



Spatial heterogeneity of child malnutrition, proximity to protected areas and environmental variabilities in Zimbabwe

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Accepted: 23 January 2023 / Published online: 14 February 2023
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Abstract Child malnutrition is the main cause of illness, a range of cognitive and physical growth deficiencies, and the death of millions of children, especially in developing regions such as sub-Saharan Africa. To address this major health concern, we employed publicly available geolocated data from 2015 Demographic and Health Surveys and spatial analysis methods to identify the distribution of malnutrition in the children under 5 in Zimbabwe and to explore the associations between some household characteristics, environmental variabilities and malnutrition. In Zimbabwe, 27% of children were short for their age or stunted. Analysis of spatial dependency indicates that the distribution of malnutrition is clustered. The highest numbers of malnourishment

were identified in the northeast of the country, which are in the Mashonaland Central and East provinces. The associations between malnutrition and proximity to the protected areas, travel time to the cities, rainfall, and household wealth index, were examined. Our findings indicate that the associations between environmental variables and malnutrition were inconsistent across the country. Results of this study provide an understanding of factors affecting child malnutrition and consequently will have policy implications in achieving the United Nations Sustainable Development Goals including the goal of zero hunger and ending all forms of malnutrition.

Keywords Spatial analysis · Malnutrition · Protected areas · Sustainable development

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Introduction

Undernutrition is responsible for about 45% of deaths in children under 5 in low and middle-income countries. Studies show that malnutrition will lead to poor academic performance in children (Amegbor et al., 2020). In addition, malnutrition in childhood can have a long-term impact throughout their adulthood. For instance, malnutrition in childhood is associated with mental disorders such as paranoia and schizoid in adulthood (Hock et al., 2018). It is also estimated that adults that used to be stunted during their childhood earn 20% less than adults that were not stunted

as a child (FAO, 2020). Chronic malnutrition that is commonly measured by stunting or having a low Height-for-Age Z-score (HAZ) is a serious health concern that is responsible for both physical and cognitive delays in children (Hailu et al., 2020; Reinhardt & Fanzo, 2014).

Stunting, which refers to the HAZ being more than 2 standard deviations below the median in WHO Child Growth Standards, is a sign of chronic undernutrition over time (WHO, 2017). According to the state of food security and nutrition in the world (FAO, 2020), globally, 21% of children under age 5, or 144 million children, were stunted in 2019. However, the distribution of malnutrition including stunting is uneven in the world. In 2019, around 40% of stunted children were living in Africa. Sub-Saharan Africa is the region with the biggest challenge regarding the reduction of stunting as in 2019, around 31% of children or 52.4 million in this region were stunted (FAO, 2020). Moreover, Sub-Saharan Africa, is the only sub-region in the world with an increased number of stunted children (FAO, 2020). Among, Sub-Saharan countries, in Zimbabwe around 27% of children under five were short for their age or stunted (ZDHS, 2016).

Reduction of stunting is one of the most important global health goals because it has remarkable short and long-term consequences (De Onis et al., 2013). To address the global challenges including hunger and malnutrition, the United Nations established seventeen interrelated Sustainable Development Goals (SDGs) in 2015 and were committed to achieving them by 2030. The SDG 2 is Zero hunger with the mission of “end hunger, achieve food security and improved nutrition, and promote sustainable agriculture”. Target 2 of SDG2, is about ending all forms of malnutrition including stunting (FAO, 2020). The 2030 agenda explicitly states that in achieving the SDGs, no one should be left behind and it pledges “to reach the furthest behind first” (UN General Assembly, 2015). However, studies show that the world is off-track to achieve the goals related to hunger and malnutrition (FAO, 2020). New technologies, analytical methods, and large geolocated datasets provide us the unique opportunity to investigate the relationships between human and natural resources more effectively. Studies show that impact of PAs on human’s nutrition is spatial dependent (Foerster et al., 2011) and living in closer proximity to PAs increased the share of nutrition provided by PAs (Guerbois & Fritz,

2017). However, despite the opportunities provided by the geospatial data and analysis in contribution to achieving the SDGs, the application of geospatial information to understand malnutrition remains limited (Scott & Rajabifard, 2017). In particular, studies suggest that the application of spatial data and analysis methods is very limited in the studies conducted on the associations between protected areas (PAs) and malnutrition (Jouzi et al., 2020).

Literature review

Historically, child malnutrition and stunting were studied through the lens of diet and food intake; however, a growing body of literature has been emerged discussing the important contributions of the natural and physical environment to child nutrition (Vilcins et al., 2018). Agriculture and food production are still the dominant areas of research regarding food insecurity and malnutrition, even though food security is more than food production (Tamburino et al., 2020). Malnutrition is a multifaceted problem (Poppy et al., 2014; del Carmen Casanovas et al., 2013) and varieties of individual, socioeconomic, and environmental variables are associated with that. Hence, nutrition-specific interventions and sectoral approaches to food insecurity cannot address the problem effectively and sustainably. To overcome malnutrition, contributions from diverse disciplines such as health, agriculture, forestry, conservation, economics, development, education, and interdisciplinary research have been advocated (Herforth, 2010; Powell et al., 2013; Tamburino et al., 2020).

There is a growing body of literature on the positive association between forest covers and food security in the developing world (Baudron et al., 2019; Rowland et al., 2016; Ickowitz et al., 2016; Powell et al., 2015). In addition, studies suggest an overlap between areas with high biodiversity and high prevalence of poverty and food insecurity (Fisher & Christopher, 2007). Given that protected area establishment is widely considered as an effective strategy for global biodiversity conservation, this prompts an important question how protected areas may impact food security. The establishment of PAs as the dominant form of conservation (De Lange et al., 2016; Pullin et al., 2013) can impact the surrounding communities in positive and negative ways. Providing ecosystem

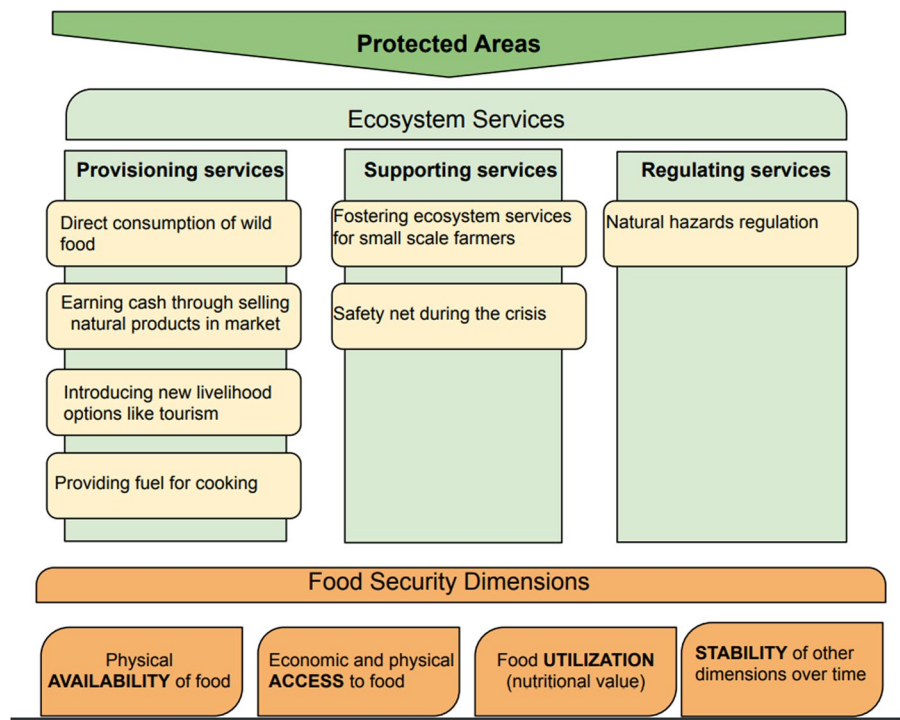
services for small-scale farmers that are heavily relied on natural resources, creating new livelihood options such as tourism, improving infrastructure such as the roads (FAO, 2014; Pullin et al., 2013), providing safety net during the crisis like drought (Naughton-Treves & Holland, 2019; Cooper et al., 2018; Guerbois & Fritz, 2017; Arnold, 2008), providing wild food for direct consumption and forest’s non-timber products for selling in the market to earn money, particularly for people from the lower socio-economic status (Harris & Mohammed, 2003; Shumsky et al., 2014) are some examples of possible pathways that PAs can positively contribute to the wellbeing and food security of adjacent communities. However, not considering communities in conservation and park management, can increase the vulnerability of people to poverty, social conflict, and displacement (Brockington & Wilkie, 2015; FAO, 2014). Other examples of possible negative impacts of PAs on food security are increasing the conflict with wildlife, and crop raiding which refers to the situation that wild animals damage farms and crops by feeding on or trampling them (Alemayehu & Tekalign, 2020; Ruda et al., 2020; Givá & Raitio, 2017; Watve et al., 2016). However, there are very few empirical studies conducted

on the association between PAs and food security and malnutrition. The results of a review on this topic found only nineteen studies in the literature of terrestrial PAs and food security (Jouzi et al., 2020).

This study used Zimbabwe as a case study to enhance our understanding of the associations between the nutritional status of children in sub-Saharan Africa and environmental variables. It is intended to contribute to the growing body of literature in the application of spatial analysis methods in public health and natural resources management and the new approaches to nutrition and food security that consider wild food as an important source of food. Specifically, we addressed a knowledge gap about associations between PAs and food security that will inform policymakers in their evidence-based decisions to reach the sustainable goals of zero hunger and sustainable conservation.

Based on the literature, a conceptual framework has been developed to explore the contributions of PAs in food security (Fig. 1). PAs provide ecosystem services which can improve food security of people living inside or around them. Each mechanism of food security enhancement provided by PAs can affect several dimensions of food security. For

Fig. 1 The conceptual framework to explore the potential contribution of PAs to increase the food security through providing different ecosystem services



example, PAs provide provisioning ecosystem services such as direct consumption of wild food that increase “availability” of food. Supporting services provided by PAs, such as fostering ecosystem services for small scale farmers and safety net during the crisis, has positive impact on food availability, access, and stability.

This study addressed two sets of research questions. First “where” the stunted children were living by visualizing the spatial pattern of HAZ in children under 5 in Zimbabwe. Second, we tried to answer “why” the clusters of stunted children were observed in some areas. Do child malnutrition occurrences increase or decrease with proximity to the PAs? What other characteristics seem to be associated with that (e.g., rainfall, access to the road, household wealth)? Where is each characteristic most important?

Methods

Study area

Zimbabwe is a landlocked country in sub-Saharan Africa, with a population of 13.81 million estimated by the World Bank in 2015. According to the World Food Program (WFP, 2017), 63% of its population are living below the poverty line and 27% of children are short for their age (stunted). Widespread poverty, unemployment, economic instability, HIV/AIDS, and recurrent climate-induced shocks are considered the main causes of food insecurity in the country (WFP, 2017). In addition, agriculture is the dominant sector in Zimbabwe’s economy at 70% of the population are engaged in this sector. Agriculture is mainly rainfed and about 73% of the agricultural lands and 98% of farmers are smallholders characterized by low productivity, with limited access to the finance and inputs, market, extension services, and high vulnerability toward weather-related shocks (WFP, 2017). Child malnutrition in Zimbabwe, is heavily influenced by long time economic and social crisis in the country. For example, the HIV/AIDS epidemic that started from mid-1980s, created serious economic and social crisis, and dramatically increased the numbers of orphans (Munro, 2015). Moreover, long term hyperinflation and poverty in the country also limited people abilities to meet their basic needs and lead to deterioration in child malnutrition (Munro, 2015).

Literature on poverty shows that children in poverty are the population that hit hardest. Specially children living in rural areas (Musiwa, 2020). It is important to note that child poverty is a multidimensional concept, and income-centric measures cannot capture it correctly. To address this issue, utilizing Zimbabwe Demographic and Health Survey 2015 dataset, a study conducted on children poverty in Zimbabwe and found that the most frequent deprivation forms in the country are early childhood development, water, healthcare, sanitation, shelter, and nutrition (Musiwa, 2020).

Data

This study utilized the 2015 Zimbabwe Demographic and Health Survey (ZDHS, 2016) to examine the association between household wealth index, environmental variabilities including proximity to PAs and roads, rainfall, and malnutrition. ZDHS 2015, provides health and population data that are representative at the national and sub-national levels. ZDHS survey had a two-stage sampling design. Zimbabwe’s Census enumeration areas (EAs) were the primary sampling units for the first stage ($n=400$). At the second stage of sampling, 11,196 households were selected from those primary sampling units. Women aged 15–49 years, men 15–54 years old, and children 6–59 months were included in the survey (ZDHS, 2016). For analysis, we used the PR dataset (household members or Persons Recode) that includes all people who are the usual household members (*de jure*) and the people who spent the last night in the household (*de facto*). Using this dataset allowed us perform analysis on all children including those that their mother has died or those children who are not living with their mother. If we used KR (Kids Recode) those children would be excluded from the analysis (Croft et al., 2018). In addition to the socio-economic, demographic, and health data, height and weight were measured for 6511 children under 5 that were living in the sampled households during the survey. ZDHS 2015 was conducted from July 6 to December 20, 2015 (ZDHS, 2016).

The unit of our spatial analysis was the cluster, because DHS data are geolocated at the cluster level. This data set contains 400 clusters of households (note: cluster 11 which is one of the clusters in the capital city of Harare doesn’t have any children under

5, so we end up working with 399 clusters with valid values for children under 5) and the GPS data were recorded for the center of clusters. However, to protect the confidentiality of data, ZDHS randomly displaced the GPS locations up to 2 km in urban areas and 5 km in rural areas with 1% of the rural cluster with a displacement up to the maximum of 10 km. To capture the GPS location shift for the center of the clusters, environmental values were measured within the 2 km (urban) or 10 km (rural) buffer surrounding the DHS survey cluster (Mayala et al., 2018).

For spatial analysis, the weighted values of HAZ were calculated for each observation and then the values were aggregated to the cluster level. Environmental variables for each cluster were extracted from the ZDHS program datasets and merged into the socio-economic dataset. Finally using ArcGIS, we linked each cluster to its recorded GPS point (the latitude and longitude of the center of the cluster). To measure child malnutrition, we used the HAZ as our dependent variable with higher values of HAZ representing children with better nutritional status. Independent variables were selected based on the literature and our proposed conceptual framework (Fig. 1). Household wealth index, calculated by DHS, used principal component analysis method and is based on ownership of items ranging from television to vehicle, ownership of bank account, land, house, and livestock, in addition to some housing characteristics such as the source of drinking water, toilet facilities, type of cooking fuel, electrification, house furniture and utilities, floor and wall materials (ZDHS, 2016). Detailed information about variables included in the wealth index and the calculation method to create the wealth index can be found elsewhere (DHS, wealth index web page). Travel time, as measured by the average time in minutes required to reach a high-density urban area (based on the year 2015 infrastructure), was obtained from the DHS program geospatial covariate datasets manual (Mayala et al., 2018). Proximity to PAs, which is the geodesic distance to the protected area in meters (based on the definition of the United Nations Environment Programme World Conservation Monitoring Centre for PAs) was obtained from the DHS program geospatial covariate datasets manual (Mayala et al., 2018). Finally, the average annual rainfall in millimeters per year, within the 2 km of urban areas or 10 km of rural areas buffer surrounding the DHS survey cluster location also

obtained from the DHS dataset (Mayala et al., 2018). For spatial analysis we used the mean average rainfall in 2010 and 2015 to capture the long-time pattern of rainfall. We made z-score for all independent variables in spatial model (note: our dependent variable is the HAZ = height-for-age z scores). Table 1, describes the component of interest, based on the framework and their operationalized variables using in this study.

Global regression model (Logistic Regression for the complex survey data)

To analyze the associations between the dependent variable ($HAZ < -200$ = stunted) and independent variables we conducted a Logistic regression model. To incorporate the sample design into the model we applied the “SURVEYLOGISTIC procedure” in SAS software (SAS Enterprise Guide 7.1).

Spatial analysis

To identify and visualize the pattern of the dependent variable, HAZ, and detecting possible spatial dependency, we applied (a) global and then (b) local spatial autocorrelation analysis. The null hypothesis in spatial autocorrelation analysis is that the attributes are randomly distributed and there is not a correlation between them. The rejection of this null hypothesis suggests the spatial pattern is matched by value similarity (Anselin et al., 2007). Moran’s I was used to check the global autocorrelation. Global autocorrelation tests, such as Moran’s I, only suggest the presence of overall clustering in the data and do not provide any information regarding the location of clusters and the type of detected autocorrelations such as correlations between high or low values (Anselin et al., 2007).

To address this issue, we applied the local spatial autocorrelation method. After calculating the weighted mean value of HAZ for each cluster, we used the cluster and outlier analysis (Anselin Local Moran’s I) in the ArcGIS software (ESRI ArcMap 10.8.1) to identify and visualize the statistically significant hotspots, cold spots, and outliers. The Anselin Local Moran’s I, classified data into four categories of significant local clusters (high-high and low-low values) and local spatial outliers (high-low and low-high). For example, in this study, areas with a high value of HAZ surrounding other high-value

Table 1 Variables used in this study and their descriptions

Variable theme	Component of interest, based on the framework	Operationalized variable	Description
Health	Food/nutrition security	Height-for-Age Z scores (HAZ)	Proxy to measure nutritional status
Socio-economic	Earning cash, fostering ecosystem services for farmers, new livelihood options, fuel for cooking	Wealth Index	Wealth index used in this study included ownership of items ranging from television to vehicle, ownership of bank account, land, house, and livestock, in addition to some housing characteristics such as the source of drinking water, toilet facilities, type of cooking fuel, electrification, house furniture and utilities, floor and wall materials
Environmental	Access to different ecosystem services provided by PAs	Proximity to protected areas	Literature shows that the contribution of PAs in human wellbeing decrease when the distance increased (Guerbois & Fritz, 2017)
	Access to the market and alternative livelihood options such as tourism	Travel time	Access to infrastructure/ roads and markets
	Safety net during crisis	Rainfall	Agriculture is the main sector in Zimbabwe's economy and it is mainly rainfed

areas are clusters of high-high values or hotspots. Areas with low HAZ values, surrounded by low values are detected as cold spots which are the areas that the clusters of malnourished children are living there.

Geographic weighted regression (GWR)

Regression models are either global or local. Global models, either spatial models such as Spatial Lag Model (SLM) and Spatial Error Model (SEM) or non-spatial models such as Ordinary Least Square (OLS), produce only one equation for the entire dataset and calculate the average estimate of the relationship between the dependent and independent variables in the model. It can mask the heterogeneity of the associations between variables within the area. In other words, the global models are constant across space and assume that the relationship between variables is constant across space as well. However, this assumption has serious limitations when we want to quantify the relationship between variables in different locations. To address this shortcoming, local models were developed (Propastin & Kappas, 2008).

In local models such as Geographically Weighted Regression (GWR), the models provide the local parameter estimates across space. In local models,

parameters are varied spatially and instead of one average parameter estimate for the entire space, there are different local parameter estimates across space. (Fotheringham et al., 2017). GWR model can be expressed as follows (Fotheringham et al., 2017):

$$y_i = \sum_{j=0}^m \beta_j(u_i, v_i) x_{ij} + \varepsilon_i$$

where y_i is the dependent variable at the location i , $\beta_j(u_i, v_i)$ shows the j th coefficient, and ε_i is the random error term. In the GWR model, for the bandwidth search (data-borrowing range/ the neighborhood size), the golden section search method was applied. Golden search identifies the distance and number of neighbors with the lowest corrected Akaike's Information Criteria (AICc). Regarding model optimization to select the best model, AICc was used and the bandwidth with the lowest AICc was selected for the model. The MGWR analysis was conducted on the ArcMap software (ESRI ArcMap 10.8.1). Finally, to examine our model and to ensure that the residuals are spatially random, we run the Spatial Autocorrelation (Moran's I) on our residual. Identifying a pattern in residual suggests that at least one key explanatory variable is missing in the model.

Results

According to data from ZDHS 2015, 26.8% of children under 5 in Zimbabwe were stunted (short for their age). Table 2 shows the descriptive statistics for the environmental variables. More than half of households (61.8%) were the poorest and poorer families. On average there was a 95,381-m distance between clusters and PAs. The mean annual rainfall was 478 mm in the country and on average there was more than an hour (77 min) distance between the clusters and the cities.

Results of the global model

The results of logistic regression analysis for the complex survey data (Table 3) suggest that at the

significant level of 0.05 there was an association between wealth index, travel time, and rainfall. Children from the richest household were less likely to be stunted compared to other. Children living in the cluster with better access to the cities and shorter travel times were less likely to be stunted. Children living in clusters with higher average rainfall were more likely to be stunted. The association between proximity to PAs and stunting was near-marginal significance ($p=0.17$). To investigate this observation further, we used geographically weighted regression to evaluate the local model of all variables.

Table 2 The descriptive statistics for the variables used in this study

Variables	Percentage	
Malnutrition indicator		
Stunted children under 5	26.8	
Household wealth index	Rural	Urban
Poorest	0.0	28.7
Poorer	0.0	28.7
Middle	0.0	28.7
Richer	39.7	11.4
Richest	60.3	2.4
Environmental variables	Mean	
Proximity to PAs in meter	95,381.0	
Mean Rainfall in millimeter	570.7	
Travel times in minutes	77.6	

Table 3 Logistic regression results (global model)

Parameter	Estimate	Pr> t	Odds ratio estimates		
			Effect	Point estimate	95% confidence limits
Intercept	- 1.190	<0.0001			
Wealth index	0.433	<0.0001	Poorest versus richest	2.865	2.126 3.861
Wealth index	0.198	0.004	Poorer versus richest	2.266	1.699 3.022
Wealth index	0.010	0.882	Middle versus richest	1.878	1.416 2.489
Wealth index	-0.023	0.765	Richer versus richest	1.815	1.389 2.373
Proximity to PAs	-1.05E-6	0.170		1.000	1.000 1.000
Travel times	-0.001	0.004		0.998	0.997 0.999
Rainfall	0.0007	0.011		1.001	1.000 1.001

Global and local autocorrelations for the dependent variable

Regarding the spatial distribution of the dependent variable, HAZ, the result of Moran's I analysis is shown in Fig. 2. The image generated as the results of the Moran's I test, indicates that the likelihood of this clustered pattern being the result of random chance was less than 1%. In addition, the calculated Z-score of 6.12 with the p value 0.000, rejected the null hypothesis that is spatial randomness. This Z-score and p value supported the alternative hypothesis and indicated the positive spatial autocorrelation, which means spatial clustering of like values.

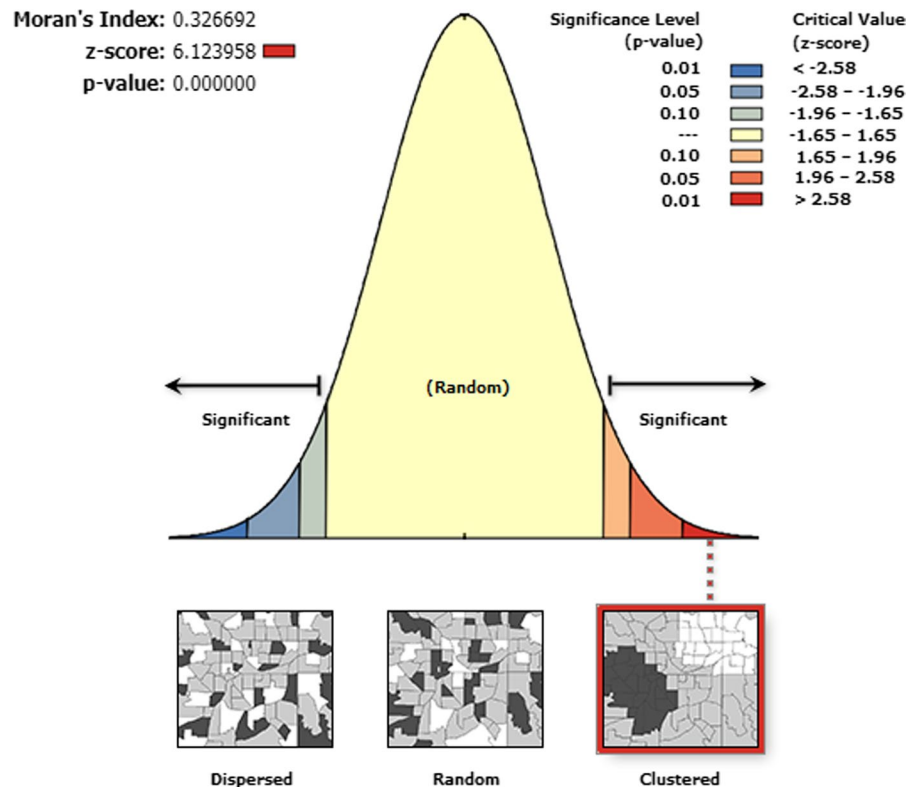
After detecting the positive clustering in our data, we applied the local test of Cluster and Outlier Analysis (Anselin Local Moran's I), to identify the location of the clusters. The results showed that the highest prevalence of low-low clusters (illustrated in blue and indicates the lower HAZ and malnourished child) were situated in the North East of the country, the capital city of Harare, and the eastern provinces (Fig. 3). On the other hand, Bulawayo and Matabeleland North and South showed the highest frequency

of high-high clusters where children had a better nutritional status (Fig. 3).

Results of geographically weighted regression

The model diagnostic showed the R-squared value for the GWR model was 0.46. This suggests that 46% of the dependent variable (HAZ) variance was accounted for by our regression model. However, the values of R-squared varied across the country, with the range of 0.01 to 0.81. Figure 4 shows the distribution of local R-squared. Clusters located in the eastern and western parts of the country have the highest values of R-squared which suggests our model worked better in those areas. To make sure that there is no local multicollinearity in our model, the condition number in the output features attribute table has been checked. Based on recommendations suggested in the ArcGIS documentations (Esri Inc. 2021), the condition number larger than 30 or null values may prove unreliable. The largest condition number in our result was 26.39, hence we did not detect a local multicollinearity in our model. Finally, to ensure that

Fig. 2 The results of global spatial autocorrelation of HAZ in Zimbabwe, 2015



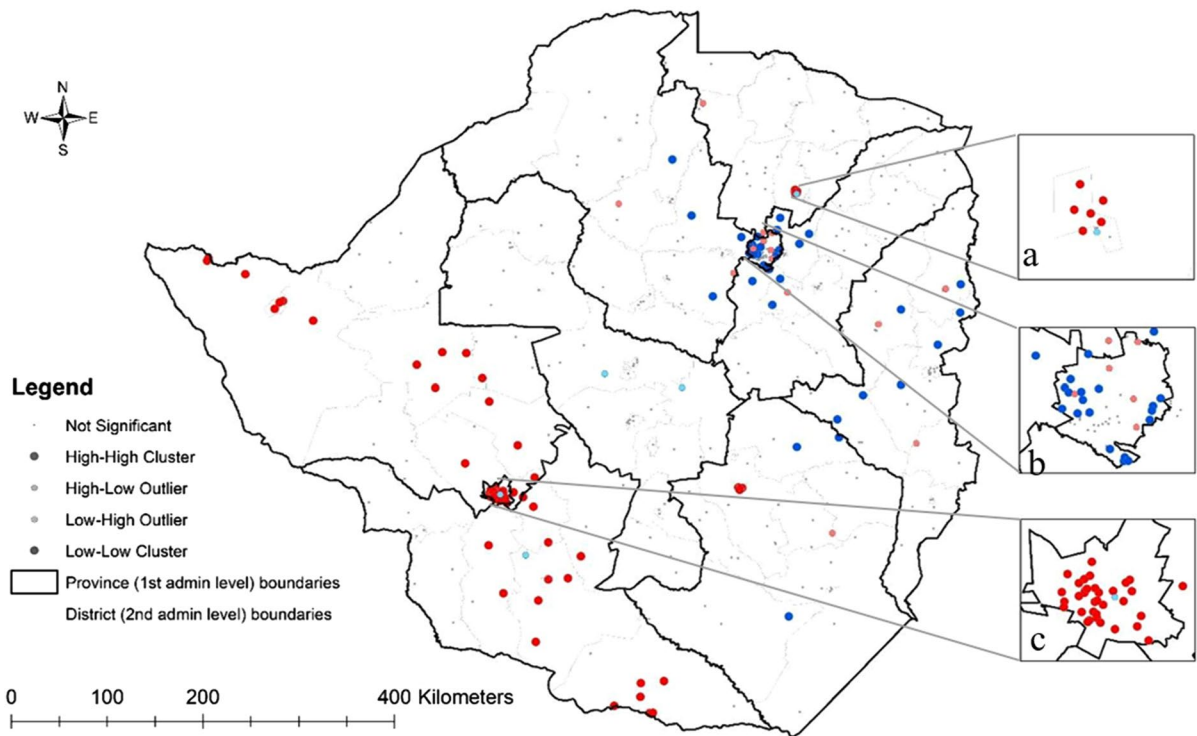


Fig. 3 Distribution of statistically significant local clusters ($n=399$) of the hotspot and cold spots and local spatial outliers for HAZ in Zimbabwe, 2015. The low-low clusters (illustrated in blue) show the clusters of malnourished children. **a** Indicates a low-low cluster (low HAZ value and malnutrition)

surrounded with high-high (high HAZ values, better nutrition), **b** the capital city of Harare mostly low HAZ with some clusters of high values, **c** Bulawayo, the second-largest city in Zimbabwe, mostly high-high clusters with one cluster of low HAZ

the residuals of the GWR model are spatially random, we used spatial autocorrelation (Moran's I) on our residuals. Given the Z-score of 0.870, the pattern of residual was random. No pattern in residual suggests that the important key explanatory variables were not missing in the model.

To improve the readability of GWR results, distribution of PAs and ZDHS cluster are illustrated (Fig. 5). The results of the GWR model for HAZ are illustrated in Figs. 5, 6, 7 and 8. Regarding the household and environmental variables, the results revealed that not only were the associations between different variables and HAZ varied across the country, but the strength of association differs spatially. Our results suggest a positive association between wealth index and nutrition in most regions of the country. Which suggests children living in clusters within richest households had a better nutritional status. However, our results show a negative local association between wealth index and HAZ in the capital city of Harare

and areas around that in the Northeast provinces of Mashonaland West and Central and some region of Mashonaland East (Fig. 6).

Regarding proximity to PAs, the results show that most clusters (illustrated in light greens with negative values of coefficient) that are closer to PAs had better nutritional status; while clusters located in the northeast and east (illustrated in dark green) had more distance to PAs and lower HAZ values (Fig. 7). Moreover, in three most populous cities of the country that are Harare, Bulawayo and Mutare the value of HAZ decreased as the proximity to PAs increased.

Regarding the association between mean rainfall and HAZ, Fig. 8 shows the negative and positive associations between rainfall and nutritional status in children. Our findings revealed a positive association between rainfall and HAZ in some clusters in provinces of Mashonaland East and West, Matabeleland North and South. It suggests more rain led to better nutritional status. These clusters are illustrated in

Fig. 4 The local values of R-squared for the GWR model

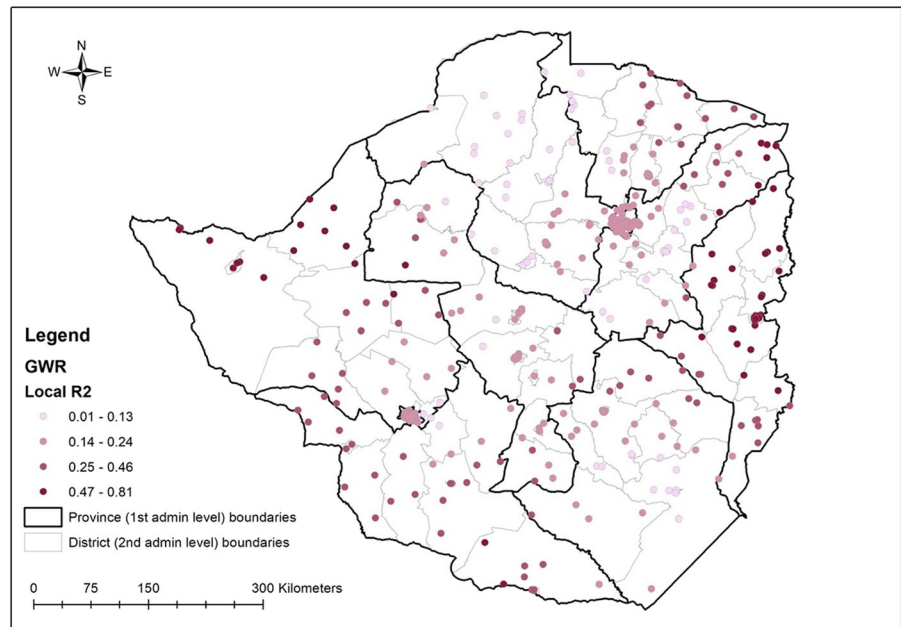
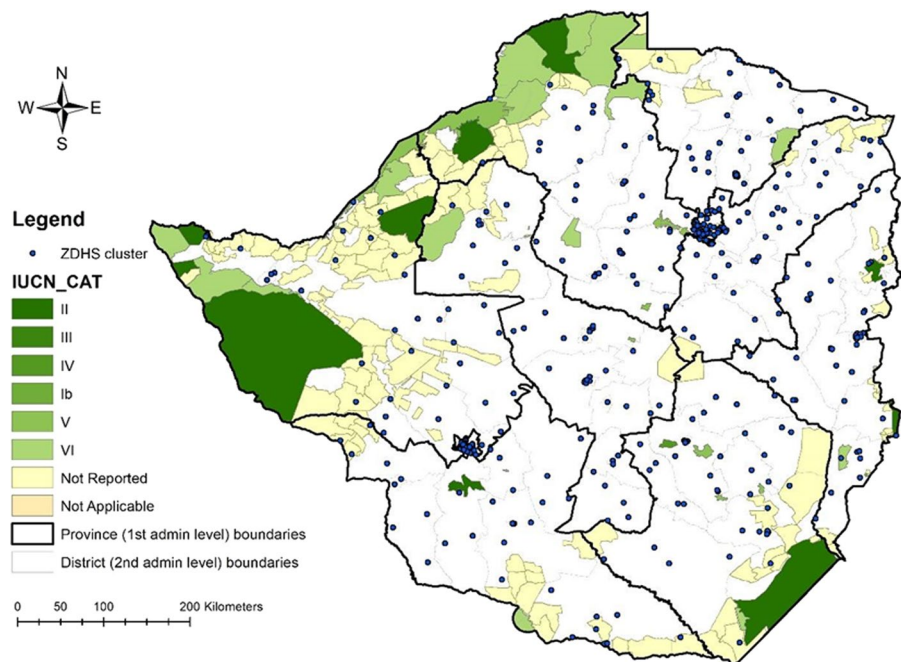


Fig. 5 The distribution of ZDHS clusters and protected areas in Zimbabwe



dark blue on the map. However, in other clusters there was a negative association. In clusters illustrated in light blue and white on the map more rainfall led to a lower value of HAZ or increased malnutrition. It is worth mentioning that, the strength of this association is not constant across the country. For instance, in

the north east provinces of Mashonaland Central and some clusters Mashonaland east, the strength of this negative association was the highest. Which suggests that high rainfall was associated with lower HAZ values and more malnourished children.

Fig. 6 The results of GWR and visualization of local estimate for wealth index (all maps were generated by the ArcGIS ESRI ArcMap 10.8.1)

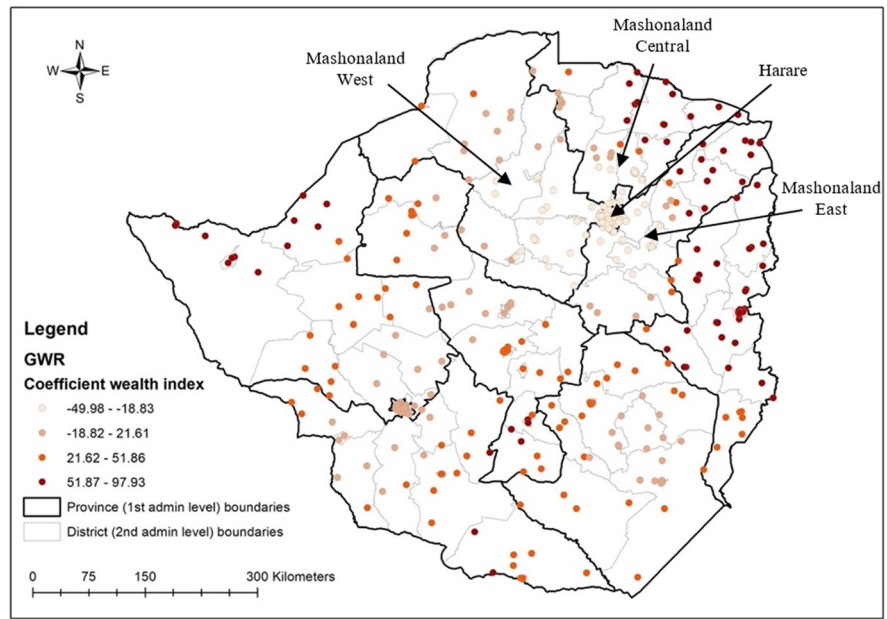
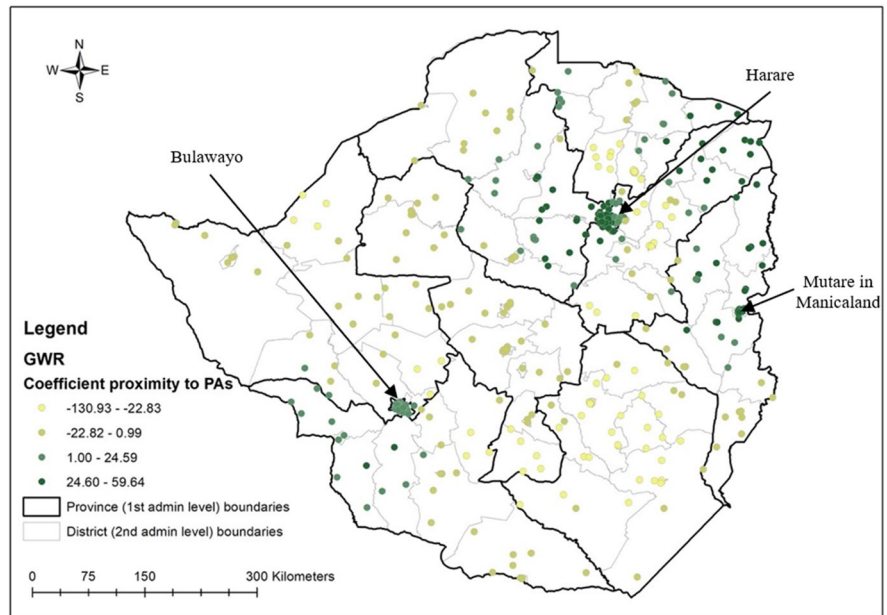


Fig. 7 Local estimates for the proximity to PAs



Concerning the associations between travel times to the city and HAZ value, the results suggest a general negative association at a county level (Fig. 9). That suggests living closer to the city was generally associated with better nutritional status. However,

the strength of association at a regional level was different. For example, in the capital city of Harare, the result shows the strongest negative association, while in the north part of Mashonaland East the strength is the weakest.

Fig. 8 Visualization of local estimates for the mean rainfall

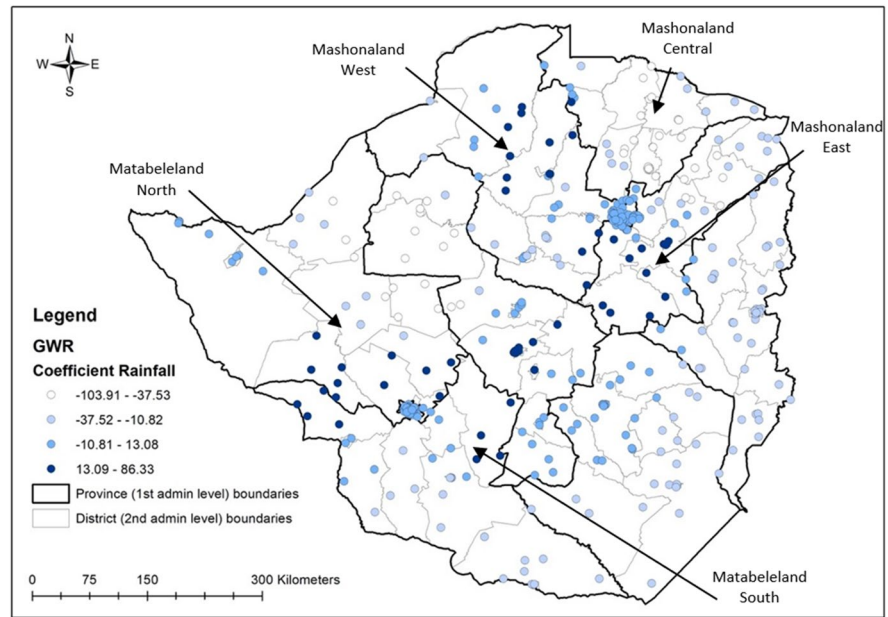
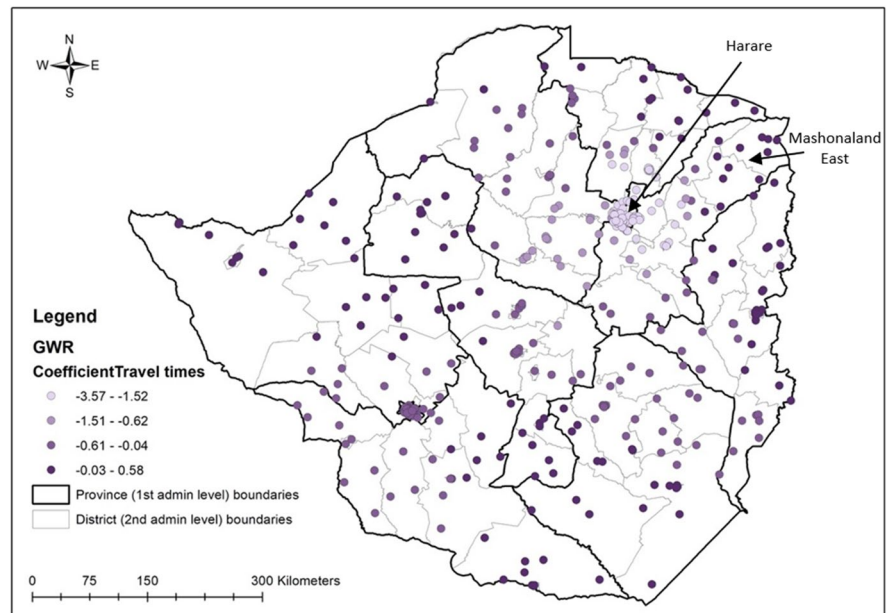


Fig. 9 Visualization of the local estimate for travel times



Discussion

This study applied spatial analysis methods to tackle the important issues of spatial dependency and spatial clustering in malnutrition and its associations with PAs and other environmental variabilities in one of the most challenged regions. The result of our

global models (logistic regression), regarding the better nutritional status of children from the richest household, is consistent with other studies using DHS data and stunting conducted in Uganda and Ethiopia (Amegbor et al., 2020; Hailu et al., 2020). However, the local model revealed a negative local association between wealth index and HAZ in Harare and regions

around the capital city. A possible explanation might be because the DHS wealth index is a better proxy for estimating the wealth in rural areas versus urban areas. Moreover, as the results of logistic regression (Table 3), showed the association between richest and richer households (expected to be located in urban areas) and HAZ were not statistically significant. Concerning the travel time, our finding of logistic regression is consistent with other studies conducted in Rwanda and Nepal that showed a positive association between child nutrition and access to the roads and cities (Aoun et al., 2015; Thapa & Shively, 2018). It can be explained by better access to the market, job opportunities for families, access to the health centers and other services provided in cities. The observed near significant ($p=0.17$) for proximity to PAs and stunting might be because in some regions there were positive associations and, in some regions, there were negative associations between proximity to PAs and HAZ values. Conducting a local model (GWR) help us test this hypothesis. Figure 7, shows the varied directions of associations in different regions (positive and negative associations).

With respect to the results of the GWR model, our findings revealed spatial heterogeneity in the strength of associations between household and environmental variabilities and child malnutrition. In addition, the directions of these associations differ across the country. This mixed, observed pattern of associations was consistent with previous studies that utilized local models such as GWR on child malnutrition (Amegbor et al., 2020). Our finding suggested a negative association between proximity to PAs and HAZ in some regions of the country; which means on average children living closer to PAs have higher HAZ or better nutritional status. This finding corroborates with the previous study on more than 87,000 children in 34 developing countries, which showed that living near PAs had positive impacts on children HAZ (Naidoo et al., 2019). However, in three main cities of Zimbabwe that are Harare, Bulawayo, and Mutare, living closer to the PAs didn't show positive impacts on child nutritional status. It can be explained by the different food systems in the cities compared to rural areas. As the direct consumption of wild food and food production through farming are more prevalent in rural areas and buying from the market is the most common method to get the food in urban areas.

The pattern of association between rainfall with child malnutrition can be explained by the agriculture sector as the source of local food production and local income generation in the country. Local agriculture in Zimbabwe heavily relies on natural resources and is mainly rainfed (FEWS, 2014). Hence, changes in precipitation have impacts on the food and income of people in the short and long term. This association had a regional pattern (Fig. 7). A negative regional association was identified between rainfall and HAZ in North East of the country in Mashonaland Central. A similar pattern of a negative association between increased rainfall and HAZ was detected in a multi-scale GWR analysis study in Uganda (Amegbor et al., 2020). The possible explanation might be the anomalies in rainfall that can damage the harvest or cause floods. Floods can impact food security both immediately and in long term through different mechanisms such as damage to infrastructure, livelihoods, croplands, livestock, and increase water-borne diseases (Reed et al., 2022). Concerning travel time and access to the roads, the result of our local GWR model indicated the directions of associations between proximity to roads and malnutrition differ across the country. In most regions children living closer to cities had better nutritional status. This is consistent with the results of other studies in Rwanda and Nepal (Aoun et al., 2015; Thapa & Shively, 2018). The main focus of this study was on the associations between living in close proximity to PAs and children nutritional status. The most important finding in this regard is that in rural areas living closer to PAs was associated with better nutrition in children. This suggests that a more holistic approach to human health and wellbeing and conservation, is required.

This study had some limitations. First, as mentioned earlier, to protect the confidentiality of data, the GPS recorded values shifted randomly to the maximum of 2 km and 5 km (1% up to 10 km) in urban and rural areas respectively. Although in environmental variables, the buffer is calculated around the center of clusters to account for these shifts, it is important to notice that the places that are visualized on the map are based on that data. Second, considering the fact that we used one cross-sectional population survey for Zimbabwe in 2015, we only could explore the associations between variables, and we cannot have any causal inference from our findings. However, it doesn't mean that we

cannot draw inference from our spatial and statistical analysis that suggested clusters of malnutrition and heterogeneity of associations between environmental variables and child malnutrition.

Another limitation of our study is the “boundary effects”, which occurs when the arbitrary boundaries (such as the international borders in our study) are imposed on unbounded spatial phenomena (Miller, 1999). For example, in our study, the flow of ecosystem services, energy, and material from PAs are unbounded and not following the human-made boundaries. In all bordering clusters, the impact of their neighboring countries was neglected in this analysis and the results should be interpreted with this caution. Finally, in this study we used the relevant and available data from DHS and for rainfall, the annual average rainfall was our best available option. However, there are several considerations that must be taken into account. For example, the ZDHS data collection took place from July through December 2015 and did not cover all 3 wettest months in Zimbabwe which are December, January, and February. Moreover, averaging the rainfall for the calendar year ignores the timing of growing season and the timing of DHS data collection, which varies depending on clusters across the country.

Future studies, can be conducted at a finer spatial scale. It is worth mentioning that reporting the average effect of PAs should be interpreted with the understanding that PAs’ impacts on human well-being, including nutrition, have spatial and temporal heterogeneity (Pullin et al., 2013). Hence, further analysis is required to investigate the associations between PAs and child malnutrition in different regions and times across the country. Moreover, further analysis is required to have a better understanding of this association in different regions of the country and with PAs with different management systems (e.g., national parks, habitat/species management areas).

This study contributes to the existing literature on child malnutrition in several ways. First, while studies in the existing literature have the main focus on socio-economic, health, and recently more natural resources and climatic variables, this study explored child malnutrition from an environmental perspective with the emphasis on the PAs, providing researchers, practitioners, and decision-makers a better understanding

of the issue. Proposing a framework about the contribution of PAs in food security, can guide policy makers and future researchers to understand how PAs can contribute to food and nutrition security. Second, regarding the analytic methods used in this study, we brought attention to the potential of geolocated data and spatial analysis in tackling the problems. This enabled us to identify various patterns of spatial associations that exist across the region. For example, the results of spatial autocorrelation tests in our study confirm spatial clustering in the distribution of malnourished children in the country. Analysis reveals that national values usually hide the inequalities within the countries and consequently the vulnerable people and communities might be overlooked (Global Nutrition Report, 2020). Our finding regarding the hotspot and cold spot of child malnutrition can be used to address the 2030 agenda and its pledge “to reach the furthest behind first” (UN General Assembly, 2015). In addition, the governmental sector in the county and international aid organizations and agencies such as FAO or WFP can use the map of the hotspot and cold spot of HAZ in Zimbabwe to identify the regions with the highest priority for food aids, nutrition, and environmental interventions.

Finally, studies show that in the world’s poorest countries, budgeting and policies are influenced by international organizations (Herten-Crabb & Davies, 2020; Andrews, 2013). The results of this study can provide data for international organizations to help them make an evidence-based decision regarding their priority areas of interventions by identifying the regions that most vulnerable children are living.

Conclusion

According to the ZDHS 2015, about one in fifteen children in Zimbabwe cannot survive past their fifth birthday. While the region is not meeting the goals of malnutrition reduction (FAO, 2020), the projections for the future show that the situation may get even worse. Sub-Saharan Africa, including Zimbabwe, is facing high population growth and more frequent and severe climate change-related events that will exacerbate food insecurity in the future of this region (Poppy et al., 2014). While new research shows a positive association between forest and food security especially for the most vulnerable, in general,

agriculture expansion happens at the expense of forests. Studies show that 80 percent of agricultural land in the tropics was the result of the conversion of forest to farms. In Africa for example, 60 percent of farms came from intact forests, 35 percent from disturbed forests, and 5 percent from shrublands (Gibbs et al., 2010). Given this trend and its significant ramifications, the role of forests and tree-based ecosystems, including those fall within PAs, in food and nutrition security needs further research to address the research gaps and inform forest and protected area management.

Acknowledgements We thank Dr. J. Aaron Hipp for his feedback on earlier version of this work.

Author contributions ZJ Conceptualization, Investigation, Formal analysis, Visualization, Writing—Original Draft, Writing—Review & Editing. SN Conceptualization, Review & Editing, Supervision. YFL Conceptualization, Review & Editing, Supervision. All authors reviewed the manuscript.

Funding This research received no external funding.

Data availability The datasets used for this study, the ‘2015 Zimbabwe Demographic and Health Survey’, were obtained from The DHS program (www.dhsprogram.com). According to the ‘Dataset Terms of Use’ we do not have permission to share this data (<https://dhsprogram.com/data/Access-Instructions.cfm>). The registered user of the website (www.dhsprogram.com), can download the survey and GPS datasets. We obtained the GIS boundary files of Zimbabwe from the Center for Humanitarian Data (<https://data.humdata.org/dataset/zimbabwe-administrative-levels-0-3-boundaries>).

Declarations

Conflict of interest The authors declare no conflict of interest.

Research involving human participants This study used data collected by Demographic and Health Survey (DHS). According to DHS, “the procedures and questionnaires for standard DHS surveys have been reviewed and approved by ICF Institutional Review Board (IRB). Additionally, country-specific DHS survey protocols are reviewed by the ICF IRB and typically by an IRB in the host country”. More information about DHS data “ethical review”, “Informed and Voluntary Participation”, and “Privacy and Confidentiality during Data Collection and Data Processing” can be found here: <https://dhsprogram.com/Methodology/Protecting-the-Privacy-of-DHS-Survey-Respondents.cfm>.

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