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Temporal variations in the relationship between educational inequality and spatial disparity: Emerging patterns across the physical region of Azerbaijan, Iran

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Abstract

Despite decades of development interventions, regional inequalities have persisted and, in many cases, become more complex in their spatial and structural configurations. One underexplored aspect of this process is the changing role of educational inequality in shaping spatial disparities. Most existing studies treat the education–space relationship as static, overlooking how its influence may weaken, transform, or re-emerge under shifting regional development. This study examines the temporal evolution of the relationship between educational inequality and spatial disparity at the regional scale. Composite indices of educational and spatial inequality were developed using Exploratory Factor Analysis, and Geographically Weighted Regression was applied to capture spatial non-stationarity across three periods. This combined approach enables the identification of spatial heterogeneity and structural change. The results reveal a three-phase transformation. Initially, educational inequality acts as the dominant driver of spatial disparity. In the second phase, its explanatory power diminishes as urban concentration and infrastructural centralization gain importance. In the most recent phase, educational inequality re-emerges within a more complex multi-causal system, interacting with infrastructural, environmental, and spatial dynamics. Overall, the findings show that spatial inequality arises from dynamic interactions among human, infrastructural, and environmental systems, highlighting the need for temporally sensitive and spatially informed policy approaches.

1. Introduction

Regional inequality remains one of the persistent challenges in development processes, emerging when the distribution of resources, opportunities for growth, and the quality of public services are uneven across different parts of a country. Such disparities often stem from centralized decision-making structures, structural differences in natural and human capacities, and unequal allocation of public investments (Rodríguez-Pose, 2012; Wei, 2015; Guo et al,2024). Consequently, some regions evolve into growth poles, while others face chronic underinvestment in infrastructure, economic stagnation, and limited access to essential services (Harahap et al., 2024; Foufri, 2025; Liu et al,2024). These imbalances extend beyond the economic domain and can undermine social cohesion, demographic vitality, and spatial efficiency. Less-developed regions frequently experience labor out-migration, erosion of human capital, and a decline in overall quality of life, whereas more advantaged areas—benefiting from institutional and economic advantages—tend to follow a more stable and sustained development trajectory (Barrios & Strobl, 2009; Wei et al., 2020). Significant disparities in employment, income, education, and access to public services thus reflect the continuation of an uneven development pattern and signal growing instability within national spatial structures (Pourfaraj et al., 2019; Karimi Moughari & Barati, 2017). Educational inequality has been identified as a critical driver of persistent socioeconomic disparities. Gaps in educational access and quality between urban and rural areas not only shape learning outcomes (Tan, 2024) but also restrict future employment and income opportunities, thereby reproducing cycles of inequality across generations (Bennett et al., 2024; Ferreira & Gignoux, 2014; Xiang & Stillwell, 2023). Recent scholarship emphasizes that education is inherently spatial, and that the geographic distribution of schools, variation in service quality, and spatial patterns of learning opportunities play decisive roles in shaping educational inequality (Garcia & Weiss, 2020; Burgess, 2021). High-quality education—enshrined as Sustainable Development Goal 4 (SDG

4)—stands among the most influential pillars of the global sustainable development agenda (Saini et al., 2023; Dastyari & Jose, 2024; Hossain et al., 2023). Assessing educational inequality is therefore crucial, as it directly affects learning quality and student achievement, and provides an empirical basis for allocating resources equitably and advancing progress toward sustainable development targets (Partey et al., 2024; Lin & Liu, 2024; Beeson et al., 2024). Understanding the spatial dimensions of educational inequality is essential for designing inclusive and equity-oriented education policies (Colombo et al., 2024). Despite its importance, the existing literature on educational inequality continues to suffer from several gaps, including the scarcity of localized and spatially detailed studies, insufficient contextual analysis at school and neighborhood levels, limitations in longitudinal and qualitative data, and inadequate exploration of the linkages between educational inequality and broader socioeconomic development (Symonds et al., 2025; Campos et al., 2025; OECD, 2024). Addressing these gaps through new empirical research is therefore vital for generating a more nuanced understanding of the spatial and social dimensions of educational inequality and for informing more effective policy interventions.

Spatial inequality refers to systematic differences in individuals', communities', or regions' access to resources, public services, and socio-economic opportunities, arising from geographic location, institutional structures, and cumulative spatial processes. These disparities manifest not only economically but also across educational, health, and technological dimensions (Zahl-Thanem, 2024; Liu et al., 2024). Spatial inequality emerges when economic, educational, and infrastructural opportunities are unevenly distributed across space; empirical studies show that the concentration of services and facilities in major urban centers intensifies core–periphery divides (Zahl-Thanem & Rye, 2024; Delprato et al., 2024). Moreover, multidimensional factors such as unequal access to technology, variation in institutional capacity, and different levels of regional development act as key mechanisms through which spatial inequality is reproduced (Liu et al., 2024; Kourtidou et al., 2025). Recent literature highlights a clear link between spatial inequality and educational inequality, as geographic context shapes school quality, access to qualified teachers, and the level of learning infrastructure (Guijarro-Garvi et al., 2024; Cantalini et al., 2025; Hu et al.,2023). In many countries, distance from urban centers and spatial marginalization are associated with reduced learning opportunities, lower educational performance, and constrained pathways for academic advancement—demonstrating the deeply spatial nature of education (Delprato et al., 2024; Zahl-Thanem & Rye, 2024). Research further shows that spatial segregation and geographic heterogeneity in residential environments generate substantial disparities in access to high-quality schools, thereby structurally reproducing educational inequality across regions. These studies underscore spatial patterns as core determinants of educational inequality (Nieuwenhuis & Xu, 2021; Burger, 2019; Cordini, 2019). Consequently, geographic location plays an independent and significant role in shaping educational outcomes, with inter-provincial and inter-regional differences accounting for a considerable share of achievement gaps—demonstrating that education is inherently spatial (Guijarro-Garvi et al., 2024; Cantalini et al., 2024). Spatial inequality thus reinforces other forms of inequality, including educational inequality (Hoseinbar & Baluch Zehi, 2021). Educational deprivation is conceptualized as a form of multidimensional poverty, involving not only the absence of schooling but also deficits in learning resources, declining instructional quality, and restricted educational opportunities (Colombo et al., 2024; Bukhari et al., 2024). Such deprivation can deepen disparities across schools and regions through unequal distribution of school

resources and infrastructure (Partey et al., 2024; Bukhari et al., 2024). Educational deprivation measured through indicators such as the pupil–teacher ratio in primary schools (Bulti et al., 2019) and in lower and upper secondary schools (Ilie et al., 2021) points to structural inequality in which the uneven allocation of teaching resources—including teacher shortages and limited access to high-quality instruction—reduces learning outcomes and perpetuates socio-economic and geographic achievement gaps (Ying & Hatta, 2025; Hanselman, 2019; Zhang et al., 2025). Accordingly, educational deprivation can be measured through indicators such as the number of schools, availability of classrooms, infrastructural deficits, teacher availability, and teacher–student ratios (Partey et al., 2024; Colombo et al., 2024). The innovation of this study lies in its integrated spatial perspective, which connects spatial inequality with educational inequality within the regional context of Azerbaijan. By combining spatial distribution analysis of schools and educational resources with the assessment of structural determinants of educational disparities, the study provides a multidimensional and geographically grounded understanding of how place shapes educational outcomes.

The novelty of this study does not lie in the mere application of EFA or GWR, which are well-established techniques. Rather, it lies in developing a spatial-temporal explanatory regime framework that uncovers how the structural drivers of inequality evolve over time. The study introduces a three-phase inequality regime model (education-driven - urban-infrastructure-driven - multi-causal fragmented regime), which has not been identified in previous research.

Unlike earlier studies that treat the relationship between educational and spatial inequality as static or linear, this work demonstrates how that relationship undergoes structural reconfiguration across decades. Furthermore, the study constructs a new longitudinal database (1996–2023) integrating satellite-derived environmental indicators, accessibility metrics, and educational resource variables—data that did not previously exist for the Azerbaijan region.

Together, this new conceptual model and the newly constructed dataset represent the core innovation of the paper.

In this context, the present study aims to examine the relationship between spatial inequality and educational inequality at the regional scale, with a specific focus on the physical-spatial region of Azerbaijan. Through the spatial analysis of school distribution, educational resources, and learning-quality indicators, along with the assessment of determinants of educational inequality, this study seeks to explain the geographic heterogeneity of educational opportunities. Utilizing regional data at the county level provides an accurate understanding of how spatial context shapes educational disparities and offers empirical evidence to support targeted policymaking, equitable resource allocation, and context-sensitive educational planning. Such an approach contributes to promoting educational equity and advancing progress toward Sustainable Development Goal 4 (SDG-4).

2. Materials and Methods

To assess the spatial relationship between spatial inequality and educational deprivation, this study integrates a set of remote sensing indicators, Google Earth Engine satellite-derived datasets, and statistical

yearbooks covering the periods 1996–2016 and 2023. A comprehensive multi-indicator framework is developed by applying exploratory factor analysis to transform the indicators of each dimension into composite factors, and geographically weighted regression (GWR) is employed to examine the spatially varying local relationships between the two phenomena. The overall methodological process is conceptually summarized in Fig. 1, which illustrates the research framework.

2.1. Study Area

The significance of selecting East Azerbaijan, West Azerbaijan, and Ardabil lies in the fact that these three provinces form a geographically contiguous and culturally cohesive region in northwestern Iran, while simultaneously displaying marked patterns of spatial inequality over recent decades. As illustrated in Fig. 2, these provinces constitute an interconnected spatial block whose regional continuity reinforces the analytical coherence of the case study. According to the 1996 census, the populations of East Azerbaijan, West Azerbaijan, and Ardabil were 3,325,540, 2,496,320, and 1,168,011, respectively; by 2016 these figures had increased to 3,909,652, 3,265,219, and 1,270,420. Consequently, between 1996 and 2016, East Azerbaijan grew by approximately 584,000, West Azerbaijan by 769,000, and Ardabil by 101,000 people—growth that continued toward 2023/2024 and has intensified pressures on services, infrastructure, and spatial equilibrium. Empirical studies also point to persistent development disparities, inter-urban gaps in livability, and spatial injustice across these provinces (Akbari, 2023; Bayramzadeh & Foadmarashi, 2023; Hosseini et al., 2020), highlighting the structural complexity of spatial challenges shaping this region.

2.2. Indicators for Analyzing Educational Inequality

A review of the educational inequality literature highlights several key indicators that capture disparities in access to quality education across different levels of schooling. Based on this body of research, the present study employs indicators that assess the ratio of students to teachers and classrooms in primary, lower-secondary, and upper-secondary education, reflecting the distribution and adequacy of instructional resources. In addition, geographic accessibility—measured through students' distance to high-quality schools—is considered an essential dimension of inequality, as spatial barriers significantly constrain learning opportunities. As summarized in Table 1, these indicators represent the core dimensions of educational inequality examined in this study. Prior studies emphasize that uneven teacher allocation, disparities in resource distribution, and geographic distance collectively shape the structure of educational inequality (Xu, 2022; Blanden, Doepke & Stuhler, 2023; Darling-Hammond, 2001; Cullinan & Flannery, 2022; Hanselman, 2019).

2.3. Indicators for Analyzing Spatial Inequality

To capture the multidimensional nature of spatial inequality across the three provinces, a set of spatial, environmental, and structural indicators was extracted using the Google Earth Engine platform. These indicators)Table 1) were selected based on robust theoretical and empirical foundations, with each representing a distinct dimension of spatial inequality. The urban footprint captures the spatial extent and intensity of built-up development and is widely used to identify uneven patterns of urban growth and infrastructural imbalance between central and peripheral areas (Seto et al., 2011; Angel et al., 2020; Zhou et

al.,2022; Kemper et al.,2018). The NDBI quantifies built-up density and helps distinguish well-developed urban zones from underdeveloped or marginalized areas (Kuffer et al., 2016; Yasin et al.,2022). The mean distance to major road networks reflects accessibility-related inequality, a fundamental mechanism through which spatial disadvantage emerges, as greater distance is associated with reduced mobility, limited-service access, and fewer socio-economic opportunities (Weiss et al., 2018; Kuffer et al., 2020). NO_2 concentration serves as an indicator of environmental inequality, with numerous studies demonstrating that disadvantaged areas often experience higher levels of pollutant exposure (Clark et al., 2014; Liu et al., 2021). Ecological metrics such as NDVI capture disparities in vegetation cover and access to ecosystem services—recognized as key elements of environmental and spatial justice (Wolch et al., 2014; Chen et al.,2022; Weigand et al.,2023; Juergens and Meyer-He,2020). Finally, Land Surface Temperature (LST) reveals thermal inequality and the uneven spatial distribution of heat exposure, commonly observed in dense, deteriorated, or socioeconomically vulnerable neighborhoods (Chen et al., 2022; Tian et al.,2025). Together, these indicators provide a comprehensive and theoretically grounded framework for analyzing spatial inequality across the three provinces.

Collectively, these indicators function as empirical representations of the broad, complex, and inherently multidimensional concept of spatial inequality, translating its abstract theoretical dimensions into measurable and spatially explicit patterns.

Table 1
Theoretical Indicators for Assessing Educational and Spatial Inequality

CATEGORY	INDICATOR	SOURCE
EDUCATIONAL INEQUALITY	Student–Teacher Ratio (Primary–Lower Secondary–Upper Secondary)	Xu (2022); Darling-Hammond (2001); Blanden, Doepke & Stuhler (2023); Cullinan & Flannery (2022); Hanselman (2019)
	Student–Classroom Ratio (Primary–Lower Secondary–Upper Secondary)	Xu (2022); Darling-Hammond (2001); Blanden et al. (2023); Cullinan & Flannery (2022); Hanselman (2019)
	Distance to High-Quality Schools	Xu (2022); Darling-Hammond (2001); Cullinan & Flannery (2022)
SPATIAL INEQUALITY	Urban Footprint	Seto et al. (2011); Angel et al. (2020); Zhou et al. (2022)
	NDBI (Built-Up Density)	Kuffer et al. (2016); Yasin et al. (2022)
	Mean Distance to Major Roads	Weiss et al. (2018); Kuffer et al. (2020)
	NO_2 Concentration	Clark et al. (2014); Liu et al. (2021)
	NDVI (Vegetation Cover)	Wolch et al. (2014); Chen et al. (2022); Weigand et al. (2023)
	LST (Land Surface Temperature)	Chen et al. (2022); Tian et al. (2025)

To reduce data complexity and organize the variables into a more coherent analytical structure, Exploratory Factor Analysis (EFA) is employed (Kim et al.,2025). This procedure is carried out separately for the years 1996, 2016, and 2023, allowing both dimensionality reduction and the examination of temporal changes in inequality patterns. The results of the EFA indicate that the indicators can be consolidated into two major latent factors: one representing educational inequality and the other capturing spatial inequality. These two components provide an interpretable and theoretically meaningful summary of the underlying structure of the variables across the three time points. To investigate the spatial association between these two factors, GWR is applied. The use of GWR enables a localized assessment of relationships, capturing spatial non-stationarity and revealing how the influence of educational and spatial conditions varies across neighborhoods (Ansong et al.,2015; Sajjad et al.,2022; Arvin et al.,2025). Prior to implementing the GWR model, Ordinary Least Squares (OLS) regression and Moran's I statistics are used to evaluate model adequacy and detect spatial clustering or autocorrelation within the variables (Fu et al.,2024; Xie et al.,2024). This preliminary assessment ensures that spatial dependence is properly accounted for before moving to the localized regression framework. Altogether, these methodological steps establish a coherent and rigorous approach for analyzing and comparing educational and spatial inequalities over the three examined years.

2.4. 1.Formulation of composite indicators using exploratory factor analysis

The underlying assumptions for all observed variables have been outlined in the Appendix. Exploratory Factor Analysis (EFA) is applied to uncover the latent structure governing the relationships among variables, based on the idea that a limited set of underlying constructs shapes their covariance patterns (Kline, 2014; McDonald, 2014; Gollar and Imani,2025). In the common-factor model, each variable is specified as a linear combination of several latent factors and a unique error component, as shown in Eq. (1):

$$X_i = \lambda_1 F_1 + \lambda_2 F_2 + \ldots + \lambda_m F_m + \alpha_i \qquad (1)$$

where X_i denotes the observed variable,

λ_{ij} represents the loading of factor j on variable i,

F_j is the latent factor,

and α_i captures the specific variance not explained by the common factors.

Based on the recommendations of Yong and Pearce (2013), exploratory factor analysis is employed to extract the underlying conceptual structures and to reduce data dimensionality prior to constructing composite indicators. The number of factors is determined using a combination of the eigenvalue-greater-than-one criterion and visual inspection of the Scree plot. To enhance the interpretability of factor patterns, an orthogonal Varimax rotation is applied. The adequacy of the dataset for conducting factor analysis is

evaluated using the KMO measure and Bartlett's Test of Sphericity, both of which indicate that the correlation matrix is suitable for factor extraction.

2.4.2. Geographically Weighted Regression for Assessing Spatially Varying Effects Across Counties

GWR is employed as a spatially adaptive regression technique that allows model parameters to vary across locations rather than remain fixed globally. This local specification enables the model to capture spatial heterogeneity in the associations among variables, addressing limitations of global approaches that assume stationarity (Griffith, 2008; Sulekan & Jamaludin, 2020). In GWR, a separate regression equation is calibrated for each spatial unit, with observations weighted according to their geographic proximity. The model formulation is expressed, as shown in Eq. (2):

$$Y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i + v_i)x + \varepsilon_i \qquad (2)$$

where (u_i, v_i)denote the geographical coordinates of observation i,
$\beta_k(u_i, v_i)$ represents the location-specific regression coefficient for predictor k,

and $\epsilon_i$is the residual term.

(McMillen,2004). Following the extraction of the two latent constructs, GWR is applied to evaluate how the influence of spatial inequality on educational inequality varies across the counties of the province. In this specification, educational inequality is defined as the dependent variable, while spatial inequality is incorporated as the main explanatory variable. By estimating location-specific parameters, the model captures differences in the strength and direction of this relationship among counties, reflecting the non-stationary nature of socio-spatial disparities. This localized analytical framework allows the identification of territorial variations that cannot be detected by global regression approaches, thereby providing a more realistic representation of inequality dynamics at the sub-provincial scale.

3. Results

3.1. Results obtained from factor analysis

To ensure the reliability of the composite indicators, separate exploratory factor analyses are conducted for each year and for both conceptual dimensions—educational inequality and spatial inequality. As summarized in Table 3, the KMO values exceed the minimum acceptable threshold of 0.50 across all years, indicating adequate sampling adequacy for factor extraction (Kaiser, 1974). Likewise, Bartlett's Test of Sphericity is statistically significant in all cases ($p < 0.001$ for most years), confirming that the correlation matrices are appropriate for performing factor analysis (Field, 2024). The extracted components and their associated diagnostics, presented in Table 2, collectively validate the suitability of the datasets for factor

extraction. Across the three temporal points (1996, 2016, and 2023), the resulting factors exhibit strong eigenvalues ranging from 1.867 to 2.771 and account for a substantial proportion of the total variance (approximately 62% to 73%). These results indicate that, for both educational and spatial inequality, a coherent and internally consistent latent structure emerges over time, and the selected variables demonstrate sufficient shared variance to define a single underlying factor. Notably, the spatial inequality factor in 2023 explains the highest proportion of variance (73.02%), reflecting a higher degree of internal consistency among the variables included for that year rather than implying any directional change in inequality itself. Furthermore, the normalized factor scores derived from these analyses are visualized in Figure 3, which displays the spatial distribution of the composite indicators across counties. Overall, the diagnostic measures and resulting factor score maps confirm that the yearly datasets possess an adequate correlation structure for factor analysis and that the extracted components provide statistically robust inputs for subsequent spatial modeling.

Table 2 Key Outputs of Exploratory Factor Analysis

Indicator Type	Year	KMO	Bartlett's Test (p-value)	Eigenvalue (Factor 1)	Variance Explained (%)	Cumulative Variance (%)
Educational Inequality	1996	0.743	< 0.001	2.332	71.29%	71.29%
Spatial Inequality	1996	0.641	< 0.001	1.867	62.24%	62.24%
Educational Inequality	2016	0.579	< 0.001	2.771	69.28%	69.28%
Spatial Inequality	2016	0.556	0.003	1.555	61.85%	61.85%
Educational Inequality	2023	0.643	< 0.001	1.943	69.00%	69.00%
Spatial Inequality	2023	0.636	< 0.001	2.010	73.02%	73.02%

Figure 3 illustrates the spatial distribution of normalized factor scores for educational and spatial inequality across the counties for 1996, 2016, and 2023. A comparative assessment of the three years reveals both persistent and evolving inequality patterns. In 1996, educational inequality is predominantly concentrated in the western and southwestern counties, while central and northeastern areas exhibit comparatively lower values. Spatial inequality, however, shows a different configuration, with the highest scores clustered around Tabriz and adjacent central counties, indicating a core-based pattern of infrastructural and spatial disparities. By 2016, the spatial distribution becomes more heterogeneous. Educational inequality intensifies in several southern and southeastern counties, whereas spatial inequality continues to display high values around the metropolitan core but expands toward surrounding counties. This suggests a widening gap between central and peripheral areas. In 2023, educational inequality shows a broader spatial spread, with new high-score areas emerging in parts of the northeast in addition to the southwest. Spatial

inequality also becomes more dispersed, forming multiple high-value clusters rather than a single dominant core. Overall, the temporal comparison indicates that educational inequality gradually shifts from a localized southwest concentration toward a more dispersed regional pattern, while spatial inequality transitions from a highly centralized structure in 1996 to a more multi-nodal distribution by 2023, reflecting evolving socio-spatial dynamics across the region.

3.2. Results Obtained from GWR

3.2.1. Global Association Between Spatial and Educational Inequality

Before implementing the GWR model, an initial Ordinary Least Squares (OLS) regression is estimated to assess the global relationship between the two conceptual dimensions under study. In this analysis, educational inequality is specified as the dependent variable, while spatial inequality is used as the explanatory variable. The purpose of this preliminary step is to determine whether a statistically meaningful association exists between the variables and to evaluate the overall explanatory power of the global model through the R^2 coefficient. Accordingly, separate OLS models are estimated for the three time periods—1996, 2016, and 2023. The results of these global regressions are summarized in Table 3 and serve as the basis for proceeding with the subsequent GWR analysis.

Table 3 Linear regression results between spatial inequality and educational inequality

Year	R	R^2	F	Sig. (Model)	B (Spatial Edu.)	Beta	t	Sig. (Coeff.)	Durbin–Watson	VIF
1996	0.662	0.531	6.790	0.012	−0.404	−0.362	−2.606	0.012	1.670	1.000
2016	0.597	0.439	1.816	0.185 (ns)	0.200	0.197	1.347	0.185 (ns)	1.776	1.000
2023	0.643	0.559	2.812	0.101 (ns)	0.266	0.243	1.677	0.101 (ns)	1.603	1.000

The OLS results show that in 1996 the relationship between spatial inequality and educational inequality is statistically significant, with an R^2 value above 0.50, indicating strong global explanatory power. This justifies the use of GWR to evaluate potential spatial non-stationarity. In 2016 and 2023, despite relatively high R values, the models are not statistically significant, suggesting that the relationship is not stable at the global scale and may vary locally. Therefore, applying GWR in these years is also warranted to uncover underlying spatial patterns.

3.2.2. Spatial Clustering Analysis (Moran's I)

The Moran's I index is one of the most important measures of spatial autocorrelation, used to identify spatial patterns of clustering or dispersion. Evaluating this index is an essential step before applying models such as GWR, since the presence of statistically significant spatial clustering is required to justify the use of geographically weighted regression (Anselin, 1995; Gedamu et al., 2024; Chen, 2023). In this

study, Moran's I was calculated, and the results show that both spatial inequality and educational inequality exhibit clear clustered patterns. These findings are presented in Figure 4.

The Moran's I results reveal that spatial distribution exhibits a clustered pattern.

After completing the required preliminary steps- including assessing spatial autocorrelation and confirming the presence of statistically significant spatial clustering -the GWR model has been applied to examine the relationship between spatial inequality and educational inequality. The results indicate that the model performs strongly across all three time periods, with R^2 values ranging from approximately 0.68 to 0.74 and adjusted R^2 values between 0.64 and 0.70, reflecting high explanatory power and model stability. In addition, the relatively low and negative AICc values- such as –32 in 1996 and around –18 and –25 in subsequent years-demonstrate the suitability of the GWR model and its improvement over the global OLS regression. Overall, these indicators confirm that the relationship between the two variables is strong, statistically meaningful, and spatially localized. Table 4 summarizes the main GWR parameters for the years 1996, 2016, and 2023.

To ensure comparability across years, the bandwidth in the GWR model was selected using the same standardized and optimal procedure for all time periods. This consistent approach ensured an unbiased spatial kernel and comparable modeling conditions, allowing valid comparison of GWR results over time.

Table 4 Summary of Key GWR Parameters Across the Three Study Years

Indicator	1996	2016	2023	Description
Bandwidth	121500	121500	121500	Optimal spatial kernel used for consistent local weighting across years
Residual Squares	0.865	1.102	0.942	Lower values indicate better overall model fit
Effective Parameters	8.45	9.12	5.21	Reflects local model complexity and degrees of freedom
Sigma	0.148	0.185	0.161	Standard deviation of residuals; smaller values show stronger fit
AICc	–32.41	–18.92	–25.87	More negative values indicate superior model performance
R^2	0.74	0.68	0.72	Proportion of variance explained by GWR, showing strong local relationships
Adjusted R^2	0.70	0.64	0.69	Adjusted for model complexity; higher values reflect stability and robustness

To enhance the clarity and interpretability of the GWR results, a series of comparative maps has been employed, as presented in Table 5.

A three-period examination of Local R^2(map a) reveals a profound spatial restructuring in the explanatory power of the education–spatial inequality relationship. In 1996, the highest explanatory power was

concentrated in the southern and southwestern parts of the region, indicating that educational inequality functioned as a primary and direct driver of spatial inequality. By 2016, this configuration had shifted markedly, with the explanatory core relocating toward the central urban belt around Tabriz, Azarshahr, and Osku, reflecting the growing influence of urban-centered dynamics. In 2023, the explanatory landscape transformed once again, this time forming new high-R^2 clusters in the eastern and northeastern subregions such as Ardabil, Meshginshahr, Sarab, and Nir. This progressive shift from south , center, east demonstrates that the education–space linkage is not static; rather, its spatial manifestation undergoes structural reconfiguration over time, responding to changing regional development regimes.

A comparison of standardized residuals (map b) across the three periods shows a clear evolution in the significance of omitted variables and unobserved factors shaping spatial inequality. In 1996, the largest residuals were concentrated in the south and parts of Khoy–Urmia, indicating that educational inequality alone could not fully explain spatial disparities in these areas and that structural factors—economic divides, settlement patterns, or infrastructural deficits—played substantial roles. By 2016, residual patterns became more dispersed, with new hotspots emerging in the northwest and northeast, signifying a gradual weakening of the explanatory influence of education. In 2023, residuals intensified and formed sharper clusters, notably in Piranshahr, Miandoab, Chaypareh, Germi, and Sarab, implying that non-educational drivers (economic restructuring, mobility, urban expansion, cross-border dynamics) increasingly shape spatial inequality. Overall, residual evolution shows that educational inequality has gradually lost its dominance over time.

The longitudinal evaluation of the Condition Number (map c) highlights an escalating complexity in the numerical stability and multicollinearity structure of the GWR model. In 1996, CN values were generally low, indicating a stable and relatively straightforward relationship, with only minor sensitivity observed along the central corridor. By 2016, heterogeneity increased, particularly in the northwest and northeast, suggesting that the underlying spatial data structure had become more intricate. By 2023, CN values rose further across extensive parts of the west, southwest, and sections of the north, signaling heightened instability and a more fragile estimation environment. This transition from a stable model (1996) to a more complex and sensitive structure (2023) reflects the increasing role of multi-causal and spatially uneven forces that interact with educational inequality, reshaping the model's diagnostic behavior over time.

The temporal pattern of t-values (map d) illustrates a significant transformation in the statistical stability of the education–spatial inequality relationship. In 1996, statistically significant coefficients were concentrated along the northern belt and parts of the central corridor, reflecting a robust and consistent association in these areas. By 2016, significance sharply declined, persisting only in a few scattered locations, indicating instability in the relationship as competing spatial factors gained prominence. In 2023, significance re-emerged but within newly formed spatial clusters such as Khoy, Piranshahr, Osku–Azarshahr, Sarab–Nir, and Aslandooz, suggesting that while the education–inequality link regained relevance, it now operates in a more selective, localized, and context-dependent manner. This trajectory—from broad significance (1996) to minimal persistence (2016) to cluster-based resurgence (2023)—highlights the shifting spatial logic of the relationship.

3.3Temporal Evolution of the Education–Spatial Inequality Relationship

To examine the temporal transformation of the relationship between educational inequality and spatial inequality, the key GWR diagnostics were compared across the three study years (1996, 2016, and 2023). As illustrated in Figure 5, the temporal trajectories of Local R^2 and the normalized Condition Number were analyzed to capture shifts in explanatory strength and numerical stability over time. This approach reveals longitudinal and structural patterns that cannot be detected through annual spatial maps alone, providing a clearer understanding of how the education–space linkage has evolved across different regional development phases.

The temporal analysis of GWR indicators reveals a structural shift in the relationship between educational inequality and spatial inequality over the three study periods. In 1996, the high Local R^2 indicates that educational disparity functioned as the dominant and relatively direct driver of spatial inequality, with the model operating under a stable explanatory structure. By 2016, the decline in explanatory power shows that education was no longer the principal factor, as urban, economic, and infrastructural dynamics increasingly shaped spatial patterns. In 2023, the rise of Local R^2—together with greater numerical complexity—suggests that the education–space relationship re-emerges but within a more heterogeneous and multi-causal environment. Overall, these trends reflect a transition from a simple, education-driven configuration to a more complex and diversified explanatory regime.

3.4 Validation and Robustness Checks

To ensure the credibility of the findings, a set of validation and robustness procedures was conducted. First, the performance of the GWR model was evaluated through comparison with a global OLS model. Lower AICc values and higher R^2 scores were observed for the GWR estimations, indicating that spatial heterogeneity had been effectively captured and that the local model provided a superior fit. Second, multicollinearity was examined using Variance Inflation Factor (VIF) statistics, all of which were found to fall within acceptable thresholds. This confirmed that the parameter estimates were not adversely affected by collinearity among the explanatory variables. Third, spatial autocorrelation in the residuals was assessed using Moran's I. The results showed no statistically significant spatial clustering of residuals across any of the three study years, suggesting that the spatial structure of the data had been appropriately modeled. In addition, a bandwidth sensitivity analysis was performed, and it was verified that small adjustments to the bandwidth parameter did not substantially alter the spatial distribution of local coefficients. This consistency confirmed the stability of the model results. Finally, the similarity of spatial patterns across the three temporal benchmarks provided an additional layer of empirical robustness to the spatial-temporal interpretations.

4. Discussion

Importantly, the results of this study enable the formulation of a three-phase explanatory regime model that provides a novel theoretical lens for understanding the temporal restructuring of inequality in regional systems. While previous research has typically examined educational or spatial inequality as isolated or

temporally fixed phenomena, the present study demonstrates that their interaction evolves through distinct developmental regimes.

The first regime (1996) reflects an education-driven structure, where foundational disparities in schooling resources operate as the primary mechanism of spatial inequality.

The second regime (2016) represents an urban-infrastructure transition, in which metropolitan expansion and spatial-economic restructuring overshadow the explanatory role of education.

The third regime (2023) marks the emergence of a multi-causal and spatially fragmented system, where educational inequality interacts with environmental, infrastructural, and cross-border processes, producing a more complex geography of disadvantage. This conceptualization contributes a theoretically grounded framework that is largely missing from the existing literature. Although numerous studies have mapped spatial or educational disparities, very few have examined how the relationship between them transforms structurally over time, or how shifts in political economy, environmental exposure, and infrastructural concentration reconfigure the causal architecture of inequality. By empirically identifying these temporal transitions, the study fills a significant gap in cross-sectional research traditions that tend to assume stability rather than transformation in the drivers of spatial inequality. Furthermore, the findings offer important implications for regional planning and policy design. The identification of shifting inequality regimes suggests that policies focusing solely on improving educational resources are unlikely to be effective in periods dominated by urban-infrastructural or environmental drivers. Conversely, interventions that fail to recognize the renewed relevance of educational disparities in the contemporary multi-causal regime may miss critical leverage points for long-term territorial equity. Therefore, the study underscores the necessity for place-sensitive, temporally adaptive, and cross-sectoral strategies capable of responding to the evolving constellation of forces shaping inequality.

By articulating these regime shifts, the study advances not only empirical understanding but also theoretical and policy-relevant insights into the dynamic nature of territorial development.

5. Conclusion

This study provides spatial–temporal evidence showing that the relationship between educational inequality and spatial inequality in Azerbaijan is neither fixed nor linear, nor confined to a single sector. Instead, it evolves within a broader regional system that has been continuously reshaped over time. By combining GWR-based spatial analysis with long-term temporal investigation, the study demonstrates that the mechanisms underlying spatial inequality have been substantially reconfigured over the past three decades. The findings point to a clear three-stage evolution in the explanatory structure of inequality. In 1996, regional disparities were largely rooted in basic educational inequalities, including uneven access to schooling, imbalanced teacher allocation, and fundamental gaps in educational provision. These educational divides translated relatively directly into socio-economic differences across regions. By 2016, however, the explanatory weight of education had diminished considerably. During this period, rapid metropolitan expansion, increasing concentration of infrastructure, and the consolidation of core–periphery spatial patterns emerged as the dominant drivers of inequality. Spatial disparities became more closely

associated with limited mobility, environmental pressures, and unequal access to urban services and economic opportunities. By 2023, the structure of inequality had shifted again. Educational inequality regained partial significance, but within a far more complex and fragmented spatial context. The results suggest the emergence of a multi-causal configuration in which education interacts with environmental stressors—such as NO_2 exposure and urban heat—alongside cross-border economic connections and differentiated rural–urban integration processes. In this phase, spatial inequality can no longer be attributed to a single prevailing factor; rather, it reflects the interaction of educational, environmental, infrastructural, and geographic processes operating across multiple spatial scales. Beyond the case of Azerbaijan, the analytical framework adopted in this study highlights the value of integrating geographically weighted models with temporally sensitive and multi-dimensional indicators. This approach is particularly relevant in regions characterized by heterogeneous spatial structures, pronounced socio-environmental gradients, and long-term transformations in development trajectories. The results confirm that GWR is especially effective in capturing how local dynamics diverge from aggregate trends, offering a methodological framework applicable to a wide range of contexts, from rapidly urbanizing regions to environmentally stressed areas in the Global South.Overall, this study contributes to a more nuanced understanding of the spatial–temporal evolution of inequality regimes and reinforces the need to conceptualize spatial inequality as a dynamic and layered phenomenon. Rather than viewing inequality as the outcome of isolated sectoral deficiencies, the findings emphasize its emergence from interacting systems that change over time and space. Recognizing this complexity is essential for analytical and planning approaches that aim to reflect the uneven and context-specific nature of spatial inequality. By tracing how the drivers of inequality intensify, weaken, or shift over nearly three decades, the study offers an empirically grounded and transferable framework for comparative regional analysis and future research in contexts where socio-spatial processes intersect with environmental and infrastructural change.

Declarations

Author Contribution

A.F.I. conceptualized the study, designed the methodology, conducted the analyses, and wrote the manuscript.

Data Availability

The data used in this study were obtained from publicly available sources, including national statistical yearbooks and satellite-derived datasets accessed through Google Earth Engine. Processed data supporting the findings of this study are available from the corresponding author upon reasonable request.

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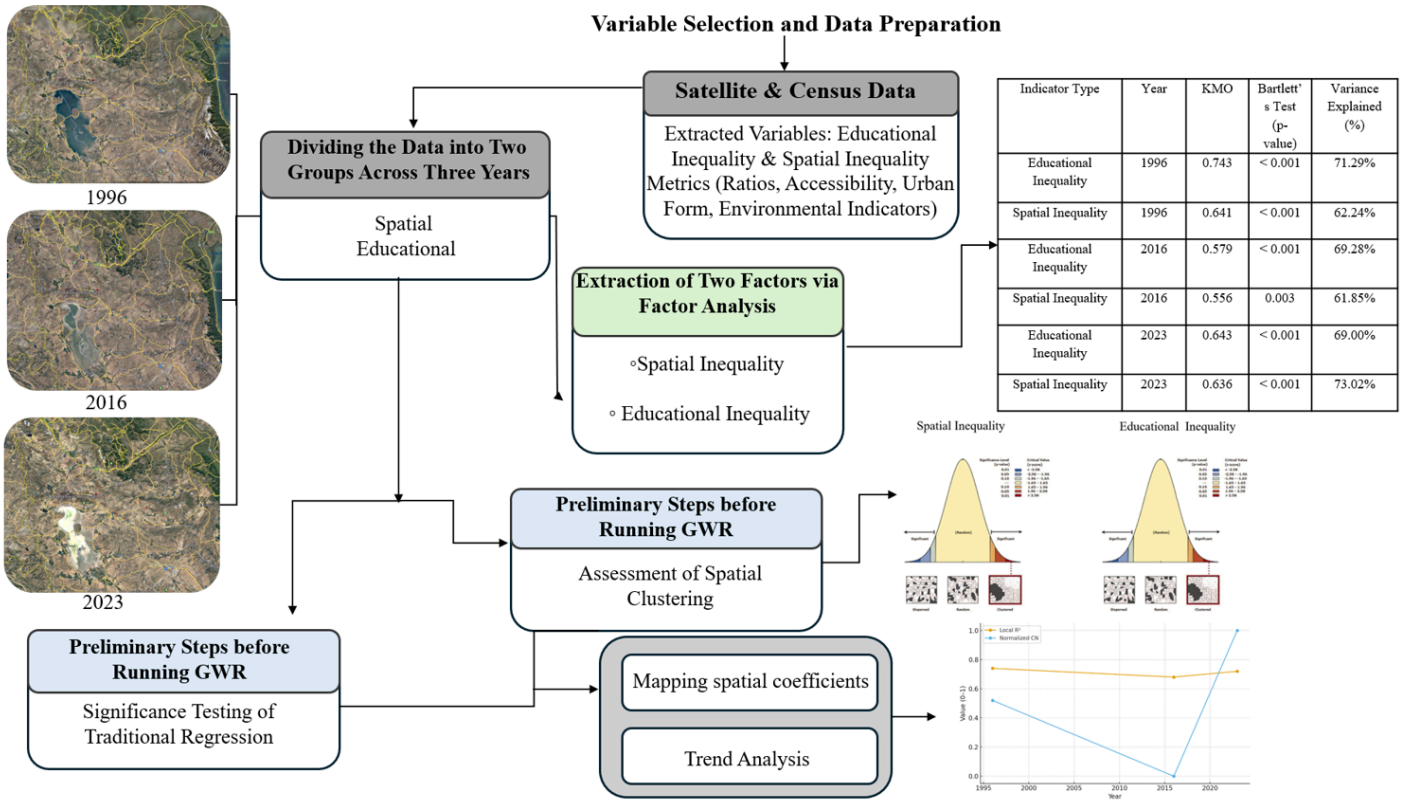
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Table

Table 5 is available in the Supplementary Files section.

Figures



Indicator Type	Year	KMO	Bartlett's Test (p-value)	Variance Explained (%)
Educational Inequality	1996	0.743	< 0.001	71.29%
Spatial Inequality	1996	0.641	< 0.001	62.24%
Educational Inequality	2016	0.579	< 0.001	69.28%
Spatial Inequality	2016	0.556	0.003	61.85%
Educational Inequality	2023	0.643	< 0.001	69.00%
Spatial Inequality	2023	0.636	< 0.001	73.02%

Figure 1

Research Framework for Spatial and Educational Inequality Analysis

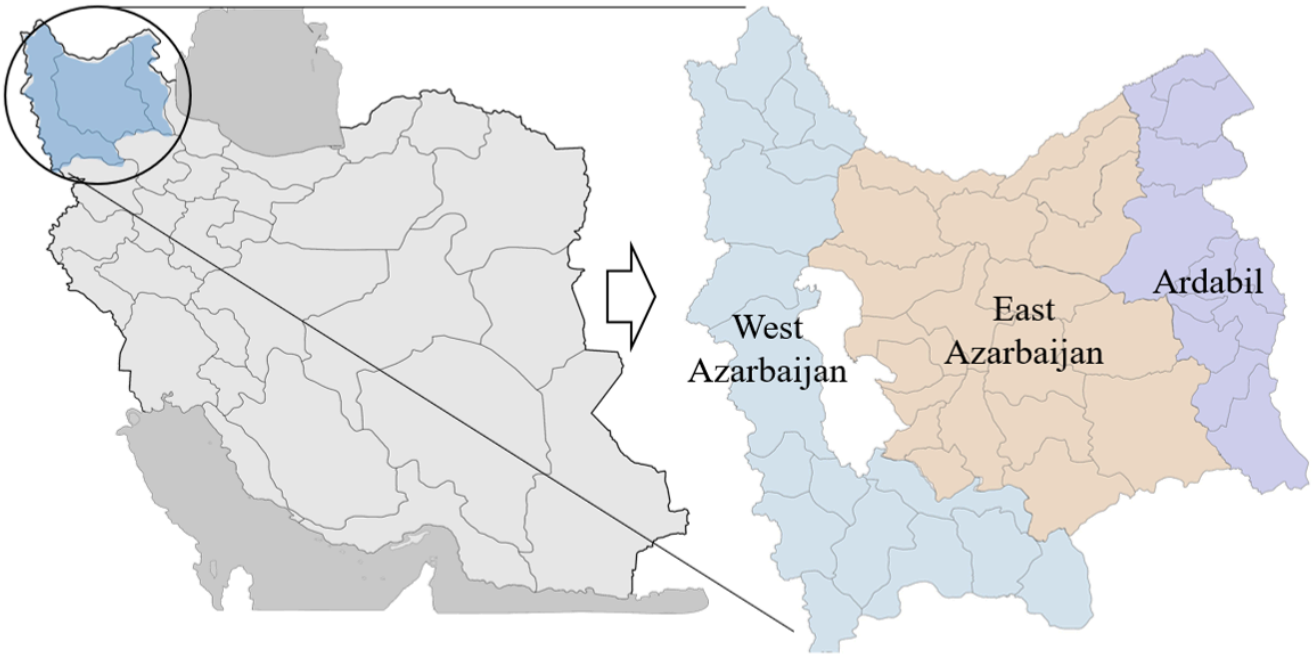


Figure 2

Geographical Location and Spatial Continuity of the Study Provinces

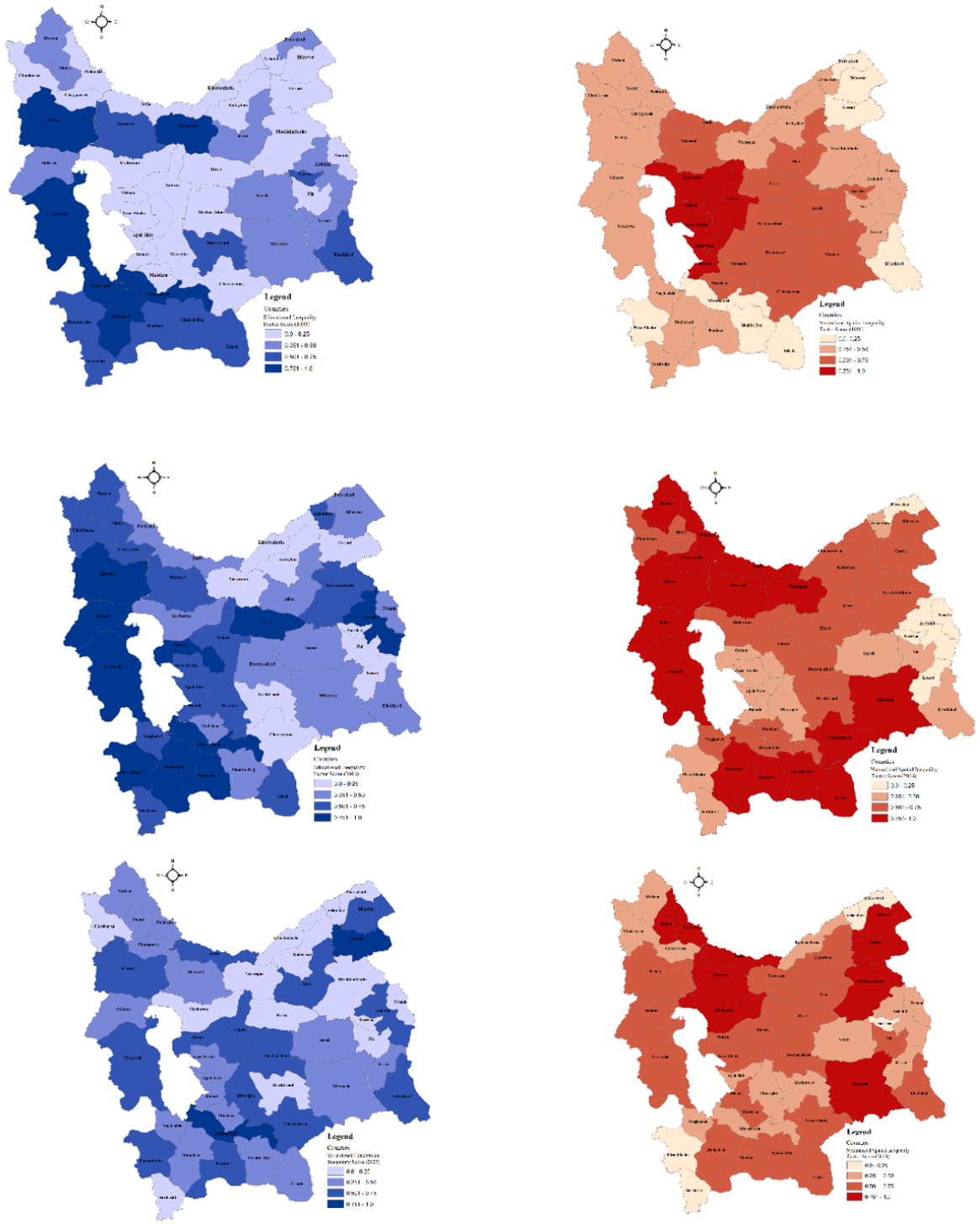


Figure 3

Spatial Distribution of Normalized Factor Scores

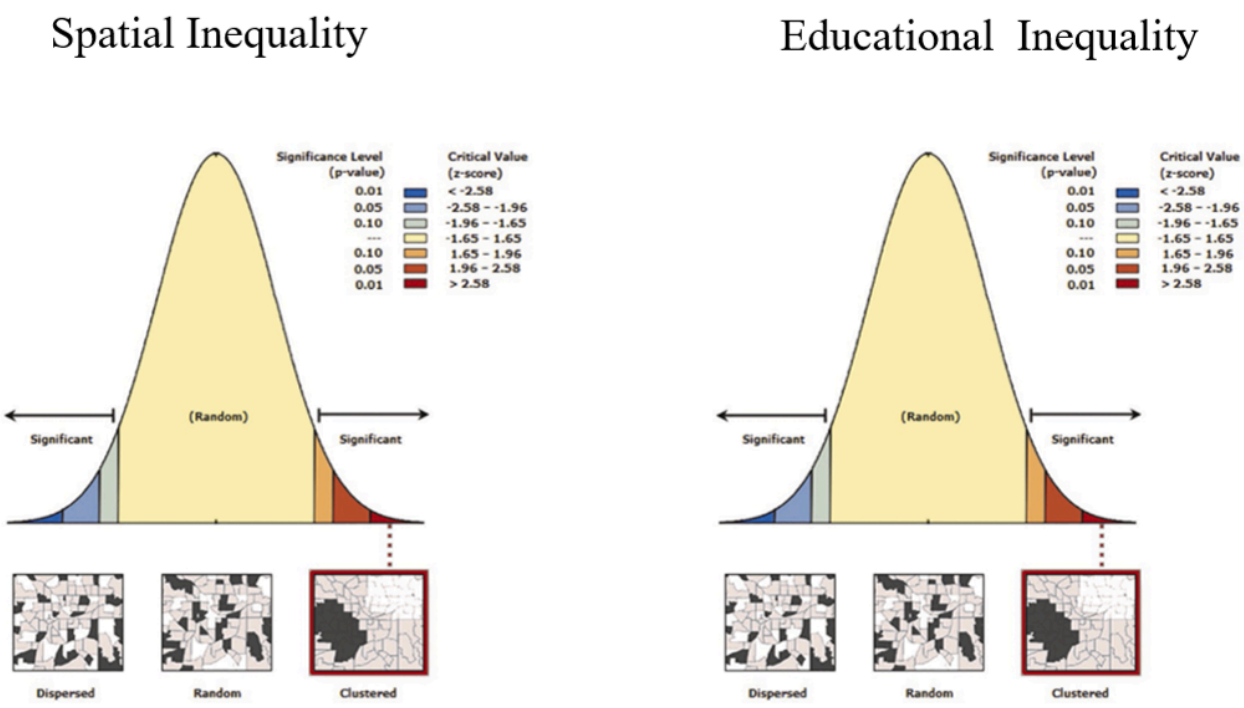


Figure 4

Spatial autocorrelation

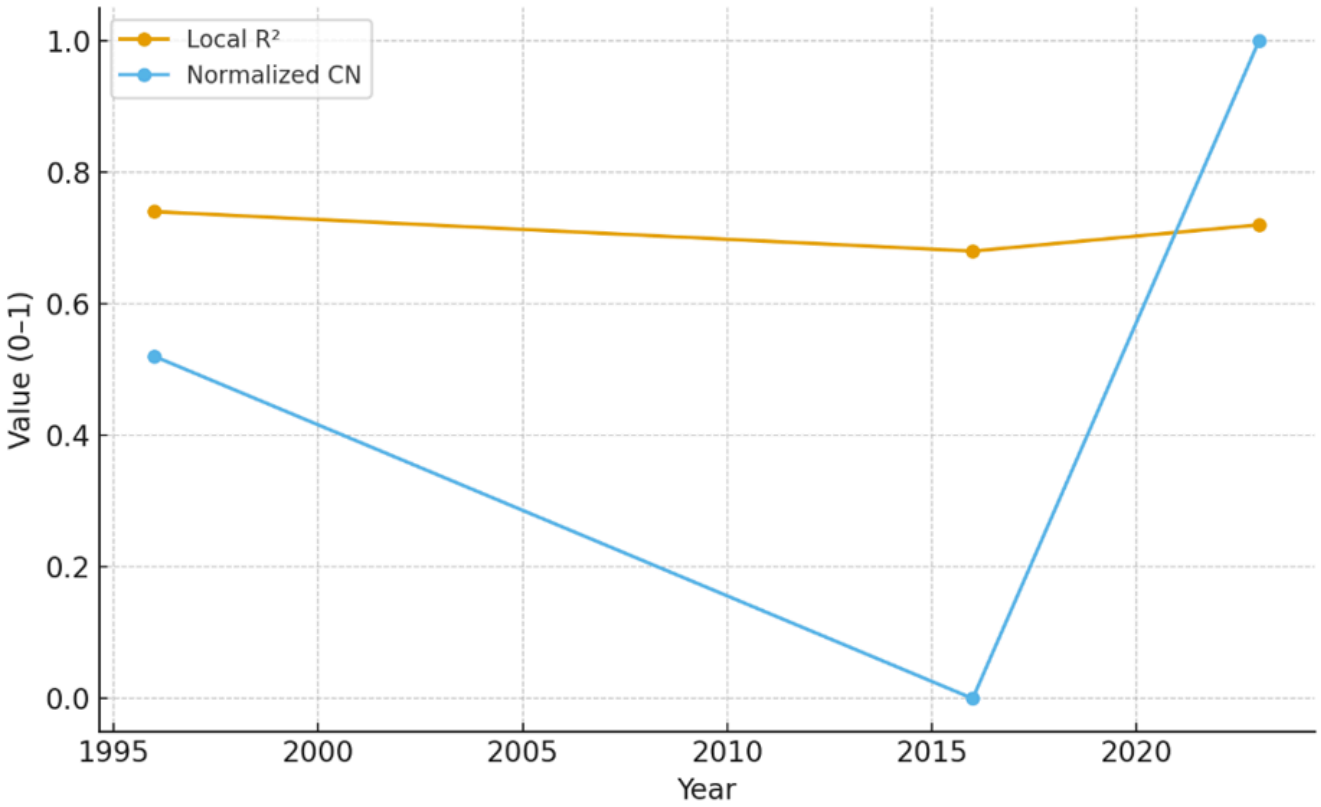


Figure 5

Temporal evolution of Local R^2 and normalized Condition Number (1996–2023)

Supplementary Files

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- Table5.docx