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Spatial analysis of under-five mortality in Africa using geographically weighted poisson regression

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Abstract

Child mortality remains a significant public health challenge in developing countries despite the global decline in under-five deaths. The disparities in child mortality rates can be attributed to socioeconomic and environmental inequalities across nations. While several studies have examined geographic variations in under-five mortality in Africa using economic and health indicators, few have applied spatial analysis to characterize these patterns. This study employs Geographically Weighted Poisson Regression (GWPR) to uncover spatially varying in effects of global indicators on under-five mortality across Africa, offering a detailed understanding not captured by conventional global models. Data on under-five mortality rates and economic and health indicators were obtained from the World Bank's World Development Indicators (WDI) for 2022 across 54 African countries. A Poisson regression model and GWPR were applied to examine the associations between under-five mortality and various socioeconomic and environmental factors. The results indicate substantial spatial heterogeneity in child mortality across countries. The GWPR model (AICc = 221.25, Pseudo R^2 = 86.5%) outperformed the conventional Poisson regression model (AICc = 360.733, Pseudo R^2 = 58.4%), highlighting the benefits of incorporating spatial variability. Key findings revealed that under-five mortality was positively associated with open defecation and negatively associated with literacy, health expenditure, access to electricity, and basic sanitation. Additionally, the relationship between under-five mortality, gross national expenditure, and access to basic drinking water varied across regions. These findings emphasize the need for localized, evidence-based interventions to address child mortality more effectively in Africa.

Keywords Under-five mortality, Geographically weighted Poisson regression, Spatial variation, Africa

1 Introduction

Globally, the United Nations Sustainable Development Goals (SDG), through goal 3, aim to prevent the deaths of newborns and children under 5 years old by 2030. Significant progress has been made in child survival over the past three decades. The worldwide

under-five mortality rate decreased by 60%, from 93 deaths per 1000 live births in 1990 to 37 in 2022 [21, 78, 83]. Despite this improvement, increasing child survival remains a critical priority, especially in low- and middle-income nations, where the majority of the 4.9 million under-five deaths in 2022 occurred [77].

Spatial inequalities in health are strongly linked to social determinants of health, including the unequal distribution of social, economic, and environmental factors [5, 9]. Infectious diseases, preterm birth complications, and issues from the postpartum period remain the leading causes of under-five mortality [36]. Socioeconomic determinants such as postnatal care, illiteracy, nutrition, delivery location, access to clean water and sanitation, skilled birth attendance, and hygiene practices significantly influence child survival [85]. Variations in these household, ecological, wellness, and socioeconomic factors contribute to differing under-five mortality rates across countries [12, 26]. Environmental factors, including lack of access to basic sanitation and clean water, also play a crucial role, accounting for a significant proportion of childhood infections [3, 17, 67, 80, 84]. Climate change and extreme weather events, such as heat, have also been identified as contributors to early childhood deaths, particularly in Africa [17, 20, 45].

Without urgent action, 35 million under-five deaths are projected before 2030, hindering many low- and lower-middle-income countries from achieving SDG targets for child mortality [30]. SDG Goal 3 aims to reduce under-five mortality to at least 25 per 1000 live births in every country by 2030 [40, 71]. Recognizing the spatial heterogeneity of under-five mortality and its determinants is crucial for designing effective, localized interventions. To address this, this study employs Geographically Weighted Poisson Regression (GWPR), a spatial regression technique that accounts for spatial correlation, unlike traditional methods like ordinary least squares [28, 29, 82]. GWPR allows for coefficients to vary spatially, capturing localized relationships between under-five mortality and socioeconomic and health indicators. This approach helps identify high-risk areas and provides spatially targeted insights for policymakers to optimize resource allocation. While the link between economic and health indicators and under-five mortality is established, its spatial heterogeneity within the African context remains largely unexplored. Therefore, this study aims to use the GWPR model to investigate the spatial variations in the relationship between under-five mortality and economic and health indicators in Africa. Furthermore, we will identify areas with relatively high needs for economic and healthcare support through a clustering analysis based on the GWPR modeling results.

1.1 Evidence from literature

The burden of under-five mortality in Africa has been extensively studied, employing various analytical approaches to understand its prevalence and associated factors. This section reviews relevant literature, focusing on the methodological landscape and justifying the selection of Geographically Weighted Poisson Regression (GWPR) for this study.

Numerous studies have investigated the association between socio-demographic features and child mortality in Africa. The literature reveals a range of statistical methods and models used to analyze under-five mortality, including structural equation modeling [72], machine learning [2, 15, 48, 53, 57], regression methods [34, 68, 74], Mulagha-Maganga, [39], and geospatial analysis [60, 62, 81]. Spatial analysis techniques, such as

spatial clustering [51] and Bayesian and spatiotemporal modeling [5, 6, 25, 44], have also been applied to explore the geographical patterns of child mortality.

Traditional regression models, particularly generalized linear models (GLMs), are commonly used in health research [24, 59]. However, these global models assume a uniform relationship between the outcome and explanatory variables across the entire study area. This assumption may not hold in reality, as the association between under-five mortality and its determinants can vary significantly within a continent like Africa due to diverse socioeconomic, environmental, and healthcare contexts [87]. Ignoring such spatial non-stationarity can lead to biased parameter estimates and misleading policy recommendations.

To address the limitations of global models, spatial regression techniques have been developed. Among these, Geographically Weighted Regression (GWR) and its variant for count data, Geographically Weighted Poisson Regression (GWPR) [28], explicitly account for spatial heterogeneity. Unlike global models, GWPR allows the regression coefficients to vary geographically, providing a more nuanced understanding of local relationships between the dependent and independent variables. While other spatial methods like Bayesian hierarchical models can also account for spatial autocorrelation and heterogeneity, GWPR offers a direct and interpretable way to map the local variations in the relationships between under-five mortality and its drivers at the country level. This direct mapping capability is particularly valuable for identifying specific regions where certain economic and health indicators have a stronger or weaker association with child mortality. This localized insight is crucial for developing targeted interventions and allocating resources effectively to reduce under-five deaths and progress toward achieving SDG targets. The ability of GWPR to reveal the spatial non-stationarity of these relationships makes it a particularly suitable method for this study, which aims to understand the geographically varying impact of economic and health indicators on under-five mortality across Africa.

2 Materials and methods

2.1 Datasets

The data utilized for this study were curated from the World Bank's World Development Indicators (WDI). This data type contains statistical information on major global development indicators compiled from officially recognized international sources, including national statistics bureaus. The WDI data is available at national, regional, and global levels. The outcome of interest considered in this study was the under-five mortality rate per 1,000 live births. Using the available information from the literature, existing studies highlight an association between economic and health development and child health [5, 14, 41, 58]. As such, our study employed economic and health indicators from the World Bank as predictors of the under-five mortality rate per 1000 live births. To ensure consistency and comparability, we focused on data from 2022, as it is the most recent year with comprehensive and publicly available records for the selected indicators across multiple countries.

Based on the evidence from existing studies, we used nine major global development indicators as determinants or predictors of the under-five mortality rate per 1000 live births. The covariates used in this study are:

- Gross national expenditure as a percentage of GDP

- Percentage of out-of-pocket expenditure of current health expenditure
- Percentage of people using at least essential drinking water services
- Percentage of the population practicing open defecation
- Percentage of the population using at least essential sanitation services
- Mean annual $PM_{2.5}$ exposure in micrograms per cubic meter
- Literacy rate
- Percentage of the urban population
- Percentage of people with access to electricity

2.2 Statistical and computational analysis methods

In this study, Poisson regression and GWPR were used to model the connection between the under-five mortality rate and global development indicators. At first, we fitted a Poisson regression model, considering spatial autocorrelation, to estimate the overall association between the nine indicators and the under-five mortality rate in Africa. This approach allowed a global evaluation of the existence of associations and the directions between the various indicators considered in this study and the outcome of interest before proceeding to analyze the effect of the association at the country level. Besides, model assumptions were tested. The difference between a Poisson model and a Negative-Binomial (NB) model is that the NB model can deal with over-dispersion, which indicates that the variance exceeds the mean of the mortality rate. In the current study, there was no problem of overdispersion.

2.3 Model specification for GWPR and model selection

In a GWPR, the mortality rate counts are predicted by a set of explanatory variables, of which the parameters are allowed to vary over space. Spatial Poisson model, a special form of spatial count model, allows parameter values to vary with spatial units u_i which is a vector describing the location *i*. A spatial Poisson model can be formulated as

$$Y_i \sim \left[\exp\left(\sum_k \beta_k\left(u_i\right) x_{ik}\right)\right]$$

x_{ik} is the kth explanatory variable in location I, β_k is the parameter for the kth explanatory variable and $u_i = (ul_i, uh_i)$ denote the vector describing the longitude and latitude at location i. The model is defined with a geographically varying coefficient $\beta_k\left(u_i\right)$ that is a function of location u_i and known geographically weighted Poisson regression (GWPR). The covariate form of the model GWPR with a group of indicators, in which the parameters are permitted to vary spatially, can be written as

$$\begin{aligned}&\log\left(\eta\right) = \lambda_0\left(u_i\right) + \lambda_1\left(u_i\right)\left(GNE\right) + \lambda_2\left(u_i\right)\left(BS\right)\\&+\lambda_3\left(u_i\right)\left(BDW\right) + \lambda_4\left(u_i\right)\left(POD\right) + \lambda_5\left(u_i\right)\left(UP\right)\\&+\lambda_6\left(u_i\right)\left(AE\right) + \lambda_7\left(u_i\right)\left(LT\right) + \lambda_8\left(u_i\right)\left(HE\right)\\&+\lambda_9\left(u_i\right)\left(PM2.5\right)\end{aligned}$$

where BS: percentage of population using at least basic sanitation services; BDW: percentage of people using at least basic drinking water services; POD: percentage of the population practicing open defecation; UP: percentage of urban population; AE: access to electricity (% of population); LT: literacy; HE: percentage of out-of-pocket expenditure

out of current health expenditure, and mean annual PM2.5 exposure in micrograms per cubic meter. We note that $\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6, \lambda_7, \lambda_8, \lambda_9$ are functions of the location, and it implies that the parameter $\lambda = (\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6, \lambda_7, \lambda_8, \lambda_9)$ may vary between countries. Therefore, in the GWPR modeling approach, spatial heterogeneity is considered, and the parameter λ can be expressed in matrix form

$$\begin{bmatrix} \lambda_0(u_{x1}, u_{\eta i})\, \lambda_2(u_{x1}, u_{\eta 1}) \ldots\ldots, \lambda_9(u_{x1}, u_{\eta 1}) \\ \lambda_0(u_{x2}, u_{\eta 2})\, \lambda_2(u_{x2}, u_{\eta 2}) \ldots\ldots, \lambda_9(u_{x2}, u_{\eta 2}) \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \lambda_0(u_{xn}, u_{\eta n})\, \lambda_2(u_{xn}, u_{\eta n}) \ldots\ldots, \lambda_9(u_{xn}, u_{\eta n}) \end{bmatrix}$$

In the matrix represented above, n represents the number of countries. The parameters for each country, which form a line in the matrix, were estimated by Fotheringham et al. [32].

$$\hat{\lambda}(i) = \left(X^T W(u_{xi,\eta i})\, X\right)^{-1} X^T W(u_{xi,\eta i})\, Y$$

In the above representation, $W(u_{xi,\eta i})$ refer to a spatial weight matrix, representing an $n \times n$ diagonal spatial weighting matrix for regression point *i* is defined as:

$$\mathrm{W}(i) = \begin{bmatrix} w_{i1} & 0 & \cdots & 0 \\ 0 & w_{i2} & \cdots & 0 \\ \cdots & \cdots & \ddots & \cdots \\ 0 & \cdots & \cdots & w_{in} \end{bmatrix}$$

where $w_{ij}\ (j = 1, 2, 3, \ldots\ldots 54)$ is the weight given to country *j* in the model adjustment for country *i*. In this model, our regression equation was estimated for each country based on observations in neighboring countries. The estimation process was repeated for all the countries, and each country was weighted by its distance from the regression point. Several spatial kernel functions can be used to determine the spatial weights described above [28]. In this study, the Bi-square adaptive kernel function was adopted to compute spatial weights, and it is defined as.

$$w_{ij} = \begin{cases} \left[1 - \left(\frac{d_{ij}}{h}\right)^2\right]^2, & \text{for } d_{ij} < h \\ 0, & \text{otherwise} \end{cases}$$

where d_{ij} represents the Euclidean distance between the i^{th} regression point and the data point at j^{th} location, while *h* represents the bandwidth size that controls the neighborhood to be captured by the kernel at any local regression point. Besides, the Bi-square adaptive kernel was adopted because it allows the calibration of the local models to change according to the density of the data at the regression point [52]. To compare and evaluate the GWPR model performance with the kernel weighting functions, we have used two most common methods of model evaluation: Akaike information criterion (AIC) [63] and corrected Akaike information criterion (AICc), meaning that the optimal bandwidth size was decided for the model calibration based on AIC and AICc. The AIC function for a model with bandwidth *q* is formulated as

$$AIC = D(q) + 2P(q)$$

where D is the deviance of the model, P is the effective number of parameters in the model, and q is the bandwidth used in the kernel weighting function for the model. A

model with a minimum AIC value has a higher goodness of fit [10]. However, in the case of a local spatial regression model with a small degree of freedom, a bias adjustment in the AIC is introduced [10]. The Akaike information criterion with bias correction (AICc) can then be defined as

$$AICc = D(q) + 2\left(P(q) + \frac{P(q)P(q)+1}{N - P(q) - 1}\right)$$

where N is the number of spatial observations. The most suitable would be the one with the lowest values of the Akaike information criterion (AIC) and corrected Akaike information criterion (AICc).

2.4 Model validation and software

Model validation was achieved through Akaike Information Criterion (AIC) and Corrected Akaike Information Criterion (AICc), which were used to select the optimal bandwidth size for spatial weighting. The model with the lowest AIC and AICc values was considered the most suitable, ensuring a balance between goodness-of-fit and complexity. To address spatial heterogeneity, the Bi-square adaptive kernel function was employed, allowing the model calibration to vary based on data density at each regression point. This ensured that local variations in under-five mortality rates were effectively captured. Additionally, the GWPR model estimated regression parameters separately for each country by weighting neighboring observations, reducing the risk of bias from assuming uniform relationships across the study region. For model integration, each variable's effect was assessed locally, allowing spatial patterns to emerge rather than relying on a single global relationship. The spatial weight matrix accounted for country-specific differences by assigning greater influence on nearby observations, refining mortality predictions. The model's robustness was further supported by testing different spatial weighting functions, confirming that the Bi-square adaptive kernel function provided the best balance between local adaptability and predictive stability. By incorporating these validation steps, the GWPR model effectively addressed spatial variability, ensuring a more precise understanding of the relationship between under-five mortality and environmental and socio-economic factors across different countries. There are several tools and software that can be implemented to model and analyze this type of study. The open-source software R has been extensively used as a sophisticated tool to fit models and analyze data in many areas. We have implemented the R software in our model framework to perform the spatial analysis and fit the geographically weighted Poisson regression models.

3 Results and discussion

3.1 Results

3.1.1 Descriptive statistics

Table 1 presents the descriptive statistics of the under-five mortality rate and the global development indicators for the fifty-four African countries in the current study period. Within the study period, a minimum of 10 and a maximum of 117 mortalities were recorded across fifty-four countries. Based on our findings, on average, about 55 children were lost due to mortality in the context of the year under investigation. The

Table 1 Statistical description of the under-five mortality and global development indicators

Indicators	Number of countries	Minimum	Maximum	Mean (SD)	Median
Under-five mortality	54	10	117	55.15(28.32)	49.00
Gross National Expenditure	54	55.22	151.20	106.39(16.05	107.72
Basic Sanitation (%)	54	9.34	100	47.22(28.09)	41.85
Basic Drinking Water Services (%)	54	35.12	100	72.70(17.70)	71.87
Practicing Open Defecation (%)	54	0.01	64.98	17.28(16.49)	15.98
Urban Population (%)	54	14.42	90.74	47.73(18.89)	45.59
Access to Electricity (%)	54	8.40	100	57.83(26.53)	55.80
Literacy	54	18.97	91.19	64.16(21.35)	69.44
Health expenditure	54	17.64	718.49	131.34(156.85)	66.49
$PM_{2.5}$	54	14.91	80.11	40.75(16.62)	37.15

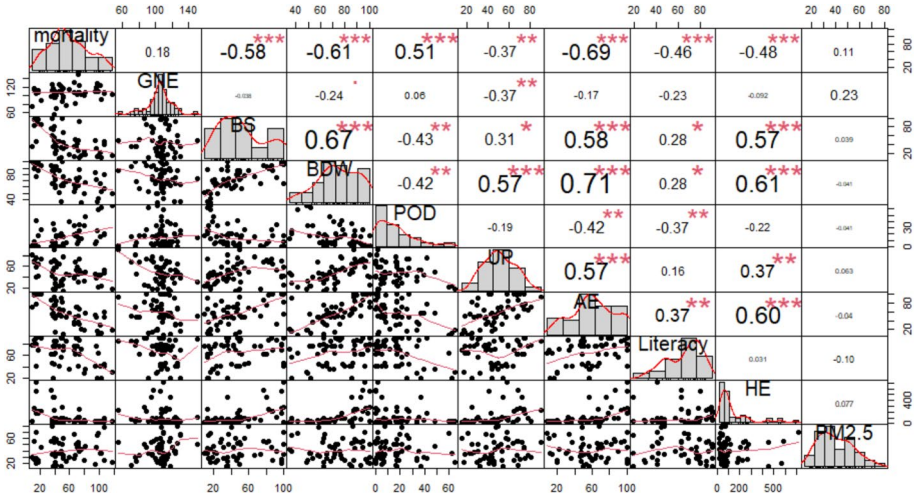

Fig. 1 Scatter matrix plot showing the distribution of global development indicators in Africa

standard deviation of the under-five mortality was moderately high, suggesting moderate disparities in the under-five mortality rate across the continent.

Additionally, we examined the distribution of all the global development indicators as displayed in Fig. 1. The distribution of each indicator is shown on the diagonal, while at the bottom of the diagonal, the bivariate scatter plots with a fitted line are displayed. It was revealed that most of the indicators were positively skewed (Fig. 1). The under-five mortality was negatively correlated with all the global development indicators except the percentage of the population practicing open defecation, mean annual $PM_{2.5}$ exposure in micrograms per cubic meter, and gross national expenditure, which were positively related to the under-five mortality.

Furthermore, the spatial map of under-five mortality suggests that the mortality was highly concentrated in the eastern, northern, and southern parts of the subregion (Fig. 2).

3.2 Summary of parameters in the Poisson regression model calibration

To begin the model calibration, we first explored the under-five mortality and the relationship between the global development indicators through the conventional Poisson regression model. We presented the estimated parameters and the associated *p*-values of the conventional Poisson regression model in Table 2. Findings from this model

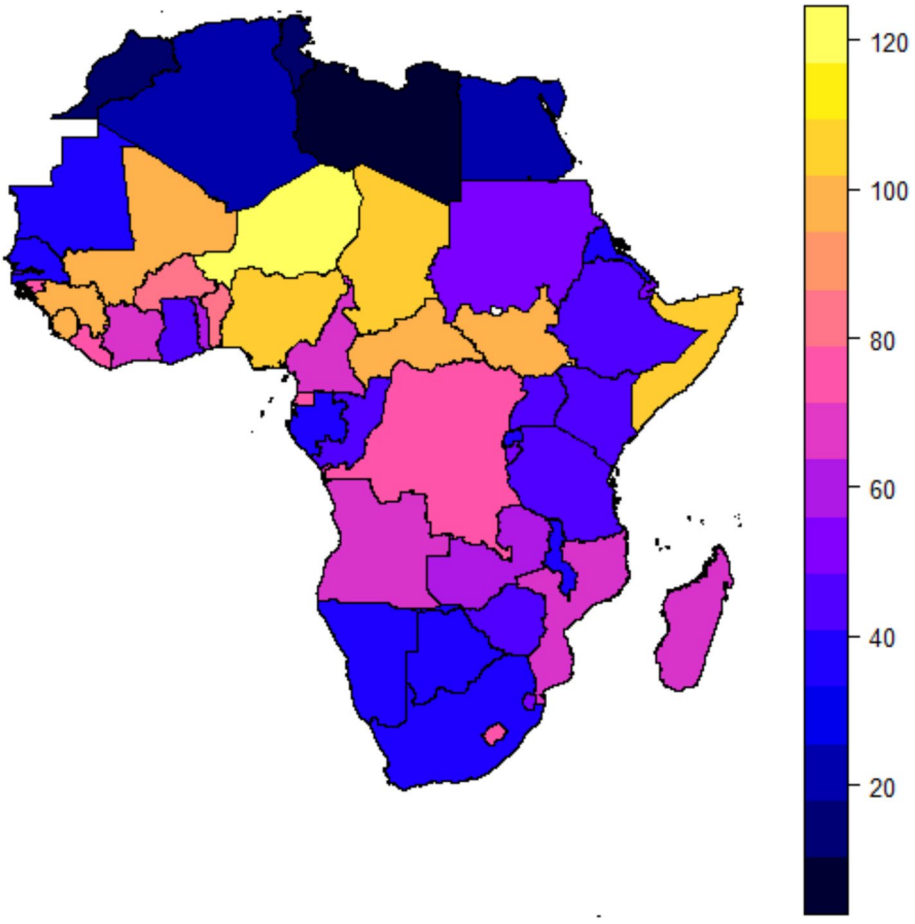

Fig. 2 Spatial distribution of under-five mortality in the African subregion

established that all the development indicators were highly statistically significant, except GNE, BDW, urban population, and $PM_{2.5}$, which were not significant at a 5% alpha level. Furthermore, these results show that constant parameters constitute a significant proportion of causing under-five mortality measured (3.926). In addition, among the significant indicators, we observed that access to basic sanitation, access to electricity, literacy, and current health expenditures were associated with a reduction in under-five mortality, while people practicing open defecation led to an increase in under-five mortality. The rate ratio of under-five mortality prevalence was expected to decrease by a factor of 0.892, 0.995, 0.831, 0.924, and 0.877 for a unit increase in basic sanitation, basic drinking water, access to electricity, literacy, and health expenditure, respectively, while holding all other variables constant. On the other hand, the rate ratio of under-five mortality prevalence was expected to increase by a factor of 1.038, 1.066, 1.039, and 1.033 for a unit increase in gross national expenditure, practicing open defecation, urban population, and $PM_{2.5,}$ while holding all the variables constant.

3.3 Summary of local parameters in the GWPR model estimation

Table 3 presents a summary of the parameter estimates in the GWRPmodel. The local parameters are described by the five indicators statistically. These are the minimum, first quartile, median, third quartile, and maximum values. The distributions of the parameters of the predictive variables over the 54 countries of Africa are shown in Fig. 3; the

Table 2 Summary of parameters in the Poisson regression model

Indicators	Estimates	Standard Error	z-values	IRR	P-values
Constant	3.926	0.020	196.776	50.704	**< 0.001**
GNE	0.037	0.022	1.646	1.038	0.099
BS	− 0.114	0.029	− 3.825	0.892	**0.0001**
BDW	− 0.005	0.032	− 0.143	0.995	0.886
POD	0.064	0.021	3.113	1.066	**0.002**
Urban population	0.039	0.027	1.428	1.039	0.153
Access to electricity	− 0.185	0.032	− 5.767	0.831	**< 0.001**
Literacy	− 0.079	0.021	− 3.786	0.924	**0.0002**
$PM_{2.5}$	0.032	0.020	1.593	1.033	0.111
Health expenditure	− 0.131	0.033	− 3.994	0.877	**< 0.001**
Model fit					
AIC	355.620				
AICc	360.733				
Pseudo R^2	58.4%				
Model diagnostics for spatial dependence					
Spatial autocorrelation of residuals (Moran's I)	0.314, p-value = 0.00043				

Table 3 Summary of the estimated parameters from the GWPR model

Indicators	Minimum	Lower quartile	Median	Upper quartile	Maximum
Constant	3.816	**3.954**	**3.998**	**4.041**	4.213
GNE	-0.092	-0.016	0.021	0.050	0.204
BS	-0.264	**-0.200**	**-0.097**	**-0.048**	0.017
BDW	-0.192	-0.035	0.009	0.060	0.107
POD	-0.077	-0.44	0.049	0.124	0.173
Urban population	-0.196	-0.123	0.033	0.107	0.128
Access to electricity	-0.316	**-0.192**	**-0.041**	**-0.022**	0.058
Literacy	-0.223	-0.119	-0.025	0.026	0.096
$PM_{2.5}$	-0.109	-0.-083	0.052	0.128	0.180
Health expenditure	-0.282	**-0.238**	**-0.190**	**-0.131**	0.091
Model fit					
AIC	163.063				
AICc	221.250				
Pseudo R^2	86.5%				

red color on the map indicates a higher value of a local parameter estimate. The parameters show clear patterns of spatial variation. The maps indicate that the nine parameter estimates are not equal for all locations. In addition, following the specification of the traditional Poisson regression model, the GWPR model was calibrated to explore the impact of the global development indicators on under-five mortality, while accounting for the spatial heterogeneity of the relationship. The goodness-of-fit statistics of the GWPR model suggest that the model improves on the results of the conventional Poisson regression model, as indicated by the AICc and pseudo R^2 from the model (Table 3). The estimates of GWPR model parameters associated with all the global development indicators varied from negative to positive, suggesting that the direction of the relationships between the under-five mortality and the global development indicators is heterogeneous across the fifty-four countries of Africa. Based on this observation, we can

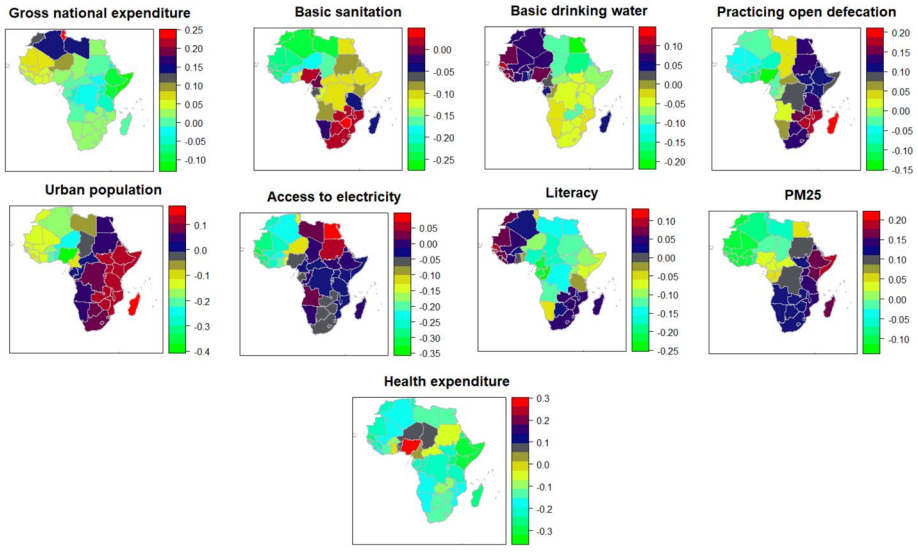

Fig. 3 Spatial map showing the distribution of the estimated GWRP model coefficients associated with the indicators variables

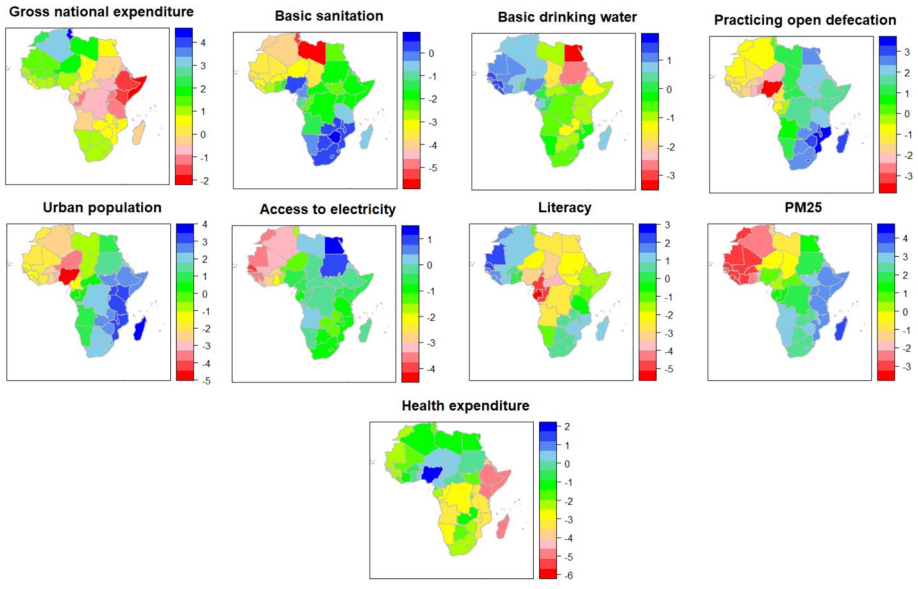

Fig.4 Spatial map showing the distribution of the *t*-values associated with the GWRP model coefficients

conclude that the single estimate as reported from the conventional Poisson regression model to describe such a relationship may be either biased or misleading.

Figures 3 and 4 show maps of the local parameter estimated (Fig. 3), and the statistically significant at $P < 0.05$ (Fig. 4), which means the t-values between -1.96 and + 1.96 are statistically not significant. The color code for the local parameter (Fig. 3) indicates the estimated risk level for under-five mortality, where the high risk is represented by red and decreases towards green. Meanwhile, the color code for the t-value (Fig. 4) indicates that only red and green colors are statistically significant and valid for this study. The relationships between socioeconomic variables and mortality were statistically significant in most of the locations (Fig. 3). The effects of different indicators vary over the regions in Africa. For instance, the gross national expenditure, urban population, and

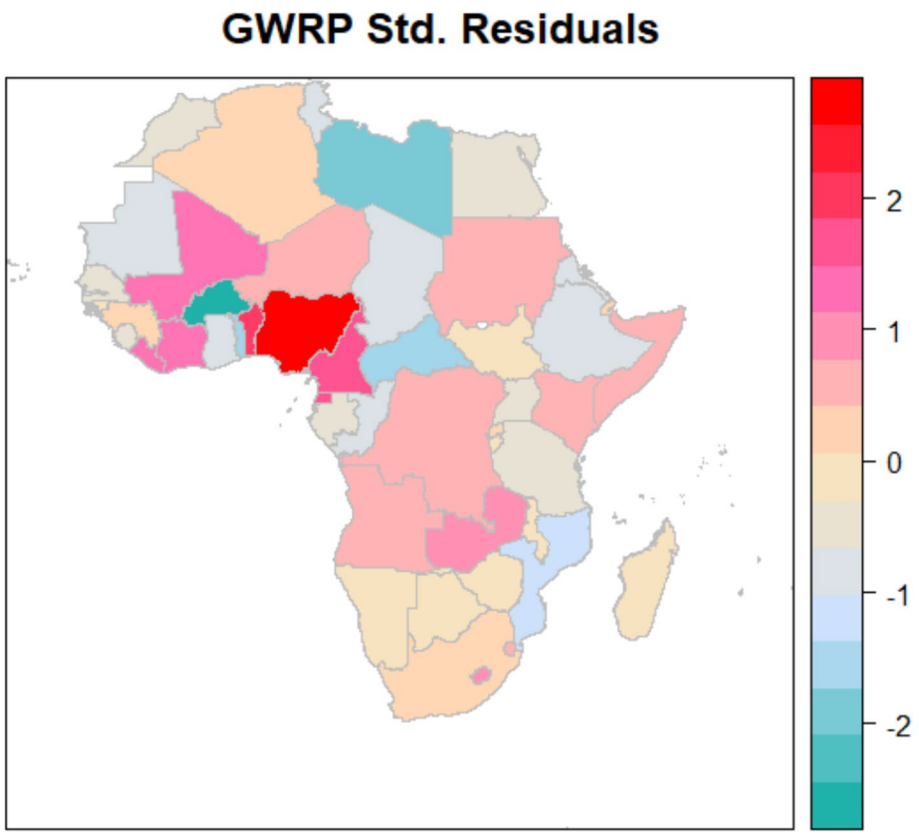

Fig. 5 Map of standardized residual

health expenditure were found to be moderately significant, even though the conventional Poisson regression model has shown that it was not statistically significant at a 5% alpha level.

Additionally, the t-value is statistically significant in most of the study areas, as indicated by green and red colors (Fig. 4). For instance, the impact of the illiteracy rate on under-five mortality was non-stationary and predominantly positive for all the countries in the sub-region.

The standardized residuals for the local model (Fig. 5) indicate that this model is spatially autocorrelated. The standardized residual of this model suggests nonstationary relationships between the under-five mortality and the development indicators. Hence, it confirms the GWRP calibration's efficacy to justify geographical variability in the current study.

4 Discussion

The descriptive statistics of under-five mortality and global development indicators (GDI) across fifty-four (54) African countries revealed significant disparities. Under-five mortality ranged from 10 to 117, with a mean of 55.15 and a standard deviation of 28.32, indicating moderate variability. This translates to an average of approximately 55 child deaths per 1000 live births annually, underscoring persistent child health challenges across the continent. These findings are consistent with studies by [11, 36, 37, 61, 64] which highlight inequalities in child mortality related to socioeconomic and environmental factors. Specifically, social variables like maternal income and education

significantly influence health outcomes. Maternal education, for example, is linked to better nutrition, reduced risk of preventable diseases, and improved healthcare-seeking behavior. Environmental factors, such as air pollution and contaminated drinking water, directly contribute to illnesses like pneumonia and diarrhea.

Most GDI exhibited positive skewness, reflecting uneven progress. Access to essential sanitation services averaged 47.22%, critical drinking water services 72.70%, and electricity access 57.83%. Urban population and literacy rates had means of 47.73% and 64.16%, respectively. The mean PM2.5 exposure was 40.75 $\mu g/m^3$, an environmental factor known for its adverse health effects, particularly in children [22]. These patterns align with studies by Song et al. [69] and Hackbarth et al. [32], which emphasize spatial heterogeneities in development metrics and health outcomes.

The study showed a negative correlation between under-five mortality and indicators like literacy, urbanization, and electricity access, highlighting their crucial role in improving child survival. Conversely, positive correlations were observed between under-five mortality and open defecation (mean: 17.28%), $PM_{2.5}$ exposure, and gross national expenditure (GNE), indicating complex relationships. The positive correlations between $PM_{2.5}$ and open defecation align with findings on the detrimental effects of poor environmental and sanitation conditions [18, 65]. The positive link between GNE and under-five mortality suggests that economic growth alone does not guarantee improved child health, especially where inequalities persist [38]. While these initial observations from the global correlations suggest important relationships, they assume a uniform effect across all African nations. To address the likelihood that the nature and strength of these relationships vary *between* countries due to differing national policies, economic structures, cultural contexts, and governance systems (governance quality can influence health policy implementation and effectiveness, impacting child mortality rates differently across nations [33],varying national health expenditure and its allocation can lead to diverse impacts on child health outcomes [16]), this study employs Geographically Weighted Poisson Regression (GWPR). Although studies such as [31, 42, 44] appropriately emphasize the importance of geographic variation in the determinants of child mortality *within* countries, our application of GWPR operates at the national level to specifically explore the heterogeneity in these relationships *across* the 54 African nations. We posit that factors such as varying national healthcare investment strategies (different levels of public health spending as a percentage of GDP can have varying effects on child mortality across countries (Filmer and Pritchett, 1999)), the effectiveness of different educational policies (national literacy programs and their reach can impact maternal health knowledge and child care practices differently [86], and distinct national environmental regulations can lead to significant inter-country differences in how GDIs influence child survival. By allowing the regression coefficients to vary spatially at the national level, GWPR enables us to map these between-country variations and identify where specific GDIs have a stronger or weaker association with under-five mortality, offering insights beyond what a single, global model can provide for continent-wide policy considerations [28].

The study revealed a negative correlation between under-five mortality and indicators such as literacy, urbanization, and access to electricity, underscoring their importance in promoting child survival. On the other hand, positive correlations were observed with open defecation (mean: 17.28%), exposure to PM2.5, and gross national expenditure

(GNE), suggesting complex and potentially specific relationships. While these initial correlations provide a broad overview, they implicitly assume that the relationship between these factors and child mortality is consistent across all African nations, an assumption that overlooks the continent's substantial heterogeneity. Recognizing that these relationships are likely to differ significantly from country to country due to fundamental structural differences such as health infrastructure capacity (e.g., Adewemimo et al., [1], who showed how spatial variations in healthcare access affect child mortality in Nigeria), governance quality and policy implementation effectiveness (e.g., Asante and Aikins, [7]), and broader national level socioeconomic conditions (e.g., Novignon and Lawanson, [55]), this study adopts Geographically Weighted Poisson Regression (GWPR).

The calibration of a conventional Poisson regression model revealed a complex interplay between socioeconomic, infrastructural, and environmental factors and under-five mortality. The model identified statistically significant predictors, including access to basic sanitation, electricity, literacy, and current health expenditures, all inversely associated with under-five mortality. Access to basic sanitation reduced under-five mortality, aligning with Mohamed [49], Momberg et al. [50], Merid et al. [47], and Alum et al. [4], who demonstrated the impact of improved sanitation in reducing diarrheal diseases. This reinforces the importance of investing in and scaling up sanitation programs. Access to electricity was linked to better child health, consistent with [3, 30], who emphasized its role in healthcare delivery and maternal care. Policies aimed at expanding electricity access, particularly in rural areas, can have significant health benefits. Literacy and health expenditures were also associated with reduced under-five mortality, reflecting findings by Ofori Boateng et al. [56], Uwizeye et al. [79]. Increased investment in education and healthcare systems is crucial for long-term improvements in child survival.

However, GNE, urban population, and $PM_{2.5}$ levels were not statistically significant at the 5% level. This contrasts with studies like Eliason [27], Daba et al. [23], Naz et al. [54], and Bickton et al. [13], which found substantial negative impacts of air pollution. The absence of significance for GNE might indicate inefficiencies in resource allocation or unequal wealth distribution, as supported by Mbachu et al. [46]. This suggests a need for greater transparency and accountability in health spending and efforts to reduce income inequality. Open defecation and $PM_{2.5}$ levels were positively associated with under-five mortality, consistent with Chakrabarti et al. [19] and Spears et al. [70], who linked open defecation to stunting and higher mortality rates. The counterintuitive positive relationship between GNE and mortality suggests that higher national expenditures do not directly translate to improved child health due to disparities in resource distribution.

Some findings presented contrasts warranting deeper consideration. For instance, urbanization was positively associated with under-five mortality, which appears counterintuitive. This may reflect urban poverty, overcrowding, and inadequate sanitation in African megacities, as noted by Titilayo, [76] and Campbell et al. (2020). This highlights the need for urban planning and development strategies that prioritize health infrastructure and address inequalities within urban centers. The lack of significance for PM2.5 exposure might be due to regional variability in exposure thresholds or differences in health resilience. Disparities between these results and other studies may arise from variations in data quality and coverage, governance and healthcare infrastructure efficiency, and contextual challenges specific to Africa. Methodological differences and

geographic variability in environmental risks and infrastructural access further underscore the importance of region-specific analysis.

Several limitations were inherent in this study. Firstly, the analysis relies on national-level aggregated data, which may suffer from the ecological fallacy. Relationships observed at the national level might not hold at finer spatial scales or for individual children. For instance, while a country might have a high average literacy rate, disparities within the country could mask the true impact of literacy on child mortality in specific regions. Future research should aim to utilize sub-national data where available to provide more granular insights. Secondly, the study may be susceptible to omitted variable bias. While we included a range of relevant socioeconomic, infrastructural, and environmental indicators, other unmeasured or unavailable factors could also significantly influence under-five mortality. These might include cultural practices, specific disease prevalence rates beyond broad categories, access to quality healthcare services (beyond expenditure), and governance effectiveness. The absence of these variables could potentially confound the observed relationships. Future research should explore the inclusion of more comprehensive datasets, potentially incorporating qualitative data to capture cultural and behavioral factors and investigate the role of governance indicators. Thirdly, there are limitations associated with the chosen modeling approach. While the conventional Poisson regression provides a baseline understanding, it assumes spatial homogeneity. The subsequent application of Geographically Weighted Poisson Regression (GWPR), which aims to address this, also has its limitations. Collinearity among the explanatory variables could inflate the variance of the coefficient estimates, making it difficult to isolate the independent effect of each factor. Furthermore, the performance of GWPR is sensitive to the choice of bandwidth, which determines the spatial extent of the weighting function. An inappropriate bandwidth selection could either oversmooth local variations or lead to unstable parameter estimates. Future research should employ techniques to assess and mitigate collinearity, and explore different bandwidth selection methods, including cross-validation approaches, to ensure the robustness of the GWPR results. Sensitivity analyses regarding bandwidth choice should be conducted and reported. Finally, data quality and availability across the 54 African countries might vary, potentially introducing measurement errors. Inconsistencies in data collection methodologies and reporting standards could affect the reliability and comparability of the indicators used in the analysis. Future research should prioritize the use of standardized and high-quality data sources and explore methods for addressing missing data and measurement errors, such as multiple imputation techniques.

Despite these limitations, this study provides valuable insights into the complex interplay of factors associated with under-five mortality in Africa and highlights the importance of considering spatial heterogeneity in developing targeted interventions. Future research should also explore the temporal dynamics of these relationships using longitudinal spatial models to understand how these associations evolve over time and in response to policy changes. Furthermore, investigating the interactions between different levels of influence (e.g., household, community, national) using multilevel spatial models could provide a more comprehensive understanding of the determinants of under-five mortality. Finally, research focusing on the specific impacts of climate change and environmental degradation on child health outcomes across different African regions is crucial for developing adaptive and resilient health systems.

5 Conclusion

This study has provided information on the spatially varying relationships between global development indicators and under-five mortality across 54 African countries. The key finding is the significant spatial heterogeneity in these relationships, demonstrating that the impact of economic, infrastructural, and environmental factors on child survival is not uniform across the continent. This spatial non-stationarity underscores the limitations of applying blanket policies and necessitates localized, context-specific interventions to effectively reduce child mortality.

The study revealed that while factors like access to electricity, sanitation, and literacy generally correlate with lower under-five mortality, their influence varies geographically. Similarly, the detrimental effects of poor sanitation and air pollution exhibit spatial variability. Notably, the complex relationship between gross national expenditure and child mortality, with a positive association observed in some contexts, highlights that economic growth alone is insufficient without equitable resource distribution and targeted health investments.

The novelty of this study lies in its application of the Geographically Weighted Poisson Regression (GWPR) model to a comprehensive dataset of African countries, explicitly mapping the spatial variations in the determinants of under-five mortality. This approach moves beyond traditional global regression models, offering a more nuanced understanding of the local factors driving child mortality and enabling the identification of high-risk regions. Our findings contribute to the field of spatial epidemiology by demonstrating the critical importance of considering geographical context in understanding health outcomes and informing public health policy. Furthermore, this research contributes to development studies by highlighting the spatial complexities of the relationship between economic development and health, emphasizing the need for spatially targeted strategies to achieve the Sustainable Development Goals related to child survival.

The study advocates for a decentralized, region-specific approach to policy formulation and resource allocation. The outlined region-specific strategies, ranging from WASH programs in Sub-Saharan Africa to improved healthcare access in North Africa and investments in maternal education in West Africa, provide a practical framework for tailored interventions. By emphasizing data-driven policymaking, public–private partnerships, and community engagement, this research offers actionable insights for reducing under-five mortality in Africa and promoting more equitable health outcomes across the continent. Future research should continue to explore the dynamic interplay of various factors at finer spatial scales and over time to further refine targeted interventions and accelerate progress toward child survival.

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Author contributions
JAO, AAO, REO, and KFA wrote the main manuscript text. REO and SM. prepared figures and graphs. All authors reviewed the manuscript.

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Data availability
The data utilized for this study were curated from the World Bank's World Development Indicators (WDI) (https://databank.worldbank.org/source/world-development-indicators.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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