1. ENVIRONMENTAL PERFORMANCE AND ECONOMIC DEVELOPMENT: A SPATIAL APPROACH

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Abstract

We explore the potential impact of countries' environmental performance (as are these proxied by the Environmental Performance Index) on their economic development by accounting for potential spatial effects modulating the interlinkages between these variables. For this purpose, we employ the Geographically Weighted Regression (GWR) approach for a 2023 dataset of 167 countries and territories. We find that geographical location matters in explaining the capacity of a country to use its environmental performance to sustain its development path. Nonetheless, the associated effects appear to be non-linear and geographically heterogeneous. Other socioeconomic variables (such as population density, urban population and oil rents) are also relevant. The findings are robust for various GWR model specifications. Some policy implications are derived.

Keyword: Economic development, environmental performance, spatial effects, Geographically Weighted Regression, urbanization, natural rents

JEL Classification: F64, O10, O19, O57, Q51, Q56

1. Introduction

An increasing amount of literature addresses the various potential effects that environmental health, climate change, biodiversity preservation, or the efficiency of pro-environmental policies can exert on the sustainable economic development. This literature disentangles such effects at regional, country, and international levels.

For instance, Xie *et al.* (2023, p.7149) finds that, for the case of China, there are empirical pieces of evidence of the spatial spillover effect of adjacent provinces' environmental regulation on local economic growth. Technological innovations may represent a non-linear transmission channel for the effects exercised by environmental regulations on economic growth (with a threshold for the

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intensity of environmental regulation that, once exceeded, can turn the stimulative impact for the development of environmental rules into a negative one) (Chen & Hu, 2022).

However, even at a regional level, a distinction can be drawn between *direct* and, respectively, *indirect* effects exercised by environmental status on growth. The last type of effects can be modulated by environmental protection expenditure of the local government on the ecological environment improvement, urbanization, technological innovations, environmental or fiscal decentralization, environmental knowledge or industrial structures (He, 2015; Yang, 2021; Shi et al., 2022; Ren et al., 2023).

At country and international level, Benhamed *et al.* (2023) reveals that climate change has direct and indirect spillover effects on economic growth, mainly in low- and middle-income countries over different time periods. Chica-Olmo *et al.* (2020) employs a spatial Durbin model to investigate the spatial dependence between GDP and renewable energy consumption for 26 European countries and concludes that spatial reliance leads to a change in renewable energy consumption that affects the GDP of neighbouring countries. In the same case of the European Union, Ren *et al.* (2021) finds that economic growth positively impacts CO2 emissions, while the spatial effects of economic growth exert negative impacts. Nonetheless, the total effects of economic growth are positive. Meanwhile, an important issue is the impact of environmental regulation intensity (ERI). Xu *et al.* (2024) shows that ERI is exercising a non-linear effect on the efficiency of sustainable economic growth (ESEG) for the European Union countries, with a clear spatial pattern encompassing various cases ranging from Western Europe to Southern Europe. They also reveal that the ERI have a spatial spillover effect on the ESEG, with the spatial spillover effect in the eastern and western regions of the EU being significantly different.

Based on this literature, this paper seeks to advance a two-fold contribution. First, it explores the capacity of spatial models (i.e. models for which the parameters are spatially varying) to capture the potential effect exercised by countries' performance on preserving the environment and maintaining their economic development. Second, it provides empirical evidence for a relationship between environmental performance and economic development for 167 countries and territories, investigating the nature of such a relationship.

The underlying argument can be summarized as follows: while most development studies reflect the myriad of economic dynamics' determinants, they frequently neglect the role played by geographical dimension of economic activity in the generative processes of this dynamics. Geographical locations and physical distances between countries might be relevant in explaining the differences in their performance in terms of ensuring sustainable development and environmental protection. Consequently, a more realistic explanatory framework should include a geographical dimension in any explanation addressing development driving forces.

One of the most important reasons is that various 'neighbourhood effects' can occur in relation to development processes. Neighbour countries exchange goods, services, labour force, technology, and knowledge. Institutional transformations and social changes can frequently arise in 'regional waves'. Similarly, negative externalities related to the adverse effects of socioeconomic activities are not limited to a single administrative area, and spillover effects can occur across borders. Indeed, the existing literature provides empirical evidence that the effect of spatial spillover (spatial dependency) is one of the leading causes of economic growth spillover effects in association with the geographical position of the trade partners (Amidi et al., 2020; Amidi & Fagheh Majidi, 2023; Evcim & Yesilyurt, 2023).

Hence, if there is an impact exercised by the environmental performance on development, then the implied transmission channels might display spatially varying features that reflect the locational determinants of both variables.

In terms of methodology, we employ the 'Geographically Weighted Regression' class of models to assess the validity of this line of reasoning. Such models can incorporate potential spatial effects in transmitting the impact of the explanatory variables. We find, for 167 jurisdictions, that location is relevant in explaining the linkage between environmental performance and development (although this seems to apply in a heterogeneous manner).

The following section includes details about the methodology used. Section 3 reports the results and carries out a robustness analysis. Section 4 discusses the findings and suggests future research directions, while the last section concludes.

2. Methodology and international data

The Geographically Weighted Regression (GWR) model

To account for the potential spatial variable effects exercised by the quality of environmental protection policies and mechanisms on economic development, we involve the framework of a 'Geographically Weighted Regression' (GWR) model. The critical advantage of GWR is that it allows the implied relationships to be spatially varying (i.e. the coefficients in GWR are functions of spatial location). In addition, the GWR models are usually robust to the effects of multicollinearity (Fotheringham & Oshan, 2016).

We consider the general form of such a model as:

$$GDP_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)EPI_i + \sum_{k=2}^{m} \beta_k(u_i, v_i)X_{ki} + \varepsilon_i \quad (1)$$

Here GDP_i is a measure of economic activity output (such as real GDP) for country *i*, EPI_i is a proxy for the environmental performance in country *i* and X_{ki} is an additional explanatory variable for country *i*. $\beta_0(u_i, v_i)$ is the intercept parameter at location *i*, $\beta_k(u_i, v_i)$ is the local regression coefficient for the k^{th} independent variable at the level of country *i* and ε_i is a local random error. Finally, (u_i, v_i) is the coordinate of country *i*.

As Fotheringham *et al.* (1998, p.1907) explains, the calibration of this model "assumes implicitly that observed data near to point *i* have more of an influence in the estimation … than data located farther from *i*. In essence, the equation measures the relationships inherent in the model *around each point i*." Therefore, the estimation of the model coefficients requires a point-wise calibration that is made for each regression location independently. The weighted least squares method is used and the matrix calculation for the estimated regression coefficients could be expressed as (Lu et al., 2011, p.93):

$$\hat{\beta}(u_i, v_i) = (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) GDP \quad (2)$$

X is the matrix of the explanatory variables with a column of 1s for the intercept, $\beta(u_i, v_i) = \left(\beta_0(u_i, v_i), \ldots, \beta_m(u_i, v_i)\right)$ is the vector of *m+1* local regression coefficients, and $W(u_i, v_i)$ is the diagonal matrix denoting the geographical weighting of each observed data for regression point *i*.

The weighting scheme $W(u_i, v_i)$ is calculated with a kernel function based on the proximities between regression point *i* and the *N* data points around it. In our estimates we consider three types of kernel functions, namely the 'Gaussian', the 'tricube' and, respectively, the 'bi-square' ones:

$$Gaussian: \quad w_{ij} = exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2\right)$$

$$Tricube: w_{ij} = \begin{cases} \left(1 - \left(\frac{|d_{ij}|}{b}\right)^3\right)^3 & if\ |d_{ij}| < b\ ; \\ 0 & otherwise \end{cases} \quad (3)$$

$$Bi-square: w_{ij} = \begin{cases} \left(1 - \left(\frac{d_{ij}}{b}\right)^2\right)^2 & if\ |d_{ij}| < b\ ; \\ 0 & otherwise \end{cases}$$

Here w_{ij} is the *j*-th element of the diagonal of the matrix of geographical weights $W(u_i, v_i)$, and d_{ij} is the distance between observations *i* and *j*. Meanwhile, *b* is the bandwidth.

The 'Gaussian' kernel is a continuous function of the distance between two observation points. The weights will be a maximum (i.e. equal to 1) for an observation at a GW model calibration point and will decrease according to a Gaussian or exponential curve as the distance between observation points increases. At the same time, the 'bi-square' and 'tri-cube' kernels are discontinuous, giving null weights to observations with a distance greater than *b*. In addition, these two kernels provide weights that decrease as the distance between observation points increases, up until the distance *b* (see for details Gollini et al., 2015, p.5).

It should be noticed that an optimum bandwidth *b* can be found by minimising a model goodness-of-fit diagnostic based on the 'corrected Akaike Information Criterion' (corrected AIC) which accounts for model parsimony. Unlike the standard AIC, the corrected version is a function of sample size (Hurvich et al., 1998).

International data

For 167 countries and territories, we select the GDP per capita, PPP (constant 2021 international $) ('GDP'), as the dependent variable (values corresponding to the 2023 year). The dataset includes developed, emerging, and frontier economies and provides a variety of cases in terms of development and environmental performance.

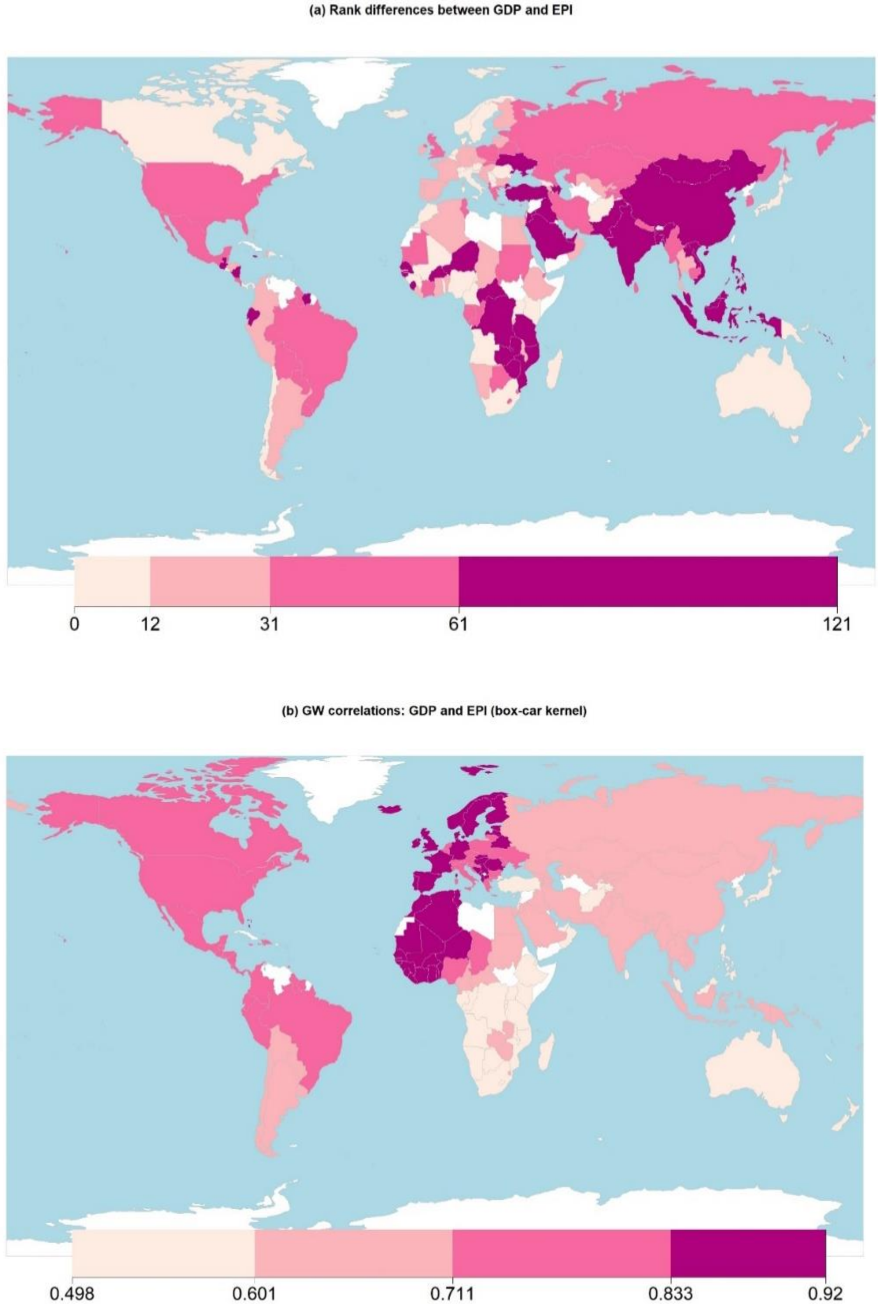
The data are collected from the World Bank database' *World Development Indicators* (The World Bank, 2024). From the same source, we also collect some socio-demographic and natural resources data as control variables: population density (people per sq. km of land area ('POPDENS'); urban population (% of the total population) ('URBAN') and oil rents (% of GDP) ('OIL').

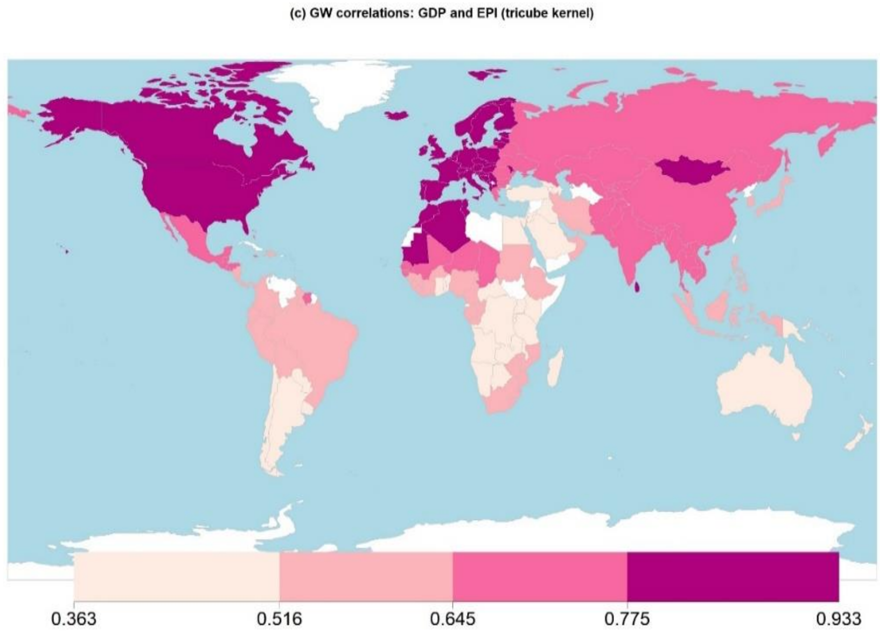
The 2024 Environmental Performance Index ('EPI') (Block et al., 2024) is the primary explanatory variable of interest. By using 58 performance indicators across 11 issue categories, the EPI ranks 180 countries on climate change performance, environmental health, and ecosystem vitality. Due to its complexity, this indicator can capture the multidimensional nature of ecological status and provide a granular view and a comparative perspective for differences between countries. To drop-out the scale effects, all the variables are transformed into their corresponding Z-scores by subtracting from their levels the sample means and dividing the outcomes with the sample standard deviation.

Finally, we use the centroid of the largest land mass as countries' coordinates (longitude and latitude).

Figure 1 shows that the sample's absolute rank differences between GDP and EPI and their GW correlations display a heterogeneous spatial pattern.

Figure 1. **Absolute rank differences and GW correlations for GDP per capita and EPI**





Notes: The figure shows (a) the absolute differences between the ranks (as computed for the considered dataset) for GDP per capita and, respectively, the EPI. Countries not included in the dataset are represented in white. It also shows (b) the 'Box-car' kernel and (c) the 'Tricube' kernel geographically weighted (GW) correlations. These correlations were obtained using an adaptive kernel bandwidth equal to 44 (around 26% of the data). Such a bandwidth was selected based on the AIC corrected (AICc) approach. The correlation statistics are implemented by the R package 'GWmodel' (Gollini et al., 2015; Lu et al., 2014a; Lu et al., 2024). The map is drawn using the R package 'world map' (South, 2011, 2023).

Moreover, Figure 1 reveals that some regions, such as North America, Northern Europe or North-West Africa, are characterized by low or medium rank differences and medium or high correlations. On the opposite side of the spectrum, countries from the Middle and Far East or Oceania are characterized by higher rank differences and lower GW correlations. Between these two clusters of countries, several intermediate cases are situated mainly in Europe, Central and South-East Africa or Central and South America.

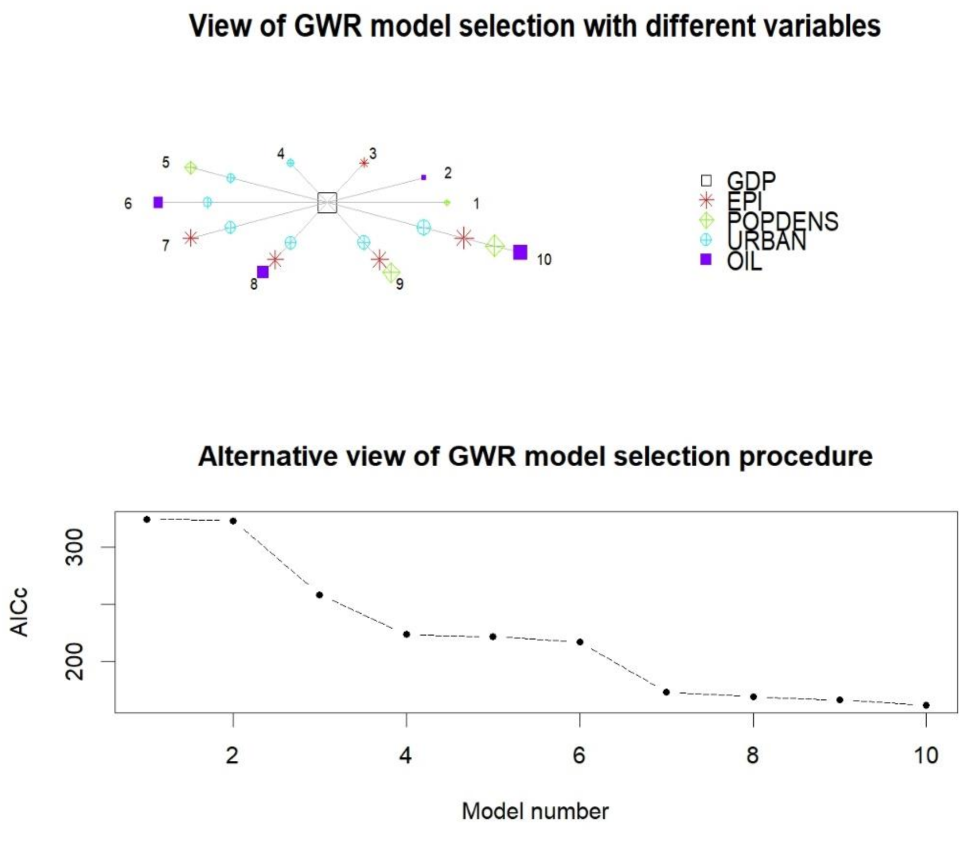
Globally, the geographical location *matters* in explaining the relationship between GDP and EPI. The following section explores this in the formal framework of GWR models.

3. Results

Main results

Figure 2 displays the results from a pseudo stepwise procedure aiming to select the explanatory variables as a preliminary analytical step. This procedure is used in a forward direction and requires four steps: (a) the calibration of all possible GW regressions by sequentially regressing a single independent variable against the dependent variable; (b) the identification of the best-performing model which produces the minimum corrected AIC; (c) the sequential introduction of a variable from the remaining group of independent variables to construct new models; and (d) repeat the previous step till all independent variables are permanently included in the model (see for details Gollini et al., 2015). Ten GW regressions result from this procedure. The first explanatory variable permanently included is the proportion of urban population, while the second is the EPI index. The last variable the selection procedure considers is the rents from oil exploitation. Supplementary Figure 1 shows the corrected AIC values from these ten fits. These values continue to fall until all independent variables are included. Therefore, they can all be further used as potential determinants of development.

Figure 2. Model view of the stepwise specification procedure and corrected AIC values



Notes: An adaptive bandwidth is used to estimate the GWR models. This is equal to 53 (number of nearest neighbours). Also, the 'Great Circle distance' metric ('orthodromic distance') is used. In addition, a 'bi-square' kernel function is considered. The procedure follows the implementation from the R package 'GWmodel' (Gollini et al., 2015; Lu et al., 2014a; Lu et al., 2024).

Table 1. Geographically Weighted Regression and Mixed Geographically Weighted Regression models

Model	EPI	PD	UP	OR	AIC corrected	BIC	Adjusted R^2
Global Regression	0.045*** (0.005)	0.123*** (0.044)	0.389***(0.055)	0.098** (0.045)	284.044	165.935	0.693
Basic GWR (kernel: 'tricube')							
Geographically Weighted Regression	[-0.001; 0.067]	[-0.694; 0.768]	[0.021; 0.699]	[-0.141; 0.339]	210.662	120.443	0.832
F1 test (Leung *et al*. 2000): 0.542 (p=0.000)							
F2 test (Leung *et al*. 2000): 2.954 (p=0.000)							
F3 test (Leung *et al*. 2000):	2.713 (p=0.000)	1.589 (p=0.046)	4.281 (p=0.000)	0.858 (p=0.604)			
F4 test (Fotheringham *et al*. 2002, p. 92): 0.439 (p=0.000)							
Basic GWR (kernel: 'bi-square')							
Geographically Weighted Regression	[-0.005; 0.069]	[-0.297; 0.719]	[0.045; 0.771]	[-0.210; 0.339]	209.197	120.077	0.833
F1 test (Leung *et al*. 2000): 0.540 (p=0.000)							
F2 test (Leung *et al*. 2000): 2.810 (p=0.000)							
F3 test (Leung *et al*. 2000):	3.099 (p=0.000)	1.442 (p=0.108)	4.142 (p=0.000)	1.376 (p=0.187)			
F4 test (Fotheringham *et al*. 2002, p. 92): 0.431 (p=0.000)							
Mixed GWR (kernel: 'tricube')							
Global coefficient				0.094			
GWR variables	[0.000; 0.069]	[-0.722; 0.782]	[0.005; 0.709]		201.800	102.700	
Mixed GWR (kernel: 'bi-square')							
Global coefficient		0.059		0.091			
GWR variables	[0.001; 0.069]		[0.036; 0.687]		201.000	95.320	

****, **,*- 1%,5% and 10% significance levels. Minimal and maximal GWR coefficients in [].*

Notes: PD - Population density (people per sq. km of land area); UP - Urban population (% of total population); OR - Oil rents (% of GDP)

For the F1 test, the null hypothesis is: "there is no significant difference between OLR and GWR models for the given data" (Leung et al., 2000, p.16). For the F2 test, the null is: "the GWR model and the OLR model describe the data equally well"(Leung et al., 2000, p.17). F3 is a spatial stationarity test with the null hypothesis that for an individual variable, the coefficients are "tested not to vary significantly over the region"(Leung et al., 2000, p.21). F4 is another goodness-of-fit test proposed by

Fotheringham et al. (2002). An adaptive bandwidth is used to estimate the GWR models. In the case of the basic GWR model, this is equal to 53 (number of nearest neighbours). Also, the 'Great Circle distance' metric ('orthodromic distance') is used. If the 'tricube' kernel is used, for the basic GWR model, the residual sum of squares is 21.820 while for the Mixed GWR model this is 22.260. If the 'bi-square' kernel is considered instead, the residual sum of squares is 21.421 while for the Mixed GWR model this is 23.210. All the models are implemented in the R package 'GWmodel' (Gollini et al., 2015; Lu et al., 2014a; Lu et al., 2024)

Based on these preliminary results, Table 1 reports the outcomes of different GWR model specifications. In the global regression model, the impact exercised by EPI on the GDP dependent variable is positive and statistically significant at 1%. The same is the case for the control variables.

For the basic GWR models (with 'tricube' and 'bi-square' kernel functions), the effects associated with EPI (as well as the other considered explanatory variables) display a specific spatial heterogeneity, with estimated values ranging from close to zero to around 0.07. The median estimates are for both kernel functions *positive* (0.043 and, respectively, 0.048) and point toward a dominant favourable effect exercised by a better environmental performance on development.

Nonetheless, as the F1, F2, and F4 tests show, the GWR models fit the data set better than a global OLS model regardless of kernel function. The F3 test shows significant spatial non-stationarity for *some* but *not for all* influences exercised by the considered explanatory variables. More precisely, the impact exercised by the oil variable appears spatially stationary, while for the rest of the variables (including the constant), this impact is spatially non-stationary. Consequently, a mixed GWR model may be more appropriate for depicting the considered variables. However, if a 'bi-square' kernel function is used, the effects associated with population density also seem spatially stationary.

By accounting for corrected AIC and BIC levels, the best explanatory model is a Mixed GWR with 'bi-square' kernel functions. In such a model, the coefficients of EPI range between close to zero and up to 0.069. Hence, the model supports the hypothesis of a *positive* impact exercised by the quality of the environment on economic development. However, such an impact displays significant geographical variations. Figure 3 displays the local coefficients for EPI, as are these estimated based on the Mixed GWR model with 'bi-square' kernel function. Higher levels of these coefficients appear for countries located in North and Central America, the North of Europe and the South-East of Africa. Correlatively, lower levels are estimated for the Middle East, South-East Asia, and Oceania countries, as well as China and India. Although there are some differences, this spatial pattern remains relatively stable across different model specifications (including those for the basic GWR model).

For the control variables, the most significant estimated impact is associated with the fraction of the urban population, followed by population density. This finding aligns with the conceptual arguments and empirical evidence provided by literature that "Urbanization plays a crucial role in the economic development of every country" (Di Clemente et al., 2021, p.1).

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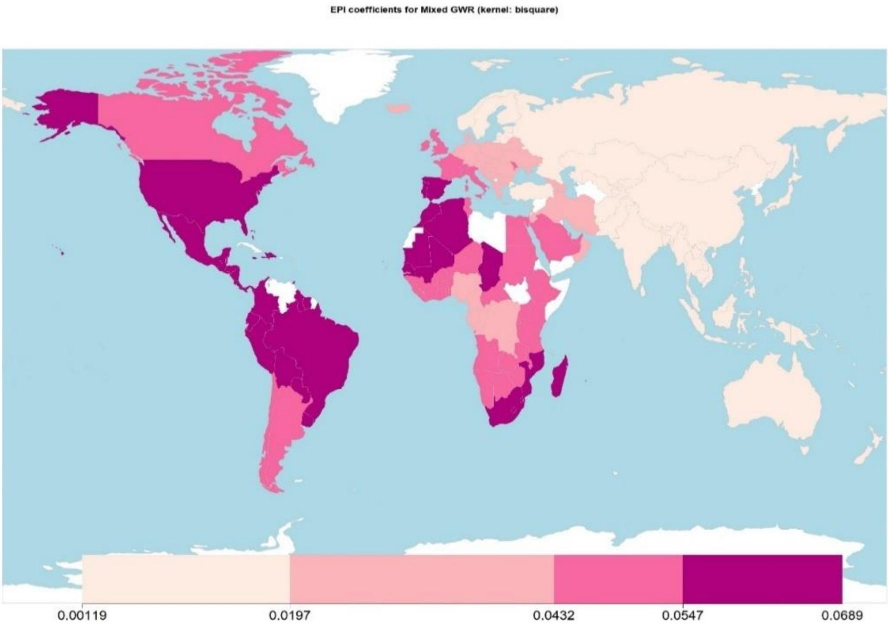
Figure 3. The coefficient for EPI in a Mixed GWR model with 'bi-square' kernel function



Notes: The results correspond to EPI coefficients for the last model in Table 1. All the specifications correspond to the ones mentioned in Table 1.

Robustness check: Multiscale GWR and Mixed GWR-SAR models

This section delivers a robust assessment of the main results. More precisely, standard GWR models assume that all implied processes operate at the same spatial scale. This happens only sometimes since, for different empirical data, variations in regression relationships may occur across different spatial scales. This strong assumption can be relaxed by considering a 'Multiscale Geographically Weighted Regression' (MGWR). The MGWR approach aims to obtain an optimal bandwidth vector, in which each element indicates the spatial scale at which a particular process occurs. In addition, greater flexibility can be achieved by searching not only for a different bandwidth for each relationship in the considered model, but also (and simultaneously) by searching for a different distance metric for each relationship (i.e. by using a 'Parameter- Specific Distance Metric GWR'- PSDM -GWR). The key idea is that the relationships between the dependent and each independent variable may display their distinctive response to the weighting computation, i.e., the choice of distance metric. Thus, the flexible bandwidth GWR can potentially provide a more realistic description of the considered effects in the model (Lu et al., 2015; Fotheringham et al., 2017; Murakami et al., 2018; Fotheringham et al., 2023).

Table 2 reports various Multiscale GWR models with non-Euclidian / Euclidian distance metrics and three different kernel functions. Several observations can be highlighted here. First, the corresponding values for the EPI coefficients appear to fail in a narrow band compared to the basic and mixed GWR models. Second, the coefficients' range is broader for the other variables. Such results hold particularly for the case of population density, for which more significant negative local coefficients are estimated. Third, the values of corrected AIC and BIC criteria are lower for all the multiscale models. This outcome suggests that such models might fit the data better. Nonetheless, the values of the residual sum of squares are comparable with those registered for basic and mixed GWR models (as are the corresponding R2). Overall, the previously identified spatial patterns for the effects exercised by the explanatory variables are not substantially modified from a qualitative point of view.

Table 2. Various Multiscale (PSDM-GWR) model specifications

Model	EPI	PD	UP	OR	AIC corrected	BIC	Adjusted R^2
Multiscale; PSDM-GWR; Non-Euclidian distance; Kernel: 'Gaussian'							
GWR variables	[0.028; 0.052]	[0.070; 0.104]	[-0.007; 0.550]	[0.071; 0.077]	197.116	87.212	0.831
Bandwidth	23	104	14	149			
Multiscale; PSDM-GWR; Non-Euclidian distance; Kernel: 'bi-square'							
GWR variables	[0.027; 0.052]	[-0.537; 0.495]	[0.011; 0.580]	[0.048; 0.117]	194.034	88.235	0.837
Bandwidth	110	64	53	133			
Multiscale; PSDM-GWR; Non-Euclidian distance Kernel: 'tricube'							
GWR variables	[0.026; 0.053]	[-0.695; 0.795]	[-0.152; 0.632]	[0.059; 0.071]	195.966	96.056	0.840
Bandwidh	110	52	32	165			
Multiscale; Euclidian distance; Kernel: 'bi-square'							
GWR variables	[0.028; 0.052]	[-0.618; 1.085]	[0.005; 0.581]	[0.078; 0.091]	194.276	92.470	0.839
Bandwidh	110	39	53	165			
Multiscale; Euclidian distance; Kernel: 'tricube'							
GWR variables	[0.029; 0.051]	[-0.649; 0.734]	[-0.069; 0.584]	[0.068; 0.080]	196.051	89.412	0.837
Bandwidh	130	53	42	165			

Notes: PD - Population density (people per sq. km of land area); UP - Urban population (% of total population); OR - Oil rents (% of GDP)

For the PSDM-GWR specifications, a' Minkowski distance' of order five is used in the case of EPI variable and, respectively, of order three for all the others. For the PSDM-GWR with a 'Gaussian' kernel, the residual sum of squares is 23.351. If the 'bi-square' kernel is considered, the residual sum of squares is 22.296, while for the 'tricube' kernel this sum is 21.616. Finally, for the model with Euclidian distance and the 'bi-square' kernel, the corresponding value is 21.701, while for the 'tricube' kernel this value is 22.698. All the models are implemented in the R package 'GWmodel' (Gollini et al., 2015; Lu et al., 2014a; Lu et al., 2024).

Furthermore, we account for the possible existence of some spatial autocorrelations at the level of the Data Generative Process (DGP) for countries' GDP per capita (i.e. correlation among values of this variable that are attributable to their relatively close locational positions). Such autocorrelation can inflate Type I errors and can generate the appearance of some 'red herrings' (Diniz-Filho et al., 2003). Several arguments can be advanced for assuming that geographically nearby GDP values tend to display similar profiles. For instance, countries that are close from a locational point of view can share more substantial flows of goods, technology and labour forces. There is also a higher chance of the spread of endogenous and exogenous shocks between them and the synchronization of their macroeconomic environment conditions.

We use a 'Mantel test' to highlight such potential spatial autocorrelation (Mantel, 1967; Mantel & Valand, 1970). This test implies a nonparametric analysis of the relationship between two dissimilarity matrices for data concerning the same individuals or sampling units. As Anselin (1995) shows, this test can be viewed as a generalization of Moran's *I* or Geary's *c* tests for spatial autocorrelations (see Legendre et al., 2015, for a critical discussion about the test). The first matrix is an 'environmental distance matrix' for the GDP per capita variable. In contrast, the second one is a 'geographic distance matrix', i.e. the physical distance between countries in our dataset. The aim is to check if the dissimilarities between countries' economic outputs are correlated or not with their proximity.

Table 3 reports the results. If Spearman's rank correlation measure is used, the hypothesis that the GDP per capita distance matrix is related to country geographic separation cannot be rejected. In other words, if countries are more distant, they become more dissimilar regarding their economic development. However, such a relationship does not appear if Pearson's product-moment correlation is instead used. Nonetheless, the assumptions implied by these two statistics are different. As Legendre *et al.* (2015, p. 1241) explains: “The first assumption is that the relationship is linear, if a cross-product or a linear correlation coefficient is used as the Mantel statistic, or monotonic if the dissimilarities are replaced by their ranks (Mantel 1967) or if a Spearman or Kendall correlation coefficient is used to compute the Mantel statistic (Dietz 1983)”. Hence, the relationship between the considered dissimilarities matrices might be monotonic, but not necessarily linear. Overall, it is perhaps more prudent to assume the existence of *some* spatial autocorrelations in the characteristic DGP for GDP per capita. For comparison, we note that the corresponding value of a Moran test applied for a regression model with GDP as the dependent variable and only a constant as the explanatory variable equals 311.320 (*p*-value =0.000). For that reason, we can reject the null that the errors of such a regression model are *i.i.d*. A SAR model can be appropriate to reflect the existence of some spatially distinctive development clusters.

Table 3. Mantel (1967) test

Mantel statistics	Based on Pearson's product-moment correlation	Based on Spearman's rank correlation
Level and *p*-value	0.020 (*p*-value=0.236)	0.052 (*p*-value=0.024)

Notes: Mantel statistic is a correlation between entries of two dissimilarity matrices. The first matrix is a GDP distance matrix created by using the' Euclidean Distance'. The second matrix is the 'Haversine distance' between countries. The null hypothesis is the is the absence of relationship between values in these two dissimilarity matrices. The null distribution (and significance level) is obtained through randomisation. The null distribution is generated by shuffling the locations (matrix rows and columns) of one of the matrices to calculate an empirical null distribution for the given data set. The implementation of the test is based on Legendre & Legendre (2012). The number of permutations is equal with 9999. The test is implemented by the R package 'vegan' (Oksanen et al., 2024).

Geniaux and Martinetti (2018) introduces a class of spatial regression models (MGWR-SAR) that simultaneously deal with spatial dependence and heterogeneity by combining mixed GWR with SAR (Spatial Auto-Regressive model). The main advantage of an MGWR-SAR model is that it allows the regression parameters and the spatial autocorrelation coefficient to vary over the space. Such models involve the spatial two-stage least squares technique for model calibration. We consider two models from this class to account for the possible spatial autocorrelations in the GDP per capita.

The first model is a *MGWR-SAR*$(0, k_c, k_v)$ specified as:

$$GDP = \lambda \text{WGDP} + \beta_c X_c + \beta_v(u_i, v_i)X_v + \varepsilon_i; X_c = \begin{pmatrix} POPDENS \\ OIL \end{pmatrix}_c ; X_v = \begin{pmatrix} EPI \\ URBAN \end{pmatrix}_v \quad (4)$$

Here W is the spatial weight matrix for spatial dependence (a sparse numeric matrix in the compressed, sparse, column-oriented format. The non-zero elements in the columns are sorted into increasing row order). X_c are the independent variables with constant coefficients β_c and X_v are the independent variables with spatially varying coefficients β_v. (u_i, v_i) denotes the x-y coordinates of the i^{th} point, and ε_i is a spatially uncorrelated term.

The second model is a MGWR-SAR$(1, k_c, k_v)$ as:

$$GDP = \lambda(u_i, v_i)\text{WGDP} + \beta_c X_c + \beta_v(u_i, v_i)X_v + \varepsilon_i;$$
$$X_c = \begin{pmatrix} POPDENS \\ OIL \end{pmatrix}_c ; X_v = \begin{pmatrix} EPI \\ URBAN \end{pmatrix}_v \quad (5)$$

Table 4 reports the results. These results suggest that a broader range of the EPI local coefficients is estimated when a SAR component is considered compared to a mixed GWR model without such a component. The median estimated levels for the EPI coefficients (0.037 and, respectively, 0.039) are lower than those for the mixed GWR without SAR term (0.042), but this difference is not significant. There are some differences between *MGWR-SAR* $(0, k_c, k_v)$ and *MGWR-SAR*$(1, k_c, k_v)$ specifications. Although the *MGWR-SAR*$(0, k_c, k_v)$ model implies larger extreme values of these coefficients, it has associated lower RMSE and residual sum of squares values (but greater corrected AIC criterion). The differences between specifications for the other explanatory variables are more pronounced concerning the effects induced by urban population. Simultaneously, for constant coefficients, the estimated levels are relatively close between specifications (as well as with those from the mixed GWR without SAR component).

Finally, the estimated **λ** parameter takes both positive and negative values in *MGWR-SAR* $(1, k_c, k_v)$ model. Such an outcome can be interpreted as generated by a non-linear relationship between the dissimilarities in economic development profiles of countries and their geographical distances. This might explain why including a SAR term does not contribute to a better model fit (accounting for corrected AIC and residual sum of squares) than the model without SAR.

Table 4. MGWR-SAR models

Model	λ	EPI	PD	UP	OR	AIC corrected	RMSE	Residual sum of squares
				MGWR-SAR$(0, k_c, k_v)$				
Global coefficient	0.008		0.040		0.096			
GWR variables		[-0.009; 0.094]		[-0.162; 0.850]		438.082	0.314	16.467
				MGWR-SAR$(1, k_c, k_v)$				
Global coefficient			0.058		0.083			
GWR variables	[-0.311; 0.925]	[-0.001; 0.069]		[0.033; 0.784]		385.181	0.383	24.481

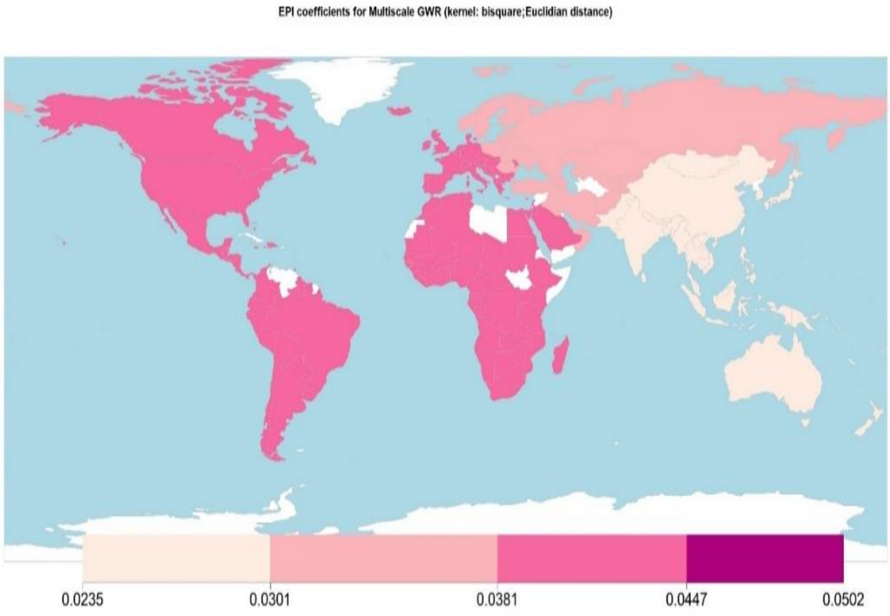
Minimal and maximal GWR coefficients in [].

Notes: PD - Population density (people per sq. km of land area); UP - Urban population (% of total population); OR - Oil rents (% of GDP).

A 'bi-square' kernel function is used. An adaptive bandwidth is used to estimate the models. This bandwidth is equal to 53 (number of nearest neighbours). The estimation technique for computing the models with spatial dependence is 'B2SLS'. A spatial weight matrix of four nearest neighbours with 0 in *diagonal is involved. The type of Generalized Kernel Product is 'GD' (only spatial). The models are implemented by using the R package 'mgwrsar' (Geniaux & Martinetti, 2018; Geniaux & Martinetti, 2023).*

Overall, the Multiscale GWR models appear to provide the best fits for our dataset in terms of the corresponding values for corrected AIC, BIC, adjusted R^2, and the residual sum of squares. Interestingly, as Figure 3 illustrates, these models provide a less heterogeneous estimation of the effects associated with the EPI variable. Indeed, large geographical areas such as Europe, Africa and the Americas now display median or higher levels of EPI impact. Correlatively, the Middle and Far East or countries from Australasian or Oceanian biogeographic realms display lower impact exercised by the EPI on economic development.

Figure 4. The coefficient for EPI in a Multiscale GWR model with 'bi-square' kernel function and Euclidian distance



Notes: The results correspond to EPI coefficients for the last model in Table 2. All the specifications correspond to the ones mentioned in Table 2

4. Comments

Our results suggest that environmental performance can influence global economic development. Nonetheless, such an influence is spatially heterogeneous. The implied effects vary substantially across different geographical regions or clusters of countries. Several observations can be formulated in regard to the plausibility of the results. First, several clusters of countries can be differentiated according the specific impact exercised by EPI. One cluster includes the European Nordic and North American countries. For these countries, high economic development is associated with high or medium-to-high performance in environmental protection. Due to their technological advances, they have achieved a sustainable development path, reducing, at the same time, economic activity's negative ecological impact. On the opposite side of the spectrum, another cluster includes countries from Africa, South America, the Middle and Far East, and Oceania, with poorer performance in both development and environmental status. Between these two clusters, at least three other groups can be found. One intermediary cluster includes high-income countries (such as Italy, Spain, Japan, Portugal, Cyprus, the Baltic countries, Singapore, South Korea or New Zealand) with average environmental performance. Another intermediary cluster consists of emerging economies (e.g. Central and Eastern European countries, Türkiye, Belarus, Kazakhstan, Malaysia, Thailand or South Africa) with low-to-medium levels of EPI. Finally, there are some apparent 'outliers' with a disconnected economic evolutionary path and environmental advancements (the Gulf countries, China, Saudi Arabia, Indonesia, Vietnam, India or the Philippines).

All these clusters of countries suggest that the effects of environmental performance are propagated non-linearly over development. The spatial nature of these effects can be explained by the distinctive content and non-uniform efficiency of the implemented pro-environmental policies and by the spatial autoregressive nature of the development processes themselves.

Second, our results can be placed in the broader framework of 'modernization theory' (Arat, 1988; Bernstein, 1971; Roxborough, 1988; Zapf, 2004). If technological advances transform economic structures, democratic institutions will more effectively ensure citizens' fundamental rights and social mobility. In such a context, traditional economic activities with a potentially disruptive environmental impact are gradually replaced by ecological-neutral or beneficial ones. Also, a larger urban population that can cover its basic needs accesses higher education, is more involved in social and political life and is becoming more concerned about environmental issues. In a democratic society, these 'post-materialist' citizens can voice their concerns on a wide range of environmental-related topics and may pressure public authorities to adopt pro-environmental public policies.

Third, our results show that various GWR models can better describe the effects exercised by the environmental performance. Yet, these models also reveal the non-linear nature of the relationship between countries' differences in terms of their economic profiles and ecological outcomes and their geographical location. The forces of globalisation are shaping this relationship in a non-uniform manner by changing the role played by geography in the socio-economic profiles' synchronisation. In other words, if spatial location matters, it matters differently than for pre-modern societies.

Fourth, in our proposed model, 'distance' is meant to reflect 'spatial effects' and not 'contextual effects'. As Feuillet *et al.* (2024) argues, the significant distinction between these two types of effects can be understood based on how geographical location is viewed: either as continuous (and thus describing 'distance effects') or as discrete (and therefore depicting 'contextual effects'). Since we are mainly interested in the consequences exercised by the distances between countries, our analysis deals with 'geographic areas' and not with 'places'. Therefore, we adopt a space-based approach involving spatially explicit models such as GWR. Of course, there is an analytical price to be paid here, namely the fact that such models do not account for the aggregation of observations within places, i.e. the effect of 'togetherness' among those observations that fall within close geographical boundaries (see Feuillet et al., 2024 for this point). Since our dataset includes, for instance, countries that are members of the European Union and, thus, are subject to some common environmental regulations, this issue might be particularly relevant for capturing the effects exercised by EPI. A more detailed analysis is required to clarify this aspect better.

Fifth, our model does not include time effects. So, we cannot capture the potential time-varying nature of the relationship between environmental performance and economic development.

Intuitively, it can be argued that such a relationship evolves as countries pass through different development stages and shift their economic structures from traditional ones to more knowledge-based ('postmodern') mechanisms of growth.

Moreover, a deeper analysis of this topic should at least advance a sound and detailed gnoseological framework able to clarify the transmission channels for the impact exercised by the natural environment on economic development, combining both spatial and time effects, address potential endogeneity issues that can arrive from the bi-univocal causality running between development and environmental status, provide extended explanations for the heterogeneity and non-linear nature of the implied effects, integrate the environment in a more complex model of development and add other relevant explanatory variables, or better clarify the role played by different multilevel structures and mechanisms or by the globalization forces.

There are two distinctive yet interrelated questions. The first one can be phrased as: Is there any relationship between environmental protection and development? Correlatively, the second question is: Does geographical location matter in explaining the shape of such a relationship? While the present analysis answers affirmatively to the second question, it does not address specific details of a possible response to the first one. A complete development model that includes the environmental sector must tackle the first question. Our results also point toward an affirmative answer to this question.

5. Conclusions

We find that a country's geographical location matters in explaining the influence exercised on its development level by its efficiency in preserving the natural environment. The implied effects are subject to significant heterogeneity across different geographic areas, and distinctive clusters of countries can be identified in this respect. One of the most exciting results is that higher levels of development are not necessarily associated with a worsening degradation of the environment. Contradictory, as the European Nordic and North American countries illustrate, by applying efficient pro-environment policies, countries may simultaneously achieve better performance in terms of both environmental performance and development. In addition, other socio-demographic variables that reflect various facets of modernization processes can jointly contribute to achieving the sustainable development.

Several policy implications can be derived from such findings. The first (and most important) is that a country cannot implement environmental policies by itself. Instead, various regional and international spatial spillovers should be accounted for. Coherent and integrated international efforts should be implemented to prevent the natural environment's degradation and mitigate its negative socioeconomic implications. Second, the model of economic growth should be reconsidered in order to achieve its long-term sustainability through a 'virtuous cycle' of 'environment protection-growth-societal sustainability' mechanisms.

Third, the weighting of various stakeholders’ interests should be carefully considered when pursuing different social objectives directly or indirectly connected with the current and future environmental status.

Although the proposed analysis has several limitations, and more research is required to clarify the subsequent implied mechanisms, its central message is straightforward: No country can stay isolated when it comes to environmental protection, and the welfare of its citizens largely depends on the welfare of their closer or distant neighbours.

References

Amidi, S., Fagheh Majidi, A. and Javaheri, B., 2020. Growth spillover: a spatial dynamic panel data and spatial cross section data approaches in selected Asian countries. *Future Business Journal,* 6, 20. https://doi.org/10.1186/s43093-020-00026-9

Amidi, S. and Fagheh Majidi, A., 2020. Geographic proximity, trade and economic growth: a spatial econometrics approach. *Annals of GIS,* 26(1), pp.49–63. https://doi.org/10.1080/19475683.2020.1714727

Anselin, L., 1995. Local Indicators of Spatial Association–LISA. *Geographical Analysis,* 27, pp.93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Arat, Z.F., 1988. Democracy and Economic Development: Modernization Theory Revisited. *Comparative Politics*, 21(1), pp.21-36. https://doi.org/10.2307/422069

Benhamed, A., Osman, Y., Ben-Salha, O., and Jaidi, Z., 2023. Unveiling the Spatial Effects of Climate Change on Economic Growth: International Evidence. *Sustainability*, 15(10), 8197. https://doi.org/10.3390/su15108197

Bernstein, H., 1971. Modernization theory and the sociological study of development. *Journal of Development Studies,* 7(2), pp.141–160. https://doi.org/10.1080/00220387108421356

Block, S., Emerson, J. W., Esty, D. C., de Sherbinin, A., Wendling, Z. A., et al., 2024. *2024 Environmental Performance Index*. New Haven, CT: Yale Center for Environmental Law & Policy. Available at: <https://epi.yale.edu/downloads>.

Chen, J., and Hu, L., 2022. Does Environmental Regulation Drive Economic Growth through Technological Innovation: Application of Nonlinear and Spatial Spillover Effect. *Sustainability,* 14(24), 16455. https://doi.org/10.3390/su142416455

Chica-Olmo, J., Sari-Hassoun, S., and Moya-Fernández, P., 2020. Spatial relationship between economic growth and renewable energy consumption in 26 European countries. *Energy Economics*, 92, 104962. https://doi.org/10.1016/j.eneco.2020.104962

Di Clemente, R., Strano, E. and Batty, M., 2021. Urbanization and economic complexity. *Nature Scientific Reports*, 11(3952), pp.1-10. https://doi.org/10.1038/s41598-021-83238-5

Dietz, E.J. 1983. Permutation tests for association between two distance matrices. *Systematic Biology,* 32, pp.21–26. https://doi.org/10.1093/sysbio/32.1.21

Diniz-Filho, J.A.F., Bini, L.M., and Hawkins, B.A., 2003. Spatial autocorrelation and red herrings in geographical ecology. *Global Ecology and Biogeography*, 12(1), pp.53–64. https://doi.org/10.1046/j.1466-822X.2003.00322.x

Evcim, N., and Yesilyurt, M.E., 2023. Spatial interaction and economic growth: a case of OECD countries. *Future Business Journal*, 9, 102. https://doi.org/10.1186/s43093-023-00270-9

Feuillet,T., Cossart, E., Charreire,H., Banos, A., Pilkington, H., Chasles, V., Hercberg, S., Touvier, M., and Oppert, J.M., 2024. Hybridizing Geographically Weighted Regression and Multilevel Models: A New Approach to Capture Contextual Effects in Geographical Analyses. *An International Journal of Theoretical Geography,* 56(3), pp.554-572. https://doi.org/10.1111/gean.12385

Fotheringham, A.S., Charlton, M.E., and Brunsdon, C., 1998. Geographically weighted regression: a natural evolution of the expansion method for spatial data analysis. *Environment and Planning A*, 30(11), pp.1905–1927. https://doi.org/10.1068/a301905

Fotheringham, A.S., Brunsdon, C., and Charlton, M., 2002. *Geographically weighted regression: the analysis of spatially varying relationships*. Chichester: Wiley. ISBN: 978-0-471-49616-8

Fotheringham, A.S., and Oshan, T.M., 2016. Geographically weighted regression and multicollinearity: dispelling the myth. *Journal of Geographical Systems*, 18, pp.303–329. https://doi.org/10.1007/s10109-016-0239-5

Fotheringham, A. S., Yang, W. and Kang, W., 2017. Multiscale Geographically Weighted Regression (MGWR). *Annals of the American Association of Geographers*, 107(6), pp.1247-1265. https://doi.org/10.1080/24694452.2017.1352480

Fotheringham, A.S., Oshan, T.M., and Li, Z., 2023. *Multiscale Geographically Weighted Regression: Theory and Practice (1st ed.)*. Boca Raton: CRC Press. https://doi.org/10.1201/9781003435464

Geniaux, G., and Martinetti, D., 2018. A new method for dealing simultaneously with spatial autocorrelation and spatial heterogeneity in regression models. *Regional Science and Urban Economics,* 72, pp.74-85. https://doi.org/10.1016/j.regsciurbeco.2017.04.001

Geniaux, G., and Martinetti, D. 2023. mgwrsar: GWR and MGWR with Spatial Autocorrelation, R package version 1.0.5.

Gollini, I., Lu, B., Charlton, M., Brunsdon, C., and Harris, P., 2015. GWmodel: An R Package for Exploring Spatial Heterogeneity Using Geographically Weighted Models. *Journal of Statistical Software,* 63(17), pp.1-50. https://doi.org/10.18637/jss.v063.i17

He, Q., 2015. Fiscal decentralization and environmental pollution: Evidence from Chinese panel data. *China Economic Review,* 36, pp.86-100. https://doi.org/10.1016/j.chieco.2015.08.010

Hurvich, C.M., Simonoff, J.S., and Tsai, C.-L., 1998. Smoothing parameter selection in nonparametric regression using an improved Akaike information criterion. *Journal of the Royal Statistical Society. Series B (Statistical Methodology)*, 60 (2), pp.271–293. https://doi.org/10.1111/1467-9868.00125

Legendre, P., and Legendre, L., 2012. *Numerical Ecology* (*Developments in Environmental Modelling volume 24), 3rd English Edition*. Elsevier. ISBN-13978-0444538680

Legendre, P., Fortin, M.-J., and Borcard, D., 2015. Should the Mantel test be used in spatial analysis? *Methods in Ecology and Evolution*, 6, pp.1239–1247. https://doi.org/10.1111/2041-210X.12425

Leung, Y., Mei, C.-L., and Zhang, W.-X., 2000. Statistical tests for spatial nonstationarity based on the geographically weighted regression model. *Environment and Planning A: Economy and Space*, 32(1), pp.9 -32. https://doi.org/10.1068/a3162

Lu, B, Harris, P., Charlton, M., and Brunsdon, C., 2014a. The GWmodel R package: further topics for exploring spatial heterogeneity using geographically weighted models. *Geo-spatial Information Science,* 17(2), pp.85-101. https://doi.org/10.1080/10095020.2014.917453

Lu, B, Charlton, M., Harris, P., and Fotheringham, S., 2014b. Geographically weighted regression with a non-Euclidean distance metric: A case study using hedonic house price data. *International Journal of Geographical Information Science* 28(4), pp.660-681. https://doi.org/10.1080/13658 816.2013.865739

Lu, B., Harris, P., Charlton, M., and Brunsdon, C., 2015. Calibrating a Geographically Weighted Regression Model with Parameter-specific Distance Metrics. *Procedia Environmental Sciences*, 26, pp.109-114. https://doi.org/ 10.1016/j.proenv.2015.05.011

Lu, B, Harris, P., Charlton, M., Brunsdon, C., and Nakaya, T., 2024. *GWmodel: Geographically-Weighted Models*, *R package version 2.3-3*.

Mantel, N., 1967. The detection of disease clustering and a generalized regression approach. *Cancer Research*, 27, pp.209-220.

Mantel, N. and Valand, R.S., 1970. A technique of nonparametric multivariate analysis. Biometrics, 26, pp.547–558. https://doi.org/10.2307/2529108

Murakami, D., Lu, B., Harris, P., Brunsdon, C., Charlton, M., Nakaya, T., and Griffith, D. A., 2018. The Importance of Scale in Spatially Varying Coefficient Modeling. *Annals of the American Association of Geographers*, 109(1), pp.50–70. https://doi.org/10.1080/24694452.2018.1462691

Ren, X., Cheng, C., Wang, Z., and Yan, C., 2021. Spillover and dynamic effects of energy transition and economic growth on carbon dioxide emissions for the European Union: a dynamic spatial panel model. *Sustainable Development*, 29, pp.228–242. https://doi.org/10.1002/sd.2144

Ren, S., Du, M., Bu, W., and Lin, T., 2023. Assessing the impact of economic growth target constraints on environmental pollution: Does environmental decentralization matter? *Journal of Environmental Management,* 336, 117618. https://doi.org/10.1016/j.jenvman.2023.117618

Shi, X., Chen, Y., and Cheng, Q., 2022. Environmental Regulation, Environmental Knowledge Spillover, and Regional Economic Growth in China: An Empirical Test Based on the Spatial Durbin Model. *Sustainability*, 14(21), 14260. https://doi.org/10.3390/su142114260

South, A., 2011. rworldmap: A New R package for Mapping Global Data. *The R Journal,* 3(1), pp.35-43.

Oksanen, J, Simpson, G., Blanchet. F., et al., 2024. vegan: Community Ecology Package, R package version 2.6-6.1.

Roxborough, I., 1988. Modernization Theory Revisited. A Review Article. *Comparative Studies in Society and History*, 30(4), pp.753-761. https://doi.org/10.1017/S0010417500015528

South, A., 2023. *rworldmap: Mapping Global Data, R package version 1.3-8*.

The World Bank, 2024. *World Development Indicators* database. Svailable at: <https://databank.worldbank.org/source/world-development-indicators> [Accessed on 03.08.2024].

Xie, F., Liu, Y. and Yang, M., 2023. Spatial spillover effect of environmental regulation on regional economic growth. *Environment, Development and Sustainability*, 25, pp.7149–7160. https://doi.org/10.1007/s10668-022-02366-8

Yang, H., 2021. An empirical analysis on spatial effects of environmental protection. *Journal of King Saud University – Science*, 33(6), 101525. https://doi.org/10.1016/j.jksus.2021.101525

Xu, Y., Liao, X., He, R., and Liu, S., 2024. Impact of environmental regulation intensity on the efficiency of sustainable economic growth in the European Union. *Journal of Cleaner Production*, 434,140047. https://doi.org/10.1016/j.jclepro.2023.140047

Zapf, W., 2004. Modernization theory - and the non-western world*. WZB Discussion Paper*, No. P 2004-003, Wissenschaftszentrum Berlin für Sozialforschung (WZB), Berlin, pp.1-14. Availablre at: <https://www.econstor.eu/handle/10419/50239>.