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Global Spatial Patterns of Unequal Longevity Using Geographically Weighted Panel Regression Model

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Abstract

Global disparities in life expectancy remain a major concern in public health research, particularly due to the spatially heterogeneous effects of socioeconomic and environmental determinants. This study investigates global patterns of unequal longevity using a geographically weighted panel regression (GWPR) model applied to balanced panel data from 139 countries over the period 2014–2023. Life expectancy at birth is modeled as a function of gross domestic product (GDP) per capita, health expenditure per capita, secondary school enrollment, $PM_{2.5}$ air pollution, and renewable energy consumption, with data sourced from the World Development Indicators. Exploratory spatial analysis using Moran's I and local indicators of spatial association (LISA) reveals strong global and local spatial autocorrelation in life expectancy and its determinants, indicating violations of spatial stationarity. Benchmark panel model selection tests favor a two-way fixed effects model; however, diagnostic results reveal significant heteroskedasticity, autocorrelation, and non-normality of residuals. GWPR with an adaptive Bisquare kernel is subsequently employed to capture spatially varying relationships. The results demonstrate substantial geographic heterogeneity in both the magnitude and significance of covariate effects, with GWPR markedly outperforming the global panel model in terms of goodness-of-fit (global R^2 = 0.989) and residual behavior. Policy-relevant findings highlight that the impacts of economic development, health investment, education, pollution, and renewable energy adoption on longevity differ widely across regions. These results underscore the limitations of one-size-fits-all global health policies and emphasize the importance of geographically targeted, context-sensitive interventions to reduce global inequalities in life expectancy.

Keywords: Geographically weighted panel regression, life expectancy, adaptive bisquare, socioeconomic and environmental determinants.

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1. INTRODUCTION

Global inequalities in life expectancy remain a persistent concern in global health and socioeconomic research. Although average longevity has increased worldwide, substantial disparities across regions and countries continue to exist, reflecting uneven progress in environmental quality, economic development, education, and health systems. Life expectancy is fundamentally shaped by the interaction between environmental and socioeconomic conditions. From an environmental perspective, long-term exposure to air pollution, particularly fine particulate matter ($PM_{2.5}$), has been consistently linked to increased cardiovascular and respiratory mortality, resulting in shorter life expectancy [1], [2]. Conversely, the transition toward renewable energy is associated with reduced emissions and improved air quality, which can support better population health outcomes and longer longevity [3].

Socioeconomic factors likewise play a central role in shaping longevity outcomes. Higher GDP per capita generally reflects improved access to nutrition, sanitation, and healthcare, although its contribution to life expectancy tends to diminish at higher income levels [4], [5]. Health expenditure strengthens disease prevention and treatment capacity, enhancing overall health system performance and survival rates [6], while education, particularly secondary schooling, promotes healthier behaviors, better health-related decision-making, and more effective use of healthcare services, thereby indirectly extending life expectancy [4].

Importantly, a growing body of evidence indicates that environmental, economic, and social determinants of health do not exert uniform effects across space but vary significantly across geographic contexts [7]. However, conventional global panel regression models commonly used in cross-country health studies assume spatial stationarity, potentially masking local dynamics and leading to overly generalized conclusions. Geographically weighted approaches, including geographically weighted panel regression (GWPR) and geographically and temporally weighted regression (GTWR), offer a flexible framework to accommodate spatial heterogeneity and have been shown to improve model performance in comparative health and development research [8]. Building on the original GWR framework [9], GWPR extends this approach by integrating spatial weighting with panel data structures, allowing relationships to vary across space while incorporating temporal information [10].

Based on this background, the primary objective of this study is to examine how key environmental and socioeconomic determinants affect life expectancy across countries in a spatially heterogeneous manner. This study aims to identify geographically differentiated patterns in these relationships and to assess whether accounting for spatial non-stationarity provides additional insights beyond those obtained from global panel models. Recent spatio-temporal evidence suggests that such determinants exhibit location-specific impacts on health outcomes, with distinct regional clusters displaying stronger or weaker associations [11], [12].

Despite this growing body of evidence, several gaps remain in the existing literature. Most cross-country studies on life expectancy rely on global panel models that impose spatially uniform coefficients, thereby concealing the geographic heterogeneity of health determinants [9]. While spatially explicit approaches such as GWR have been applied in health-related research, existing applications remain largely confined to subnational or single-country contexts, for instance, Liu et al. [13] analyzed life expectancy determinants across cities in China, and Hu et al. [14] examined the spatial effects of air pollution on life expectancy across Chinese Provinces, leaving global-scale spatial panel analyses of longevity largely unexplored. Spatial panel approaches applied at the multi-country level have similarly been restricted to specific subregions: Zeng and Niu [15] employed a Dynamic Spatial Durbin model to examine healthy life expectancy determinants in West Africa. Furthermore, the simultaneous inclusion of environmental determinants, particularly $PM_{2.5}$ and renewable energy, alongside socioeconomic variables in a spatially varying framework has not been comprehensively examined across a globally representative sample of countries. Studies that do incorporate multi-country panels tend to focus on a narrow set of predictors, single regions, or non-spatial estimators: Roy [16] analyzed clean energy and life expectancy across 190 countries using pooled panel models without spatial differentiation, while Vatamanu et al. [17] examined renewable energy and life expectancy in 27 European countries only. This study addresses these gaps by applying GWPR to a balanced panel of 139 countries over 2014–2023, simultaneously modeling five key determinants of life expectancy while allowing their effects to vary freely across geographic space.

2. METHODS

2.1. Data

This study utilizes annual panel data obtained from the World Development Indicators (WDI) published by the World Bank [18]. The study period spans 2014 to 2023, a decade chosen for three

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reasons. First, 2014 marks a point of relative stabilization in the systematic reporting of environmental health indicators, particularly $PM_{2.5}$ and renewable energy data, by the World Bank across a sufficient number of countries. Second, this period aligns with the post-adoption phase of the sustainable development goals (SDGs, adopted September 2015), making it analytically relevant for examining determinants of SDG 3 (Good Health and Well-being) under a consistent global policy framework. Third, extending the window beyond 2023 would introduce increasing missingness for more recent years, while starting before 2014 would substantially reduce the number of eligible countries due to sparse environmental data. The dataset initially covers more than 200 countries; however, due to missing or incomplete records across the selected variables, only 139 countries satisfy the requirement of complete observations for the full study period, as illustrated in Figure 1.

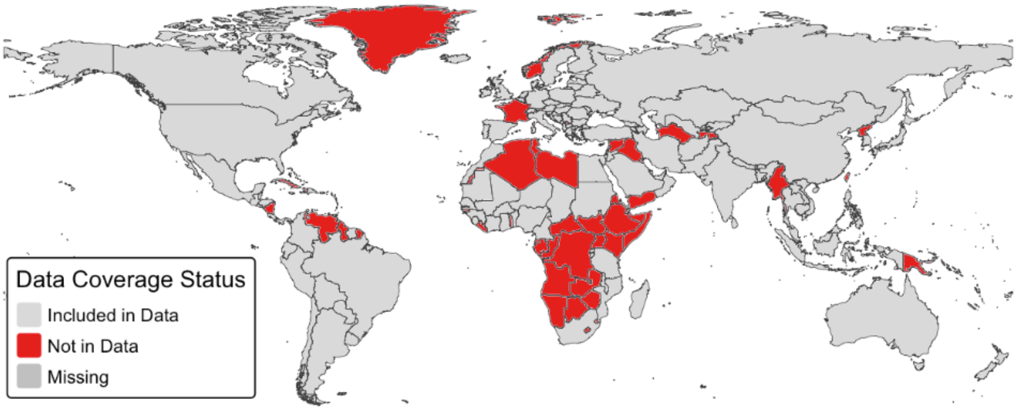

Figure 1. Map of countries included in the study.
Source: Author's elaboration based on WDI.

Missing data were handled using linear interpolation, applied exclusively to fill isolated gaps of no more than five consecutive years within a country's time series. Linear interpolation assumes a constant rate of change between observed data points, which is a reasonable approximation for the macroeconomic and environmental indicators used in this study, given that variables such as GDP per capita, health expenditure, and school enrollment typically follow gradual and near-monotonic trends over short time horizons. Interpolated values were used only when a country had observed data on both sides of the gap, thereby avoiding extrapolation. While interpolation introduces a smoothing effect that may marginally attenuate within-country volatility, its impact on cross-sectional and spatial patterns, which are the primary focus of this study, is expected to be minimal. Countries with more than 50% missing observations across any variable were excluded entirely to prevent excessive reliance on imputed values. The Variables that were used consist of life expectancy at birth (dependent variable) and five independent variables: $PM_{2.5}$ concentration, renewable energy consumption, GDP per capita (PPP), health expenditure per capita, and secondary school enrollment as shown at Table 1.

Table 1. Variables definition

Variables	Unit
Life Expectancy (LE)	Years
$PM_{2.5}$ Air Pollution (Pol)	Mean annual (micrograms /cubic meter)
Renewable Energy (RE)	% of total final energy consumption
GDP per Capita (GDP)	PPP (constant 2021 international $)
Health Expenditure per Capita (HE)	PPP (current international $)
School Enrollment (SE)	secondary (% gross)

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2.2. Data Analysis

The analytical stages of this study are summarized as shown at Figure 2 below. The analysis starts with panel data preparation and exploratory analysis, followed by global panel regression and model selection using LM, Chow, and Hausman tests. After validating classical assumptions, spatial non-stationarity is tested using the Breusch–Pagan test. If significant spatial effects are found, the analysis continues with GWPR modeling, including bandwidth selection, kernel weighting, local estimation, and diagnostic evaluation; otherwise, the global panel model is retained.

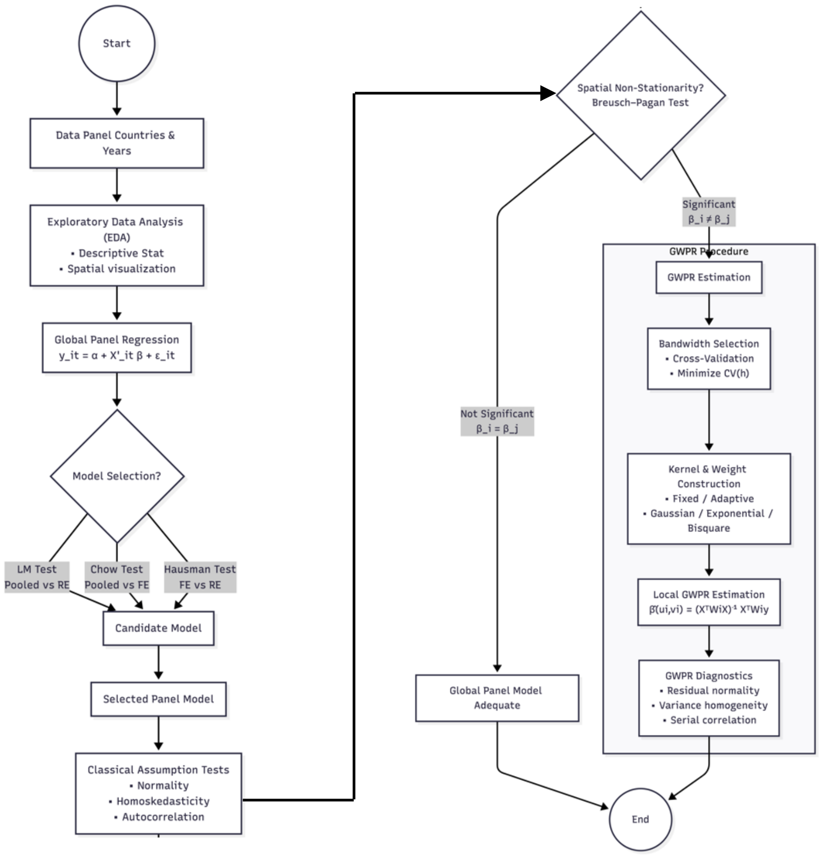

Figure 2. Flowchart of research

1. Exploratory Data Analysis (EDA)

   The response variable (life expectancy) and predictor variables (GDP per capita, health expenditure, $PM_{2.5}$ exposure, renewable energy consumption, and school enrollment) were examined using descriptive statistics and spatial visualization to identify distributional patterns and potential spatial clustering.

2. Global Panel Regression Analysis

   A conventional panel regression model was first estimated as a benchmark.

   a. Model selection employed the lagrange multiplier (LM) test, the Chow test, and the Hausman test to discriminate between pooled OLS, fixed effects (FE), and random effects (RE) specifications [19].

   b. Classical assumptions of the panel model were tested, including normality, homoskedasticity, and autocorrelation [20].

   The general panel model estimated is:

$$y_{it} = \alpha + X'_{it}\beta + \varepsilon_{it} \tag{1}$$

   Where $i = 1, \dots, N$ countries and $t = 1, \dots, T$ years.

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3. Testing Spatial Non-Stationarity

Spatial heterogeneity of coefficients was evaluated using the Breusch–Pagan (BP) test, where the null hypothesis assumes spatial stationarity:

$$H_0: \beta_i = \beta_j \ \forall_{i,j}$$

Significance of the BP statistic indicates the presence of geographically varying relationships. GWPR estimation proceeded through the following steps [21], [22]:

a. Determination of the optimal bandwidth h_i for each year using cross-validation (CV), selecting the bandwidth that minimizes:

$$CV(h) = \sum_{i=1}^{N} \left(y_i - \hat{y}_{i(h)}\right)^2 \quad (2)$$

b. Identifying neighboring locations within the spatial window h_i based on great-circle distances d_{ij}.

c. Construction and comparison of weight matrices using both fixed and adaptive kernel functions. Kernel weights w_{ij} are defined in Table 2:

Table 2. Weight matrices

	Gaussian	Exponential	Bisquare
Fixed	$\mathbb{w}_{ij} = \exp\left(-\frac{d_{ij}^2}{2h^2}\right)$	$\mathbb{w}_{ij} = \exp\left(-\frac{d_{ij}}{h}\right)$	$\mathbb{w}_{ij} = \left[1 - \left(\frac{d_{ij}}{h}\right)^2\right]^2$ $for\ d_{ij} \le h, else\ 0$
Adaptive	$\mathbb{w}_{ij} = \exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{b_i}\right)^2\right)$	$\mathbb{w}_{ij} = \exp\left(-\frac{d_{ij}}{b_i}\right)$	$\mathbb{w}_{ij} = \left[1 - \left(\frac{d_{ij}}{d_{i(k)}}\right)^2\right]^2$

where $d_{i(k)}$ is the distance to the k-th nearest neighbor.
d_{ij} = distance between i and j
b_i = bandwidth at i

d. Applying weights to the full panel such that:

$$\mathbb{w}_{ii} = 1, \mathbb{w}_{ij} \in (0,1] for\ all\ j \neq i \quad (3)$$

e. Estimating locally weighted panel regression:

$$y_{it} = \alpha(u_i, v_i) + \sum_{k=1}^{p} \beta_k (u_i, v_i) x_{kit} + \varepsilon_{it} \quad (4)$$

where (u_i, v_i) denote the coordinates of country i.
for location i, weighted matrix denotes as:

$$\mathbb{W}_{i_i} = \begin{bmatrix} w_{i1} & 0 & \cdots & 0 \\ 0 & w_{i2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_{in} \end{bmatrix} \quad (5)$$

So local regression is:

$$\hat{\beta}(u_i, v_i) = (X^\top \mathbb{W}_i X)^{-1} X^\top \mathbb{W}_i y \quad (6)$$

f. Repeating the local fitting process (steps d–e) for all spatial locations $i = 1, \dots, N$
g. Constructing the final set of local GWPR coefficient surfaces for all countries.
h. Evaluating GWPR assumptions that was considered superior when it exhibited (i) normally distributed residuals, (ii) reduced heteroskedasticity and serial autocorrelation, and (iii) the

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absence of remaining spatial autocorrelation in the residuals, as indicated by non-significant Moran's I statistics.

4. Interpretation of Spatial Variability

Spatial coefficient surfaces and significance maps were analyzed to identify clusters, gradients, and regions exhibiting distinct socioeconomic and environmental impacts on longevity. Synthesis of GWPR results to infer global patterns of unequal longevity and derive geographically tailored policy implications.

The stages and analyses of the GWPR were conducted using `R` statistical software. The implementation relied on several specialized packages, including `GWmodel` for geographically weighted regression and spatial weighting functions, `spgwr` for kernel-based spatial regression support, and `plm` for panel data structure handling and preliminary model specification. Spatial data manipulation and visualization were facilitated using `sf`, `sp`, and `tmap`, while dplyr and tidyr were used for data preprocessing and management.

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistic

Table 3 presents descriptive statistic of life expectancy and its socioeconomic and environmental determinants across five continents.

Table 3. Descriptive statistic of the variables

Variable		Africa	America	Asia	Europe	Oceania
LE	Mean	63.99	74.31	74.61	78.98	70.71
	Min	51.14	61.43	60.42	68.99	60.83
	Max	77.24	82.16	84.56	84.53	83.30
	SD	5.97	3.74	5.33	3.74	6.96
RE	Mean	54.31	25.19	18.59	24.86	13.26
	Min	1.2	2.8	0.0	3.2	0.0
	Max	91.3	66.2	85.2	82.9	35.7
	SD	28.67	17.63	21.20	16.02	12.16
POL	Mean	41.97	18.74	32.46	13.66	9.27
	Min	8.49	6.23	7.23	4.89	5.45
	Max	107.14	33.74	97.70	33.81	14.64
	SD	20.59	6.38	17.91	5.81	2.96
SE	Mean	54.20	93.30	89.29	107.66	100.13
	Min	18.89	46.11	33.21	82.44	53.39
	Max	112.31	141.20	126.04	164.08	159.11
	SD	24.20	19.20	16.53	16.29	25.42
HE	Mean	300.31	1711.25	1310.76	3767.54	1786.52
	Min	48.69	348.22	89.95	611.94	91.01
	Max	1626.35	12434.43	6657.93	10667.95	7072.17
	SD	369.04	2165.81	1368.49	2237.33	1885.93
GDP	Mean	6329.30	21502.27	27982.25	46786.96	18573.44
	Min	828.58	5603.26	1981.71	11641.12	3118.39
	Max	34346.07	74158.72	133571.96	136772.44	60461.16
	SD	6786.73	13836.19	28924.10	24030.40	18763.40

The descriptive statistics in Table 3 reveal pronounced continental gradients across all variables, consistent with the spatial heterogeneity motivating this study. The most striking disparity is in life expectancy: Europe averages 78.98 years compared to 63.99 years in Africa, a gap of 15 years that reflects

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deeply entrenched inequalities in socioeconomic and environmental conditions. This African deficit coincides with the highest $PM_{2.5}$ levels (mean 41.97 μg/m^3), the lowest secondary school enrollment (mean 54.20%), and the lowest health expenditure per capita (mean USD 300.31), while Europe leads on all three. Africa's paradoxically high renewable energy share (54.31%) reflects structural dependence on traditional biomass and hydropower rather than a clean energy transition, which explains the negative bivariate correlation between renewable energy and life expectancy observed later. The large within-continent standard deviations, particularly in Africa (LE SD = 5.97), Asia (GDP SD = 28,924), and the Americas (HE SD = 2,166), further confirm that continental averages mask substantial intra-regional heterogeneity, strengthening the case for a spatially explicit modeling approach.

3.2. Correlation Matrix

The correlation matrix reveals clear and theoretically consistent associations between life expectancy and its socioeconomic and environmental determinants as shown Figure 3. Life expectancy is strongly and positively correlated with secondary school enrollment ($r = 0.78$), GDP per capita ($r = 0.73$), and health expenditure per capita ($r = 0.70$), indicating that countries with higher educational attainment, greater economic capacity, and stronger health investment tend to achieve longer population longevity. In contrast, life expectancy shows moderate negative correlations with renewable energy share ($r = -0.51$) and $PM_{2.5}$ exposure ($r = -0.49$). The negative association with air pollution aligns with established evidence on the adverse health impacts of long-term pollution exposure, while the negative bivariate correlation with renewable energy likely reflects structural differences across countries and underscores the importance of multivariate and spatially explicit modeling.

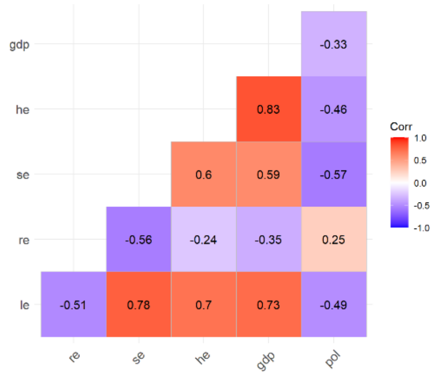

Figure 3. Correlation matrix

Among the explanatory variables, GDP per capita and health expenditure are highly correlated ($r = 0.83$), reflecting the close linkage between economic development and public health investment. School enrollment also exhibits moderate positive correlations with GDP ($r = 0.59$) and health expenditure ($r = 0.60$), suggesting that social and economic development dimensions tend to co-evolve. Pollution is negatively correlated with GDP ($r = -0.33$), health expenditure ($r = -0.46$), and education ($r = -0.57$), indicating that countries with stronger socioeconomic capacity generally experience lower pollution burdens. Renewable energy shows a weak positive correlation with pollution ($r = 0.25$), highlighting heterogeneous energy transitions across countries

3.3. Moran I Value

Moran's I is a global measure of spatial autocorrelation that quantifies the degree to which similar values of a variable are clustered or dispersed across geographic space. It was formally introduced by Moran (1950) and has since become a foundational statistic in spatial econometrics for assessing whether spatial patterns deviate from randomness [23]. Table 4 shows that life expectancy and all examined socioeconomic and environmental determinants exhibit strong and statistically significant positive spatial autocorrelation, with Moran's I values ranging from 0.61 to 0.83 ($p < 0.001$).

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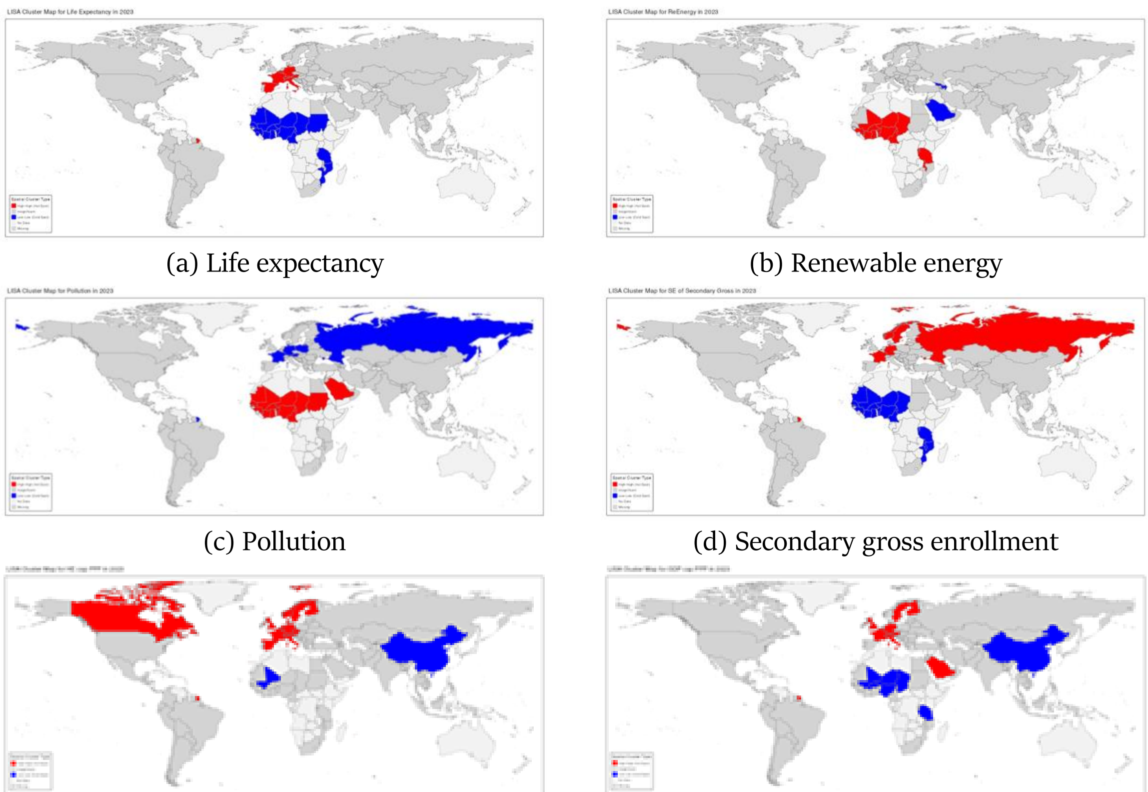
Table 4. Global Moran'I

Variable	Moran I	Variance	p-value
LE	0.81	0.006	2.2e-16
RE	0.61	0.006	9.886e-16
POL	0.83	0.006	2.2e-16
SE	0.73	0.006	2.2e-16
HE	0.76	0.006	2.2e-16
GDP	0.63	0.006	2.2e-16

Air pollution and life expectancy display the highest levels of clustering, followed by health expenditure, education, and GDP per capita, indicating that health outcomes and development factors are strongly regionalized rather than randomly distributed. Renewable energy use also shows significant but relatively weaker spatial dependence, reflecting greater heterogeneity in energy structures. Overall, these results provide robust evidence of spatial structure in both life expectancy and its determinants, violating the assumption of spatial independence and strongly motivating the use of geographically weighted panel regression to capture spatially heterogeneous relationships.

3.4. Local Indicator of Spatial Association

Local indicators of spatial association (LISA) are used to identify and measure the presence of local spatial autocorrelation, allowing researchers to detect spatial clusters and spatial outliers that may be hidden in global statistics. Introduced by Anselin [24], LISA provides a theoretical framework for understanding how relationships between observations vary across space rather than assuming spatial homogeneity.



(a) Life expectancy (b) Renewable energy

(c) Pollution (d) Secondary gross enrollment

(e) GDP per capita (f) CO_2 emissions

Figure 4. LISA cluster maps of selected variables in 2023.
Source: Author's elaboration

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According to Figure 4(a–f), the LISA maps reveal pronounced local spatial dependence in life expectancy and its key socioeconomic and environmental determinants, with clear clustering patterns that vary substantially across regions. In these maps, red indicates high–high clusters (areas with high values surrounded by high values), while blue indicates low–low clusters (areas with low values surrounded by low values). High–high clusters of life expectancy, education, health expenditure, and GDP per capita are concentrated mainly in Western and Northern Europe (and Canada for health spending), while extensive low–low clusters persist across Sub-Saharan Africa and parts of Asia, reflecting entrenched regional inequalities. Renewable energy use shows high–high clustering in several African regions, largely driven by structural reliance on hydropower and traditional biomass, whereas $PM_{2.5}$ pollution exhibits high–high clusters in North and Central Africa and low–low clusters across Eurasia, shaped by shared climatic and environmental conditions. Many other regions display weak or insignificant local association, underscoring strong spatial heterogeneity rather than uniform global patterns.

3.5. Panel Data Regression Model

The multicollinearity diagnostic based on the Variance Inflation Factor (VIF) indicates that the regression model does not suffer from serious multicollinearity.

Table 5. VIF value

Variable	RE	POL	SE	HE	GDP
VIF	1.57	1.62	2.68	3.97	3.77

As shown at Table 5, all VIF values lie well below the commonly accepted threshold of 5, ranging from 1.57 for renewable energy consumption to 3.97 for health expenditure per capita. These results suggest that the explanatory variables are not highly correlated with one another and that each variable contributes distinct information to the model. Consequently, the estimated coefficients can be interpreted reliably, and the model is appropriate for further panel and spatial regression analyses.

The panel model selection tests consistently reject the pooled specification in favor of models that account for unobserved heterogeneity. Based on result at Table 6 below, we compare between three panel models.

Table 6. Hasil uji LM, Chow, dan Hausman

Result	LM	Chow	Hausman
Chi-sq	5171	-	173.64
F-cal	-	144.62	-
df1	1	138	5
df2	-	1246	-
p-val	< 2.2e-16	< 2.2e-16	< 2.2e-16

The Breusch–Pagan lagrange multiplier test yields a highly significant result ($p < 0.001$), indicating the presence of panel effects and supporting the random effects model (REM) over the common effects model (CEM). Similarly, the Chow (F) test strongly rejects CEM in favor of the fixed effects model (FEM), confirming the existence of significant individual (country-specific) effects. Finally, the Hausman test produces a statistically significant result ($p < 0.001$), implying that the REM assumptions are violated and that the FEM provides consistent estimates. Taken together, these results indicate that country-specific heterogeneity is both statistically significant and correlated with the regressors, leading to the conclusion that the fixed effects model is the most appropriate baseline panel specification for the subsequent analysis.

The assumption tests for the fixed effects model indicate clear violations of classical error assumptions.

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Table 7. Assumption test result

Assumption	Test Statistic	p-value	Decision	Conclusion
Normality of Residuals	Shapiro–Wilk (W = 0.902)	< 2.2e−16	Reject H_0	Residuals are not normally distributed
	Jarque–Bera (χ^2 = 5328.5)	< 2.2e−16	Reject H_0	Strong non-normality (skewness & kurtosis)
	Kolmogorov–Smirnov (D = 0.393)	< 2.2e−16	Reject H_0	Distribution deviates from normal
Homoskedasticity	Breusch–Pagan (BP = 26.287)	7.85e−05	Reject H_0	Heteroskedasticity detected
Independence of Errors	Runs Test (Z = −10.357)	< 2.2e−16	Reject H_0	Residuals are autocorrelated

As we can see at Table 7, normality tests (Shapiro–Wilk, Jarque–Bera, and Kolmogorov–Smirnov) all strongly reject the null hypothesis, which shows substantial deviations in the tails and the presence of outliers. The studentized Breusch–Pagan test provides significant evidence of heteroskedasticity, implying non-constant error variance across observations. In addition, the Runs test rejects randomness of the residuals, indicating the presence of serial correlation. Taken together, these results suggest that the residuals are non-normal, heteroskedastic, and autocorrelated, implying that conventional panel regression assumptions are violated. These violations are not merely diagnostic footnotes but carry direct methodological implications. Heteroskedasticity in a global panel model suggests that error variance is not constant across countries, which is consistent with the hypothesis that the relationship between covariates and life expectancy differs in magnitude across geographic space, a form of spatial non-stationarity. Serial autocorrelation in the residuals further indicates that the FEM fails to fully capture systematic temporal structure within countries. Non-normality with strong kurtosis and skewness points to the presence of outlier country-groups whose local data-generating processes diverge substantially from the global average. Taken together, these violations motivate the transition from FEM to GWPR: the adaptive kernel weighting in GWPR implicitly accounts for local heteroskedasticity by allowing each location to have its own locally estimated variance structure, while the geographically varying coefficients directly address spatial non-stationarity. The GWPR framework is therefore not merely an alternative model but a methodologically warranted response to the specific pattern of assumption violations detected in the FEM residuals.

3.6. Bandwidth Selection in GWPR

The inclusion of geographic coordinates (latitude and longitude) in the extended linear model slightly improves overall model fit but does not resolve the violations of classical assumptions. The Shapiro–Wilk test still rejects normality of the residuals, although the test statistic indicates a closer approximation to normality compared with the baseline panel model. The studentized Breusch–Pagan test remains highly significant, providing strong evidence of heteroskedasticity, while the Runs test rejects the null hypothesis of randomness, indicating residual dependence.

In GWPR, the optimal spatial weight matrix is determined through bandwidth selection based on cross-validation (CV). For each kernel specification, the CV criterion evaluates predictive performance by minimizing the sum of squared leave-one-out prediction errors, thereby selecting the bandwidth that yields the most accurate local estimates [9]. Formally, the optimal bandwidth h^* is obtained by.

$$h^* = \arg\min_h CV\ (h)$$

where the CV score reflects the goodness of fit of the corresponding kernel-based spatial weight matrix $\mathbb{W}_i(h)$.

Table 8. Bandwidth selection result

Kernel Type	Bandwidth Type	RSS	R^2	Adjusted R^2	AIC	AICc
Bisquare	Adaptive	14.99	0.9892	0.9843	−1961.85	−1263.52
	Fixed	102.93	0.9259	0.9204	408.74	503.71
Gaussian	Adaptive	57.63	0.9585	0.9528	−341.15	−169.27
	Fixed	18.59	0.9866	0.9807	−1666.05	−977.87
Exponential	Adaptive	67.44	0.9514	0.9454	−143.06	−0.28
	Fixed	17.29	0.9876	0.9824	−1800.48	−1203.84

As shown at Table 8, empirical comparison across these candidate spatial weight matrices shows that the adaptive Bisquare kernel, selected via the minimum CV score among the evaluated bandwidths, delivers the best overall model performance in terms of RSS, R^2, adjusted R^2, AIC, and AICc. The Moran's I test applied to the GWPR residuals with the adaptive Bisquare kernel indicates that spatial autocorrelation has been effectively removed by the model. The Moran's I statistic is close to zero and slightly negative (−0.032), with a very high p-value (0.981), implying a failure to reject the null hypothesis of spatial randomness. This result suggests that no significant spatial clustering remains in the residuals after accounting for spatially varying relationships through GWPR.

3.7. Parameter Extraction and Local Regression Model

Within the GWPR framework, parameter extraction does not yield a single regression equation as in conventional global models. Instead, the analysis produces multiple local regression models, with the number of models equal to the number of spatial units. In this study, GWPR generates 139 local regression models, one for each country. Each model contains a country-specific intercept and slope coefficients for renewable energy consumption, air pollution ($PM_{2.5}$), education, health expenditure, and GDP per capita, estimated using a location-specific spatial weighting matrix derived from the adaptive Bisquare bandwidth.

Local R2

Each country-specific model is characterized by a Local R2 value, reflecting the local goodness-of-fit, and corresponding local significance tests (p-values), indicating that the influence of a given variable may be statistically significant in some countries but not in others. Local R^2 is presented in the Figure 5.

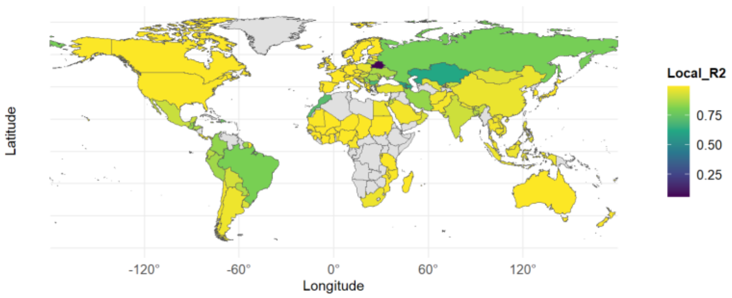

Figure 5. GWPR Result – Local R2. Source: Author's elaboration

Based on the GWPR Local R^2 map, clear spatial variation is observed in the model's explanatory power across countries. High Local R^2 values (> 0.85) are predominantly found in North America (the United States and Canada), South America (notably Brazil and Argentina), Western Europe, Australia, and parts of East and South Asia such as China and India, indicating that the GWPR model explains local variability very well in these regions. Moderate Local R^2 values (0.75 – 0.85) appear across large and heterogeneous areas such as the Russian Federation and several Central Asian countries, suggesting partial explanatory strength with notable spatial heterogeneity. In contrast, low Local R^2 values (< 0.5) are observed in parts of Eastern Europe, Central and Western Asia, and several African countries, implying weaker local model performance, potentially due to strong regional heterogeneity, unobserved local factors, or data limitations.

Cluster of Significance

The GWPR cluster-of-significance results reveal substantial spatial heterogeneity in the set of locally significant variables across countries as shown at Figure 6.

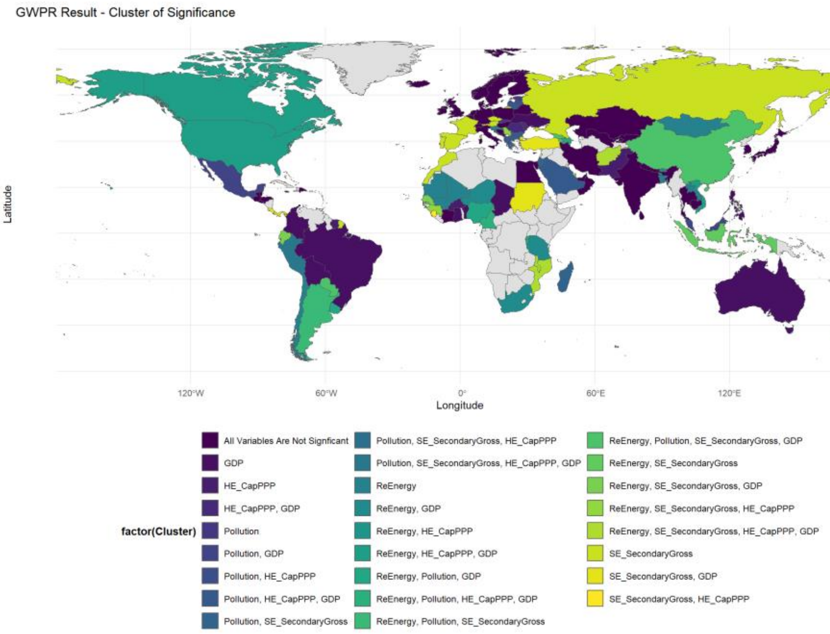

Figure 6. GWPR result – cluster of significance.
Source: Author's elaboration

Several countries exhibit significance in only one explanatory variable, most commonly renewable energy or GDP, indicating that local relationships are dominated by a single key driver. Countries such as Afghanistan, Argentina, China, Indonesia, Canada, and the United States fall into this category. A smaller group of countries shows significance in two variables, most frequently combinations involving renewable energy with GDP, school enrollment, pollution, or health expenditure, reflecting moderately complex local dynamics. Fewer countries demonstrate significance in three or four variables simultaneously, notably Armenia, China, Georgia, Paraguay, and Peru, suggesting strong and multidimensional local relationships captured by the GWPR model. In contrast, a large number of countries, primarily in Western Europe, East Asia, and high-income regions, exhibit no locally significant variables, implying either stable global relationships, weak local effects, or limited spatial variability.

Coefficient Significant Map

The GWPR results reveal pronounced spatial heterogeneity in both the significance and direction of coefficients across all explanatory variables.

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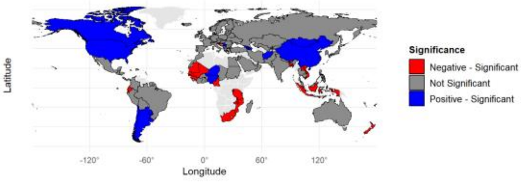
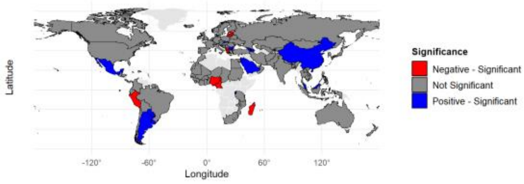
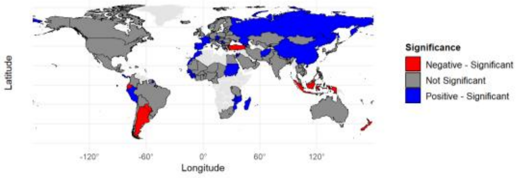


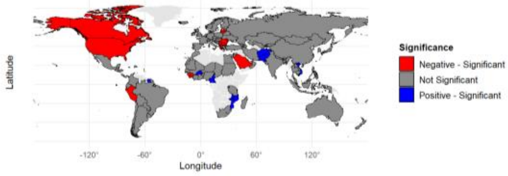
(a) Renewable energy



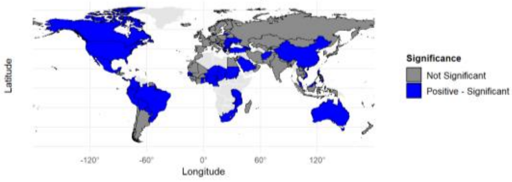
(b) Pollution ($PM_{2.5}$)



(c) School enrollment (secondary)



(d) Health expenditure (per capita, PPP)



(e) GDP per capita

Figure 7. Coeficient significance: renewable energi, pollution, SE, HE, GDP.
Source: Author's elaboration

In these maps, red indicates significantly negative coefficients, blue indicates significantly positive coefficients, and grey denotes statistically insignificant regions. Renewable energy exhibits mixed effects: positive and significant relationships are concentrated in North America (the United States and Canada), East Asia (China), and parts of South America (notably Argentina), while negative and significant effects appear in Sub-Saharan Africa, Southeast Asia (including Indonesia), and selected regions of South Asia and Oceania; many countries in Europe, Central Asia, the Middle East, Australia, and parts of South America show no significant effect. Pollution also displays spatially varying impacts, with positive and significant effects in countries such as China, Argentina, Chile, Mexico, and parts of Southeast Asia, contrasted by negative effects in Peru, Nigeria, Madagascar, and parts of Southern and Central Europe, whereas most other regions exhibit non-significant coefficients.

Similar spatial heterogeneity is observed for school enrollment, health expenditure, and GDP as presented at Figure 7. Secondary school enrollment shows positive and significant effects mainly in China, Russia, Eastern Europe, and Central Asia, but negative effects in South America, particularly Chile, and isolated areas in Southeast Asia and the Pacific, with largely non-significant effects elsewhere. Health expenditure presents negative and significant coefficients in North America and parts of Eastern and Southeastern Europe, alongside Peru and Saudi Arabia, while positive effects are found in Afghanistan, Pakistan, and several Sub-Saharan African countries; many other regions show no significant relationship. In contrast, GDP consistently exhibits positive and significant effects across much of the world, including the Americas, Europe, China, Russia, South and Southeast Asia, Australia, and parts of Africa, with no evidence of negative effects, although its significance weakens in some parts of Africa, the Middle East, and Central Asia.

3.8. Model Fit Test

The model fit comparison indicates that the GWPR model provides a substantially better representation of the data than the two-way fixed effects model (FEM).

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Table 9. Comparasion between GWPR and FEM

Model	R^2	Adjusted R^2	RSS
GWPR	0.9892	0.9843	14.9904
FEM	0.0751	−0.0310	21.9134

The F-test comparing GWPR and FEM yields an F statistic of 0.8896 with a corresponding p-value of 0.0276, which is below the 5% significance level. This result indicates that the reduction in residual variance achieved by GWPR is statistically significant, supporting the superiority of GWPR over the global panel specification. This result is reinforced by standard goodness-of-fit measures. As shown at Table 9, the GWPR model attains an exceptionally high R^2 (0.989) and adjusted R^2(0.984), reflecting its strong explanatory power when spatially varying coefficients are allowed. In contrast, the two-way FEM exhibits very low explanatory capacity (R^2 = 0.075, adjusted R^2 =−0.031), which warrants a careful methodological explanation. This stark discrepancy is not indicative of model failure but rather reflects a fundamental difference in what each model measures and how R^2 is computed in a within-transformation framework.

The low within-R^2 of the two-way FEM (0.075) arises directly from how the within-transformation partitions variance in panel data. The FEM demeans the data by removing both country-specific and year-specific fixed effects before regressing the covariates on life expectancy. Specifically, it subtracts the country mean, the year mean, and adds back the grand mean from every observation. This transformation eliminates all between-country variation, which constitutes the dominant source of variation in life expectancy across 139 countries, leaving only the within-country, over-time variation to be explained. Since life expectancy changes very slowly within a single country over the ten-year study window (2014–2023), the residual within-variation is extremely small. Consequently, even though the covariates (GDP, health expenditure, education, pollution, renewable energy) can explain a reasonable share of the cross-sectional differences between countries, the FEM R^2 is evaluated solely against this demeaned, within-country variation, yielding a low value by construction. This is a well-known property of fixed effects models in health and development panel studies with slowly evolving outcomes [14]. Notably, from the script output, the pooled OLS (Common Effects Model) applied to the same standardized data achieves R^2 = 0.731 on exactly the same variables, confirming that the predictors do explain a large share of the total cross-sectional variance. The FEM's low R^2 thus reflects the removal of between-country heterogeneity rather than poor model explanatory power per se.

The GWPR R^2 of 0.989, by contrast, is computed against the total (non-demeaned) variation in the original scaled data, including both within- and between-country components. More importantly, GWPR fits 139 separate local regression models, one per country, each weighted by geographic proximity. This locally adaptive approach allows each country's model to capture its own cross-sectional context rather than being constrained by a global homogeneous slope. The adaptive Bisquare kernel further concentrates weight on nearby observations, enabling the model to closely track the dominant spatial gradients in life expectancy that the FEM's within-transformation had explicitly removed. In essence, GWPR recovers the spatial between-country structure that FEM discards by design. The two metrics therefore measure fundamentally different quantities: the FEM R^2 measures how well time-varying changes in the predictors explain year-to-year changes in life expectancy within each country, while the GWPR R^2 measures how well spatially varying local regressions explain the full distribution of life expectancy across all countries and years. This non-comparability of R^2 across the two estimators is the primary reason for the apparent gap, and the superiority of GWPR is more rigorously demonstrated by the F-test comparing residual sums of squares (F = 0.8896, p = 0.028), which directly accounts for the difference in effective degrees of freedom between the two models.

A natural concern with a global R^2 as high as 0.989 is the possibility of overfitting, that the model may be capturing noise rather than genuine spatial structure. Several lines of evidence argue against this interpretation. First, the adjusted R^2 (0.984) is nearly identical to the unadjusted R^2, indicating that the penalty for the large number of locally estimated parameters does not substantially erode explanatory power, and that the model is not exploiting excess degrees of freedom. Second, the bandwidth selection procedure based on cross-validation (CV) is inherently a regularization mechanism: by minimizing leave-one-out prediction error, CV selects the bandwidth that generalizes best to unseen observations rather than the one that minimizes in-sample fit. A severely overfitted model would produce a very small bandwidth (fitting each location almost exclusively to itself), whereas the adaptive Bisquare bandwidth selected here incorporates a meaningful spatial neighborhood, reflecting genuine regional smoothness in the data. Third, and most critically, the Moran's I statistic applied to the GWPR residuals yields a value of −0.032 ($p = 0.981$), confirming the absence of any remaining spatial autocorrelation. An overfitted model would typically leave systematic spatial patterns in its residuals; the near-zero Moran's I indicates that all spatially structured variation has been legitimately explained rather than absorbed through overfitting. Collectively, these diagnostics support the conclusion that the high R^2 reflects the genuine spatial heterogeneity of life expectancy determinants across 139 countries, rather than an artifact of model over-parameterization.

The GWPR results provide substantive insights into how socioeconomic and environmental determinants shape life expectancy across different geographic contexts. The positive association between GDP per capita and life expectancy observed in many regions reflects the role of income in improving access to nutrition, sanitation, housing, and healthcare. However, the spatial variability of this effect indicates diminishing marginal returns in higher-income countries, where additional income gains translate into relatively smaller improvements in longevity. This pattern is consistent with recent empirical evidence showing nonlinear income–health relationships and stronger income effects in low- and middle-income regions, where economic growth remains a critical driver of survival gains [25], [26].

Health expenditure generally exhibits a positive but geographically uneven relationship with life expectancy. Stronger effects are observed in regions with higher institutional quality and more efficient health systems, where additional spending is more effectively transformed into preventive services, disease management, and improved population health outcomes. Conversely, weaker or insignificant effects in some countries may reflect inefficiencies in health financing, unequal access to healthcare, or governance constraints that limit the effectiveness of public health investments [27], [28].

The negative association between $PM_{2.5}$ exposure and life expectancy is consistently observed across most regions, although its magnitude varies spatially. This heterogeneity aligns with epidemiological and environmental health evidence demonstrating that long-term exposure to fine particulate matter significantly increases cardiovascular and respiratory mortality, particularly in regions with higher baseline pollution levels and weaker regulatory enforcement. Regions with stricter environmental policies or lower pollution exposure tend to exhibit attenuated adverse health impacts, highlighting the role of environmental governance in shaping pollution-related health burdens [29], [30].

Renewable energy consumption is generally associated with longer life expectancy, especially in regions where fossil fuel dependence is high and the transition toward cleaner energy sources leads to substantial air quality improvements. This finding is consistent with recent studies indicating that renewable energy adoption contributes to improved environmental conditions and reduced health risks associated with pollution. Nevertheless, the spatial variation in this relationship suggests that the health benefits of renewable energy are context-dependent, influenced by national energy mixes, industrial structures, and the scale of emission reductions achieved [31], [32].

Finally, the spatially varying effects of education underscore its indirect yet critical role in shaping longevity. Higher levels of educational attainment and school enrollment are associated with healthier behaviors, improved health literacy, and more effective utilization of healthcare services. A global meta-analysis confirms a consistent dose-response relationship between years of schooling and reduced adult mortality, though the magnitude of this effect differs by region and sex [33]. Regional panel evidence further shows that inequality in educational attainment is negatively associated with life expectancy,

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reinforcing the relevance of within-region disparities in education as a driver of spatial heterogeneity in health outcomes [34]. Collectively, these findings reinforce the notion that the determinants of life expectancy operate through multiple, interacting mechanisms whose impacts are inherently spatially heterogeneous.

4. CONCLUSION

This study demonstrates that global disparities in life expectancy are driven by spatially heterogeneous socioeconomic and environmental processes that cannot be adequately captured by conventional global panel models. Applying GWPR to a balanced panel of 139 countries over 2014–2023, the results show that the impacts of GDP per capita, health expenditure, secondary school enrollment, $PM_{2.5}$ air pollution, and renewable energy consumption vary substantially in both magnitude and direction across geographic space. Moran's I and LISA analyses confirm strong positive spatial autocorrelation in life expectancy and all five determinants, validating the presence of spatial clustering and rejecting the assumption of spatial stationarity. The two-way Fixed Effects Model, while theoretically appropriate given the Hausman test result, exhibits significant violations of classical assumptions and yields a low within-R^2 (0.075) by construction of the within-transformation. GWPR with an adaptive Bisquare kernel resolves these issues, achieving a global R^2 of 0.989, eliminating residual spatial autocorrelation (Moran's I = −0.032, p = 0.981), and providing 139 country-specific coefficient surfaces that reveal the geographic heterogeneity of health determinants. GDP per capita exhibits the most consistently positive and geographically widespread effect on longevity, while health expenditure, renewable energy, pollution, and education display more spatially differentiated patterns with varying directions of effect across regions.

These findings carry important implications for global health policy and future research. The spatial heterogeneity of determinant effects means that uniform, one-size-fits-all global health strategies are unlikely to reduce longevity gaps effectively. Geographically targeted interventions are essential: pollution control measures are most critical in high-exposure regions of Africa and Asia; strengthening health system efficiency, rather than merely increasing spending, is most relevant in North America and Eastern Europe where health expenditure shows diminishing returns; and promoting clean energy transitions yields the greatest longevity benefits in fossil-fuel-dependent economies. For future research, the limitations of this study, including the use of country-level aggregates, the absence of explicit spatial spillover effects, potential endogeneity among socioeconomic variables, and the exclusion of 61 countries due to data constraints, point toward several promising directions. These include applying subnational GWPR, incorporating spatial dynamic panel models that account for cross-country health spillovers, and developing causal identification strategies to separate the effects of health investment from broader development trajectories.

REFERENCES

[1] A. J. Cohen et al., "Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: An analysis of data from the Global Burden of Diseases Study 2015," *The Lancet*, vol. 389, no. 10082, pp. 1907–1918, 2017, doi: https://doi.org/10.1016/S0140-6736(17)30505-6.

[2] R. Burnett et al., "Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter," *Proc. Natl. Acad. Sci. U.S.A.*, vol. 115, no. 38, pp. 9592–9597, 2018, doi: https://doi.org/10.1073/pnas.1803222115.

[3] M. T. Majeed, T. Luni, and G. Zaka, "Renewable energy consumption and health outcomes: Evidence from global panel data analysis," *Pakistan J. Commerce Social Sci.*, vol. 15, no. 1, pp. 58–93, 2021. [Online]. Available: https://hdl.handle.net/10419/233768.

https://doi.org/10.13057/ijas.v9i1.114551
E-ISSN: 2621-086X

[4] D. M. Cutler, W. Huang, and A. Lleras-Muney, "Economic conditions and mortality: Evidence from 200 years of data," *NBER Working Paper* no. 22690, 2016, doi: https://doi.org/10.3386/w22690.

[5] G. Sart, Y. Bayar, and M. Danilina, "Impact of education and income inequalities on life expectancy: Insights from the new EU members," *Frontiers in Public Health*, vol. 12, Art. no. 1397585, 2024, doi: https://doi.org/10.3389/fpubh.2024.1397585.

[6] J. L. Dieleman et al., "Spending on health and HIV/AIDS: Domestic health spending and development assistance in 188 countries, 1995–2015," *The Lancet*, vol. 391, no. 10132, pp. 1799–1829, 2018, doi: https://doi.org/10.1016/S0140-6736(18)30698-6.

[7] A. S. Fotheringham, W. Yang, and W. Kang, "Multiscale geographically weighted regression (MGWR)," *Ann. Amer. Assoc. Geogr.*, vol. 107, no. 6, pp. 1247–1265, 2017, doi: https://doi.org/10.1080/24694452.2017.1352480.

[8] T. M. Oshan, Z. Li, W. Kang, L. J. Wolf, and A. S. Fotheringham, "MGWR: A Python implementation of multiscale geographically weighted regression for investigating process spatial heterogeneity and scale," *ISPRS Int. J. Geo-Inf.*, vol. 8, no. 6, Art. no. 269, 2019, doi: https://doi.org/10.3390/ijgi8060269.

[9] A. S. Fotheringham, C. Brunsdon, and M. Charlton, *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. Chichester, U.K.: Wiley, 2002.

[10] S. Sifriyani, I. N. Budiantara, M. F. F. Mardianto, and A. Asnita, "Determination of the best geographic weighted function and estimation of spatio-temporal model — Geographically weighted panel regression using weighted least squares," *MethodsX*, vol. 12, Art. no. 102605, 2024, doi: https://doi.org/10.1016/j.mex.2024.102605.

[11] Z. Zhang et al., "Renewable energy reduces domestic depression but increases depression for neighboring countries: Evidence of spatial effects from 181 countries worldwide," *BMC Public Health*, vol. 25, Art. no. 1676, 2025, doi: https://doi.org/10.1186/s12889-025-22323-0.

[12] M. Li and H. Yang, "Exploring spatial–temporal heterogeneity in new-type urbanization's impact on health expenditure: A GTWR analysis," *Int. J. Health Geographics*, vol. 24, Art. no. 26, 2025, doi: https://doi.org/10.1186/s12942-025-00413-x.

[13] T. Liu, S. Yang, R. Peng, and D. Huang, "A geographically weighted regression model for health improvement: Insights from the extension of life expectancy in China," *Applied Sciences*, vol. 11, no. 5, Art. no. 2022, 2021, doi: https://doi.org/10.3390/app11052022.

[14] K. Hu, X. Zhang, X. Yang, and M. Yu, "A study on the spatial distribution of life expectancy and its air pollution factors in China based on geographically weighted regression," *Frontiers in Public Health*, vol. 13, Art. no. 1565744, 2025, doi: https://doi.org/10.3389/fpubh.2025.1565744.

[15] M. Zeng and L. Niu, "Spatiotemporal patterns of healthy life expectancy and the effects of health financing in West African countries, 1995–2019: A spatial panel modelling study," *Journal of Global Health*, vol. 13, Art. no. 04123, 2023, doi: https://doi.org/10.7189/jogh.13.04123.

[16] A. Roy, "A panel data study on the role of clean energy in promoting life expectancy," *Dialogues in Health*, vol. 6, Art. no. 100201, 2024, doi: https://doi.org/10.1016/j.dialog.2024.100201.

[17] A. F. Vatamanu, M. Onofrei, E. Cigu et al., "Renewable energy consumption, institutional quality and life expectancy in EU countries: A cointegration analysis," *Energy, Sustainability and Society*, vol. 15, Art. no. 2, 2025, doi: https://doi.org/10.1186/s13705-024-00507-7.

https://doi.org/10.13057/ijas.v9i1.114551
E-ISSN: 2621-086X

[18] World Bank, "World Development Indicators: Real effective exchange rate index (PX.REX.REER)," World Bank DataBank. [Online]. Available: https://databank.worldbank.org/source/world-development-indicators/Series/PX.REX.REER.

[19] B. H. Baltagi, *Econometric Analysis of Panel Data*, 6th ed. Cham, Switzerland: Springer, 2021.

[20] D. N. Gujarati and D. C. Porter, *Basic Econometrics*, 6th ed. New York, NY, USA: McGraw-Hill, 2020.

[21] A. Djuraidah, *Penerapan dan Pengembangan Regresi Spasial dengan Studi Kasus pada Kesehatan, Sosial, dan Ekonomi*. Bogor, Indonesia: IPB Press, 2020.

[22] A. Djuraidah and R. Anisa, *Analisis Statistika untuk Data Geospasial dengan Ilustrasi Penerapan Menggunakan R*. Bogor, Indonesia: IPB Press, 2023.

[23] L. Anselin, *Spatial Econometrics: Methods and Models*. Dordrecht, The Netherlands: Kluwer Academic Publishers, 1988.

[24] L. Anselin, "Local indicators of spatial association — LISA," *Geographical Analysis*, vol. 27, no. 2, pp. 93–115, 1995, doi: https://doi.org/10.1111/j.1538-4632.1995.tb00338.x.

[25] F. Bilgili, E. Kocak, and U. Bulut, "The impact of economic growth on life expectancy: A panel data analysis," *J. Econ. Stud.*, vol. 47, no. 6, pp. 1373–1391, 2020.

[26] A. Deaton, "Health, inequality, and economic development," *J. Econ. Lit.*, vol. 41, no. 1, pp. 113–158, 2016, doi: https://doi.org/10.1257/002205103321544710.

[27] R. Moreno-Serra and P. C. Smith, "Broader health coverage is good for the nation's health: Evidence from country-level panel data," *J. Health Econ.*, vol. 44, pp. 88–104, 2015, doi: https://doi.org/10.1016/j.jhealeco.2015.09.002.

[28] V. Zarulli, E. Sopina, V. Toffolutti, and A. Lenart, "Health care system efficiency and life expectancy: A 140-country study," *PLOS ONE*, vol. 16, no. 7, p. e0253450, 2021, doi: https://doi.org/10.1371/journal.pone.0253450.

[29] C. A. Pope III, M. Ezzati, and D. W. Dockery, "Fine-particulate air pollution and life expectancy in the United States," *N. Engl. J. Med.*, vol. 360, no. 4, pp. 376–386, 2009, doi: https://doi.org/10.1056/NEJMsa0805646.

[30] V. A. Southerland, M. Brauer, A. Mohegh, et al., "Global urban temporal trends in fine particulate matter (PM2.5) and attributable health burdens: Estimates from global datasets," *Lancet Planet. Health*, vol. 6, no. 2, pp. e139–e146, 2022, doi: https://doi.org/10.1016/S2542-5196(21)00350-8.

[31] Q. Wang, L. Wang, and R. Li, "Does renewable energy help increase life expectancy? Insight from the linking renewable energy, economic growth, and life expectancy in 121 countries," *Energy Strategy Rev.*, vol. 50, p. 101185, 2023, doi: https://doi.org/10.1016/j.esr.2023.101185.

[32] M. T. Majeed, T. Luni, and G. Zaka, "Renewable energy consumption and health outcomes: Evidence from global panel data analysis," *Pak. J. Commer. Soc. Sci.*, vol. 15, no. 1, pp. 58–93, 2021. [Online]. Available: https://www.econstor.eu/handle/10419/233768.

[33] M. Balaj, C. Henson, A. Aronsson, et al., "Effects of education on adult mortality: A global systematic review and meta-analysis," *Lancet Public Health*, vol. 9, no. 3, pp. e155–e165, 2024, doi: https://doi.org/10.1016/S2468-2667(23)00306-7.

[34] G. Sart, Y. Bayar, and M. Danilina, "Impact of education and income inequalities on life expectancy: Insights from the new EU members," *Front. Public Health*, vol. 12, art. 1397585, 2024, doi: https://doi.org/10.3389/fpubh.2024.1397585.