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Perspective

Analysis of the spatial distribution of multidimensional poverty in Colombia, an approach based on Moran's index

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Abstract: This study examines the spatial distribution of socioeconomic conditions in Colombia, using Moran's Index as a tool for spatial autocorrelation analysis. Key indicators related to education, health, infrastructure, access to basic services, employment, and housing conditions are addressed, allowing the identification of inequalities and structural barriers. The research reveals patterns of positive autocorrelation in several socioeconomic dimensions, suggesting a concentration of poverty and underdevelopment in certain geographic areas of the country. The results show that municipalities with more unfavorable conditions tend to cluster spatially, particularly in the northern, northwestern, western, eastern, and southern regions of the country, while the central areas exhibit better conditions. Permutation analyses are employed to validate the statistical significance of the findings, and LISA cluster maps highlight the regions with the highest concentration of poverty and social vulnerability. This work contributes to the literature on inequality and regional development in emerging economies, demonstrating that public policies should prioritize intervention in territories that exhibit significant spatial clustering of poverty. The methodology and findings provide a foundation for future studies on spatial correlation and economic planning in both local and international contexts.

Keywords: inequality; LISA clusters; regional development; social vulnerability

1. Introduction

Colombia has historically faced a series of structural challenges in its socioeconomic development (Ocampo, 1992). Despite being a country with considerable agricultural, tourism, and energy-mining potential, marked inequalities persist in terms of poverty and access to essential public services. These inequalities affect the quality of life of its inhabitants and limit the growth and development opportunities of its municipalities.

The study of multidimensional poverty in Colombia has gained increasing relevance in the academic and public policy agenda due to the need to understand its spatial patterns and persistence over time (Estrada & Moreno, 2013). Poverty, understood not only in monetary terms but also as the deprivation of multiple dimensions of well-being, requires methodologies that enable the analysis of its geographic distribution and the interdependence between territories. In this context, the use of spatial econometrics tools, such as Moran's Index, facilitates the identification of poverty clusters and the detection of spatial autocorrelation patterns that can inform territorial intervention strategies (Gutiérrez et al., 2020).

The relevance of space lies in the fact that all events occurring on our planet are tied to a specific point, both in terms of geographic location and time (Bravo, 2021). Events taking place in a given location generate impacts not only in neighboring areas but also in others that, at first glance, may seem distant. Spatial autocorrelation is a fundamentally geographic method that allows the analysis of georeferenced data at different scales, particularly highlighting the relationships and patterns of association between contiguous spatial units (Celemín, 2009).

This article focuses on the analysis of the socioeconomic conditions of the country's municipalities, covering key aspects such as the census-based Multidimensional Poverty Measure (MPM) at the municipal level. The indicators presented reflect various dimensions of multidimensional poverty in Colombia's municipalities, addressing aspects such as education, health, housing, employment, and access to basic services. These include illiteracy rates, school lag and absenteeism, and low educational attainment, which point to difficulties in academic development. Barriers to access to health and childcare services, as well as health insurance coverage, highlight inequalities in social protection. Housing factors such as critical overcrowding and the use of inadequate wall and floor materials, along with lack of access to improved water sources and adequate sanitation, underscore precarious living conditions. In addition, indicators of child labor, labor informality, and economic dependency affect the population's well-being and financial stability. The analysis of the spatial distribution of multidimensional poverty in Colombia, based on the application of Moran's Index, made it possible to identify geographic concentrations of deprivation and to assess the level of spatial dependence among municipalities.

The central hypothesis posits that there are significant spatial patterns of multidimensional poverty, which stem from historical socioeconomic dynamics and the interaction among regions with similar characteristics. The study is grounded in spatial economics and regional development theory, drawing on previous approaches that have examined the territorial distribution of poverty in various geographic contexts.

The spatial analysis of these indicators, using Moran's Index, allowed for the identification of possible spatial autocorrelation patterns (Encarnacion et al., 2023), that is, whether municipalities with similar socioeconomic characteristics are contiguous, or conversely, whether poverty levels and service access are distributed randomly (Zang, 2024). This approach helps to determine whether socioeconomic inequalities are geographically concentrated, thereby identifying the existence of "clusters" of poverty or social exclusion (Giungato & Maggio, 2023).

In a context like Colombia's, where infrastructure is heterogeneous and services do not reach all populations uniformly, a spatial analysis of this kind is necessary to redirect efforts and resources toward the most disadvantaged areas. Moreover, such studies contribute to the ongoing debate on how to reduce regional disparities and improve living conditions in the most vulnerable areas.

This study contributes to the existing literature by applying Moran's Index to multidimensional poverty in Colombia, offering an updated analysis of its spatial distribution and its implications for public policy design. From this perspective, the aim is to generate empirical evidence that enables a better understanding of the territorial dynamics of poverty and guides intervention strategies to reduce inequalities in the country.

2. Literature review

2.1. Spatial analysis, economic growth, and development

Spatial analysis has proven to be a practical tool for investigating complex phenomena across a variety of fields, including urban planning, social justice, sustainability, and public health. The Local Indicators of Spatial Association (LISA) is one of the key methods used to detect spatial patterns of concentration or dispersion, particularly useful for assessing how resources and opportunities are distributed across different regions (Anselin, 1995). This method has been applied in studies ranging from urban inequality to the distribution of basic services and remains essential in contemporary research.

An important area where spatial analysis has gained traction is in the distribution of resources and services in both urban and rural areas. Feitosa et al. (2023) addressed this issue from the perspective of housing inequalities, applying a spatial approach to distinguish between different forms of injustice related to access to housing spaces. The study highlights the importance of urban policies that promote housing equity, a persistent challenge in large cities where planning decisions tend to benefit affluent areas over marginalized ones.

Urban sustainability, another widely discussed topic in recent literature, has been examined using spatial approaches to identify development patterns and their environmental impacts (García et al., 2022; Saputra et al., 2023). In the case of Bogotá, Colombia, Escorcia Hernández et al. (2024) used spatial impact analysis to study sustainability in the context of social housing environments. Their findings underscore the inherent difficulties in balancing urban development with sustainability in areas marked by socioeconomic vulnerability, emphasizing the need for policies that integrate environmental perspectives into the design of affordable housing.

Within urbanization studies, the relationship between transport infrastructure and population dynamics has received increasing attention (Jiao et al., 2024). Lei et al. (2024), for instance, explored the spatiotemporal relationship between metro networks and expanding urban populations. Their analysis shows that public transport networks can significantly influence population concentration and the expansion of urban boundaries.

2.2. A breakdown of the dimensions of poverty worldwide

Regarding the spatial distribution of poverty and inequality, Rodríguez et al. (2023) conducted an analysis in Colombian cities to explore socioeconomic disparities and their relationship with urban mortality. This study employed geographic mapping techniques to identify areas with high mortality rates, revealing a strong correlation between poverty and vulnerability to disease and premature death.

Beyond economic and social aspects, spatial analysis has been used to investigate public health issues. Kibuuka et al. (2021) conducted a study in South Africa examining the relationship between tuberculosis mortality and socioeconomic factors using spatial analysis techniques. The results revealed high tuberculosis prevalence in areas with adverse economic conditions, highlighting the need for targeted public health interventions to address disparities in disease distribution. Another relevant study employing spatial techniques is that of Coelho et al. (2020), who used geospatial analysis to assess the risk of hospital admissions related to respiratory infections, allowing for the identification of geographic patterns of vulnerability.

Spatial data analysis has also been applied to examine the relationship between urbanization and building density. Isazade et al. (2023) integrated various techniques, such as Geographically Weighted Regression (GWR) and spatial autocorrelation analysis, to study how building density affects land subsistence in urban areas. This methodological approach offered a specific understanding of how land use changes can influence soil stability.

Spatiotemporal analysis has also been employed to study patterns of malnutrition in children under five. Maniragaba et al. (2023) conducted a study in Rwanda (East Africa) that revealed severe malnutrition patterns in rural areas, linking these conditions to socioeconomic factors and limited access to health services. This study highlighted how spatial analysis can help identify critical areas for government intervention.

The spatial analysis of multidimensional poverty has developed through various methodological approaches, including spatial econometric techniques, geographically weighted regression models, and exploratory spatial data analysis tools. Current literature has emphasized the importance of spatial autocorrelation in poverty studies, noting that regions with greater deprivation often cluster in specific patterns, indicating the presence of territorial poverty traps (Garrocho, 2016; Kaztman, 2003).

2.3. The Moran's Index in the Latin American context

In the Latin American context, recent research has applied Moran's Index and other spatial dependence measures to study poverty distribution in countries such as Mexico, Brazil, and Argentina, finding that multidimensional poverty tends to concentrate in regions with low levels of economic development and limited social infrastructure (Núñez & Medina, 2024; A. Rodríguez, 2024; Sánchez & Gómez, 2021). In Colombia, earlier studies explored the spatial dimension of poverty, but mostly relied on traditional income-based approaches (Laverde & Gómez, 2015; Ramírez et al., 2016). More recent research has incorporated spatial analysis methodologies to assess multidimensional poverty, highlighting the persistence of territorial disparities and the need for geographically differentiated policies (Muñetón & Manrique, 2023; L. A. Rodríguez et al., 2023).

3. Materials and methods

This study applied a spatial autocorrelation analysis using Moran's I Index to identify spatial patterns in the distribution of socioeconomic indicators across Colombia's municipalities (Grekousis, 2020). This index, a spatial analysis technique, measures the degree to which a geographically distributed dataset exhibits spatial relationships (C. Zhang et al., 2023), enabling the determination of whether areas with similar characteristics—such as poverty levels or access to public services—tend to cluster together. The study design adopts a quantitative approach, analyzing key variables such as the Multidimensional Poverty Measure (MPM) and the coverage of essential public services (water supply, sewerage, natural gas, and internet).

To compute Moran's I Index, a spatial weights matrix based on municipal contiguity was employed (Weladee & Sanit, 2023). This model assigns higher weights to municipalities that share geographic borders, allowing for the measurement of how the socioeconomic characteristics of one municipality influence its neighbors (Siabato & Guzmán, 2019). In this regard, Moran's I Index identifies whether there is positive spatial autocorrelation (neighboring municipalities with similar characteristics clustering together) or negative autocorrelation (neighboring municipalities exhibiting opposite characteristics). Both the global index value is calculated to assess overall autocorrelation and statistical significance maps (LISA) were produced to identify potential clusters or areas where high or low values of the variables are concentrated.

Although this study focuses on descriptive spatial autocorrelation, future research could incorporate additional spatial regression models to quantify spillover effects and control for potential endogeneity issues.

3.1. Description of the study area

The study area encompasses the entire municipal territory of Colombia, comprising 1122 local administrative entities whose socioeconomic conditions exhibit marked territorial heterogeneity (see **Figure 1**). This diversity is reflected in the multidimensional poverty indicators, which vary widely across municipalities, with values ranging from relatively low levels to extremes nearing 98%, highlighting deep structural inequalities. The variables selected for this study are drawn from official statistical sources, namely the geoportals of the National Administrative Department of Statistics (DANE), and are standardized to ensure comparability across municipalities. The data were processed using a spatial analysis method with the specialized software GeoDa, which enables the calculation of Moran's I Index, the visualization of spatial patterns through thematic maps, and the generation of multivariate correlational analysis.

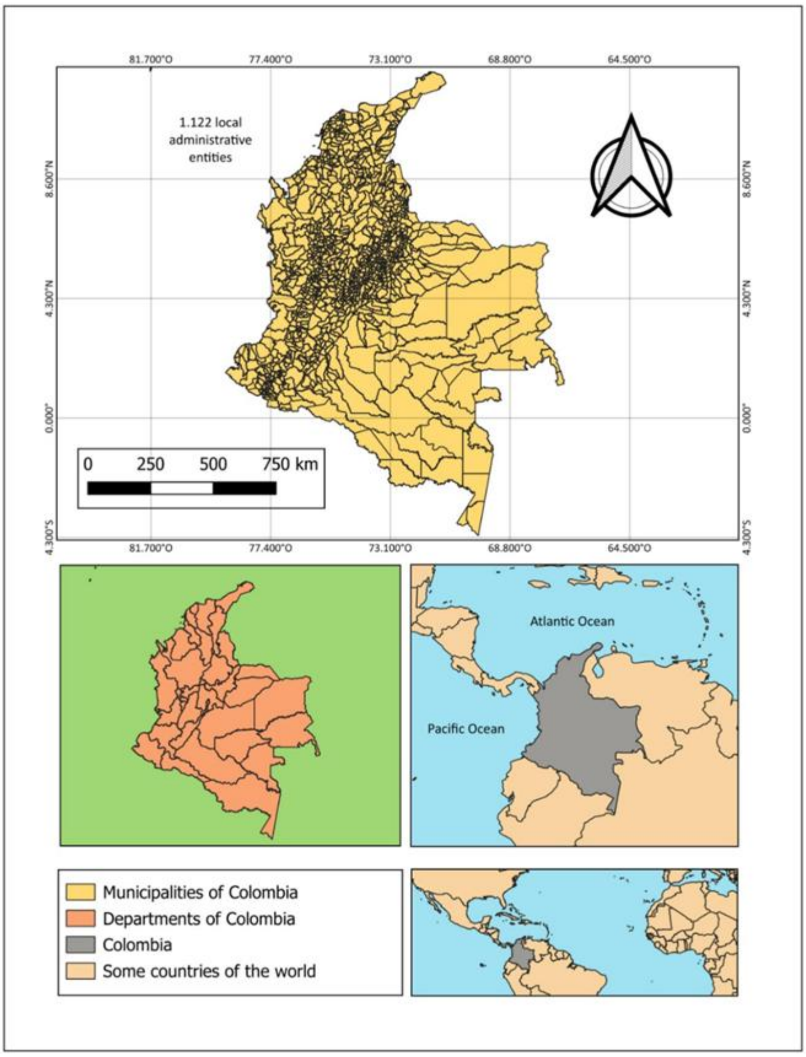


Figure 1. The location map situates Colombia regionally and illustrates its municipal spatial distribution. National Geostatistical Framework (MGN). DANE, 2024, and Basic Cartography at 1:100,000 Scale. IGAC (2024).

To complement the quantitative analysis, spatial weights matrices are developed to identify contiguity or neighborhood relationships among municipalities. This methodology also allows for the identification of poverty clusters and the detection of possible diffusion processes of this condition (Pérez, 2005).

3.2. Mathematical Basis of Moran´s Index

Let x_i be a socioeconomic variable observed in n spatial units (in this case, municipalities or local administrative units), where i = 1,..., n. The observed values are represented by the vector x = (x_1, x_2,..., x_n)^T. The global Moran's I index is defined as:

$$I = \frac{n}{\sum i \sum j\ wij} \cdot \frac{\sum i \sum j\ wij(xi - \bar{x})(xj - \bar{x})}{\sum i\ (xi - \bar{x})2} \tag{1}$$

where:

$\bar{x}$ is the mean of the variable;

w_{ij} are the elements of the spatial weights matrix W, with w_{ii}=0;

n is the total number of spatial units.

The expected value under spatial independence is:

$$E\,[I] = -\frac{1}{n-1} \tag{2}$$

3.3. Spatial weights matrix

To model spatial interaction, a first-order contiguity matrix $W \in \mathbb{R}^{n\text{x}n}$ was constructed, where:

$$w_{ij} = \begin{cases} 1 \text{ if municipalities i and j share a border} \\ 0 \text{ Otherwise} \end{cases} \tag{3}$$

This matrix was row-standardized as follows:

$$W_{ij}^{*} = \frac{wij}{\sum j\, wij} \tag{4}$$

This study relies exclusively on spatial weight matrices based on contiguity. Future research should compare alternative matrices that incorporate geographic distance, population mobility, or economic interactions, particularly in Colombia's mountainous regions, where geographic proximity does not necessarily imply physical accessibility.

3.4. Local Moran's I (LISA)

To identify local clusters, the Local Moran´s I statistic I_i was used, defined as:

$$I_i = (x_i - \bar{x}) \cdot \sum_j w_{ij}\,(x_j - \bar{x}) \tag{5}$$

The I_i values are classified into quadrants based on their relationship with the global mean:

High-High

Low-Low

High-Low

Low-High

Equations (1)–(5) follow the standard formulation of Moran's Index as presented by Anselin (1995) and subsequently refined by Grekousis (2020).

3.5. Empirical application

The variables were normalized using z-score to ensure comparability. GeoDa was used to compute Moran's I, LISA, significance maps, and simulations with 999 permutations. Simple linear regressions were applied between MPM and complementary indicators such as TDE and HC, and the model structure was evaluated with the Chow test. Finally, the analysis was complemented with thematic maps, LISA significance maps, and cluster maps. The results of the spatial analysis serve to formulate targeted public policy recommendations aimed at improving equity in access to services and reducing poverty gaps in the most vulnerable areas (Qi et al., 2022; Y. Zhang & Liu, 2023).

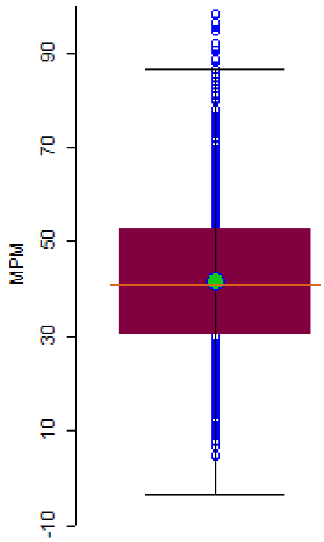
The use of 999 permutations is justified because it is a widely accepted standard in spatial autocorrelation analysis to approximate the null distribution of the test statistic with sufficient precision (Anselin, 1995). A large number of permutations reduces the variance of the significance estimate, and 999 provides statistical robustness, enabling the detection of non-random patterns with an appropriate level of confidence (Anselin, 2020).

Furthermore, the choice of z-score normalization responds to the need to standardize variables so they are comparable in scale and dispersion, eliminating differences due to units of measurement or absolute magnitudes (ArcMap, 2021). By transforming the values to a distribution centered at zero with a standard deviation of one, the z-score facilitates the interpretation of spatial relationships and ensures that the results of Moran's index are not biased by heterogeneous scales among the variables analyzed (Chen, 2023).

4. Results and discussion

In most Latin American countries, a significant portion of the population faces high levels of deprivation in terms of access to formal employment, adequate nutrition, healthcare services, and quality education, placing them in conditions of poverty (Medina et al., 2021).

The Multidimensional Poverty Measure (MPM) in Colombia's municipalities (1122 observations in this study—understood as local administrative entities) shows substantial variability, with values ranging from 4.5 to 98.5. The median of 40.8 indicates that half of the municipalities have an MPM below this value. However, the standard deviation of 17.35 and the presence of outliers reflect significant inequalities, with some municipalities experiencing much higher poverty levels. The interquartile range of 22.5 reveals moderate dispersion in the central part of the data (see **Figure 2**).



	MPM
min	4.5000
max	98.5000
Q1	30.2000
median	40.8000
Q3	52.7000
IQR	22.5000
mean	41.7924
s.d.	17.3455

Figure 2. Boxplot—Statistical Measures Associated with Multidimensional Poverty by Municipality.

Figure 3 shows a positive relationship between Multidimensional Poverty (MPM) and the Economic Dependency Ratio (TDE_TOT) in Colombian municipalities, with a coefficient of determination (R^2) of 0.628. This indicates that 62.8% of the variability in economic dependency is explained by the level of multidimensional poverty experienced by the municipalities. The regression yields a constant of 16,373 and a slope of 0.591, both of which are highly significant (p-value = 0). This demonstrates that higher levels of multidimensional poverty are associated with a greater economic dependency burden in the municipalities.

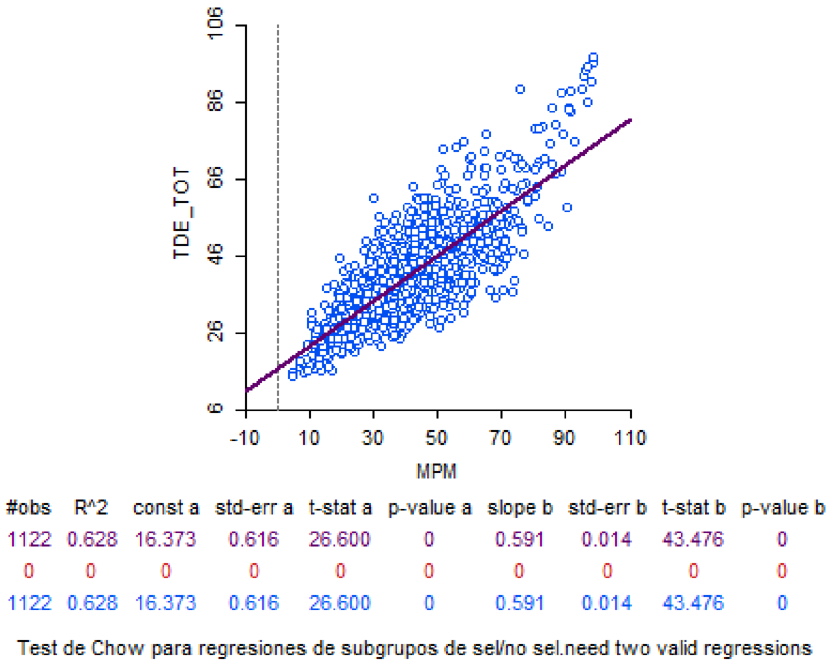


Figure 3. Scatter Plot—Correlation between Multidimensional Poverty and Economic Dependency Ratio by Municipality.

It is important to note that the Chow Test is used to determine whether there are significant differences between two regressions across distinct data subgroups (Aronov et al., 2024). In this case, the test could not be properly conducted due to issues with model specification. The test requires dividing the data into two meaningful subsets (e.g., north vs. south, urban vs. rural, high-poverty vs. low-poverty regions). However, in this study, such subgroups were not properly defined, or one of them lacked sufficient observations or variability. The test is useful only when a structural change in the MPM–TDE_TOT relationship is suspected between groups, which has neither been proposed nor visually detected in the scatter plot.

If the test had been correctly executed, its outcome would indicate whether it is valid to combine both subgroups in a single regression model, or whether it is necessary to model them separately due to structural differences in the relationship between Multidimensional Poverty (MPM) and the economic dependency ratio (TDE_TOT). This test would be particularly useful if the aim were to compare whether the MPM → TDE_TOT relationship differs across specific regions (e.g., Caribbean vs. Andean), or to assess whether the impact of poverty on dependency varies between urban and rural municipalities.

Figure 4 presents conditional maps generated using the GeoDa software, which analyze the relationship between Multidimensional Poverty (MPM), the Total Economic Dependency Ratio (TDE_TOT), and the Total Critical Overcrowding Rate (HC_TOT) in Colombian municipalities. The maps show that municipalities with high levels of multidimensional poverty tend to coincide with those reporting high dependency and overcrowding rates, particularly in the northeastern region of the country, where darker shades indicate a strong concentration of these factors. This analysis helps to identify relevant spatial patterns.

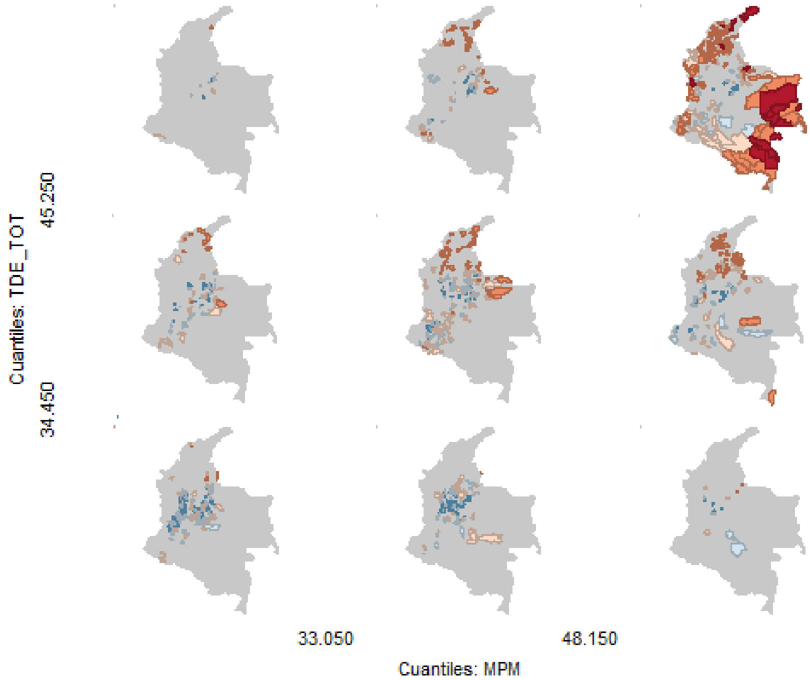


Figure 4. Conditional Maps—Correlation between Multidimensional Poverty, Economic Dependency Ratio, and Total Critical Overcrowding Rate by Municipality.

The spatial distribution of these statistical values shows that poverty conditions are highly correlated with demographic dependency burdens and housing precarity, underscoring the need for targeted interventions in these areas. At the same time, there are municipalities with lower multidimensional poverty levels that also report low dependency and overcrowding rates, revealing outliers in the regional incidence of these indicators (see **Figure 4**).

4.1. An approach using Moran's I Index

Given that Moran's I is primarily used to analyze spatial data across areas and serves as a global test of spatial structure, this index assesses whether the values of a variable in neighboring areas tend to vary similarly to the value of that variable in a central area (Muñeton & Vanegas, 2014) (see **Figure 5**).

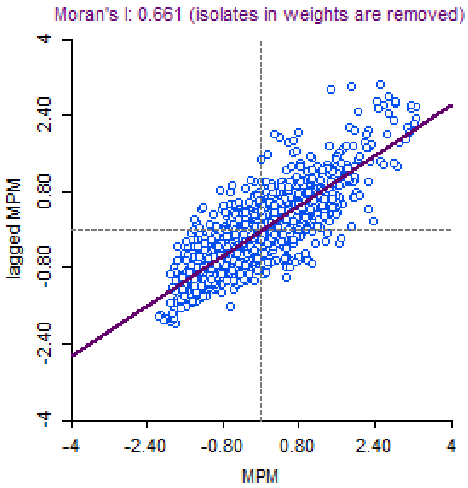


Figure 5. Scatter Plot of the Local Moran's I for the Multidimensional Poverty Measure by Municipality.

The scatter plot of the local Moran's I shows a strong positive spatial autocorrelation in the Multidimensional Poverty Measure (MPM) at the municipal level in Colombia, with a Moran's I value of 0.661. This result indicates that municipalities with high levels of multidimensional poverty tend to cluster spatially with others experiencing similar conditions, while municipalities with low poverty are also located near others with low poverty. The positive linear trend in the graph reinforces this spatial dependency, showing that poverty is not randomly distributed across the territory but instead follows well-defined regional patterns. These findings indicate that the socioeconomic conditions that shape multidimensional poverty are influenced by spatial and structural factors, underscoring the need for policy tools characterized by a differentiated territorial approach that promotes development in the most affected regions (see **Figures 6** and **7**).

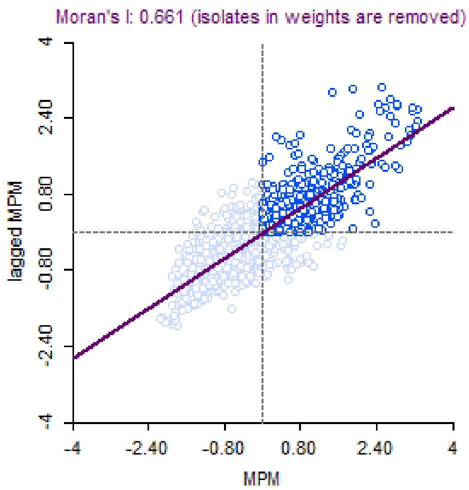


Figure 6. Scatter Plot of the Local Moran's I for the Multidimensional Poverty Measure by Municipality—High-High Quadrant.

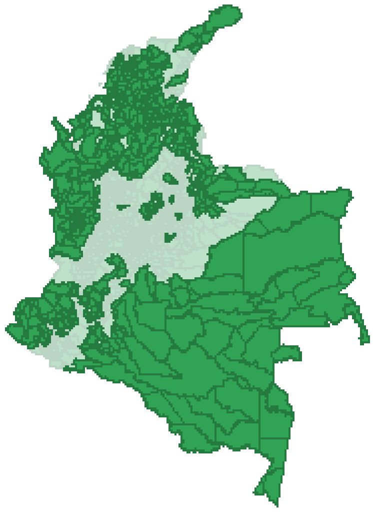


Figure 7. Map Derived from the Local Moran's I Scatter Plot—High-High Quadrant.

The highlighted quadrant corresponds to the high-high category, indicating that observations with high MPM values are surrounded by neighbors with similarly high values. This pattern reveals the existence of spatial clusters—areas where high values of the variable tend to group together—indicating strong positive spatial autocorrelation (see **Figure 8**).

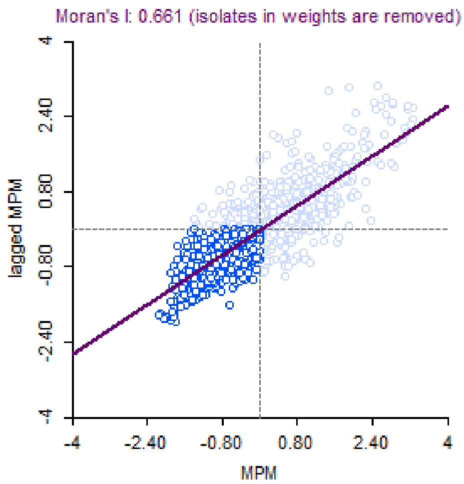


Figure 8. Scatter Plot of the Local Moran's I for the Multidimensional Poverty Measure by Municipality—Low-Low Quadrant.

The lower-left quadrant of the Moran's scatter plot represents the low-low relationship. This means that observations with low MPM values are surrounded by neighbors with similarly low values. This pattern confirms the presence of low-intensity spatial clusters, showing that in certain areas, low values of the variable are not randomly dispersed but tend to concentrate in specific regions with similar characteristics, as illustrated in **Figure 9**.

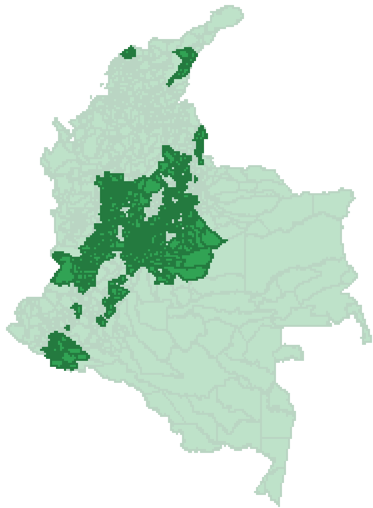


Figure 9. Map Derived from the Local Moran's I Scatter Plot—Low-Low Quadrant.

Table 1 summarizes the main statistical findings of the study, highlighting the significance and magnitude of the spatial autocorrelation of poverty, its relationship with economic dependency, and the identification of territorial clusters. These results support the need for regionally differentiated policy approaches.

Table 1. Key Quantitative Results.

Indicator/relationship	**Statistical value**	***p*-value/significance**	**Interpretation**
Global Moran's I for MPM	0.661	0.001	High positive autocorrelation
R^2 between MPM and TDE_TOT	0.628	0.000	Significant positive relationship
Regression: Slope (MPM → TDE_TOT)	0.591	0.000	Higher poverty → higher dependency
Regression: Intercept	16.373	0.000	Base level of dependency
LISA Clusters (High-High)	154 municipalities	<0.05	Significant geographic clustering
LISA Clusters (Low-Low)	189 municipalities	<0.05	Clustering of low poverty

Source: Own elaboration based on GeoDa Software

The LISA significance map displays the distribution of municipalities where the spatial autocorrelation of Multidimensional Poverty (MPM) is statistically significant (see **Figure 10**).

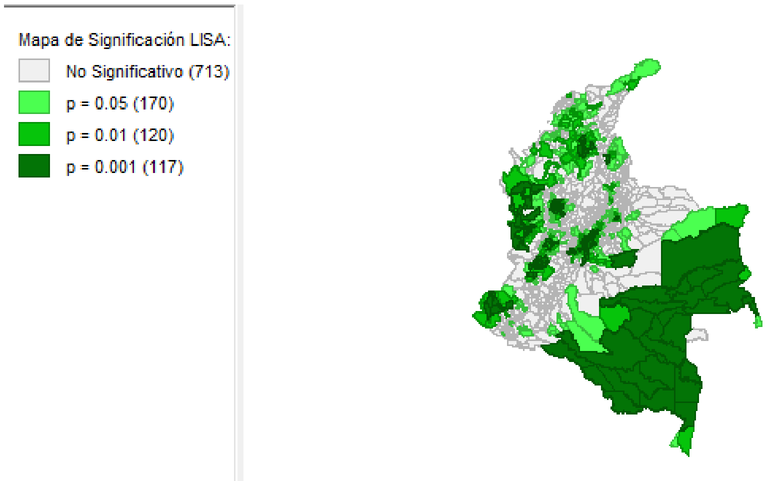


Figure 10. Statistical Significance Map—Multidimensional Poverty by Municipality.

The green tones indicate varying levels of significance, where the darker shades (p = 0.001) reflect areas with the highest statistical certainty of spatial clusters, while lighter shades (p = 0.05) denote lower significance, yet still within the threshold of relevance. Municipalities with high statistical significance are mainly concentrated in the southern and northeastern parts of the country, indicating the presence of well-defined spatial patterns in poverty distribution. In contrast, large areas of the territory (shown in gray) represent municipalities without statistical significance, suggesting a more scattered or random distribution in those cases. This analysis reinforces the importance of targeting strategies toward regions with higher statistical significance, as they exhibit a consistent spatial structure likely influenced by persistent structural and contextual factors perpetuating multidimensional poverty in these areas.

The LISA cluster map shows the spatial distribution of Multidimensional Poverty (MPM) in Colombia, identifying patterns of significant spatial autocorrelation (**Figure 11**).

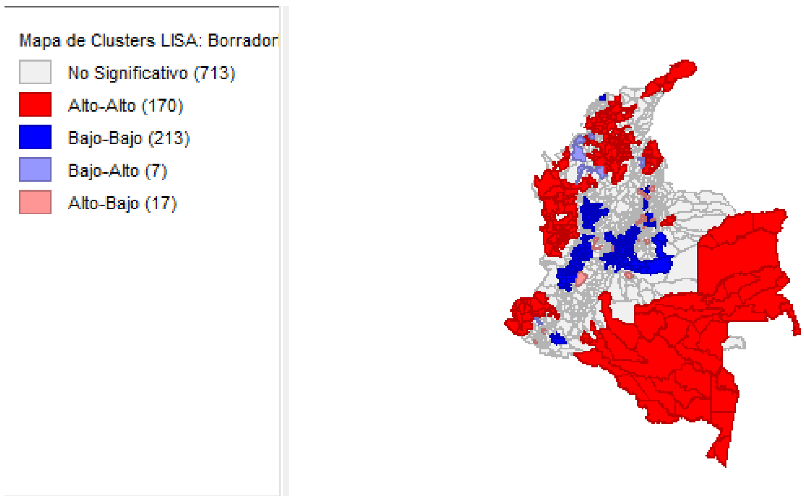


Figure 11. Cluster Map—Multidimensional Poverty by Municipality.

All Local Moran's I statistics were significant at a $p < 0.05$ level, based on 999 permutations, confirming the presence of non-random clustering.

Regions in red (High-High) are mainly located in the southern and northeastern parts of the country, indicating a concentration of municipalities with high multidimensional poverty surrounded by others with similar conditions. In contrast, blue areas (Low-Low) are primarily located in the central and northwestern regions, reflecting municipalities with low poverty levels surrounded by similar environments. The map also identifies some light blue areas (Low-High) and pink areas (High-Low), representing outliers where high-poverty municipalities are surrounded by low-poverty neighbors and vice versa. The presence of these clusters demonstrates that poverty in these areas is not randomly distributed, but follows specific spatial patterns.

Regarding the recognition of spatial dependence as a structural feature of poverty, in Colombia the global and Local Moran's I reveals significant positive autocorrelation, identifying clusters of high multidimensional poverty in regions that have historically lagged in territorial development—similar to the "spatial traps" patterns detected via Moran's I in Hubei (Liu et al., 2023), Guizhou (G. Li et al., 2022), and Eastern Tibet (Tian et al., 2024). This underscores that poverty tends to clusters in territories with persistent geographical disadvantages such as elevation, slope, and isolation, as observed in the Loess Plateau (T. Li et al., 2020) and Sichuan (He et al., 2021).

Whereas Chinese studies employ GWR/MGWR to model local heterogeneity and propose zone-specific interventions (improving accessibility, restoring ecosystems), and the Indonesian case (Gai et al., 2025) advocates for adaptive social protection linked to tourism, the Colombian approach—by mapping multidimensional hotspots and coldspots (income, education, health, housing)—provides a lighter, more direct diagnostic tool for targeting comprehensive policies in data-scarce contexts. It enables the prioritization of conditional cash transfers, basic infrastructure investment, and educational programs in high-autocorrelation municipalities, thereby validating the Asian findings and building a methodological bridge toward policies that combine cross-sectional analysis with structural transformation in Latin America.

5. Discussion

The spatial analysis of multidimensional poverty in Colombia reveals the existence of geographic concentration patterns that reflect structural inequalities across the territory. Regions with higher poverty levels tend to cluster in specific areas, particularly in the south and northeast of the country, while areas with lower poverty are concentrated in the center and northwest. The evidence presented confirms that multidimensional poverty in Colombian municipalities is heterogeneous and follows well-defined spatial patterns, with high levels of autocorrelation. The strong relationship between poverty, economic dependency, and overcrowding suggests that these factors must be addressed jointly through targeted policies.

According to the results, public investment priorities should align directly with the identified High–High and Low–Low clusters. For instance, the High–High clusters in the south, west, north, east, and northwest require targeted programs in infrastructure, education, and employment, whereas the Low–Low clusters in the center and northeast can serve as models for replicating best practices.

The identification of spatial poverty clusters highlights the need for differentiated strategies based on territorial context, prioritizing interventions in the most affected regions. Moreover, the correlation between multidimensional poverty and factors such as dependency ratio and overall overcrowding underscores the interconnection of socioeconomic variables that affect population well-being. In municipalities with the highest levels of poverty, high levels of dependency and precarious housing conditions are also observed. This study clearly demonstrates that poverty, while often seen as an income-related issue, also involves multiple dimensions that impact people's quality of life.

6. Conclusion

The statistical significance of spatial poverty clusters confirms that unfavorable conditions are not randomly distributed; rather, they are the result of persistent structural factors. This implies that any poverty reduction strategy must adopt differentiated approaches based on location, as solutions must respond to specific regional realities.

The study statistically demonstrates the existence of spatial poverty clusters, but it is prudent to note that the model does not incorporate historical, institutional, or political variables—such as decentralization, the legacies of conflict, or disparities in governance—that could reinforce these spatial patterns. Future studies could integrate these dimensions to enrich causal interpretation. Finally, Moran's Index confirms a strong positive spatial autocorrelation regarding multidimensional poverty in the territories, reinforcing the idea that the economic and social development of municipalities is shaped by their geographic environment. The high concentration of municipalities with similar conditions underscores the urgency of regional development strategies aimed at breaking these cycles of inequality, while also fostering social mobility. This calls for strengthened investment in infrastructure, education, and job creation in the most affected regions.

In parallel, the interventions mentioned within the framework of the research results must be prioritized according to the cluster's intensity (Moran's Index value and p-significance) and the level of multidimensional poverty, ensuring that the most vulnerable territories receive priority in resource allocation.

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