to increase. The U-shape functions displayed by Fig. 3d



(a) Non-linear effects of age.

(b) Non-linear effects of the number of children living in the household.

(c) Non-linear effect of annual precipitation.

(d) Non-linear effect of mean temperature.

Fig. 3. Nonlinear estimates for obesity. Shown are the posterior means (represented by the center line) together with 95% and 80% pointwise credible intervals based on fully Bayesian approach estimated with MCMC techniques.

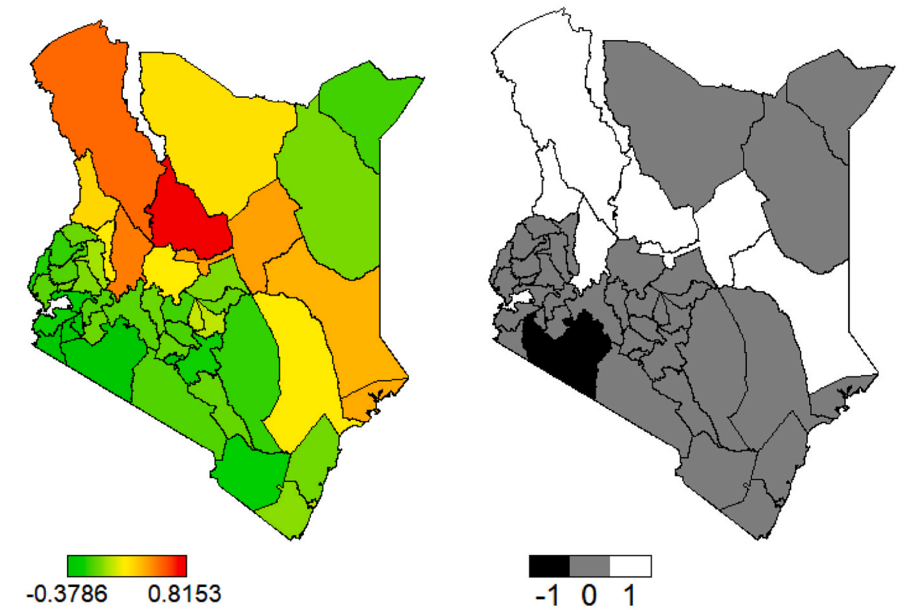
show that as temperatures rise to 17°*C*, the chances of being obese decrease, and then, between 17°*C* and 25°*C*, the chances of being obese stabilize before rising.

3.3. Spatial effects

Results for the spatial effects are presented in Figs. 4–6. The left panel of the Figures presents the maps of the posterior mean estimates while the right panel displays the maps of the location of the 95% credible intervals, which are used to decide on the significance of the posterior means. For all maps displaying credible intervals, black color signifies locations with strictly negative credible intervals, implying that both the upper and lower intervals are negative, which suggests lower chances for the events. The white color signifies locations with strictly positive credible intervals, implying higher chances for the event, while estimates for counties shaded in gray color are not significant. The spatial effects for underweight presented in Fig. 4 show that women in Turkana, Samburu, West Pokot, Isiolo, Garissa, and Baringo counties are more likely to be underweight whereas those living in Narok County are less likely to be underweight. Estimates for overweight (Fig. 5) reveal that women in counties of Kirinyag'a and Kitui are more likely to be overweight, whereas women in West Pokot, Turkana, Samburu, Bungoma, Nandi, and Kakamega counties are less likely. Women who dwell in the counties of Elgeyo-Marakwet, and Trans-Nzoia are less likely to be obese, as shown in Fig. 6. There are however higher chances of obesity among women living in Lamu, Taita Taveta, Kiambu, Murang'a, and Kirinyag'a counties.

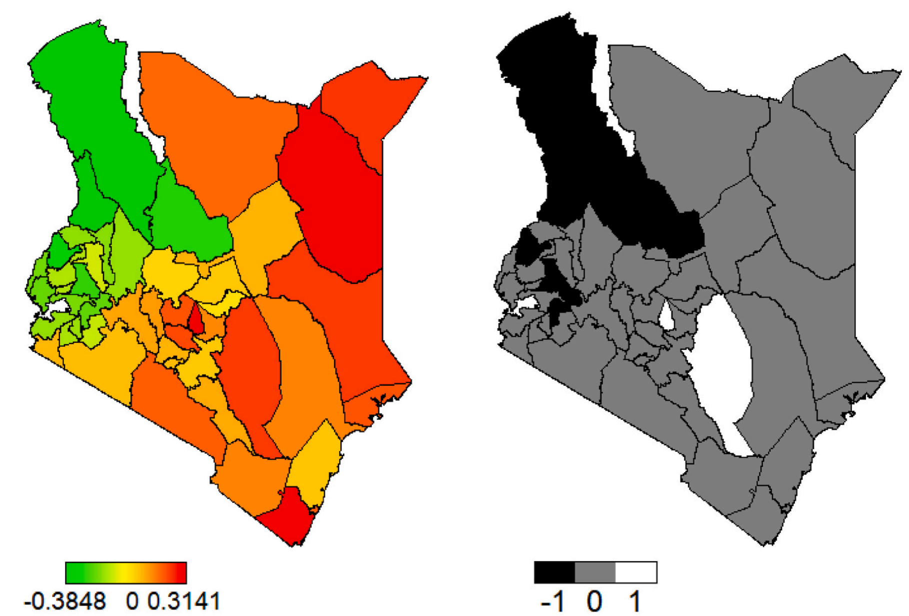
4. Discussions

This study investigates spatial patterns and estimates how some climate and environmental factors affect various forms of malnutrition among women in Kenya, and therefore provides insights into the double burden of malnutrition. A geoadditive regression method was used, which allowed for the estimation of covariates at various levels of malnutrition based on the woman's BMI. Surrogate indicators of unobserved spatially correlated risk variables for malnutrition are included in the model via structured spatial effects. These patterns indicate possible unobserved risk factors for malnutrition, which may be local or global. Findings on spatial effects show that the burden of malnutrition among women in Kenya has structured spatial effects that depict neighboring counties sharing similar patterns. This could be attributed to shared



(a) Map of Kenya showing posterior means. (b) Map of Kenya showing 95% credible intervals.

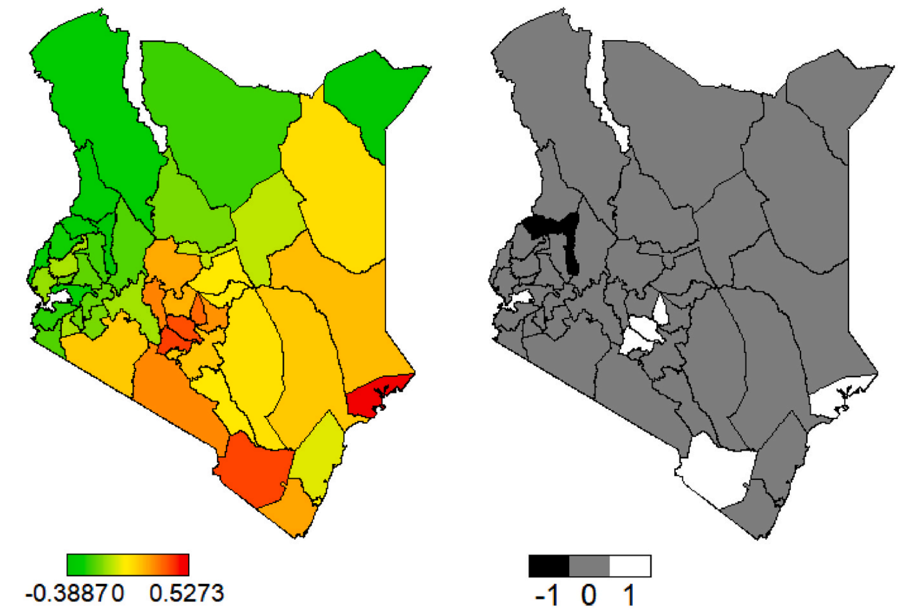
Fig. 4. Shown are the spatial effects for underweight level of malnutrition.



(a) Map of Kenya showing posterior means. (b) Map of Kenya showing 95% credible intervals.

Fig. 5. Shown are the spatial effects for overweight level of malnutrition.

cultural beliefs, practices, and norms that affect women from neighboring communities who exhibit specific nutrition traits (Gayawan, 2014). There are communities in Kenya that have taboos that influence the food intake of women, and there are those who restrict the use of healthcare services due to ignorance. Such practices often result in wide variations in the nutritional indicators of women and their children, as found in the case of Nigeria (Akeresola & Gayawan, 2020). Counties such as Turkana, Wajir, Samburu, West Pokot, Tana River, Narok, Kwale, Garissa, Kilifi, Isiolo, and Lamu are deemed to be the most marginalized due to high poverty, low levels of education, and very low development (Stiftung, 2012). People in these counties rely on pastoral farming, subsistence agriculture, and small-scale fishing, all of which are limited due to fluctuating climate change. These occupations are often done in a way that relies on physical activities, which could further reduce the chances of overweight and obesity among women (Miles, 2017). The devolved units in Kenya have created office jobs remotely with a variety of sedentary jobs where women who work in such offices sit for long hours each day, and probably tend to rely on processed junk foods regularly and are less engaged in physical activities, subjecting them to overweight and obesity (Proper et al., 2007). Further, as seen in



(a) Map of Kenya showing posterior means. (b) Map of Kenya showing 95% credible intervals.

Fig. 6. Shown are the spatial effects for obesity level of malnutrition.

some African countries, plump women are considered to be sexy and this prompts some women to engage in activities that can increase their body weight in order to be attractive and acceptable in the society (Rhode, 2010).

The results further revealed that women who are working are more likely to be obese and underweight. On one hand, women might work and earn little, thus having limited access to costly nutrient-rich foods. On the other hand, working women are empowered and have high purchasing power and, therefore, they are not limited to the kind and variety of food they eat and sometimes engage in overeating. Similar findings were reported from India, Bangladesh, and Indonesia (Khan et al., 2009; Yadav et al., 2015). Women with lower levels of education are more likely to be underweight, whereas those who have attained higher levels are more likely to be overweight or obese. Educated people often belong to the high-class segment of society and these people often consume foods rich in carbohydrates and fats, and sugared sodas, which lead to dietary excess and overeating that constitutes obesity (Muttarak, 2019). This is evidenced by studies that have portrayed a positive link between educational status and being overweight or obese (Ziraba et al., 2009; Kamadjeu et al., 2016; Dake et al., 2011). Furthermore, women in the wealthiest quintiles are considered to have higher socioeconomic status and therefore possess the resources and knowledge of the importance of a healthy diet and physical activity, but do not always use them due to a variety of social and cultural barriers, promoting obesity (Griffiths & Bentley, 2005). Because of inadequate nutrition, limited access to health care, and frequent illnesses, women in low-income households are more likely to be underweight (Tebekaw et al., 2014).

Considering the case of mass media, which is a key source of information on nutrition-related issues, women who have access to any television, newspaper, or radio ought to be better informed about healthy eating habits and lifestyles, as reported in the case of younger people in Botswana (Letamo & Navaneetham, 2014). In our case, however, except for the estimate for television in the case of obesity, the other estimates are not statistically significant, implying that the impact of the mass media is insufficient to make a difference between women who have access to them and those who do not. This is unlike the findings which claimed that access to mass media is associated with weight gain through mechanisms such as advertisements that promote the consumption of high-calorie unhealthy foods (Gius, 2011). The higher likelihood of obesity estimated for women who watch television may be because these women spend long hours watching home movies rather than engaging in physical activities, thus promoting obesity (Boulos et al., 2012). In the case of water sources and toilet facilities, women in households with protected water sources and improved toilet facilities are considered to be of high socioeconomic status and are not prone to undernutrition. Whereas, those who use unimproved facilities and unprotected water sources tend to suffer from nutritional problems and are prone to health issues. The same findings were reported elsewhere in Ghana, Niger, and Malawi (Ziraba et al., 2009).

According to the findings, the response variable seems to have a nonlinear relationship with the women's age, the number of children living in the household, annual precipitation, and mean temperature. Using the assumption of linear relationships could have resulted in erroneous conclusions. This is in agreement with a study in Ethiopia where a nonlinear relationship between rainfall and underweight was observed (Hagos et al., 2014).

Results show that as annual precipitation and temperature increase, the likelihood of being underweight reduces. This is in agreement with a study in Ethiopia where decreasing stunting patterns and underweight were observed among youths as the country experienced high rainfall (Hagos et al., 2014). Reduced undernourishment in Kenya is attributed to the growth of the economy that has enabled the government to formulate food and nutrition policies that address food insecurity in the country (Mohajan, 2014). Kenya has been experiencing global warming over recent decades that depletes land moisture and possibly leads to water scarcity and destruction of nutritious crops, prompting women to eat non-nutritious foods that are susceptible to obesity (Popkin et al., 2012). Due to rising temperatures, rainfall is also becoming unpredictable and variable over time, causing droughts and famines, thus prompting food insecurity (Lokuruka, 2020).

Findings further revealed that for every unit increase in age, the tendency to be underweight reduces, whereas the tendency to be overweight or obese increases. This implies that the most affected people by underweight are teenagers who can't afford to provide for themselves, but rather rely on their parents, who might not be able to provide the required nutritious foods (Keeley et al., 2019). Underweight has been reported among young people in LMICs (Tebekaw et al., 2014), while increased obesity with age is associated with lower levels of physical activity and sedentary lifestyles (Letamo & Navaneetham, 2014).

5. Conclusion

This study uses a Bayesian geoadditive regression model to create an explanatory model of the spatial and climate aspects of the double burden of malnutrition among women in Kenya. The socio-economic variables and spatial patterns at different levels of malnutrition provide a clear picture that contributes to understanding the general spread of under- and over-nutrition indicators among Kenyan women, particularly based on spatial locations. The statistical significance of the variables discussed in the linear effect can be used to formulate programmes for interventions and policy planning. The nonlinear effects give a clear indication that climate indicators such as temperature and rainfall patterns influence the nutritional status of women, thus contributing to the double-burden of malnutrition. The spatial maps captured all the profounding factors that affect the double-burden of malnutrition among women in Kenya that could have been neglected in classical regression settings. The generated spatial maps identify hot spots of the double-burden of malnutrition that can assist government agencies and policymakers to channel resources efficiently and formulate strategies for improving national nutritional status. A comprehensive approach that institutes a combination of efforts and interventions from all stakeholders in the sector is needed to curb the issue of double-burden of malnutrition. Findings reveal that the challenges of the double-burden of malnutrition posed by climate change due to increased temperature and changes in rainfall patterns require carefully thought-out policy plans. It is worthwhile to note that the socioeconomic status of the populace could offer some protective buffer against the effects of poor climatic conditions on malnutrition outcomes. If so, it would be worth the effort if this issue is explored in future studies.

Ethical consideration

The data for this study was requested and approved upon submission of an abstract to the DHS program. Confidentiality and privacy were observed, and no effort was made to identify any household or individual respondent interviewed in the survey. The DHS data was only used for statistical analysis and reporting for registered research.

Authors contribution

Japheth Muema Kasomo: Writing - Original draft preparation; Conceptualization; Methodology; Software; Visualization.

Ezra Gayawan: Writing - Reviewing and Editing; Investigation; Supervision; Software; Validation.

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Declaration of competing interest

The authors have conflicts of interest to declare.

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