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Spatial Patterns and Risk Factors of Stunting Among Under-five Children in Kenya: A Multilevel and Spatial Analysis

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Abstract: Stunting remains a significant public health burden in sub-Saharan Africa and has far reaching consequences. Identifying the drivers of stunting and high burden regions is key to developing effective and targeted intervention strategies. The objective of the study was to identify the risk factors and explore spatial patterns of stunting across counties in Kenya. Secondary data from 2022 Kenya Demographic Health Survey (KDHS) was utilized. A total of 13,016 children aged between 0 - 59 months were included in the analysis. A multilevel logistic regression was applied to identify individual, household and community level determinants of stunting, spatial regression models to analyze spatial dependency and geographically weighted regression to explore spatial heterogeneity in the association between childhood stunting and county level determinants. In the multilevel logistic regression, Children from urban residence exhibited a significantly increased odds of stunting compared to those in rural areas (aOR = 1.25, 95% CI: 1.03 - 1.51, p = 0.02). Children from households categorized as poorer, middle, richer, and richest all exhibited significantly reduced odds of stunting compared to those from the poorest households. Children whose mothers had attained secondary education exhibit higher odds of stunting compared to those with no education (aOR = 1.32, 95% CI: 1.01 - 1.72, p = 0.04). Male children show significantly higher odds of stunting compared to females (aOR = 1.50, 95% CI: 1.33 - 1.70, $p < 0.001$). Children aged 12-23 months exhibit the highest odds of stunting (aOR = 2.65, 95% CI: 2.23 - 3.14, $p < 0.001$) compared to those aged < 6 months). Spatial analysis indicated that stunting prevalence varies geographically, with some areas exhibiting higher clustering. The geographically weighted regression further revealed that the influence of socioeconomic and climatic factors on stunting prevalence differed across locations highlighting the need for geographically targeted interventions.

Keywords: Child Malnutrition, Stunting, Prevalence, Multilevel Logistic Regression, Odds Ratio, Geographically Weighted Regression, Spatial Regression, Climate Change

1. Introduction

Childhood stunting, a condition characterized by impaired growth and development due to chronic malnutrition, has emerged as a critical public health issue bearing both immediate and enduring health implications [1]. It is a worldwide concern, affecting millions of children across various regions. Globally, the prevalence of stunting varies significantly, with the highest burden observed in low and middle-income countries. African countries including Kenya encounter unique challenges, such as poverty, inadequate access to clean water and sanitation, and limited healthcare infrastructure which significantly contribute to the issue. The World Health Organization (WHO) has a goal to reduce the prevalence of stunting by 40% in 2025 [2]. According to the UNICEF report 2019, the Government of Kenya has targeted a reduction of stunting rate to 14.7% by 2030.

Childhood stunting has been the subject of many studies as evidenced by the literature whether in form of scoping reviews to identify determinants for given countries classified by income groups (low, middle and high), see for example [3-6] regional blocks, for example Sub-Saharan Africa (SSA) [7], East Africa [8] and South East Asia [9] or country level analyses that utilize Demographic and Household Surveys (DHS) data to identify local risk factors by applying various statistical techniques, for recent works see [10, 11]. The World Health Organization conceptual framework on child stunting [12] is a useful tool to review the available literature and identify what has been studied and can be concluded about the determinants of child stunting in various contexts, see for example [13] in the case of Indonesia. Collectively , these studies attest to individual setting or country peculiarities and the multifaceted nature of the associated risk factors which vary within and between countries.

Studies on the determinants of childhood stunting use the conceptual framework adapted from UNICEF [14] and WHO [12] frameworks for undernutrition to categorize potential predictors. Examples include immediate (individual level), intermediate (individual/household level) and underlying (maternal, household and regional level) factors [15, 16], parental, child and household-level factors [17], individual and contextual factors [18], household characteristics, maternal characteristics, antenatal care services, and child characteristics [19], household, sub-district and province level determinants [20]. The categories are determined by the data available mainly from Demographic Health Surveys as well as the scope of the study.

Variations in childhood stunting across geographical regions are well documented, reflecting changes in contextual factors such as the extreme temperature, rainfall, temperature and drought episodes from one area to another. This underscores the significance of geography as a pivotal component in understanding childhood stunting [21]. In Sub-Saharan Africa (SSA), various studies indicated the spatial variation of stunting among under-five children [22-25, 18]. Understanding the level of the specific spatial distribution of stunting using current national data is important in planning and implementing geographically targeted and optimized nutritional interventions.

A wide range of modeling techniques have been employed in the literature within this landscape to address various research questions. Standard generalized linear models are commonly used to identify associated determinants for stunting see, [26-28] multivariate logistic regression models [29-31] ordinal logistic regression . Multilevel generalized linear regression models have also been employed to account for the hierarchical nature of the data and to identify associated determinants, multilevel binary logistic regression model [32-37] and multilevel ordinal logistic regression model [38-40].

Geo-spatial and multilevel analyses have also been employed to explore the spatial distribution across regions within countries and to identify predictors of stunting. A mixed effect logistic regression is employed in [41] to identify individual and household level factors associated with stunting while accounting for the hierarchical nature of DHS data.The Global Moran's index spatial autocorrelation was done to test whether stunting was clustered, dispersed, or randomly distributed. Spatial lag, spatial error and geographically weighted regression models are employed in [25]. Bayesian geostatistical modelling is considered in [24] to study the spatial pattern of stunting in children less than five years considering anthropometric, socioeconomic and demographic risk factors in Rwanda. Multilevel and spatial analysis of stunting is explored in [18] using multilevel binary logistic regression and spatial regression models respectively. The authors note that while existing studies have examined the association between climatic factors and childhood malnutrition, their methodological approaches do not address the issue of spatial dependence and spatial heterogeneity in this association. That is, the findings of these studies assume the association between climatic factors and childhood malnutrition is the same or stationary across the study area. Research in other health issues has observed the existence of spatial autocorrelation and clustering in the association between socioeconomic, geographical factors, and major health outcomes.

2. Materials and Methods

2.1. Study Design and Setting

A comprehensive analysis of secondary data was conducted utilizing the 2022 Kenya Health Demographic Survey (KHDS 2022). The KHDS is conducted every five years to gather health-related statistics at both national and regional levels across Kenya. In terms of administrative divisions, Kenya's regions are subdivided into counties, and counties into sub-counties. Each sub-county is further divided into smaller administrative units known as wards. The 2022 Kenya Demographic and Health Survey (KDHS) utilized the Kenya Household Master Sample Frame (K-HMSF) to select its sample. The K-HMSF is a framework used by the Kenya National Bureau of Statistics (KNBS) for conducting household-based surveys in the country. The sample was drawn from one of the four subsamples of the K-HMSF, developed in 2019. The 2022 KHDS sample was chosen using a stratified, two-stage cluster design, with 1692 clusters selected as the primary sampling units for the first stage and households for the second stage. For a detailed explanation of the sampling procedure, refer to the complete KHDS report.

2.2. Multilevel Modeling

In the multilevel analysis, a multilevel a logistic regression model with a two-level structure was applied, with counties as the second-level units and under five children as the first level units. This is basically the analysis of county wise variation of stunting among under-five children. This implies that children are nested in counties. The stunting status denoted by Y (1 = stunted and 0 = not stunted) is used as the response variable. Let Y_{ij} denote the nutrition status of the i^{th} child belonging to the j^{th} county and let the vector X_{ij} denote the corresponding values of the considered explanatory variables (individual and household). The ordinary LR model is one of the most commonly used generalized linear regression models to predict the probability of a child being stunted given the values of explanatory variables. Assuming independence of children and $Y_{ij} \sim \texttt{Bernoulli}(\pi_{ij})$ the logistic regression model can be defined as

$$\text{logit}\left(Y_{ij}=1|X_{ij}^T\right)=\log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right)=\beta_0+\beta X_{ij}^T \tag{1}$$

where $\pi_{ij}=\texttt{pr}\left(Y_{ij}=1|X_{ij}^T\right)$ is the conditional probability of $Y_{ij}=1$ given X_{ij}, β_0 is the overall intercept and β is the vector of regression coefficients. This is a single level model. Generalized linear mixed modeling focuses on subject/cluster-specific estimation. Random intercept logistic regression model is a special form of GLMM, where the intercept is assumed to vary and the slopes are assumed to be constant over the counties. The model can be defined as follows

$$\text{logit}\left(Y_{ij}=1|X_{ij}^T,b_{oj}\right)=\log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right)=(\beta_0+b_{oj})+\beta X_{ij}^T \tag{2}$$

where b_{oj} is random intercept at the county level and assumed to follow a normal distribution with constant variance σ_u^2. It has the capability to capture the effect of unobserved county level characteristics on the probability of children being stunted which cannot be accounted for by the ordinary logistic regression.

2.3. Spatial Regression Models

Spatial regression models are used when the outcome of interest in a given spatial unit is correlated with the outcomes of its neighbors (conditional on other variables). If there is no spatial dependency, the ordinary least squares (OLS) estimation method may be a better choice. These models are applied to examine spatial dependency in stunting across counties while adjusting for county level factors. The spatial error model (SEM) takes into account the dependency of error values from neighboring counties. The SEM can be represented as:

$$Y=X\beta+u \text{ and } u=\lambda W+\epsilon \tag{3}$$

where Y is an $n\times 1$ vector of the variable of interest (percentage of children under 5 years who are stunted per county), X is an $n\times p$ design matrix of county level explanatory variables, β is a $p\times 1$ vector of regression coefficients, u is an $n\times 1$ vector of error terms, λ is scalar which is a coefficient of spatial error that indicates the degree of correlation of spatial error influence from one region to another region around it, W is an $n\times n$ spatial weighting matrix and ϵ is $n\times 1$ vector of error terms that are independent and normally distributed.

The Spatial Lag Model(SLM) assumes stunting prevalence in a given county is directly influenced by stunting in its neighbors. It can be represented as follows :

$$Y=X\beta+\rho W_y+\epsilon \tag{4}$$

where Y is an $n\times 1$ vector of the variable of interest ((percentage of children under 5 years who are stunted per county), X is an $n\times p$ design matrix of county-wise explanatory variables, β is a $p\times 1$ vector of regression coefficients, ρ is a spatial coefficient, W_y is an $n\times n$ spatial weighting matrix and ϵ is $n\times 1$ vector of error terms that are independent and normally distributed. positive value of ρ indicates that counties are expected to have higher rates of stunting if, on average, their neighbors have high rates. The three models are fitted and evaluated based on the Akaike information criteria. The best model is the one with the lowest AIC value.

2.4. Geographically Weighted Regression

To explore the spatial heterogeneity in the effect of county level socioeconomic and climatic factors on the rate of stunting among children aged under five a geographically weighted approach was adopted. Rather than providing an average global estimate for the relationship or association in the model as traditional regression (such as OLS) and global spatial regression (such as SEM and SAL) models do, GWR allows the model parameters to vary across the geographic units. That is, the relationship between the predictor variables and childhood stunting is shown for each geographical unit in the study. This approach allows us to explore the county-level factors and their effects on stunting at counties. The model is represented as follows,

$$Y_i=\beta_o\left(\upsilon_i v_i\right)+\sum\beta_o\left(\left(\upsilon_i\nu_i\right)X_{ik}+\varepsilon\right. \tag{5}$$

where Y_i is the variable of interest, (u_i,v_i) are coordinates of the i^{th} point in space, $\beta_0(u_i,v_i)$ is a continuous functions of β, $X_{i1},\ldots,X_{ik}$ s the explanatory variables at point i, and ε is an error.

3. Results

3.1. Descriptive Statistics

Table 1 gives a summary of the study variables. A total of 13,016 children aged between 0 - 59 months were included in the study. Among the children aged under 5 in Kenya 17.4% were stunted.

The descriptive analysis of the factors in relation to stunting status in Kenya yielded several noteworthy findings. Across the sample of 13,016 participants, the distribution of stunting status varied significantly by various factors. Notably, access to improved water sources showed a stark contrast in stunting prevalence, with only 15.7% of children in households with improved water sources classified as stunted compared to 22.3% in households with unimproved sources, suggesting a potential correlation between water quality and stunting. Similarly, the place of residence emerged as a significant factor, with urban areas exhibiting a lower prevalence of stunting (12.6%) compared to rural areas (20%), indicating a potential urban-rural disparity in stunting rates.

Table 1. *Characteristics of the respondents included in the analysis.*

Factor	Not stunted	Stunted
Water Source	**N=10,746**	**N=2,270**
Improved	7809 (84.3%)	1451 (15.7%)
Unimproved	2666 (77.7%)	763 (22.3%)
Not a dejure resident	271 (82.9%)	56 (17.1%)
Residence		
Rural	6851 (80.0%)	1,708 (20.0%)
Urban	3,895 (87.4%)	562 (12.6%)
Wealth		
Poorest	2,845 (74.3%)	982 (25.7%)
Poorer	1,837 (80.0%)	460 (20.0%)
Middle	2,000 (84.6%)	365 (15.4%)
Richer	2,299 (88.1%)	310 (11.9%)
Richest	1,765 (92.0%)	153 (8.0%)
Mothers education		
No education	1,894 (78.4%)	522 (21.6%)
Primary	3,674 (79.2%)	965 (20.8%)
Secondary	3,383 (84.7%)	613 (15.3%)
Higher	1,795 (91.3%)	170 (8.7%)
Toilet facility		
Improved	6,729 (86.3%)	1,067 (13.7%)
Unimproved	2,301 (77.8%)	655 (22.2%)
No facility	1,445 (74.6%)	492 (25.4%)
Not a dejure resident	271 (82.9%)	56 (17.1%)
Sex of child		
Female	5,454 (85.2%)	948 (14.8%)
Male	5,292 (80.0%)	1,322 (20.0%)
Breastfeeding duration		
Ever breastfed	2,334 (78.5%)	638 (21.5%)
Never breastfed	93 (75.0%)	31(25.0%)
Still breastfeeding	5,435 (83.2%)	1,101 (16.8%)
Age in months		
< 6	1,675 (89.8%)	191 (10.2%)
6-11	1,716 (87.1%)	255 (12.9%)
12-23	2,558 (77.0%)	765 (23.0%)
24-35	1,913 (77.4%)	558 (22.6%)
36-47	1,609 (82.9%)	333 (17.1%)
48-59	1,275 (88.4%)	168 (11.6%)

Furthermore, socioeconomic factors such as wealth quintile and maternal education also appeared to influence stunting status significantly. Children from the poorest households had the highest prevalence of stunting at 25.7%, compared to only 8.0% among the richest households. Similarly, maternal education showed a gradient effect, with higher levels of education associated with lower stunting rates, as evidenced by the 21.6% stunting prevalence among children whose mothers had no education compared to only 8.7% among those whose mothers had higher education.

Additionally, the descriptive analysis revealed notable associations between stunting status and factors related to sanitation and hygiene. Children living in households with no toilet facility exhibited a higher prevalence of stunting (25.4%) compared to those with improved toilet facilities (13.7%), suggesting a potential link between sanitation practices and stunting outcomes. Moreover, disparities in stunting prevalence were observed based on the sex of the child, with males exhibiting a higher prevalence (20.0%) compared to females (14.8%). This gender disparity in stunting rates warrants further investigation to understand the underlying factors contributing to differential outcomes between male and female children.

Age group emerged as another significant factor influencing stunting status, with varying prevalence rates across different age groups. Children aged 0-5 years had the highest prevalence of stunting, with 10.2% classified as stunted, whereas older age groups exhibited decreasing prevalence rates, with children aged 6-11 years showing a stunting prevalence of 12.9%. This age-related trend underscores the importance of early childhood interventions to prevent and address stunting, as well as the need for targeted strategies to address stunting among older children. Figure 1 shows the prevalence of childhood stunting across the 47 counties as estimated from the data set.

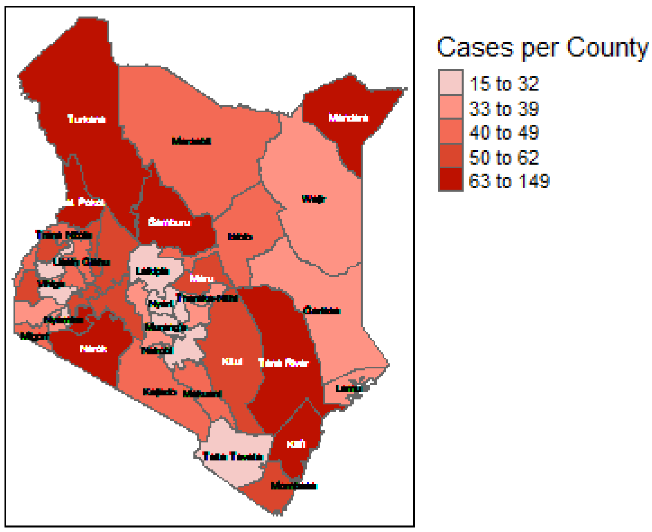

Figure 1. *Stunting prevalence across counties in Kenya.*

Regional disparities in stunting prevalence were evident, with considerable variation observed across different counties shedding light on areas with particularly high burdens of stunting. The prevalence rates ranged from a minimum of 8.2% to a maximum of 35% with about a third of the counties exhibuting stunting rates above the national average. Regions such as Kilifi , West Pokot and Samburu emerged as areas with notably high stunting prevalence rates, with 35% , 32% and 30% of children classified as stunted, respectively. Conversely, Murang'a and Kisumu exhibited comparatively lower stunting prevalence rates of (8.2%) and (8.9%) respectively. Overall, stunting prevalence varies not only between rural and urban areas but also within regions.

3.2. Multilevel Modeling Results

Table 2 shows results from a multilevel logistic regression analysis, it summarizes the adjusted odds ratios (aOR), 95% confidence intervals (CI), and corresponding p-values for the examined variables. The model incorporates a random intercept for county to account for regional variations. The results indicated the following;

Table 2. *Multilevel mixed effects model logistic regression results of stunting status.*

Variable	Adjusted odds ratio (aOR)	(95% CI)	P-value
(Intercept)	0.10	(0.07 - 0.14)	0.00
Residence			
Rural (RC)	1.00	-	-
Urban	1.25	(1.03 - 1.51)	0.02
Wealth Index of households			
Poorest (RC)	1.00	-	-
Poorer	0.74	(0.60 -0.90)	0.00
Middle	0.57	(0.45 - 0.71)	0.00
Richer	0.46	(0.35 -0.60)	0.00
Richest	0.29	(0.20-0.42)	0.37
Mother's Education level			
No Education (RC)	1.00	-	-
Primary	1.23	(0.97-1.55)	0.09
Secondary	1.32	(1.01-1.72)	0.04
Higher	1.17	(0.82-1.66)	0.39
Father's Education level			
No Education (RC)	1.00	-	-
Primary	0.91	(0.72-1.15)	0.41
Secondary	0.84	(0.64 -1.08)	0.18
Higher	0.65	(0.47 -0.90)	0.01
Breastfeeding duration			
Never breastfed (RC)	1.00	-	-
Ever breastfed	0.68	(0.42-1.11)	0.12
Still breastfeeding	0.80	(0.49 -1.30)	0.36
Toilet Facility			
No facility (RC)	1.00	-	-
Unimproved	1.07	(0.86-1.34)	0.53
Improved	1.02	(0.88 - 1.19)	0.75
Drinking water supply			
Unimproved (RC)	1.00	-	-
Improved	1.07	(0.86-1.34)	0.53
Gender of the child			
Female (RC)	1.00	-	-
Male	1.50	(1.33 - 1.70)	0.00
Age Group			
<6 (RC)	1.00	-	-
6-11	1.30	(1.06 - 1.59)	0.01
12-23	2.65	(2.23 -3.14)	0.00
24-35	2.60	(2.17 -3.10)	0.00
36-47	1.88	(1.55 - 2.28)	0.00
48-59	1.19	(0.95 -1.49)	0.12

Regarding the residence type, urban residence exhibited a significantly increased odds of stunting compared to rural areas (aOR = 1.25, 95% CI: 1.03 - 1.51, p = 0.02), suggesting that children residing in urban settings are more likely to experience stunting. Socio-economic status, as measured by household wealth index, demonstrated a pronounced effect on stunting prevalence. Children from households categorized as poorer, middle, richer, and richest all exhibited significantly reduced odds of stunting compared to those from the poorest households.

Maternal education level also emerged as a significant predictor of stunting, with children whose mothers had attained secondary education exhibiting higher odds of stunting compared to those with no education (aOR = 1.32, 95% CI: 1.01 - 1.72, p = 0.04). In contrast, paternal education level showed a protective effect against stunting, with children whose fathers had attained higher education demonstrating significantly lower odds of stunting (aOR = 0.65, 95% CI: 0.47 - 0.90, p = 0.01).

Furthermore, gender disparities were evident, with male children showing significantly higher odds of stunting compared to females (aOR = 1.50, 95% CI: 1.33 - 1.70, $p < 0.001$). Age group also exerted a notable influence on stunting prevalence, with children aged 12-23 months exhibiting the highest odds of stunting (aOR = 2.65, 95% CI: 2.23 - 3.14, $p < 0.001$) compared to the reference group (children aged $<$6 months). Breastfeeding duration, type of toilet facility and drinking water supply showed no significant association with stunting prevalence. Children from households with unimproved toilet facilities or unimproved drinking water supply did not demonstrate significantly different odds of stunting compared to those with improved facilities ($p > 0.05$).

3.3. Spatial Regression Modeling Results

The study employs spatial regression techniques to investigate the spatial distribution of stunting in Kenya and identify the underlying factors contributing to spatial disparities in stunting prevalence. This section presents the results from the descriptive analysis, spatial auto correlation tests and spatial regression models. Table 3 presents a summary of the predictors considered in the spatial models. It gives mean, standard deviation ,minimum and maximum of the examined variables.

Table 3. *Summary of study variables for spatial modeling.*

Predictor variables	Mean	SD	Min	Max
Stunting(%)	16.96	5.65	8.15	35.32
Uneducated mothers(%)	15.37	25.86	0.00	88.46
Poorest and poorer households(%)	26.17	21.52	0.00	75.24
Mean aridity	27.89	11.47	6.51	48.20
Mean temperature	22.10	3.51	16.10	28.90
Mean rainfall	1400.60	596.40	359.40	2507.80
Mean diurnal temperature	12.23	1.84	6.88	14.46

The variables presented in table 3 are applied to analyse spatial dependency in stunting across counties in Kenya. In particular, the percentage of stunted chidren in each county is regressed against the percentage of poor and poorest households, percentage of uneducated mothers, mean annual rainfall, mean annual temperature, mean annual aridity and mean diurnal temperature. The results for the non-spatial (OLS) regression are presented in table 4. The model shows that the percentage of poor households, mean annual aridity,mean temperature and mean rainfall are significantly related with stunting.

Table 4. *Results for the non-spatial (OLS) regression model.*

Variable	Coefficient	Std. Error	P-value
Uneducated mothers(%)	-0.0440	0.0226	0.0517
Poorest and poorer households(%)	0.1840	0.0161	0.0000
Mean aridity	-0.2661	0.0909	0.0035
Mean temperature	-0.8885	0.2234	0.0000
Mean rainfall	0.0038	0.0013	0.0040
Mean diurnal temperature	-0.2424	0.2584	0.3485
R squared : 0.0907	Adj-R squared :	0.0875	AIC : 13985

Table 5. *Global Moran's I for the non-spatial (OLS) regression.*

Metric	Value
Moran's Index	0.0380
Expected Index	-0.0032
Variance	0.0001
z-score	4.349
p-value	0.0000

The results for the Global Moran I for regression residuals of the non-spatial model are given in table 5. The results (pvalue < 0.05) show that residuals are not independent and randomly distributed in the study area indicating the presence of spatial autocorrelation.

The results for the spatial error model are presented in the table 6. The results indicate that the percentage of poorest and poor households, mean annual aridity, mean annual temperature and mean annual rainfall are significantly related to the percentage of stunted children. The estimated lag error parameter is $\lambda = 0.23109$ and is statistically significant as indicated by the LR test, Z-test, and the Wald test ($p < 0.05$). The lag on the error is significant pointing out the need to control for the presence of spatial autocorrelation in the errors.

Table 6. *Results for the Spatial Error Model (SEM) regression model.*

Variable	Coefficient	Std. Error	P-value
Uneducated mothers(%)	-0.0146	0.0245	0.5508
Poorest and poorer households(%)	0.1711	0.0167	0.0000
Mean aridity	-0.2690	0.1091	0.0137
Mean temperature	-0.9987	0.2708	0.0002
Mean rainfall	0.0044	0.0015	0.0043
Mean diurnal temperature	-0.3934	0.3223	0.2222
AIC=13972			

The results for the spatial lag model (SLM) that accounts for the spatial dependence in the response variable (percentage of stunted children) across the region is presented in table 7 displayed below.

Table 7. *Results for the Spatial Lag Model (SLM) regression model.*

Variable	Coefficient	Std. Error	P-value
Uneducated mothers(%)	-0.0333	0.0224	0.1372
Poorest and poorer households(%)	0.1682	0.0161	0.0000
Mean aridity	-0.2289	0.0905	0.0114
Mean temperature	-0.8390	0.2228	0.0002
Mean rainfall	0.0036	0.0013	0.0060
Mean diurnal temperature	-0.3629	0.2561	0.1565
AIC=13970			

The results from the SLM model show that the percentage of poor households, mean annual aridity, mean annual temperature and mean annual rainfall have a significant effect on the percentage of stunted children. The estimated spatial lag parameter captures the influence of the percentage of stunted children in neighboring regions as defined by the spatial weighting matrix. The estimated coefficient $\rho = 0.2239$ is positive and statistically significant as indicated by the LR test, Z-test, and the Wald test ($p < 0.05$). These findings indicate that when the percentage of stunted children in surrounding regions increase, on average, the percentage in each region also increases, even after adjusting for other covariates in the model. The LM test detects whether spatial autocorrelation is present in the residual. The test value is 0.0185 and $p = 0.8917$ indicating that the model is better than the non-spatial OLS regression model in terms of accounting for spatial auto correlation. Estimates of the total and direct, indirect and total effect of each of the explanatory variables is shown in table:

Table 8. *Estimates for the direct, indirect, and total effect of the variables.*

Variable	Direct	Indirect	Total
Uneducated mothers(%)	-0.0334	-0.0095	-0.0429
Poorest and poorer households(%)	0.1689	0.0478	0.2167
Mean aridity	-0.2298	-0.0651	-0.2949
Mean temperature	-0.8425	-0.2386	-1.0811
Mean rainfall	0.0036	0.0010	0.0046
Mean diurnal temperature	-0.3644	-0.1032	-0.4676

A comparison of the three spatial regression models based on the model diagnostic criteria shows that non-spatial model (AIC=13985), spatial error model (AIC=13972) and spatial lag model (AIC = 13970). The analysis suggests that the spatial lag model is a better fit than alternative models. This indicates that the percentage of stunted children under five in a particular area is spatially dependent, meaning it's influenced by the prevalence of stunting in neighboring areas. More specifically, if the cases in the neighboring areas increase then the cases in that area also increase.

3.4. Geographically Weighted Regression Results

The study employs GWR to investigate the spatial patterns of stunting prevalence in Kenya and identify the geographical determinants driving spatial disparities in stunting outcomes. The aim is to uncover spatially varying relationships between predictors and stunting prevalence across different regions of Kenya. Figures 2-5 present the spatial heterogeneity in the effect of climatic variables on stunting prevalence. The findings reveal that the association between climatic conditions and childhood stunting varies across counties. A different pattern is observed for each of the four factors evidenced by varying color shade distribution in the maps. Specifically, maps of the regression coefficients for mean annual aridity, mean annual diurnal temperature, mean annual temperature and mean annual rainfall show areas with darker shades have a stronger positive association between these environmental variables and childhood stunting. This means counties in these areas may be more susceptible to the negative effects of of climatic variables on stunting rates. In contrast, areas with lighter shades may have a weaker association or even a negative association between climatic factors and stunting. The maps for socio-economic factors shows that poverty has a stronger influence on stunting in regions located in the lower part compared to upper regions. It is also observed that in some regions there is positive association between childhood stunting in some regions while in others a negative association is revealed.

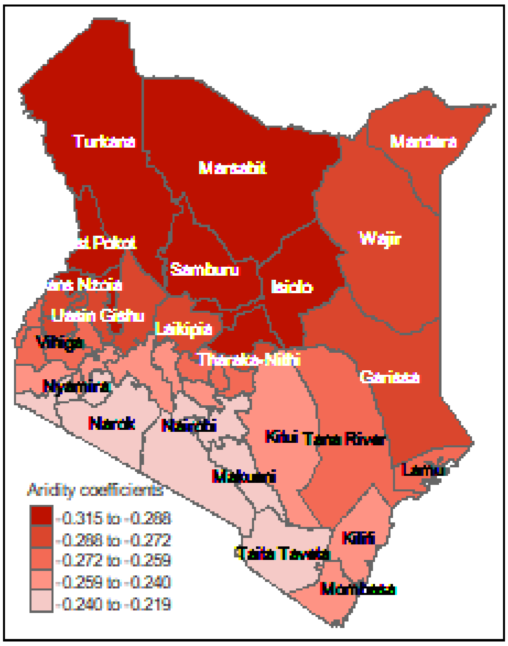

Figure 2. Spatial distribution of GWR local estimates for mean annual aridity.

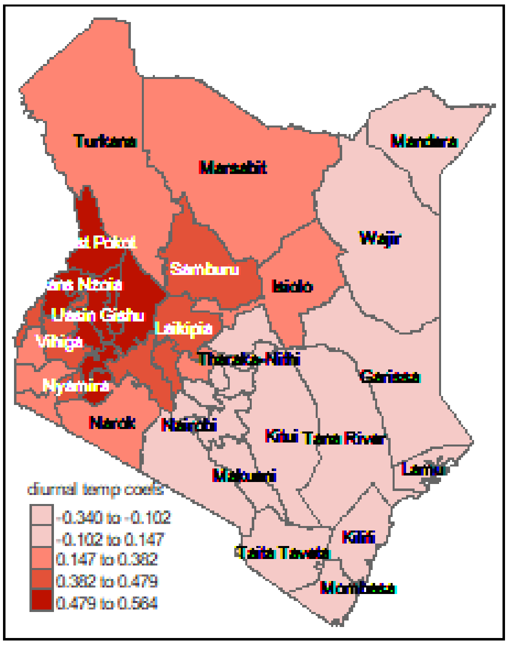

Figure 3. *Spatial distribution of GWR local estimates for mean annual diurnal temperature.*

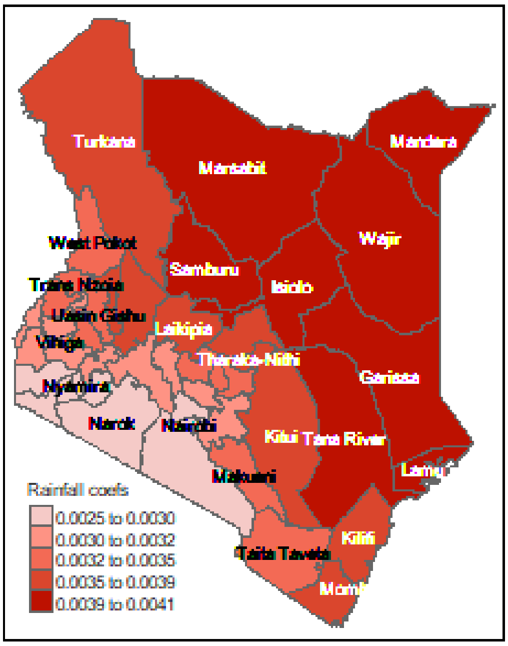

Figure 4. *Spatial distribution of GWR local estimates for mean annual rainfall.*

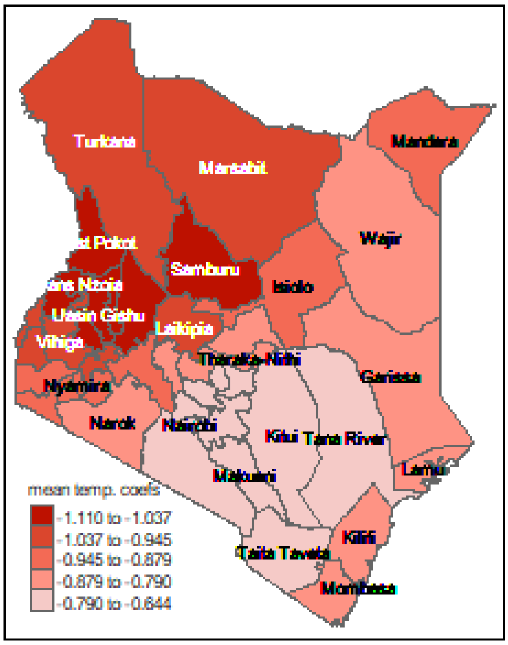

Figure 5. *Spatial distribution of GWR local estimates for mean annual temperature.*

Figures 6 and 7 present the spatial variability of the association between socio-economic characteristics and stunting across the counties. As it can be observed the percentage of poor and poorer households and uneducated mothers have a varying effect on the percentage of stunted children.

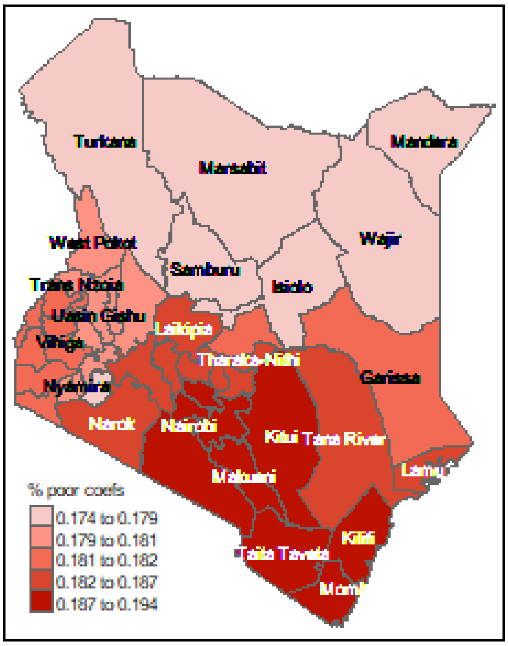

Figure 6. *Spatial distribution of GWR local estimates for % of poor households.*

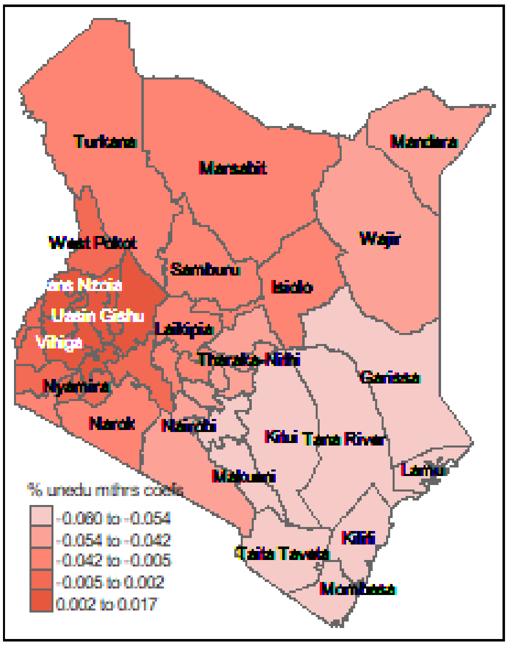

Figure 7. *Spatial distribution of GWR local estimates for% of uneducated mothers (right).*

4. Discussion

The multilevel logistic regression analysis was conducted to explore individual, household and community-level factors associated with childhood stunting in Kenya. The analysis revealed several key findings. Children residing in urban areas were more likely to be stunted compared to their rural counterparts. Socioeconomic status, as measured by household wealth index, emerged as a critical determinant. Children from wealthier households had a significantly lower risk of stunting, highlighting the importance of economic well-being in ensuring child health. Parental education also played a significant role. While mothers with secondary education showed a slightly increased risk of having a stunted child compared to those with no education, fathers with higher education levels had children with a lower risk of stunting.Furthermore, the analysis indicated a gender effect, with male children being more likely to be stunted compared to females. Age was another significant factor, with children aged 12-23 months exhibiting the highest odds of stunting. Notably, breastfeeding duration, type of toilet facility, and drinking water source were not significantly associated with stunting prevalence.

Previous research has explored the link between climatic factors and childhood malnutrition. However, these studies often employ methodologies that fail to capture the nuanced spatial aspects of this relationship. The analysis of spatial dependency through spatial regression models revealed significant spatial autocorrelation in the data, indicating that the prevalence of stunting in one county is not independent of the prevalence in neighboring counties. A global Moran's I test confirmed this spatial dependence. To account for this spatial effect, two spatial regression models, the spatial error model (SEM) and the spatial lag model (SLM), were employed. Both models yielded similar results regarding the significant relationships between stunting and socioeconomic factors (percentage of poor households), climatic factors (mean annual aridity, mean annual temperature, and mean annual rainfall), but the SLM provided a better fit based on the AIC criteria. Geographically weighted regression. The results underscore the profound impact climate change has on the health and well-being of vulnerable populations

Geographically weighted regression revealed significant non-stationarity in the relationship between stunting and county level socioeconomic and climatic factors. The analysis reveals a positive correlation between mean annual aridity and the percentage of stunted children across counties. Counties with higher aridity are observed to have a greater prevalence of stunting. A negative association emerges between county-level stunting rates and mean annual rainfall. Counties receiving less rainfall exhibit a higher prevalence of stunted children. The results for mean annual and diurnal temperature reveal complex spatial pattern in the association with positive and negative association observed across the regions. The impact of poverty on stunting appears to be more pronounced in southern counties compared to their northern counterparts. Further, the percentage of uneducated mothers is negatively correlated to stunting prevalence in a majority of the counties.

5. Conclusions and Recommendations

Overall, socioeconomic status, parental education, and child gender were identified as key determinants. The spatial analysis revealed a spatial dependence in stunting prevalence, emphasizing the need for geographically targeted interventions. Based on these findings, several recommendations can be made : Implementing programs aimed at improving socioeconomic status in areas with high stunting prevalence is crucial.Promoting the importance of education, particularly for mothers and fathers, can improve child health outcomes. Focusing on early identification and intervention for children aged 12-23 months, who are at a higher risk of stunting, is essential.

Given the spatial dependence of stunting prevalence, it is crucial to design geographically targeted interventions. Areas with high stunting rates, particularly those surrounded by counties with similar challenges, should be prioritized for resource allocation and program implementation. These interventions may address socioeconomic factors by promoting programs that alleviate poverty, environmental factors by focusing on improving agricultural productivity in arid regions, and may target broader community-level factors that influence health outcomes for children under five. In addition to geographically targeted interventions, further research is needed to explore the mechanisms underlying the spatial dependence of stunting to inform more effective strategies for addressing this public health challenge. There is a potential for future research to integrate important environmental factors such as soil type, local vegetation, and food production systems into the analysis. These factors are likely to influence food insecurity and childhood malnutrition rates. By incorporating these environmental elements, researchers can develop more comprehensive models that account for the complex interplay of various contributing factors. Further studies could explore how childhood malnutrition varies geographically and over time. This longitudinal approach would provide valuable insights into the relationship between childhood malnutrition and environmental, climatic, child-related, parental, and household-level factors. This could involve analyzing data across different regions and tracking changes in malnutrition rates over time.

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Conflicts of Interest

The authors declare no conflicts of interest.

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