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Climate variability, armed conflicts and child malnutrition in sub-saharan Africa: A spatial analysis in Ethiopia, Kenya and Nigeria

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ABSTRACT

Background: Sub-Saharan Africa (SSA) has one of the highest prevalence of malnutrition among children under 5 in the world. It is also the region most vulnerable to the adverse effect of climate change, and the one that records the most armed conflicts. The chains of causality suggested in the literature on the relationship between climate change, armed conflict, and malnutrition have rarely been supported by empirical evidence for SSA countries.
Methods: This study proposes to highlight, under the hypothesis of spatial non-stationarity, the influence of climatic variations and armed conflicts on malnutrition in children under 5 in Ethiopia, Kenya, and Nigeria. To do this, we use spatial analysis on data from Demographic and Health Surveys (DHS), Uppsala Conflict Data Program Georeferenced Event Dataset (UCDP GED), Climate Hazards center InfraRed Precipitation with Station data (CHIRPS) and Moderate Resolution Imaging Spectroradiometer (MODIS).
Results: The results show that there is a spatial autocorrelation of malnutrition measured by the prevalence of underweight children in the three countries. Also, local geographically weighted analysis shows that armed conflict, temperature and rainfall are positively associated with the prevalence of underweight children in localities of Somali in Ethiopia, Mandera and Turkana of Wajir in Kenya, Borno and Yobe in Nigeria.
Conclusion: In conclusion, the results of our spatial analysis support the implementation of conflict-sensitive climate change adaptation strategies.

1. Introduction

Malnutrition is a major public health problem in Sub-Saharan Africa [1]. It mainly refers to chronic malnutrition (i.e., wasting, being underweight and stunting), and being overweight or obese. People with malnutrition exhibit a decrease in physical and mental functions, and sometimes it leads to impaired clinical outcome of a disease [2]. In addition, in adulthood, malnourished children will have low work capacity and lower productivity [3,4]. Estimates by the Food and Agricultural Organization (FAO) revealed that in 2020, about 37 % of children in SSA were stunted, 6.7 % suffered from wasting and 5.7 % were overweight [5].

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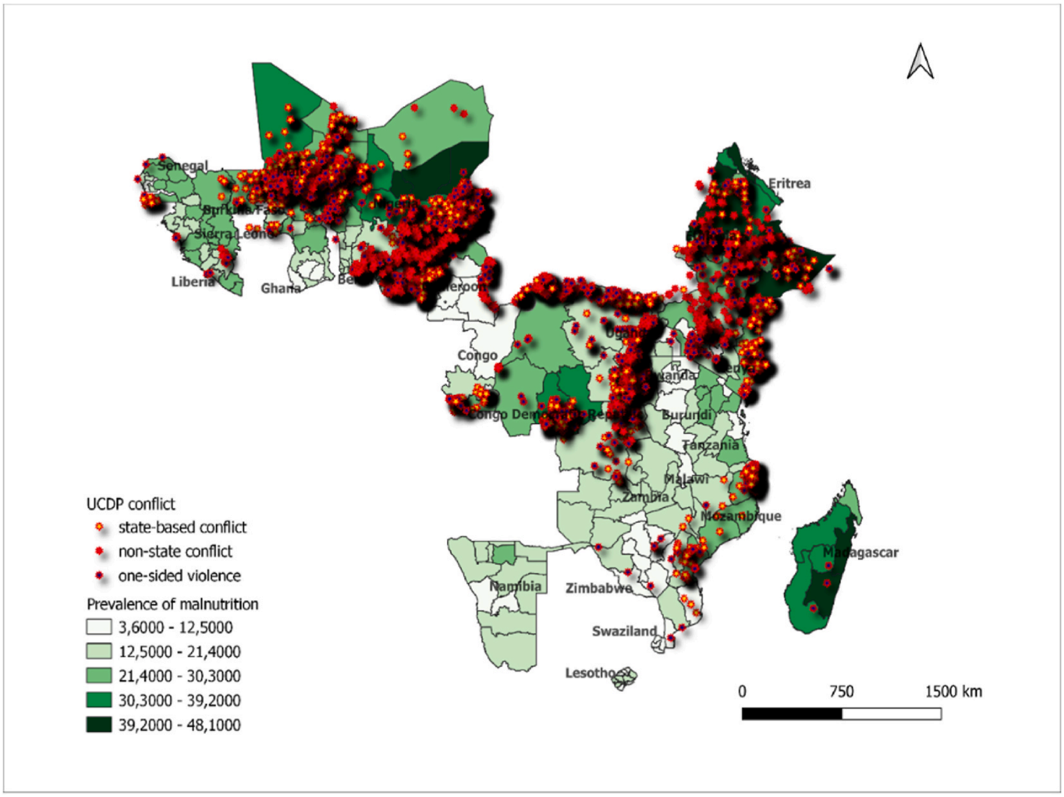

Fig. 1. Distribution of the prevalence of malnutrition and armed conflicts between 2010 and 2020.
Source: Authors based on DHS and UCDP data.

Among the factors that determine the nutritional status of children in SSA, climatic conditions and armed conflicts are regularly cited as the main causes of famine crises characterized by peaks in the prevalence of malnutrition [6,7]. Indeed, according to the Intergovernmental Panel on Climate Change (IPCC), SSA is the region of the world most vulnerable to the effects of climate change and will experience an increase in the frequency and intensity of precipitation and severe episodic droughts (IPCC, 2014). At the same time, it is the region most affected by armed conflicts since the end of the Cold War [8]. The interaction between increasingly prolonged drought episodes and armed conflicts contribute to further intensify the threats to food security in the region, leading to a decrease in the availability of food resources [9].

Considerable progress has been made in understanding how climate change can generate or interact with conflict, and ultimately affect health outcomes such as nutrition. In regions where natural resources (water, food and land) are scarce, the consequences of climate change such as drought and desertification could intensify competition for these resources, leading to conflict between communities [10]. These conflicts lead to a decline in agricultural production as crops and livestock are looted [28,29], and limit people's access to markets and health care, increasing the risk of malnutrition [30]. For example, the Lake Chad basin, characterized by diminishing water resources (its surface area has shrunk from 25,000 km^2 to 2000 km^2 in 40 years) due to global warming [11], is experiencing an explosion of security crises (Jihadi upsurge: boko Haram and Islamic State) and pastoral violence due to competition for reduced resources [12], which have contributed to worsening food insecurity in the zone [32].

A closer review of the literature reveals that the mediating effect of climate change in the relationship between conflict and malnutrition would disappear if a number of socio-economic and institutional conditions (high dependence on agricultural incomes, inability to mitigate the negative effects of climate change, pre-existing tensions and conflicts) were not met [11]. Moreover, whether this mediating effect of climate change exists or not, it can influence the nutritional status of children by affecting the quality and quantity of food crops such as wheat, barley, rice and sorghum [12], the main staple foods in sub-Saharan African countries. Some researchers have shown that climate change is likely to adversely affect the production of more than 30 % of farmers in developing countries (IPCC, 2014). Similarly, Yordanov et al. [13]; Barnabás et al. [14] have noted that drought leads to a substantial drop in crop yields due to its negative effects on plant growth, physiology and reproduction.

In addition, several publications highlight that climate change has a direct impact on health outcomes [12–17]. Indeed, extreme weather events, sea-level rise and climate variations impact food production systems and water resources [18], as well as the rates of spread and transmission of vector-borne, foodborne and waterborne diseases [19,20]. Exposure to extreme heat are associated with increased emergency room visits, increased deaths from cardiorespiratory disease, and adverse pregnancy and childbirth outcomes [15]. During flooding and sea level rise, water can be contaminated with environmental pathogens such as Campylobacter spp., Salmonella spp. and Shigella spp that cause diarrheal disease in children and result in malnutrition [16]. Xu et al. [17], Asmall et al. [18] show that in Ethiopia and Kenya, children under 5 years born during a drought were more likely to be underweight than those born in non-drought years.

Previous research has strongly focused on modeling the effects of climatic conditions or armed conflict on malnutrition over space and time [19–21], paying less attention to the situation where conflict and climate extremes events occur at the same time, particularly in SSA countries. Moreover, among the studies identified [22], none considered the spatial dependence of the observations and the spatial non-stationarity of the postulated relationships between climate change, conflict and malnutrition in their methodological approaches. In other words, the results of these studies assume that the effect of climate variables armed conflicts on malnutrition is identical or stationary throughout the study area. This assumption of stationarity is debatable. Cockx and Canters [23], Stewart Fotheringham et al. [24] show that based on this, a large amount of spatial information is lost as the relationships examined can exhibit significant spatial variation. Several studies have not only shown that malnutrition is characterized by a spatial dependence of observations [25–28], but also that armed conflicts [29,30] and climate change [31–33] in a locality have spillover effects on neighboring regions in SSA. Thus, taking into consideration the hypothesis of stationarity of the effects in the whole study area seems to us of little relevance. This research aims to highlight, under the hypothesis of spatial non-stationarity, the influence of climatic variations and armed conflicts on malnutrition among children under 5 in Ethiopia, Kenya and Nigeria. To do this, we use spatial analysis through Local Indicator of Spatial Analysis (LISA) and global (Spatial Error Model and Spatial Lag Model) and local spatial regression (Geographically Weighted Regression) models. This analysis uses voronoï polygon method on Demography Health Survey (DHS) spatial databases of countries considered in order to generate geographical areas from GPS coordinates of each cluster. Voronoï polygons are used to analyse spatial distribution of data by generating polygon layers from point layers. This study also uses geolocated conflict data from Uppsala Conflict Data Program (UCDP), and climate data from Climate Hazard center InfraRed Precipitation with Station data (CHIRPS) and Moderate Resolution Imaging Spectro radiometer (MODIS).

The countries chosen in our study are among those most exposed to armed conflicts within the period 2010 to 2020 as shown in Fig. 1. During this period, for instance, Nigeria experienced a series of conflicts in the North-east, more specifically in the Borno and Yobe regions following the insurrection of the Islamist sect Boko Haram [34]. The country has also had to deal with other conflicts, one of the deadliest of which is associated with the Fulani militia. Regarding Ethiopia, the periods from 1961 to 1991 and 1998–2000 marked the period of conflicts at the borders between Eritrea and Ethiopia that resulted in more than 80,000 deaths [35]. In recent decades, there has been a resurgence of conflict between the Ethiopian government supported by Eritrea and the Tigray Liberation Front (LFT). Meanwhile, Kenya has experienced intra-state conflicts related to natural resources, ethnicity (particularly in the Rift Valley), and land which have sometimes claimed many lives [36]. Most of Kenya's elections have been preceded by electoral violence (1997, 2002, 2007, 2013 and 2017) which took the form of armed conflicts [37].

In addition, each of these countries has a food system that is significantly dependent on local rain-fed crops [38–40] and faces persistent malnutrition as shown in Fig. 1. In Kenya, during the 2004–2006 and 2008–2009 and 2013 droughts, annual agricultural growth declined by over 6 % [40]. In Ethiopia, the spatial and temporal variability of rainfall has increased. The duration of the rainy season(s) is decreasing, while the temperature (maximum, minimum, average) is increasing [41], severely affecting the crop and livestock sectors and resulting in food insecurity [42]. Several studies in Nigeria [38,43] have shown that climate change has a negative impact on agricultural production of rice and cocoa.

2. Materials and methods

2.1. Data

This study uses data from the UCDP Georeferenced Event Dataset (UCDP GED) Global version 21.1 (available from: https://ucdp.uu.se/downloads/), the Demographic and Health Surveys (DHS) of Ethiopia (DHS-2016), Kenya (DHS-2014) and Nigeria (DHS-2013) and GPS data from each DHS (available from: https://dhsprogram.com/data/available-datasets.cfm), the Climate Hazards center InfraRed Precipitation with Station data (CHIRPS), the CHIRTS max (available from: https://www.chc.ucsb.edu/data) and the Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices (MOD13A3) Version 6 (available from: https://lpdaac.usgs.gov/products/mod13a3v006/.)

The UCDP GED 21.1 database that results from a joint project between the Uppsala Conflict Data Program (UCDP) of Uppsala University and the Center for Civil War Studies of the International Peace Research Institute of Oslo (PRIO), provides geolocated data on conflicts around the world [32,44]. As for DHS, they provide data relating to population, health and nutrition. In addition, they provide information on the Global Positioning System (GPS) of clusters, i.e., longitude (in decimal degrees up to, at least, 6 decimal places), latitude (in decimal degrees up to, at least, 6 decimals) and the altitude (in meters). The geolocation of each cluster is carried out during the enumeration phase. To protect respondent's confidentiality, the locations of each cluster have been moved from their actual location by 2 km (for urban points) and 10 km (for rural points). DHS data has the advantage of being comparable across countries and are freely accessible. The geographic areas (polygon layers) derived from the voronoï polygon method were generated around the coordinates of each DHS cluster (point layers), so that sampled households belonging to a cluster were included in the corresponding polygon.

The Climate Hazards Center InfraRed Precipitation with Station data (CHIRPS) provides near-global rainfall data over a period of 30 years. CHIRPS and CHIRTSmax data were developed by United State Geological Survey (USGS) scientists in collaboration with the Climate Hazards Group at the University of California, Santa Barbara. The first provides satellite images at a resolution of 0.05° of the precipitation grid around the world [45], while the second produces data on maximum temperature. CHIRPS and CHIRTS max data are quite accurate and efficient in assessing climatic conditions in Africa [46]. Moreover, Funk et al. [45]showed using spatial R 2 values, mean bias errors (MBE) and mean absolute errors (MAE) that climatological information from CHIRPS is consistently better than that from national meteorological agencies, the Climatological Research Unit (CRU), and the Worldclim. This is based on a sample of the following countries: Afghanistan, Colombia, Ethiopia, Mexico, Senegal, Burkina Faso, Mali, Niger and Chad. The MOD13A3 Version 6 database provides monthly information on NDVI indicator (Normalized Difference Vegetation Index) with a spatial resolution of 1 km.

The final database was obtained after several steps. First, the GPS data of each DHS cluster (point layer) were merged with the corresponding DHS survey data for each of the countries considered from the Stata14 software using the command “merge 1:1″ and the “dhs_clust” variable as the key to merge the files. Then, the climatic (temperature and precipitation) and vegetation (NDVI) data for each DHS-cluster (point layer) were extracted from the CHIRPS, CHIRTSmax and MOD13A3 raster databases and joined to the attribute table of these DHS-cluster using the “Point Sampling Tool” of the QGIS software. Finally, after applying the voronoï polygon method to each DHS cluster (point layer), the conflict data (point layer) from the UCDP databases were joined to each DHS voronoï polygon using the QGIS spatial join tool “Join by Location".

2.2. Dependent variable

The concept of malnutrition is subdivided into three categories: stunting, wasting and underweight. Each category is operationalized through appropriate anthropometric measurements. In this study, malnutrition was measured by moderate underweight. The measurement of the latter is based on the weight-for-age index. It is severe when the weight-for-age z-score is less than −3 standard deviations, below the average of WHO 2006 Child Growth Standards. Whereas it is moderate if the weight-for-age z-score is less than −2 standard deviations. Thus, by cluster DHS we calculated the prevalence of moderate underweight in children under 5.

2.3. Independent variables

2.3.1. Armed conflicts and climatic variables

According to UCDP, armed conflict is a situation of incompatibility that results in at least 25 battle-related deaths per year in a specific country. It decomposes in three dimensions: inter- or intra-state armed conflict, non-state conflict and unilateral violence [47]. Although there is no specific time period between exposure to conflict and health outcomes for children in the literature, some researchers consider conflicts that take place in the last 3–12 months or the most recent month prior to the survey [22,48]. Building on the work of Grace et al. [22], we select conflicts that occurred in the last 3–6 months prior to the start of DHS data collection for Ethiopia (2016) i.e., January 18, 2016 [49], Kenya (2014) i.e., May 7, 2014 [50] and Nigeria (2013) i.e., February 15, 2013 [51]. In this study, the armed conflict variable takes the value 1 for areas in conflict and 0 for areas in peace. Climatic variables such as monthly rainfalls and maximum monthly temperatures respectively from the CHIRPS and CHIRTSmax databases are extracted three months before the collection of DHS data on the nutritional status of children in the three countries included in this study. The main reason for this three-month lag is based on the work of Grace et al. [22], Randell et al. [52] who show that it takes about three months to feel the effects of climatic conditions on nutritional status.

2.3.2. Other explanatory variables

Several control variables are introduced in this study. Among these, we have the Normalized Difference Vegetation Index (NDVI) from the MOD13A3 version 6 data, which is a spectral indicator of plant biomass that is commonly used to measure agricultural drought conditions [53,54]. It varies between −1.0 and +1.0, and measures the relative abundance and spatial distribution of vegetation, positive values indicating increased vegetation and negative values indicating features which are not vegetated, such as urban areas, bare soil/land, water and ice [55]. More specifically, moderate values between 0.2 and 0.3 represent shrubs and grasslands, while high values between 0.6 and 0.8 indicate temperate and tropical rainforests. NDVI values close to 0 represent bare soil and negative values, water bodies. Many researchers uses this index as an indicator of the impact of climate variability on food availability to explain the nutrition outcomes of children [22,56,57]. Also, we use the proportion of poor households in each DHS cluster. Siddiqui et al. [58] show that the prevalence of malnutrition is higher in poor areas. Poverty is characterized by unstable financial conditions that hamper the ability of households to access safe, sufficient and nutritious food [59].

We also have the proportion of households using unimproved water sources in each DHS cluster. Indeed, the most direct link between unsanitary water use and malnutrition is the occurrence of episodic diarrhea [60]. Kemajou [61] shows that access to unimproved water sources increases the prevalence of diarrhea in SSA. In addition, the proportion of women with secondary education and above, the proportion of working women and the proportion of non-breastfeeding women in each DHS cluster are other variables we use in this study. Regarding exclusive breastfeeding, it has been demonstrated that it provides newborns and young children with the nutrients necessary for their health. Thus, it reduces the negative effects of nutrition on cognitive development in early childhood [62,63].

2.4. Statistical analysis

Spatial analysis using Geographic Information System (GIS) has been widely applied to health and epidemiology research in most SSA countries [21,22]. In this study, the voronoï polygon method was used on the GPS data (point layers) of each DHS cluster to generate geographic areas (polygon layers), instead of basing the analysis on administrative units or sub-administrative units of countries in our sample such as municipalities and provinces. This method is efficient in space allocation and partitioning [64].

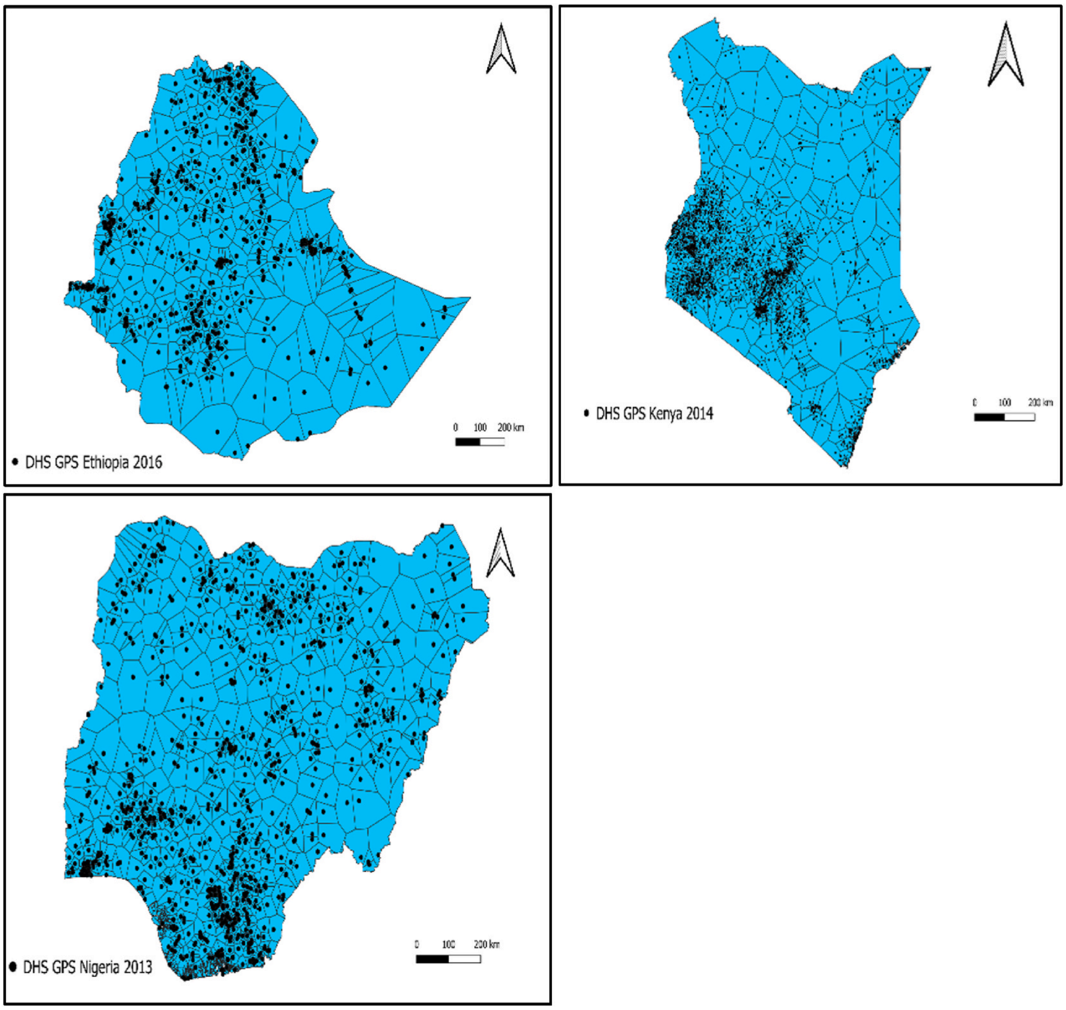

Fig. 2. DHS clusters in Ethiopia, Kenya and Nigeria based on the voronoï polygon method.

Furthermore, it makes it possible to take the disparities that exist within a fairly large geographical area such as regions and divisions [65]. Fig. 2 shows the geographical areas resulting from the application of the voronoï polygon method to GPS points representing the geographical location of the DHS clusters in each of the territories considered. This study thus uses spatial analysis on the geographical areas generated by this method with QGIS 3.8.1 software. Spatial analysis is based on bivariate Local Indicator of Spatial Association (LISA) analysis with Geoda software and on spatial regression models estimated with R 4.0.0 software using the spatialreg and spgwr libraries.

2.5. Bivariate spatial association

In order to highlight the nature of spatial association between malnutrition measured by prevalence of moderate underweight and climatic variables in conflict zones, we use the Local Indicator of Spatial Association (LISA) with two variables [66]. The latter enables the identification of spatial patterns, i.e., either the spatial association is positive between malnutrition and climatic variables (High-High, Low-Low), or the spatial association is negative (High-Low, Low -High). In this analysis, the significance of the LISA statistic is assessed at 1 % level. The formula for the bivariate LISA statistic is defined as follows:

$$I_B = \frac{\sum_i \sum_j w_{ij} y_j * x_i}{\sum_i x_i^2} \tag{1}$$

In equation (1), y_j, x_i are the centered and reduced observations of two variables located in i and j; w_{ij} are weights that measure the neighborhood structure between the spatial units. The choice of the specification of the neighborhood matrix $W = (w_{ij})_{1 \leq i \leq n, 1 \leq j \leq p}$ is a crucial step in spatial analysis models [67]. The approaches commonly used to model neighborhood structure rely on the contiguity of

Rook, Bishop and Queen, K-nearest neighbors and the distance [66,68]. In this study, the notion of distance was used to determine the neighborhood matrix.

The interpretation of the Lisa bivariate analysis is based on the analysis of the significance map and the cluster map. The first map shows the locations where the local statistic is significant, the degree of significance increases as you move towards darker shades of green. The map starts with $P < 0.05$ and shows all the categories of significance that are meaningful for the given number of permutations. P is the pseudo p-value given by $P = \frac{R+1}{M+1}$ where R is the number of times the computed Moran's I from the permuted data sets and M represent the number of permutations. In our study, since there were 999 permutations, the smallest pseudo-P-value is 0.001, with four such locations (the darkest shade of green). The cluster map with reference to the significance map gives the significant locations where the spatial association between two variables can be positive (High-high and Low-low) or negative (High-low and Low-high).

2.6. Spatial regression models

To consider the spatial autocorrelation or spatial dependence of the observations when it exists, we use two models: global spatial regressions (LAG and SEM model) and local spatial regressions (Geographically Weighted Regression [GWR]). In the global model, when the spatial structure depends on the residuals the appropriate model is the Spatial Error Model (SEM), and when this structure is present in the dependent variable, the Spatial Lag Model (LAG) is most suitable. The estimated coefficients from these two models do not vary in space. In contrast, the GWR estimates coefficients that vary across geographic areas. In other words, the influence of an explanatory variable on the dependent variable varies from one place to another [69,70]. The idea behind the GWR method is that parameters can be estimated at any locations in the study area (here for each DHS voronoi polygon), from a dependent variable and a set of one or more independent variables. Thus, it could be that a globally non-significant variable in a study area is locally significant in the sub-units that constitute it [71].

2.6.1. Spatial lag model

One way to introduce spatial autocorrelation into regression models is to introduce either a lagged endogenous variable *Wy* or one or more lagged exogenous variables *WZ* into the classical Ordinary Least Squares (OLS) model. This gives the following formulations:

$$y = \rho Wy + X\beta + \varepsilon \tag{2}$$

$$y = X\beta + WZ\delta + \varepsilon \tag{3}$$

In equations (2) and (3), W is the weight matrix, Wy is the lagged dependent variable, ρ is the autoregressive spatial parameter that measures the intensity of the spatial interaction between observations y. The interpretation of the results of the LAG model is based on the calculation of the direct, the indirect and the total effects [68,72]. The direct effect measures the average effect of an increase of one unit of the independent variable on the dependent variable in the same locality. While the indirect effect measures the average effect of a one-unit increase in the independent variable in neighboring localities j on the dependent variable in the locality $i(i \neq j)$.

2.6.2. Spatial error model

To specify the spatial autocorrelation, we also use an autoregressive error process:

$$y = X\beta + \varepsilon \tag{4}$$

The ε term in equation (4) is decomposed as follows:

$$\varepsilon = \mu W\varepsilon + u \tag{5}$$

The parameter μ in equation (5) determines the intensity of the interdependence between the residuals. $u \sim N(0, \sigma^2 I)$ is the error term and σ^2 the variance of the error term. Wrongly omitting a spatial autocorrelation of errors produces unbiased and inefficient estimators [66,68].

2.6.3. GWR model

GWR is a spatial regression method that examines non-stationary spatial relationships, that is, the fact that the influence of an explanatory variable on the dependent variable may across geographical areas [24,73,74]. These are represented by the voronoï polygons associated with each DHS cluster. The GWR is used to identify localities in which climatic variables and armed conflicts influence the prevalence of malnutrition. The GWR is given as follows:

$$y_j = \beta_0(u_j, v_j) + \sum \beta_i(u_j, v_j)x_{ij} + \epsilon_j \tag{6}$$

In equation (6), (u_j, v_j) is the coordinates of the *jth* position; y_j and x_{ij} are the dependent and independent variables respectively. $\beta_0(u_j, v_j)$ and $\beta_i(u_j, v_j)$ are the regression coefficients; ϵ_j is the error term. In this study, we use the coordinates of the DHS clusters of each region of the countries considered. The weights are obtained on the basis of a spatial Kernel function, in particular Gauss kernel function. We also use the CV (Cross Validation) method, widely used in the literature to determine the optimal kernel bandwidth [75–77].

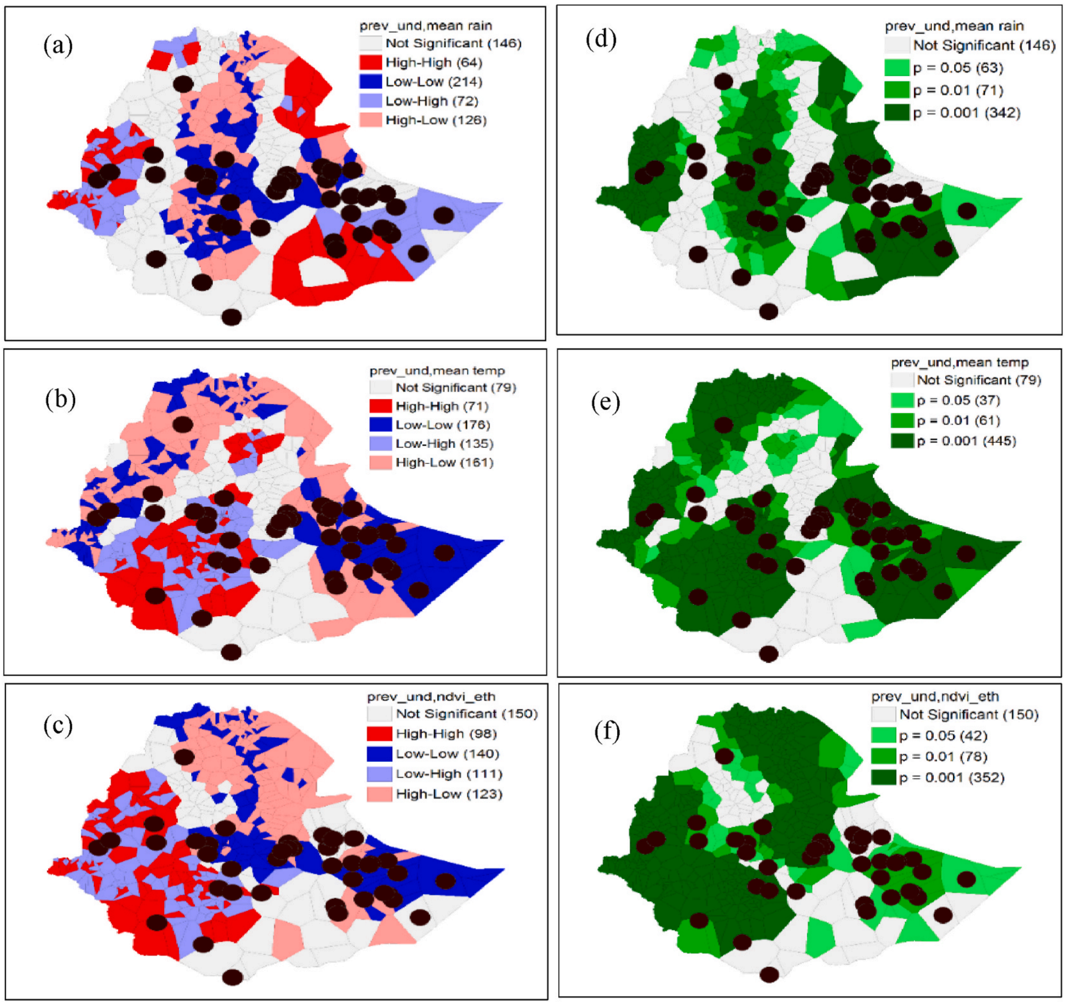

Fig. 3. LISA bivariate spatial association (**a-b**) and areas of significance (**d-f**) in Ethiopia in 2016. ● Areas of armed conflict; Pred_und = prevalence of underweight; mean temp = mean temperature; mean_rain = mean rainfall; ndvi = normalize difference vegetation index.

2.7. Evaluation of models

Multicollinearity is assessed using the variance inflation factor (VIF). The presence of multicollinearity is indicated if the VIF values are greater than 5 in the OLS model. For model evaluation and comparison, likelihood ratio (LR) tests are performed to compare models. Also, to make the choice between the spatial error model (SEM model) and the spatial lag model (LAG model), the Lagrange multiplier (LM) test is used [78]. In addition, Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used to compare the results of Ordinary Least Squares (OLS) and spatial regression models.

3. Results

This section presents the results of the paper. First, descriptive spatial analysis is presented to characterize the nature of the bivariate spatial association (negative or positive) between climate variables and prevalence of moderate underweight in conflict areas in Ethiopia, Kenya and Nigeria. Then, the results of the spatial regression models will be presented.

3.1. Results of bivariate LISA analysis

3.1.1. Ethiopia

There is a negative and significant spatial association (High-Low) between the prevalence of moderate underweight and average rainfall, and between prevalence of underweight and NDVI index in localities (Shabelle, Korahe, and Afder in Somali Region, and Semen Gondar in Amhara Region, and Mi'irabawi in Tigray Region) subject to intra-state conflict between the Ethiopian government and the Ogaden National Liberation Front (ONLF) group (Fig. 3). Moreover, there is a negative and significant spatial association (Low-

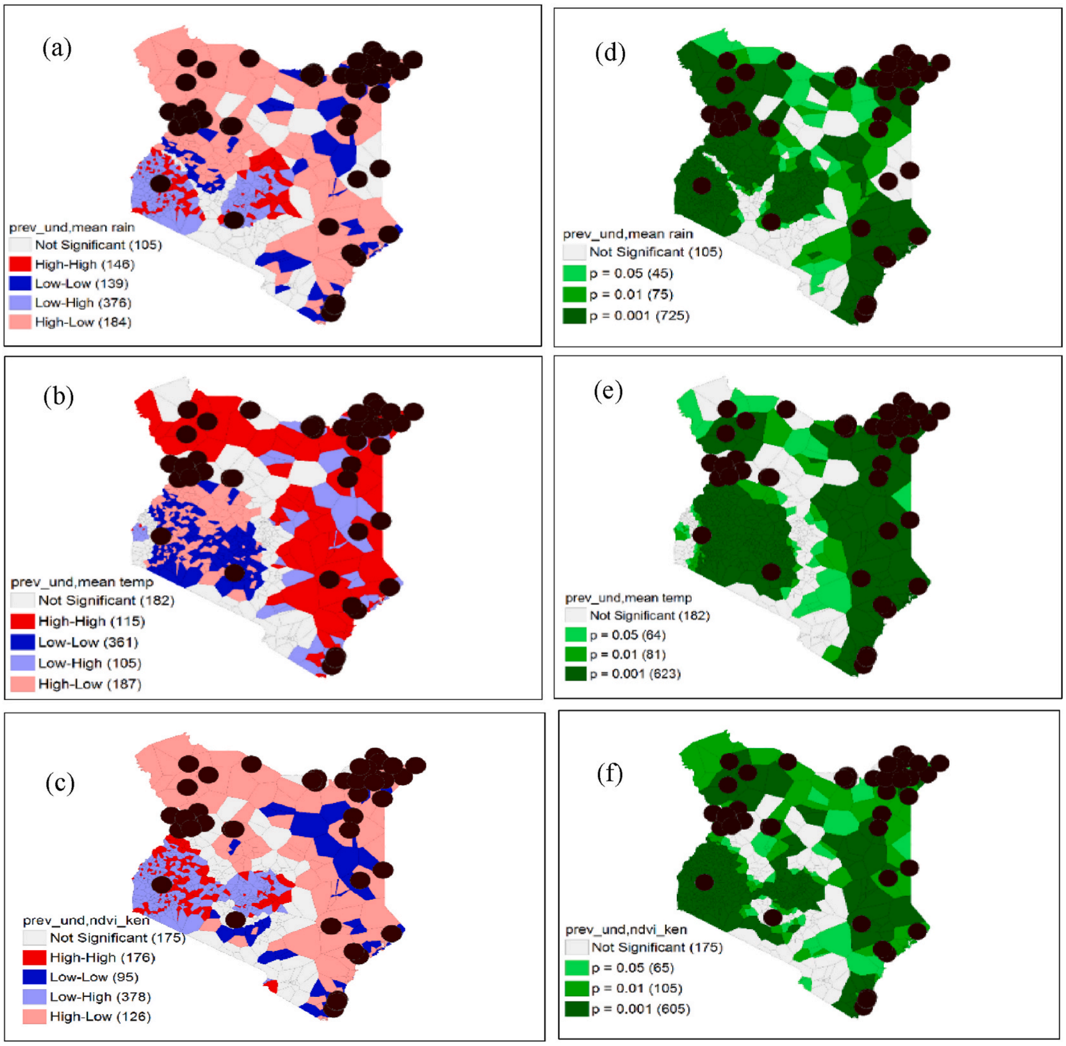

Fig. 4. LISA bivariate spatial association (**a-b**) and areas of significance (**d-f**) in Kenya in 2014. ● Areas of armed conflict; pred_und = prevalence of underweight; mean temp = mean temperature; mean_rain = mean rainfall; ndvi = normalize difference vegetation index.

High) between the prevalence of moderate underweight and the maximum temperature in the localities of Jarar, Doo and Fafan. The latter are also subject to conflicts between the government and the ONLF group.

3.1.2. Kenya

There is a negative and significant spatial association between the prevalence of moderate underweight and average rainfall (High-Low), and a positive and significant spatial association between the prevalence of moderate underweight and maximum temperatures (High-High) in localities in the North-eastern that are subject to violence between the Degodia and Garre clans (Mandera, Banissa, Fafi, Ijara, Wajir, Tarjab), and in Coast, Central, Nyanza and Rift Valley localities subject to violence between Dassanetch-Turkana, Borona-Burji, Borona-Gabra herders and the government of Kenya and Al Shabaab (Fig. 4). In addition, Fig. 4 shows that there is a negative and significant spatial association between the prevalence of moderate underweight and the NDVI index in some localities in the Northeast, the Rift Valley and the Coast.

3.1.3. Nigeria

In Borno, Yobe, Kano, Sokoto, Delta, Edo, Ogun, Cross River, and Akwa Ibom states where conflicts emerged in 2013 between the Nigerian government and the Jama'atuAhlus-Sunna Lidda'AwatiWal Jihad (Boko Haram), Deebam and Deewell cults, and the Black Axe and Eiye sects [79], there is a negative and significant spatial association (High-Low and Low-High) between underweight prevalence and average rainfall (Fig. 5). Fig. 5 also shows a negative and significant spatial association between the prevalence of moderate underweight and the NDVI index which, beyond the states mentioned above, extends to the states of Kebi, Bauchi (High-Low), Benue and Kwara (Low-High). In addition, there is a positive and significant spatial association (High-high and

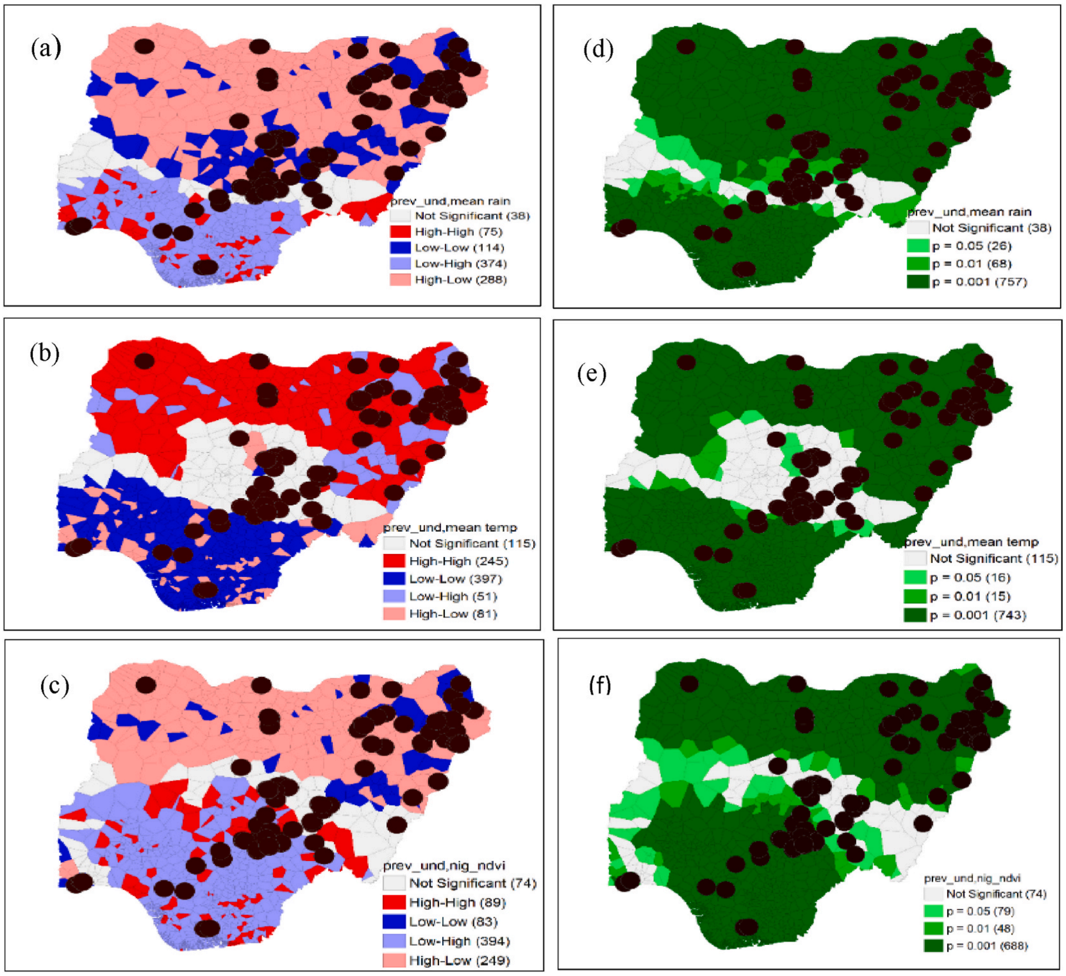

Fig. 5. LISA bivariate spatial association (**a-b**) and areas of significance (**d-f**) in Nigeria in 2013. ● Areas of armed conflict; Pred_und = prevalence of underweight; mean temp = mean temperature; mean_rain = mean rainfall; ndvi = normalize difference vegetation index.

Table 1
Results of Moran's I autocorrelation test and Lagrange multiplier tests.

	Ethiopia		Kenya		Nigeria	
Tests	Value	p-value	value	p-value	Value	p-value
Moran I	0.19	2.2e-16	0.27	2.2e-16	0.53	2.2e-16
LMerr	25.67	4.051e-07	17.908	2.318e-05	639.67	2.2e-16
RLMerr	1.1296	0.2879	4.9037	0.0268	166.64	2.2e-16
LMlag	34.67	3.905e-09	62.011	3.442e-15	577.07	2.2e-16
RLMlag	10.13	0.001459	49.006	2.551e-12	104.04	2.2e-16

Lower-Lower) between the prevalence of moderate underweight and maximum temperatures in the states of Borno, Yobe, Kano, Sokoto, the states of the Delta, of Edo, of Ogun, of Cross River and of Akwa Ibom.

3.2. Results of spatial regression models

The results presented in Table 1 show the existence of a positive spatial autocorrelation in the analysis of malnutrition in the three countries (Moran's I for Ethiopia: 0.19, Kenya: 0.27 and Nigeria 0.53). Also, according to Table 2 the LAG model is better than MCO model in Ethiopia (AIC Lag: 4967.12 < AIC Mco: 4987.1), Kenya (AIC Lag: 7217.4 < AIC Mco: 7233.4) and Nigeria (AIC Lag: 6494.4 < AIC Mco: 6501.5). It appears that the Rho parameter, which measures the spatial dependence, is statistically significant at the 5 % level for the three countries. The VIF value of the explanatory variables is below the threshold of 5, which reflects the absence of multicollinearity.

Table 2
Results of estimation using the OLS, SEM and LAG in Ethiopia, Kenya and Nigeria.

	Ethiopia				Kenya				Nigeria			
	VIF	OLS	SEM	LAG	VIF	OLS	SEM	LAG	VIF	OLS	SEM	LAG
max temp	1.602	−0.032	−0.058	−0.098	1.681	−0.132	0.029	−0.107	4.832	−0.411	1.394***	0.162
		(0.072)	(0.092)	(0.071)		(0.111)	(0.151)	(0.108)		(0.340)	(0.438)	(0.302)
mean rain	1.802	−0.058	−0.086	−0.038	1.831	−0.072***	−0.066***	−0.047***	3.863	−0.066***	0.014	0.004
		(0.062)	(0.081)	(0.061)		(0.014)	(0.018)	(0.014)		(0.012)	(0.019)	(0.010)
NDVI	2.093	−6.415**	−3.482	−3.284	1.565	0.686	3.818	2.590	1.971	−11.659***	1.564	0.353
		(2.879)	(3.337)	(2.842)		(2.966)	(3.138)	(2.881)		(2.332)	(2.408)	(2.058)
Conflict	1.079	5.564**	2.827	4.000*	1.035	−3.026**	0.008	−0.542	1.088	3.711**	0.998	1.111
		(2.273)	(2.237)	(2.209)		(1.360)	(1.487)	(1.339)		(1.529)	(1.382)	(1.341)
Water	1.558	0.006	0.001	−0.0001	1.749	0.025**	0.021*	0.024*	1.833	0.015	0.019*	0.020*
		(0.021)	(0.020)	(0.020)		(0.012)	(0.012)	(0.012)		(0.013)	(0.012)	(0.011)
Poor	1.924	0.149***	0.153***	0.145***	2.597	0.103***	0.088***	0.085***	3.566	−0.004	−0.018	−0.023
		(0.022)	(0.022)	(0.022)		(0.013)	(0.014)	(0.013)		(0.017)	(0.016)	(0.015)
Work of women	1.819	0.015	0.016	0.013	1.209	−0.047*	−0.044*	−0.039*	1.409	0.032	0.031	0.036**
		(0.022)	(0.022)	(0.021)		(0.024)	(0.024)	(0.024)		(0.021)	(0.020)	(0.018)
time water	1.475	0.034	0.022	0.022	1.572	0.036**	0.037**	0.033*	1.161	0.036**	0.051***	0.040**
		(0.025)	(0.025)	(0.024)		(0.018)	(0.018)	(0.017)		(0.018)	(0.017)	(0.016)
no_breastfeeding	1.033	−0.063*	−0.036	−0.044	1.107	−0.013	−0.069	−0.052	1.219	−0.113***	−0.070**	−0.084**
		(0.035)	(0.035)	(0.034)		(0.098)	(0.097)	(0.095)		(0.040)	(0.035)	(0.035)
Unsanitary	1.237	0.089***	0.068***	0.064***	1.536	−0.022*	−0.017	−0.019	1.209	0.022	−0.007	−0.010
		(0.019)	(0.021)	(0.019)		(0.012)	(0.012)	(0.011)		(0.016)	(0.016)	(0.014)
second et plus	1.924	−0.091***	−0.079***	−0.074***	1.809	−0.004	0.017	0.014	3.858	−0.138***	−0.077***	−0.077***
		(0.024)	(0.025)	(0.024)		(0.025)	(0.025)	(0.025)		(0.022)	(0.021)	(0.019)
Observations		622	622	622		950	950	950		889	889	889
AIC		4987.1	4970.2	4967.12		7233.4	7217.4	7198.2		6707.4	6494.4	6501.5
Rho				0.429***				0.293***				0.827***

Note: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$; standard error are given in the brackets. Water: proportion of households using unimproved water sources in each dhs cluster, poor: proportion of poor households in each dhs cluster, work of women: proportion of working women, no breastfeeding: proportion of non-breastfeeding women in each dhs cluster, unsanitary: proportion of households using unimproved water sources in each DHS cluster, proportion second & plus: proportion of women with secondary education and above.

Table 3
Results of the estimation of the direct and indirect effects of the LAG model.

	Ethiopia			Kenya			Nigeria		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
max temp	−0.098	−0.053	−0.152	−0.107	−0.079	−0.187	0.168	0.773	0.941
mean rain	−0.038	−0.020	−0.058	−0.047	−0.035	−0.082	0.004	0.017	0.021
NDVI	−3.306	−1.783	−5.088	2.609	1.933	4.542	0.365	1.679	2.044
Conflict	4.028	2.172	6.199	−0.546	−0.404	−0.951	1.151	5.288	6.439
Water	0.146	0.079	0.225	0.024	0.017	0.042	0.021	0.096	0.116
Poor	−0.0001	−0.000	−0.000	0.085	0.063	0.149	−0.023	−0.107	−0.130
Work of women	0.013	0.007	0.020	−0.039	−0.029	−0.069	0.037	0.171	0.208
time water	0.022	0.001	0.034	0.033	0.024	0.057	0.041	0.189	0.231
No breastfeed	−0.045	−0.022	−0.069	−0.052	−0.039	−0.091	−0.087	−0.402	−0.488
Unsanitary	0.064	0.034	0.099	−0.019	−0.014	−0.032	−0.011	−0.049	−0.060
second_&_plus	−0.075	−0.040	−0.115	0.013	0.010	0.024	−0.080	−0.369	−0.449

Note: Water: proportion of households using unimproved water sources in each dhs cluster, poor: proportion of poor households in each dhs cluster work of women: proportion of working women, no breastfeeding: proportion of non-breastfeeding women in each dhs cluster, unsanitary: proportion of households using unimproved water sources in each DHS cluster, proportion second & plus: proportion of women with secondary education and above.

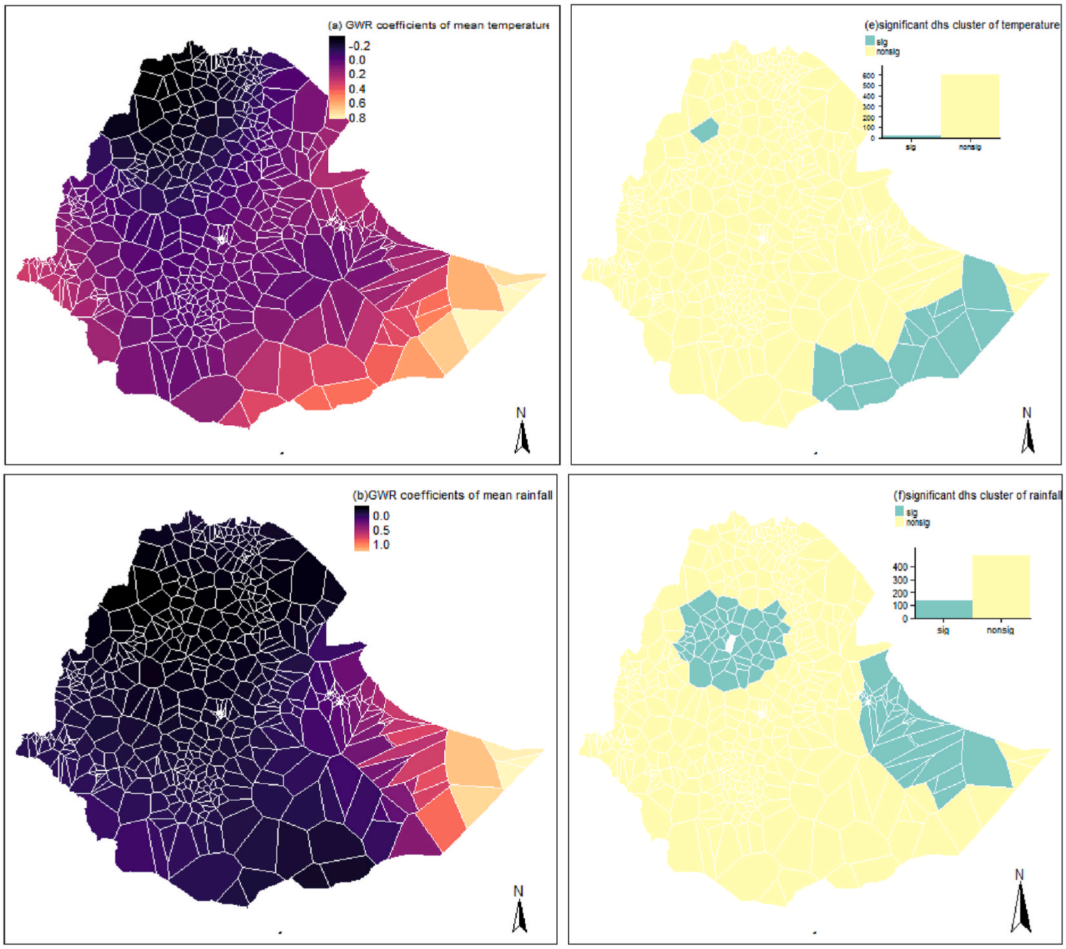

Fig. 6. GWR coefficients (a–d) and areas of significance (e–h) in Ethiopia.

3.2.1. Ethiopia

According to Table 2, the LAG model shows that there is no significant association between average rainfall, maximum temperatures, armed conflicts and the NDVI index and prevalence of moderate underweight. In contrast, the proportion of poor households

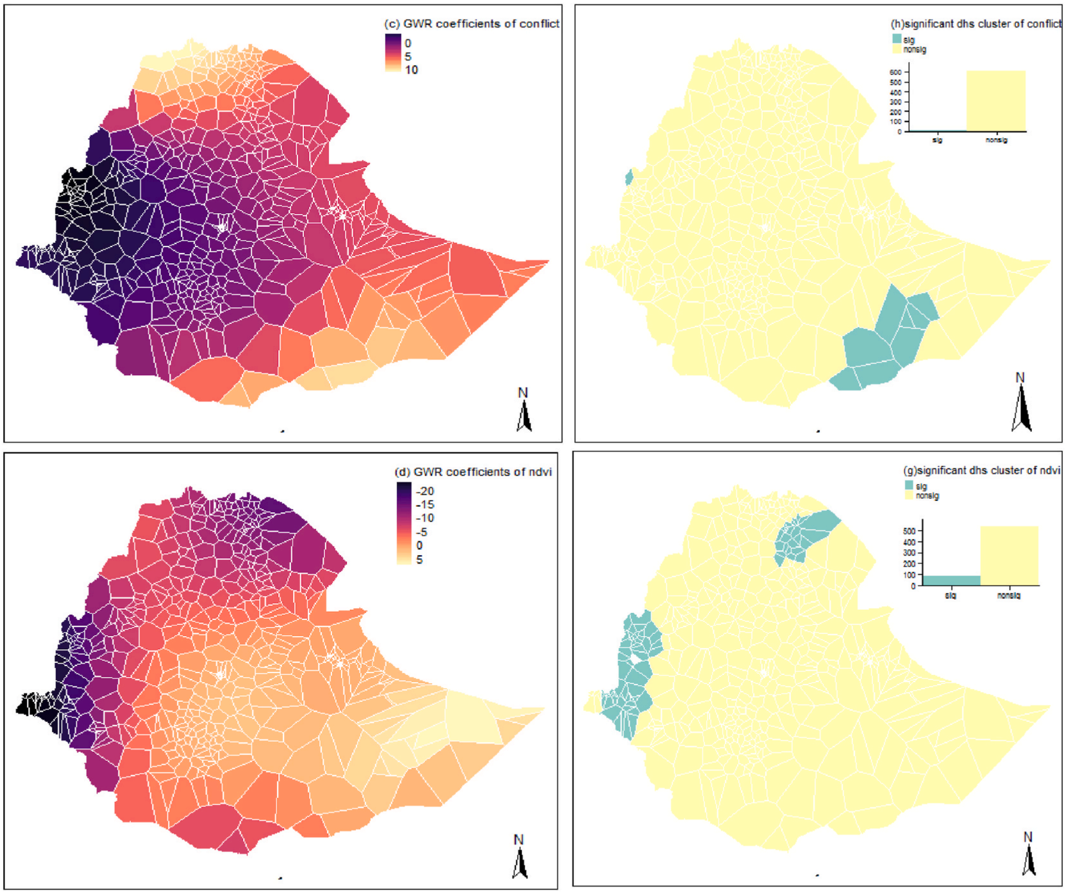

Fig. 6. (*continued*).

and the proportion of households using unimproved toilet facilities are negatively associated with the prevalence of moderate underweight, while the association between the proportion of women with secondary education is negative and significant. For significant variables, Table 3 shows that the effect of a 1-point increase in the proportion of households using unimproved toilet facilities and the proportion of women with secondary education and above in a locality leads respectively to an increase and a reduction in the prevalence of moderate underweight of 6.4 and 7 points (direct effect) in that locality.

Contrary to the results of the global LAG model, the local GWR analysis of Fig. 6 shows that there are a positive and significant association between maximum temperatures, the presence of armed conflicts and the prevalence of moderate underweight in the localities of the Somali region, in particular of Afder, Liben and Shabelle. In the same line, an increase in average rainfall leads to an increase in the prevalence of moderate underweight in the localities of Jijiga, Dire Dawa, Bircot and DegehBur in the Somali region. Similarly, the increase in the density of vegetation (NDVI) leads to a more pronounced drop in the prevalence of malnutrition in Kelemwellega, Mirabwellega, Asosa and Nuer, localities located in the regions of Oromia and Benshangul -gumaz.

3.2.2. Kenya

For Kenya, the LAG model results included in Table 2 show that the maximum temperatures, armed conflicts, the proportion of working women, the proportion of women with secondary education and above and the NDVI index are not significant. On the other hand, the relationship between the prevalence of moderate underweight and average rainfall is negative and significant, and positive and significant with the proportion of the poor. The direct and indirect effects summarized in Table 3 show that the effect of a 1 mm increase in average rainfall in a locality leads to a decrease in the prevalence of underweight in that locality by 4.7. Furthermore, a one-point increase in the proportion of poor people in a locality increases the prevalence of moderate underweight in that locality by 8 points (direct effect). On the other hand, the prevalence of moderate underweight in a locality increases by 6.3 points when the proportion of poor households increases in neighboring localities.

The local GWR model shows that the presence of conflicts increases the prevalence of moderate underweight in the localities of Ijara, Garissa Township and Dadab located in the Garissa region (Fig. 7). In addition, higher average rainfall is associated with lower prevalence of moderate underweight in Marsabit, Samburu, Turkana de Wajir and Mandera regions. This negative association being stronger in the region of Mandera. Also, higher maximum temperatures are positively associated with the prevalence of underweight under 5s in the Kwale, Taveta, Kilifi and Tana River regions.

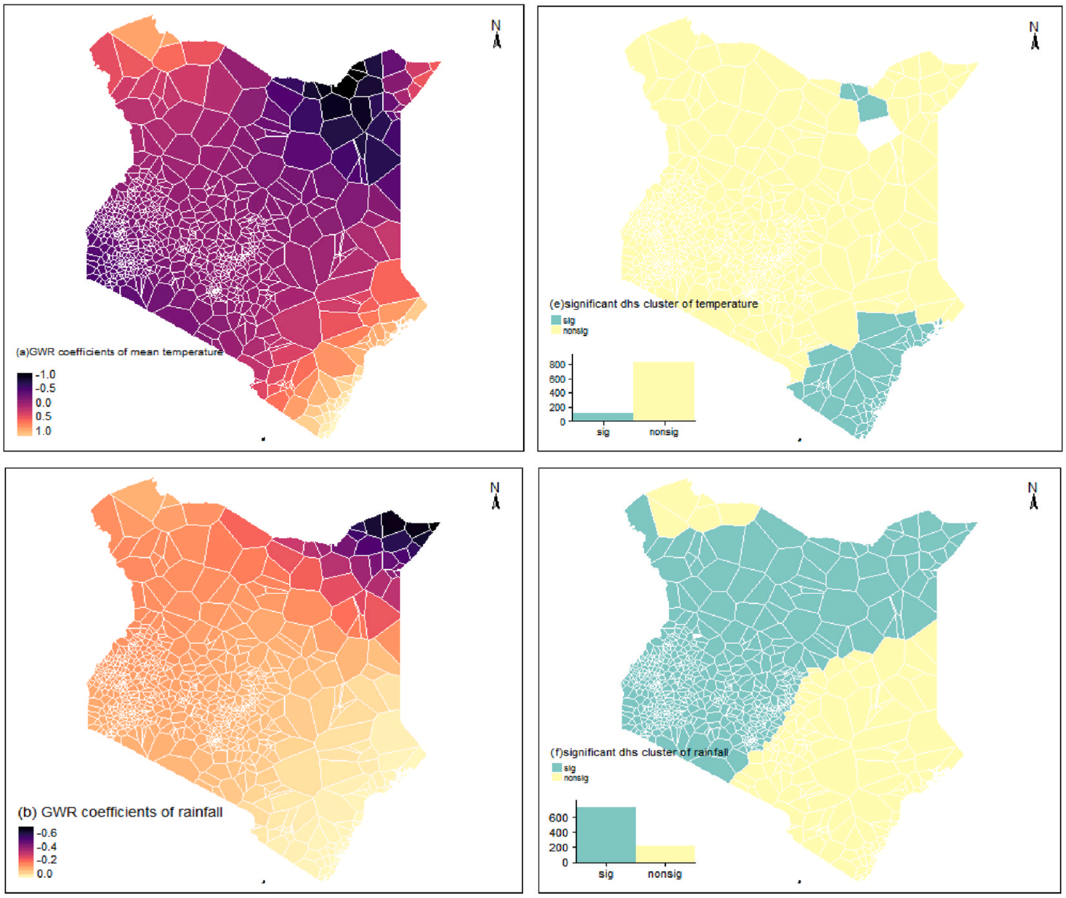

Fig. 7. GWR coefficients (a–d) and areas of significance (e–h) in Kenya.

3.2.3. *Nigéria*

The results of the LAG model for Nigeria (**Table 2**) show that mean rainfall, maximum temperature and conflict are not statistically associated with the prevalence of moderate underweight, except for the proportion of households using unimproved water sources and the proportion of women with secondary education. According to Table 3, the effect of a 1-point increase in the proportion of households that use unimproved water sources in a locality leads to an increase in the prevalence of moderate underweight by 4 points (direct effect). On the other hand, the direct effect of an increase in the proportion of women with secondary education and above on underweight is negative (−0.08). It also emerges from this table that the neighborhood effects (indirect effects) are higher than the direct effects.

The local GWR analysis for Nigeria (Fig. 8) shows that higher average rainfall is negatively associated with the prevalence of moderate underweight in the states of Zamfara, Katsina, Kaduna, Jugawa, Kano, Bauchi and Gombe. This association is even more pronounced in Yobe and Borno states. In addition, Fig. 8 shows that association between the density of vegetation (NDVI) and the prevalence of moderate underweight is significant and negative. The latter is greater in Borno and Yobe states than in Niger and Kaduna states in Nigeria. Moreover, the presence of armed conflicts is still not statistically significant.

4. Discussion and conclusion

This study examines spatial patterns and estimates under the assumption of spatial non-stationarity, the influence of armed conflicts and climatic variables (temperature and precipitation) on malnutrition measure by prevalence of moderate underweight among children under 5 in Ethiopia, Kenya and Nigeria. The spatial analysis carried out here highlights the existence of spatial autocorrelation of malnutrition in the three countries considered. Also, while the spatial LAG and SEM models indicate that the effect of conflict, average rainfall and maximum temperature on malnutrition may be globally insignificant, the GWR model shows locally significant effects.

The results from the estimation of the LAG model show that the relationship between armed conflicts and the prevalence of moderately underweight under 5s is not significant in Ethiopia, Kenya and Nigeria. This result is in line with the results of Grace et al.

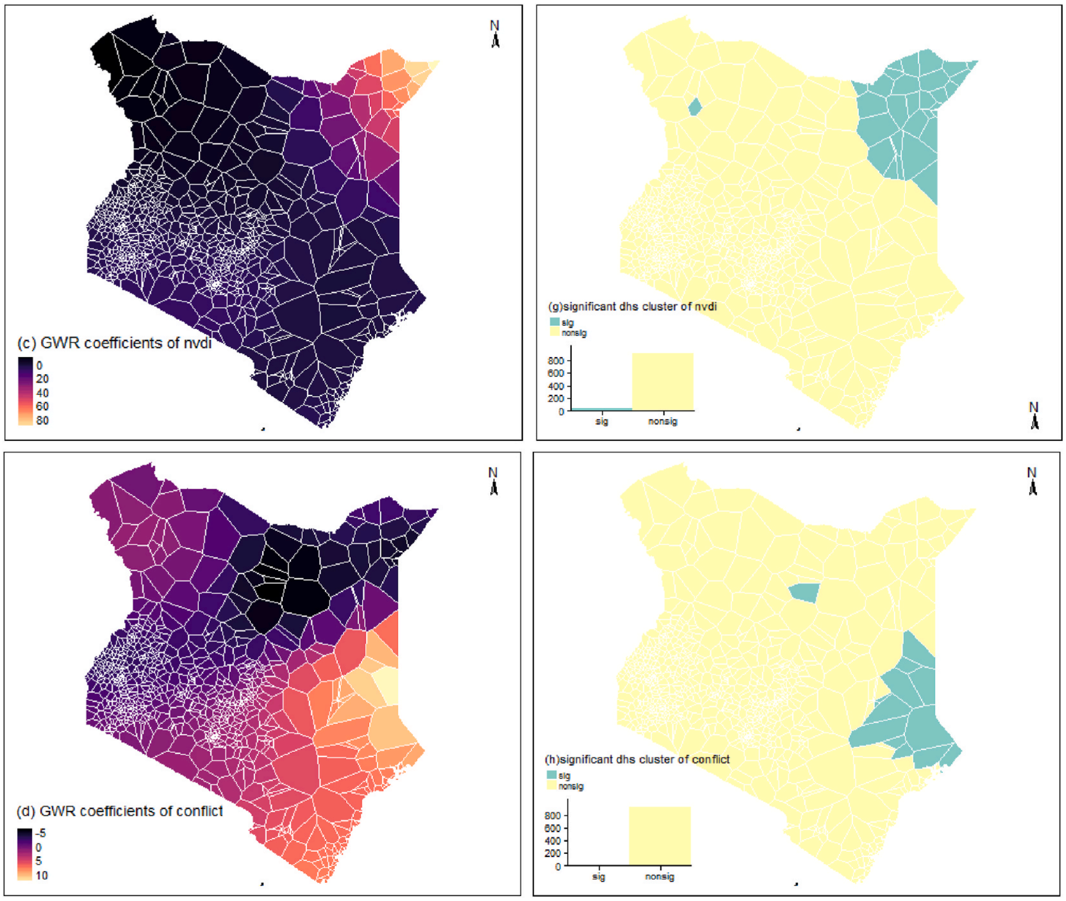

Fig. 7. (*continued*).

[22] and is contrary to those obtained by Minoiu and Shemyakina [80] and Dahab et al. [21]. However, according to the results of the local GWR analysis, it appears that armed conflicts have a positive and significant influence on the prevalence of underweight under 5s in the localities of Afder, Liben and Shabelle of the Somali region of Ethiopia, and of Ijara, Garissa township and Dabaab in the Garissa region of Kenya. In recent years, Garissa and Somali regions have recorded a significant number of unresolved intra-clan conflicts and attacks by Al-Shabaab militias in Kenya and ONLF in Ethiopia [35,36] with negative consequences on the food supply chain, a determinant of malnutrition [19,20].

The results on the absence of association between conflict and malnutrition in Nigeria are contrary to those found by Makinde et al. [81]. However, they did not take into account the fact that there is a latent period between exposure to conflict and the first signs of malnutrition among children. This could have biased their results. Thus, the absence of an association between conflict and underweight children in Nigeria could be explained by the fact that populations, especially women, in the context of war have adopted food survival strategies inherited from past conflicts such as the Biafran war (1967–1970) to ensure that their offspring are well fed. Bonkat [82], Iwuagwu [83] have shown that during the Biafran war, the Igbo developed food survival strategies, especially by adapting to the consumption of several plants and animals hitherto unknown in their food habits such as termites, mushrooms, snails, crickets or locusts. Also, according to the same authors, lemon grass was harvested, boiled and sieved, and the drink consumed as tea, cold or hot according to preference, to alleviate famine.

Food security and agricultural production in Ethiopia, Kenya and Nigeria, key determinants of malnutrition, are threatened by rising temperatures and changing rainfall patterns [46]. Our results show that higher average rainfall is associated with lower prevalence of moderately underweight under 5s in Marsabit, Samburu, Turkana, Wajir and Mandera regions in Kenya and Borno, Yobe, Kaduna, Jugawa, Kano, Bauchi, Gombe in Nigeria. The regions of Borno, Yobe and Mandera represent the areas where the negative effect of rainfall is most accentuated. These regions are characterized by their mainly rainfed agriculture based on the production of cereals, millet, sorghum and wheat, which constitute the means of subsistence of many families [84,85]. Reduced rainfall is likely to exacerbate malnutrition among children by directly reducing the availability of crop and animal production, and indirectly by limiting the income generated by pastoral households from agricultural activities [86]. In the Mandera region, Tawane et al. [87] showed that extreme climatic conditions caused food insecurity among pastoral communities. In contrast, in the case of Ethiopia, our results show a positive relationship between rainfall and the prevalence of malnutrition in the Somali region.

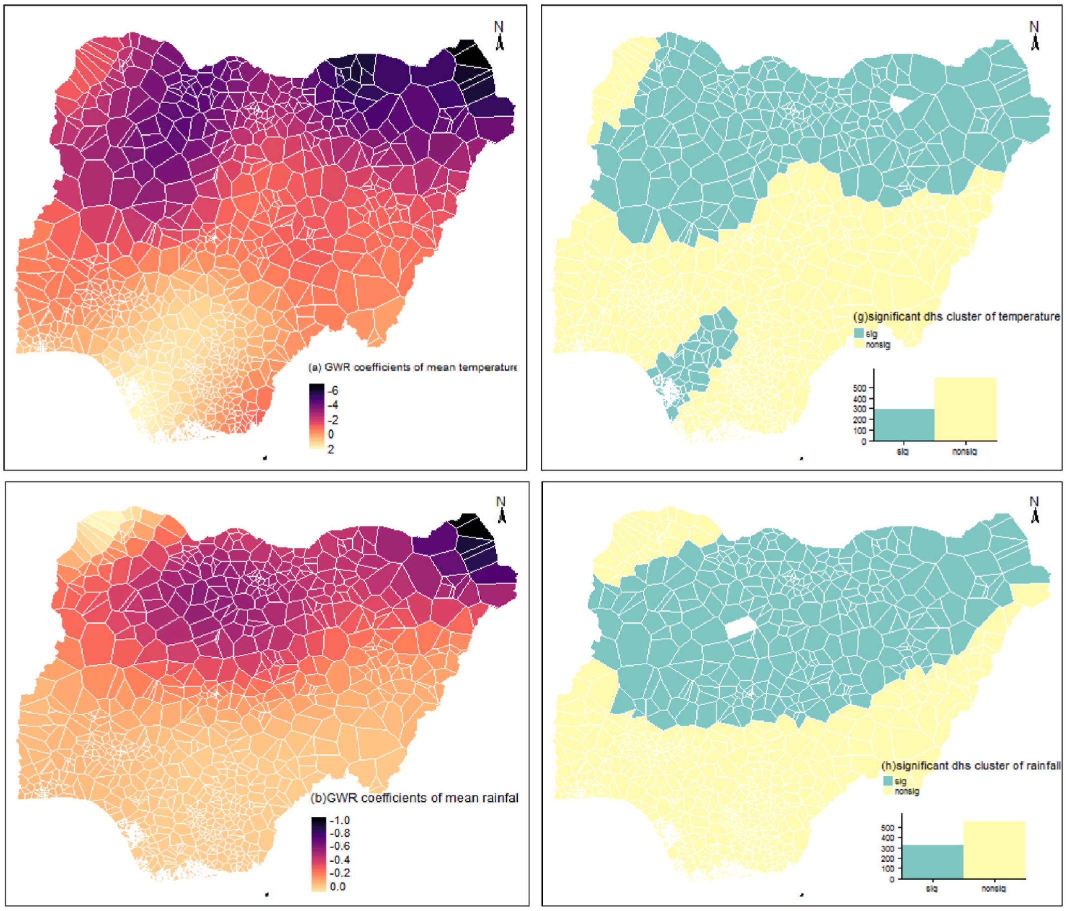

Fig. 8. GWR coefficients (a–d) and areas of statistical significance (e–h) in Nigeria.

Higher temperatures have an impact on children's nutrition either by affecting the quantity and quality of food available in a given region and therefore on food prices and their access [88], or by increasing the risk of infectious diseases [46]. In SSA, higher temperatures may be associated with a higher risk of diarrheal diseases, which may affect nutrition in children [61,89]. Our results show that the rise in temperatures leads to an increase in the prevalence of moderately underweight under 5s in some localities of the Somali region of Ethiopia, notably Afder, Liben and Shabelle, Kwale, Taveta, Kilifi and Tana River in Kenya. On the other hand, in Nigeria, the increase in maximum temperatures leads to a decrease of child malnutrition. On this point [46,90], note that warmer temperatures are positively associated with the presence of vegetation and should increase yields of certain crops. This suggests that these crops may have benefited from warmer temperatures, and therefore contributed to providing the household nutritional needs in Nigeria.

The results also show that the increase in the density of vegetation (NDVI) leads to a decrease in the prevalence of moderate underweight in the localities of Oromia and Benshangul-gumaz regions in Ethiopia; and Borno, Yobe, Niger and Kaduna state in Nigeria. These results converge with those of Johnson and Brown [91], Bauer and Mburu [56], Mburu [56], Sandler and Sun [57], Grace et al. [22]. For example, Johnson and Brown [91] show that low NDVI values are associated with high rates of malnutrition (underweight and wasting) in children under five years in several West African countries. In the case of Nigeria, Arowolo et al. [92] showed through a spatiotemporal analysis that whereas cultivated land increased in all the states of the northern region, particularly Yobe and Borno, it decreased in the South. Thus, the explanation of our result is based on the increase in food availability reflecting the increase in the NDVI index, which would ultimately lead to a reduction in malnutrition.

Several limitations can be attributed to this study. Firstly, to better understand the mechanisms by which climatic factors and armed conflicts affect nutritional status of children and food security, it is necessary to set up quantitative and qualitative surveys specific to the affected regions. Secondly, given that conflict and climate interact to determine the level of malnutrition, it would be important to introduce conflict-climate interaction variables into the non-spatial model. Thirdly, the use of grid (raster) data to measure the effect of extreme precipitation exposures has been shown to moderate the outcome estimates, suggesting that the associations presented here may be underestimated. Fourthly, the GWR assumes that all modeled processes operate at the same spatial scale (fixed bandwidth). This assumption is limited. Future analysis could be extended by incorporating multiple imputation through Multi-scale Geographically Weighted Regression (MGWR). Finally, in terms of implications, our results support the need of conflict-

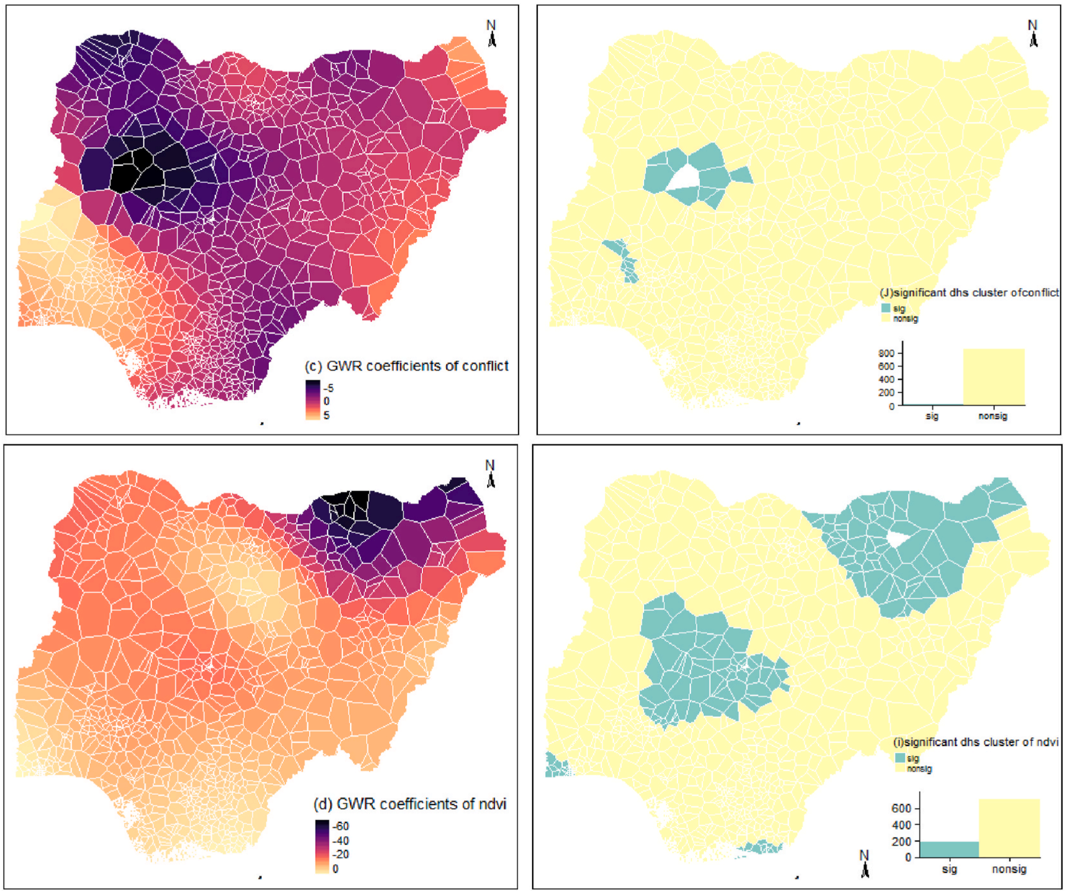

Fig. 8. (*continued*).

sensitive climate change adaptation measures adapted to each region.

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Not applicable.

Data availability statement

The datasets generated and/or analyzed during the current study are available in the DHS program (https://dhsprogram.com/data/available-datasets.cfm), UCDP PRIO (https://ucdp.uu.se/downloads), CHIRPS (https://www.chc.ucsb.edu/data) and MODIS (https://lpdaac.usgs.gov/products/mod13a3v006/).

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Donald Kemajou Njatang: Writing – review & editing, Writing – original draft, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Franklin Bouba Djourdebbé:** Writing – original draft, Resources, Methodology, Formal analysis, Conceptualization. **Natacha Darléne Adda Wadou:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

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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Abbreviations

CHIRPS	Climate Hazards center InfraRed Precipitation with Station data
DHS	Demographic and Health Surveys
GIS	Geographic Information System
GWR	Geographically Weighted Regression
MODIS	Moderate Resolution Imaging Spectroradiometer
SEM	Spatial Error Model
UCDP	Uppsala Conflict Data Program (UCDP)
VIF	Variance Inflation Factor

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