Journal of Ecohumanism
2024
Volume: 3, No: 8, pp. 6953 – 6965
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i8.5297

Influence of Spatial Factors on Human Development: The Peruvian Case

Alfredo Pelayo Calatayud-Mendoza[1], Cristóbal Rufino Yapuchura Saico[2], Roberto Arpi Mayta[3], Germán Belizario-Quispe[4], Edilberto Huaquisto-Ramos[5], Willy Miguel Mamani Huanacuni[6], Adderly Mamani-Flores[7]

Abstract

The objective of this study was to estimate the influence of spatial factors on the Human Development Index (HDI) using a spatial econometric model, specifically the SARAR model (Spatial Autoregressive with Autoregressive Errors), which incorporates both the spatial effect of the dependent variable and the spatial lag of errors. The data used comes from the report of the United Nations Development Program (UNDP), the National Institute of Statistics and Informatics (INEI) and the Ministry of Energy and Mines, covering a total of 1,872 districts of Peru in 2019. The results reveal that the HDI of a district is positively related to accumulated public investment, urban population agglomeration, and mining district status. On the contrary, the HDI is negatively affected by the altitude of the district capital and the geographical distance between the district capital and the nearest district. On average, mining districts have a higher HDI compared to non-mining districts. In addition, a positive relationship is observed between the HDI of a district and that of its geographically close neighbors (p<0.01), evidencing a spatial contagion effect. These findings underscore the importance of considering space as a key element for the design and implementation of public policies that promote equitable and sustainable human development.

Keywords: *Spatial Autocorrelation, Spatial Heterogeneity, Urban Agglomeration, Altitude, Population Density, Geography, Mining Districts.*

Introduction

In the last two decades, Peru has shown significant progress in social welfare, evidenced by the increase in the Human Development Index (HDI) from 0.366 in 2003 to 0.586 in 2019, according to the United Nations Development Program (UNDP, 2019b). This indicator combines life expectancy, educational attainment, and per capita income, providing a comprehensive measure of human development. However, inequalities persist, especially in regions with adverse geographical conditions and limited infrastructure (Álvarez, 2016; Hernández Mota, 2016). These gaps underscore the need for public policies that address both the structural and territorial factors that condition human development.

The HDI was developed in 1990 under the framework of UNDP and has established itself as a key tool for comparing and assessing human progress across regions and countries (Dasic et al., 2020). This indicator includes three fundamental dimensions: life expectancy, education and income, which makes it a reference for designing development strategies. However, as they point out (Anselin, 1988) and (Aragón & Rud, 2013) (LeSage & Pace, 2010), Traditional analyses of human development tend to omit the spatial component, ignoring how geographic features and location affect levels of well-being. In this sense, the present study incorporates spatial factors such as altitude, urban agglomeration and proximity to urban centers to better understand these dynamics.

Public investment is one of the main instruments that the State can use to improve human development, especially in regions with significant backwardness. Studies such as those of (Kogan & Bondorevsky, 2016)

[1] Facultad de Ingeniería Económica – Universidad Nacional del Altiplano Puno, Perú, https://orcid.org/0000-0002-1213-0035
[2] Facultad de Ingeniería Económica – Universidad Nacional del Altiplano Puno, Perú, https://orcid.org/0000-0003-1956-3922
[3] Facultad de Ingeniería Económica – Universidad Nacional del Altiplano Puno, Perú, https://orcid.org/0000-0002-0585-2064
[4] Facultad de Ingeniería Agrícola – Universidad Nacional del Altiplano Puno, Perú, https://orcid.org/0000-0001-9805-3714
[5] Facultad de Ingeniería Agrícola – Universidad Nacional del Altiplano Puno, Perú, https://orcid.org/0000-0003-1671-0747
[6] Facultad de Ingeniería Agrícola – Universidad Nacional del Altiplano Puno, Perú, https://orcid.org/0009-0007-1207-9333
[7] Facultad de Ciencias Sociales – Universidad Nacional del Altiplano Puno, Perú, https://orcid.org/0000-0002-5141-1366

Volume: 3, No: 8, pp. 6953 – 6965
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i8.5297

and (Hurtado & Pinchi, 2019) They highlight that an efficient allocation of resources in infrastructure and basic services can have a direct impact on people's quality of life. In addition, public investment not only contributes to physical development, but can also strengthen human capital, reducing disparities and promoting access to opportunities(Pinilla-Rodriguez et al., 2014).

Spatial factors such as altitude, urban agglomeration and proximity to urban centers play a determining role in human development. According to (Guerra Carrillo & Castañeda Núñez, 2020) and (Gerónimo Antonio et al., 2020), these variables can directly influence the living conditions of populations. For example, districts located at high altitudes face significant barriers related to agricultural productivity and access to services. On the other hand, urban agglomeration and connectivity can generate economies of scale and improve access to economic and social opportunities(Zubia-Mendoza, 2021).

The use of spatial analysis tools, such as those used by (Paelinck et al., 2015) and (Liu et al., 2021), it has made it possible to identify patterns and geographical groupings of human development. These techniques, which include exploratory analysis of spatial data and spatial econometric models, have facilitated the identification of priority areas for public policies. In this context, the present study uses the SARAR model to analyze how spatial characteristics, together with public investment, condition human development in the districts of Peru.

Finally, this article seeks to demonstrate how spatial factors directly and indirectly affect human development levels, considering four key aspects: public investment, altitude, urban agglomeration, proximity between district capitals and whether or not the district is mining. In addition, the role of public investment as an exogenous variable that can compensate for spatial inequalities is analyzed. Following authors such as (LeSage & Pace, 2010), (Hurtado & Pinchi, 2019) and (Li et al., 2017), The importance of integrating spatial aspects into the design of public policies to ensure equitable and sustainable development is underlined.

Methodology

Spatial econometrics is a key tool for analyzing georeferenced data, as these often present multidirectional relationships known as spatial dependence or autocorrelation, which can invalidate the assumptions of classical econometrics. According to (Pérez, 2006), This autocorrelation can be caused by measurement errors in spatial units or by substantive spatial interactions, where events in one territory affect others due to diffusion effects or spillovers. Therefore, it is essential to properly identify and model spatial dependence in analyses.

The model **SARAR** (Spatial Autoregressive with Autoregressive Errors) is an econometric tool used to analyze georeferenced data and spatially dependent phenomena. This model combines two key elements: the spatial dependence on the dependent variable, represented by the parameter ϱ, and the spatial dependence on the errors, captured by λ. According to (LeSage & Pace, 2010), The parameter ϱ\rhoϱ reflects how the values of a variable in one region are influenced by the values in neighboring regions, capturing the so-called "spatial contagion effect". For example, in human development studies, the HDI of one district may affect that of nearby districts due to socioeconomic interactions. Following to (Herrera, 2017) The cross-sectional model is proposed:

$$y = \lambda W y + X\beta + WX\theta + u$$

$$u = \rho W u + \varepsilon$$

$$y = \lambda W y + X\beta + u$$

$$u = \rho W u + \varepsilon$$

Journal of Ecohumanism
2024
Volume: 3, No: 8, pp. 6953 – 6965
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i8.5297

Where: is the dependent variable, is the matrix of explanatory variables, are parameters to be estimated, are random errors of the estimated model and W is a matrix of spatial weights. $yX\beta, \lambda, \rho\varepsilon, \mu$On the other hand, the parameter λ corrects for spatial correlation in errors, an important aspect when there are unobserved factors affecting multiple nearby regions. (Anselin, 1988) and (Pérez, 2006) stresses that this component is essential to properly model spatial relationships and avoid bias in estimates. In addition (Arbia, 2014)**Arbia (2014)** (Arbia, 2001) highlights that the SARAR model is especially useful in contexts where both observed and unobserved variables present spatial structures, which makes it a powerful tool for territorial analysis and public policy design. By separating direct and indirect effects, this model allows us to understand how the characteristics of a region not only influence locally, but also in neighboring regions.

Spatial autocorrelation describes the dependence between values of a variable in different geographic locations, implying that events in one region can influence neighboring regions. According to (Pérez, 2006), This dependence may be due to measurement errors in observations or to substantive spatial interactions, known as spillovers. (Anselin, 1988) He points out that spatial autocorrelation can invalidate the assumptions of independence in classical econometric models, requiring specific techniques for their analysis. For its part, (LeSage & Pace, 2010) They highlight that properly identifying and modeling autocorrelation is essential to understand complex spatial phenomena and improve accuracy in the estimation of geographic impacts. One of the most widely used tests to contrast spatial autocorrelation in a regional context is the global Moran index (I)

$$I = \frac{N}{S_0} \frac{\sum_{ij}^{N} W_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=j}^{N}(X_i - \bar{X})^2}, i \neq j$$

$$I = \frac{N}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\ (X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=j}^{N}(X_i - \bar{X})^2}$$

$$S_0 = \sum_i \sum_j W_{ij} = \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}$$

Where xi is the quantitative variable in the region i, x is the sample mean, wij is the weights of the matrix W, N is the sample size and .$S_0 = \sum_i \sum_j W_{ij}$

Matrix of weights, also called matrix of contacts, contiguities, weights, distances or interactions) is an instrument that merges the fact of interdependence and multidirectional relationships are the matrices of spatial weights, delays or contacts, defined with the letter W (for the English word weight, weight) and represented as follows:

$$w_{ij} = f(d_{ij}) = \frac{1}{d_{ij}}$$

$$w_{ii} = 0$$

Where: = distance between two points.d_{ij}

$$W = \begin{bmatrix} 0 & w_{12} & w_{1N} \\ w_{21} & 0 & w_{2N} \\ w_{N1} & w_{N2} & 0 \end{bmatrix}$$

The W matrix is non-stochastic is of order nxn, where n is the total number of spatial units, in this context n=1872 districts.

Journal of Ecohumanism
2024
Volume: 3, No: 8, pp. 6953 – 6965
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i8.5297

On the other hand, the Local Index of (LISA) is a local contrast, in an asymptotic context and with the assumption of uncorrelated residuals, the standardized Moran's I is distributed as a standard normal.

$$I_i = \frac{z_i}{\sum_i z_i^2 / N_j} \sum_i w_{ij} z_j$$

Where is the value of the variable corresponds to region i, it is the set of regions neighboring i. A high, positive (negative) and significant value of the statistic results in the existence of a cluster around region i of similar high (low) values. Based on the local index, it is possible to find its contribution to the global index, I, and detect its extreme values which makes it a LISA.$z_i N_j I_i$

Likewise, Geary's C contrasts in the same way as the previous one, with Ho = No autocorrelation vs. H1 = spatial dependence; however, it is interpreted with another meaning. Thus, a negative (positive) standardized C of Geary will indicate positive (negative) dependence.

$$C = \frac{N - 1 \sum_{ij}^{N} W_{ij}(X_i - X_j)}{2S_0 \sum_{i=j}^{N}(X_i - \bar{X})^2}, i \neq j$$

Where xi is the quantitative variable in the region i, x is the sample mean, wij is the weights of the matrix W, N is the sample size and $S_0 = \sum_i \sum_j W_{ij}$

Spatial econometrics (SE) is a key tool for analysing geographical phenomena, as it allows us to identify whether the spatial dependence observed in the Human Development Index (HDI) between municipalities or districts is due to characteristics of neighbours or to explanatory factors of human development, such as economic, social, historical and cultural aspects (Gerónimo Antonio et al., 2020). In addition, it considers direct and indirect effects, highlighting the importance of spatial heterogeneity for an optimal allocation of social spending (Hong et al., 2022). This approach has evolved rapidly, producing techniques such as spatial error models (SEM), spatial lag (SLM) and the SARAR model, which integrates spatial elements in the dependent variable and in errors, allowing complex phenomena to be addressed (Paelinck et al., 2015).

Recent studies have applied spatial econometric models to analyze the determinants of the HDI, highlighting the influence of factors such as altitude, urban agglomeration, and proximity to nearby cities(Gonzales de Olarte & Del Pozo, 2018). For example, it is recognized that regions at higher altitudes face significant barriers to human development, while urban agglomerations offer benefits associated with economies of scale. In fact, the variables that were considered in this study are found in Table 1.

Table 1. Identification and Quantification of Georeferenced Variables

Variables	Quantification
Human Development Index (HDI)	Its value is between 0 and 1
Logarithm of cumulative public investment	Logarithm of the execution of accumulated public investment/total population, from 2005 to 2019 in soles.
Altitude of the district capital	In meters above sea level
Urban agglomeration	Urban population / Total population
Distance between districts	Geographical distance between the district capital and the nearest district
District Type	1=Miner 0=Non-Mining
Length of the district capital	In decimals
Latitude of the district capital	In decimals

Journal of Ecohumanism
2024
Volume: 3, No: 8, pp. 6953 – 6965
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i8.5297

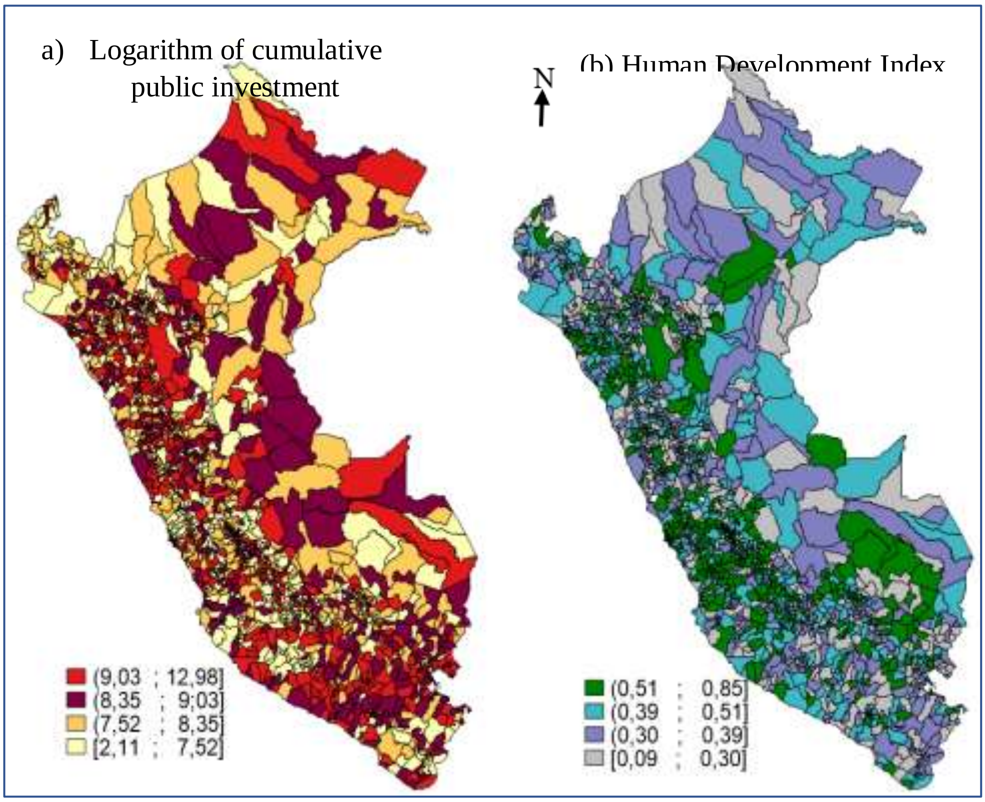
Note. Own elaboration based on data

Two main sources of information were used for this study. The data of the Human Development Index (HDI) at the district level for the year 2019 were obtained from the report of the United Nations Development Program (UNDP). On the other hand, the data on the total population, urban and rural population, as well as the area of the districts, were extracted from the national censuses of 2007 and 2017 carried out by the National Institute of Statistics and Informatics (INEI), and were subsequently projected to the year 2019. For the creation of the matrix of spatial weights (Wij), the distances between the geographical coordinates of the district capitals were used.

Analysis of Results and Discussion

In the **Figure 1**, the cumulative public investment maps and the Human Development Index (HDI) map are mutated, the relationship between cumulative public investment and the Human Development Index (HDI) in the districts of Peru shows that areas with the highest investments, such as Lima and Arequipa, tend to achieve the highest levels of human development (HDI > 0.85), while high Andean and rural regions, such as Puno and Huancavelica, with lower investment, have lower HDIs (HDI < 0.39). This pattern is consistent with what has been pointed out by (Aragón & Rud, 2013), who found that investment in resource-rich regions improves human development, although its effect depends on proper resource management. Likewise (Tapia Martínez, 2020) highlights that inequality in the distribution of public investment significantly affects HDI results between districts. For its part, the United Nations Development Programme (UNDP, 2019a) stresses that investment should be strategically targeted towards disadvantaged regions to reduce territorial gaps and improve well-being in rural and urban areas.

Figure 1. Map of Public Investment Quantiles and Human Development Index – 2019



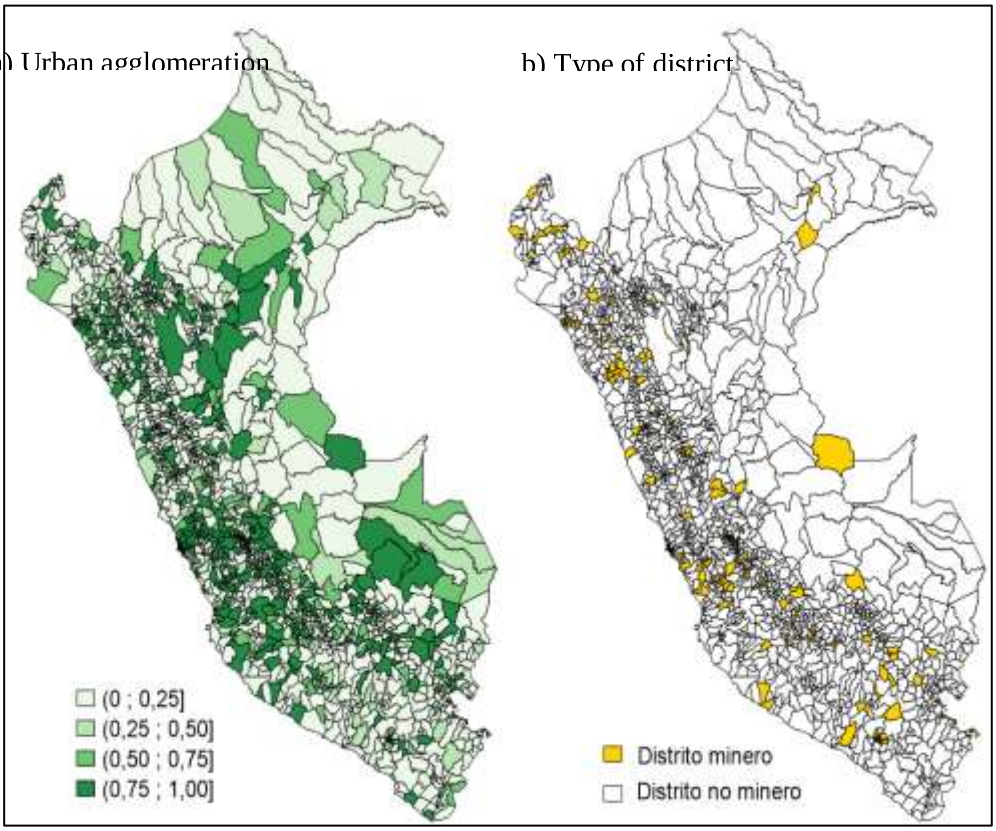
Note. Own elaboration

Urban agglomeration and mining are key factors in human development in Peru, although they present contrasting dynamics depending on the region. Urban areas, such as Lima and Arequipa, with high levels

Journal of Ecohumanism
2024
Volume: 3, No: 8, pp. 6953 – 6965
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i8.5297

of population concentration, benefit from economies of scale and better access to services, which boosts productivity and well-being (Ciccone & Hall, 1996). On the other hand, mining districts, located mainly in the highlands, generate significant income that can improve human development, provided that there is adequate management of resources(Aragón & Rud, 2013). However, these benefits are not always distributed equitably, especially in rural regions, leading to inequalities. (Tapia Martínez, 2020) It highlights that these gaps underscore the need for comprehensive public policies that take advantage of the opportunities of urbanization and mining to reduce territorial inequalities and promote sustainable development throughout the country.

Figure 2. Map of Urban Agglomeration and District Type



Note. Own elaboration

The first stage of the analysis consisted of performing an exploratory analysis of spatial data (AEDE) to evaluate the presence of spatial effects in the data, since omitting this step could generate specification errors in the model(Acevedo Bohórquez & Velásquez Ceballos, 2008). This univariate exploratory analysis focused on the spatial autocorrelation of all the variables identified, with emphasis on public investment. The results indicated a significant spatial autocorrelation of the HDI with its spatial lag, reflecting systematic spatial variation. According to (Anselin, 1988), this type of spatial dependence indicates that high HDI values in one district are associated with high values in neighboring districts, and the same is true for low values. This suggests a significant positive spatial pattern, as confirmed by Moran's test ($p<0.01p < 0.01p<0.01$), rejecting the null hypothesis.

The positive spatial autocorrelation detected supports the existence of geographic clusters of high and low human development, highlighting the need to integrate spatial components into the econometric model to avoid specification problems. As they point out (LeSage & Pace, 2010), The appropriate use of spatial tools improves the ability to capture territorial dynamics in socioeconomic phenomena. The main findings of this study are consistent and robust, as evidenced by the validation tests carried out, strengthening the reliability of the results.

Journal of Ecohumanism
2024
Volume: 3, No: 8, pp. 6953 – 6965
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i8.5297

Table 2 shows the results of the Moran spatial autocorrelation tests and the Geary index for the Human Development Index (HDI). The Moran index (I = 0.187, p<0.01) indicates a significant positive spatial autocorrelation, i.e., districts with high or low HDI values tend to cluster spatially. On the other hand, the Geary index (c = 0.824, p<0.01) also confirms spatial autocorrelation, since values less than 1 imply that the spatial units present similarities in their HDI values with respect to their neighbors. Both results support the existence of systematic spatial patterns in the HDI distribution, suggesting the need to integrate spatial components into the analysis to capture these dynamics.

Table 2. Spatial Autocorrelation Tests On HDI

	I	E(I)	sd(I)	With	p-value
Moran	0,187	-0,001	0,002	93,46	0,00
Geary c	C	And©	Sd©	Z	p-value
	0,824	1,00	0,003	-51,72	0,00

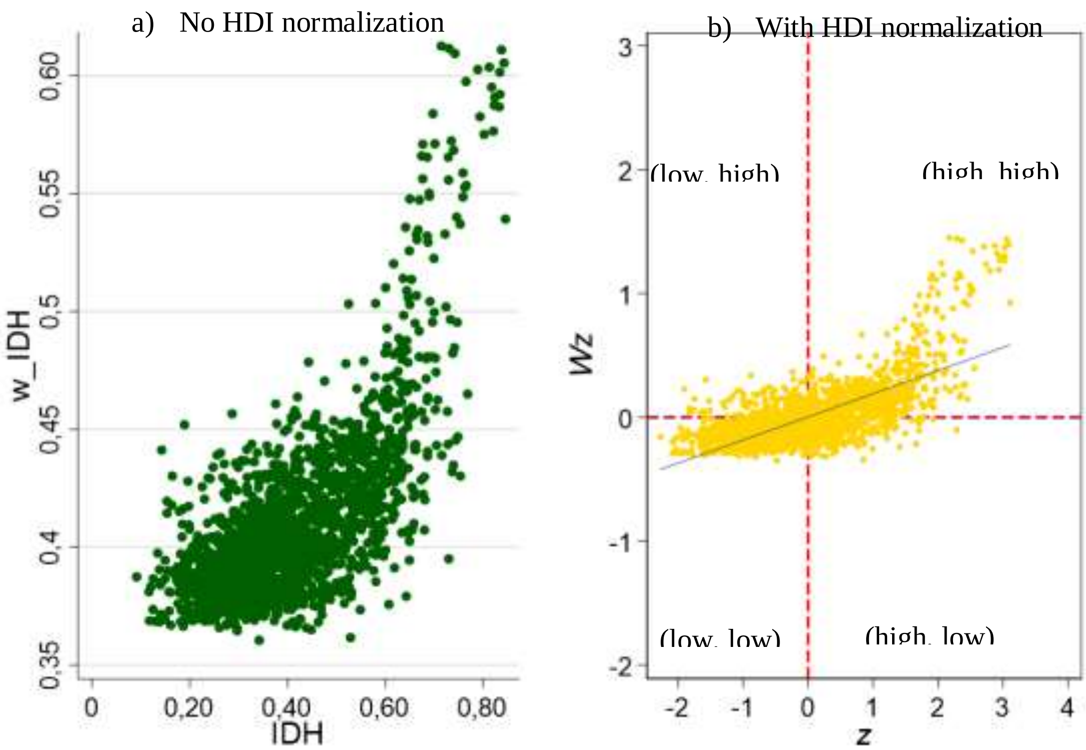
Note. Own elaboration

The results of the study on the HDI in Peru reveal that this indicator is not randomly distributed, but presents defined spatial patterns, where the HDI of one district influences that of neighboring districts. This phenomenon of "spatial contagion", as they point out (LeSage & Pace, 2010), It shows the importance of incorporating the territorial component in public policies, especially in the planning and execution of public investment, to maximize its impact on human development. These findings confirm the need to consider space as a key structural element in the analysis of economic and social phenomena(Anselin, 1988).

Likewise, the results of the spatial autocorrelation tests show that the spatial lag of the HDI is positively associated with the HDI itself, forming spatial clusters of districts with similar values, such as the "high-high" groups. This behavior, as they point out (Paelinck et al., 2015), highlights the relevance of spatial analyses to identify these territorial dynamics. This suggests that districts with high levels of human development tend to cluster geographically, as do those with low levels, underscoring the importance of coordinated regional strategies to address territorial disparities.

Journal of Ecohumanism
2024
Volume: 3, No: 8, pp. 6953 – 6965
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i8.5297

Figure 3. Spatial Autocorrelation of HDI (Moran I)



Note. Own elaboration

Figure 5 shows the spatial heterogeneity in spatially related districts through indirect effects and spatial feedback effects. However, the effects are significantly heterogeneous across quantiles.

Tables 3 and 4 show the distribution of districts according to statistical significance and the spatial clusters of the Human Development Index (HDI). In **Table 3**, 45.03% of the districts (843) present statistical significance at a level of p=0.01p = 0.01p=0.01, indicating a strong spatial autocorrelation, while 39.21% (734 districts) do not show significance. In **Table 4**, the spatial clusters show that 29.65% of the districts (555) belong to the Low-Low group, reflecting a concentration of low HDI values in neighboring areas. On the other hand, 19.02% of the districts (356) are part of the Alto-Alto conglomerate, highlighting clusters of districts with high levels of HDI. These results confirm the existence of significant spatial patterns in the HDI and highlight the need for specific strategies to address regional disparities.

Table 3. Significance and Number of Districts

Probability	Number of districts	%	Accumulated
p=0,01	843	45,03	45,03
p=0,05	172	9,19	54,22
p=0,10	123	6,57	60,79
In the signifier	734	39,21	100
Total	1,872	100	

Note. Own elaboration

Journal of Ecohumanism
2024
Volume: 3, No: 8, pp. 6953 – 6965
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i8.5297

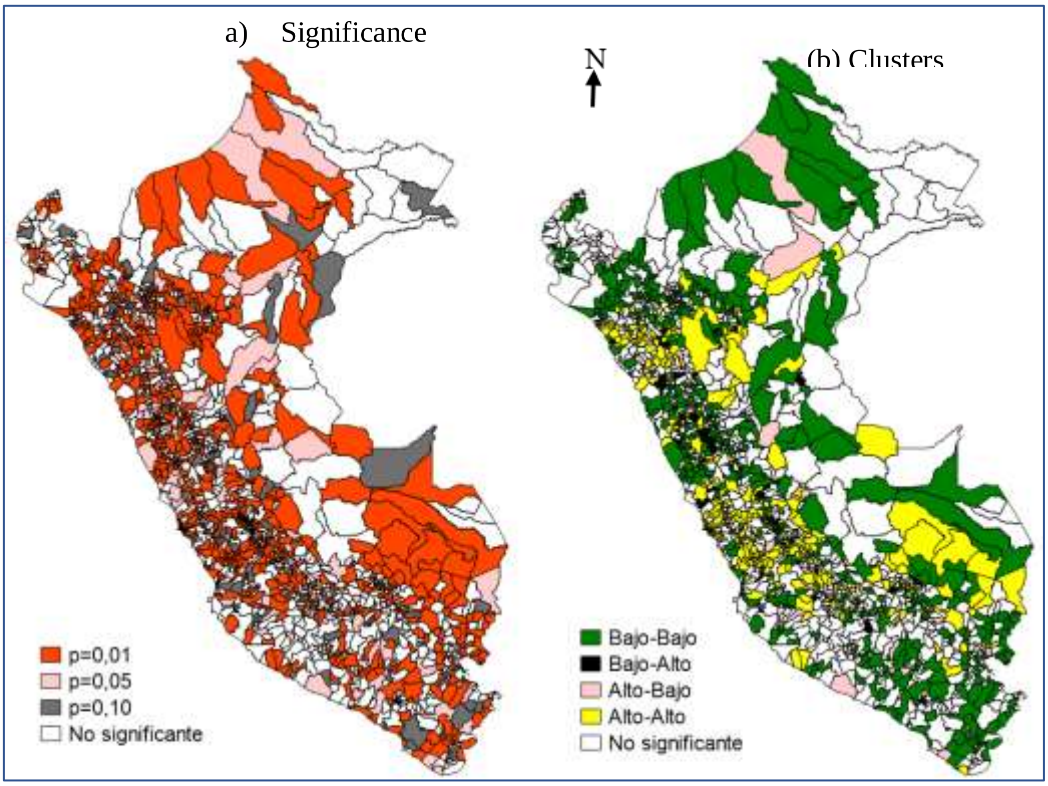
Table 4. Clusters and Number of Districts

Conglomerates	Number of districts	%	Accumulated
Low-Low	555	29,65	29,65
Low-High	39	2,08	31,73
Low	65	3,47	35,2
High-High	356	19,02	54,22
In the signifier	857	45,78	100
Total	1,872	100	

Note. Own elaboration

Figure 4a shows the statistical significance of the spatial autocorrelation of the Human Development Index (HDI), where the areas in red represent districts with high significance (p=0.01p = 0.01p=0.01), indicating strong spatial patterns, while the areas in white do not show significance. Figure 4b) shows the spatial clusters, where the Low-Low group (dark green) highlights the concentration of districts with low HDI values surrounded by similar districts, while the High-High group (yellow) shows clusters of districts with high HDI levels. These patterns reinforce the need to address territorial disparities through regional and focused public policies.

Figure 4. HDI Spatial Heterogeneity Map (LISA Test)



Note. Own elaboration

Next, the spatial factors influencing the HDI were identified, for this the SARAR model was estimated, the coefficients show that the HDI is significantly influenced by economic, geographical and social factors. A 1% increase in public investment increases the HDI by 0.0118, the integration of the spatial component in the design and execution of public policies is key to reducing disparities in income, education and life expectancy, investment in public services and physical infrastructure in health and education not only

Journal of Ecohumanism
2024
Volume: 3, No: 8, pp. 6953 – 6965
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i8.5297

promotes human development, but also strengthens relative revenues by expanding the supply of services and promoting regional development from a joint and contextualized approach.

Altitude is another influential factor in human development, for each additional meter in altitude the HDI is reduced by 0.0000241, reflecting disadvantages in high areas. Urban agglomeration increases the HDI by 0.1459, highlighting the benefits of economies of scale. On the other hand, a greater geographical distance between the capital of the district and the nearest district reduces the HDI by 0.00327, which shows that less proximity to other districts can limit access to resources or services, one of the limiting factors in this case are distances and transportation costs. As district capitals are closer together and transportation costs decrease, opportunities and facilities for human development increase. In addition, mining districts have, on average, an HDI 0.04527 points higher than non-mining districts, underscoring the positive economic impact of local mining.

The spatial parameters of the SARAR model, λ (1.918) and ϱ (2.9725), indicate a strong spatial interdependence in terms of error and in the Human Development Index (HDI), respectively. λ reflects that unobserved factors affecting the HDI in one district are correlated with those of neighboring districts, while ϱ shows a spatial contagion effect, where the HDI of one district is influenced by the HDI of nearby districts. These results highlight the need for regional approaches in public policies, considering territorial dynamics to maximize the impact on human development.

Table 5. Influence of Spatial Factors on the Human Development Index (HDI)

Variables	WRAPS
Logarithm of public investment	0,0118***
	(0,0019)
Altitude in m.a.s.l.	-0,0000241***
	0,0000021
Urban agglomeration	0,1459***
	(0,0062)
Geographical distance	-0,00327***
	0,00077)
District Type (1=Mining and 0=Non-Mining)	0,04527***
	(0,00987
Lambda (λ)	1,918***
	(0,0529)
Rho (ϱ)	2,9725***
	(0,09104)
Coefficient of determination (R2)	
Wald's test (3 g.l.)	763,98***
Log Likelihood	2095,108
Number of observations.	1872

Note. Own elaboration

Indirect effects are fundamental in spatial analysis, as they reflect how the characteristics of an area influence its environment, highlighting regional interdependence. (LeSage & Pace, 2010)They emphasize that indirect effects allow the identification of spatial externalities, essential to understand the spread of economic and social impacts between regions. Likewise (Anselin, 1988) It stresses that these effects are crucial for assessing the diffusion of territorial policies and phenomena, providing a holistic perspective on development.

In this context, the indirect effects of the SARAR model are more important than the direct ones, as they reflect how the characteristics of a district influence neighboring districts, highlighting spatial interdependence in human development. Public investment, with a positive indirect effect (0.029835),

Journal of Ecohumanism
2024
Volume: 3, No: 8, pp. 6953 – 6965
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i8.5297

shows that its benefits are not only local, but also extend to nearby areas, underlining the importance of its strategic distribution. Altitude has a negative indirect effect (-0.0000504), evidencing that adverse geographical conditions not only affect the district, but also impose barriers on neighboring districts. In the case of urban agglomeration, the significant positive indirect effect (0.365055) reflects how the benefits of the concentration of urban resources and services expand to nearby districts, boosting their development.

Geographical distance, with a negative indirect effect (-0.00077), limits connectivity and hinders access to shared opportunities between districts. For mining districts, the positive indirect effect (0.00987) highlights that the economic benefits of mining also reach neighboring areas, favoring their development. Finally, the spatial lag of the HDI, with a significant indirect effect (6.21383), reinforces the idea that the levels of development of nearby districts have a profound influence, generating a strong regional interdependence. These results justify the need for comprehensive territorial approaches, since development is not an isolated phenomenon, but one deeply connected in space.

Table 6. Marginal Effects on the HDI

Variables	Direct effect	Indirect effect	Full effect
Logarithm of public investment	0,01190	0,029835	0,041735
Altitude in m.a.s.l.	-0,0000241	-0,0000504	0,0000745
Urban agglomeration	0,146186	0,365055	0,511241
Geographical distance	-0.00327	-0.00077	-0.00404
District Type (1=Mining and 0=Non-Mining)	0.04527	0.00987	0.05514
HDI spatial lag	2,97772	6,21383	9,19160

Note. Own elaboration

The influence of spatial factors on the Human Development Index (HDI) in the districts of Peru is supported by various studies. (Aragón & Rud, 2013)they conclude that mining generates income and increases the HDI. Likewise, the findings of (Tapia Martínez, 2020), who points out that factors such as altitude and the unequal distribution of public investment significantly condition human development, regions located at higher altitudes often face additional challenges, such as lower agricultural yields and difficulties in accessing health and education services, which can have a negative impact on the HDI. In addition, the United Nations Development Programme (UNDP, 2019a) stresses the importance of decentralized policies to address territorial disparities, especially in remote or hard-to-reach regions, reflecting the need to consider the geographical context.

From a theoretical and methodological perspective, the spatial econometric models used in this study, such as those developed by (LeSage & Pace, 2010), allow us to capture the effects of neighbourhood and spatial dependence, which are key to understanding the impact of the HDI on nearby districts. This aligns with (Bosker & Garretsen, 2012) who highlight how geographical proximity and connectivity can boost regional development. Likewise (Gonzales de Olarte, 2003) It stresses that disparities in human development reflect historical and structural problems, and advocates effective decentralization that allows for a more equitable redistribution of resources.

Urban agglomeration and economic density are also crucial factors. (Ciccone & Hall, 1996) and (Edward L. Glaeser et al., 1992) They argue that areas with higher economic activity density experience higher levels of human development due to economies of scale and more efficient access to services. In the Peruvian

Journal of Ecohumanism
2024
Volume: 3, No: 8, pp. 6953 – 6965
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i8.5297

context, these dynamics are observed in urban districts with a higher population concentration, but they also reveal challenges in extending these benefits to rural areas, as he points out (Chong & Calderón, 2000), who emphasize the importance of solid institutions for an equitable distribution of income.

Finally, public investment and its impact on human development have been the subject of study by multiple authors. (Tapia Martínez, 2020) and the Peruvian Institute of Economics (IPE, 2021) they stress that public investment, particularly at the local level, has a positive effect on the HDI. However (Gonzales de Olarte, 1986) It warns that incomplete decentralization can limit the effectiveness of these investments, perpetuating regional inequalities. This reinforces the need for comprehensive policies that consider both geographical particularities and coordination between levels of government.

Conclusions

The study concludes that spatial factors have a significant influence on the Human Development Index (HDI) of Peru's districts. Public investment, urban agglomeration and mining activity are factors that increase the HDI, while altitude and geographical distance generate limitations that reduce its value. The results also highlight the importance of considering the territorial context and the interactions between districts, since the SARAR model shows a strong spatial interdependence, evidenced by the spatial lag of the dependent variable and errors.

In addition, indirect effects outweigh direct effects, underlining how the characteristics of a district influence the development of neighboring districts. This reinforces the need for public policies with a territorial focus that prioritize regional equity, connectivity, and investment in basic services such as health and education. In this way, the positive effects of human development can be maximized and disparities between districts reduced.

References

Acevedo Bohórquez, I., & Velásquez Ceballos, H. (2008). Some concepts of spatial econometrics and exploratory analysis of spatial data. Ecos de Economía: A Latin American Journal of Applied Economics, 12(27), 9–34. http://publicaciones.eafit.edu.co/index.php/ecos-economia/article/view/705

Álvarez, A. M. (2016). Challenges for Latin America: the Agenda for Sustainabale Development and Negotiations in the Twenty-First Century. Problemas Del Desarrollo, 47(186), 9–30. https://doi.org/10.1016/j.rpd.2016.08.002

Anselin, L. (1988). Spatial Econometrics: Methods and Models (L. Anselin (ed.)). Kluwer Academic Publishers. https://books.google.com.pe/books?hl=es&lr=&id=3dPIXClv4YYC&oi=fnd&pg=PA3&dq=Spatial+Econometrics:+Methods+and+Models&ots=gWOFw64rDX&sig=ghLDluEaGqIiyK66rraOxJIjRHk#v=onepage&q&f=false

Aragón, F. M., & Rud, J. P. (2013). Natural Resources and Local Communities: Evidence from a Peruvian Gold Mine. American Economic Journal: Economic Policy, 5(2), 1–25. https://doi.org/10.1257/pol.5.2.1

Arbia, G. (2001). Modelling the geography of economic activities on a continuous space. Papers in Regional Science, 80(4), 411–424. https://doi.org/10.1111/j.1435-5597.2001.tb01211.x

Arbia, G. (2014). A Primer for Spatial Econometrics: With Applications in R. In PalgraveTexts in Econometrics. https://books.google.com/books?id=P16oBAAAQBAJ&pgis=1

Bosker, M., & Garretsen, H. (2012). Economic Geography and Economic Development in Sub-Saharan Africa. The World Bank Economic Review, 26(3), 443–485. https://doi.org/10.1093/wber/lhs001

Chong, A., & Calderón, C. (2000). Institutional Quality and Income Distribution. Economic Development and Cultural Change, 48(4), 761-786. https://www.journals.uchicago.edu/doi/epdfplus/10.1086/452476

Ciccone, A., & Hall, R. E. (1996). Productivity and the density of economic activity. The American Economic Review, 86(1), 54–70. https://www.jstor.org/stable/2118255

Dasic, B., Devic, Z., Denic, N., Zlatkovic, D., Ilic, I. D., Cao, Y., Jermsittiparsert, K., & Le, H. Van. (2020). Human development index in a context of human development: Review on the western Balkans countries. Brain and Behavior, 10(9), 1–12. https://doi.org/10.1002/brb3.1755

Edward L. Glaeser, Hedi D. Kallal, José A. Scheinkman, & Andrei Shleifer. (1992). Growth in Cities. Journal of Political Economy, 100(6), 1126–1152. https://scholar.harvard.edu/files/shleifer/files/growthincities.pdf

Gerónimo Antonio, V. M., Marina Clemente, J. A., & Vázquez Hernández, A. R. (2020). Patterns and spatial dynamics of human development in the municipalities of Mexico. Development and Society Journal, 2020(85), 111–155. https://doi.org/10.13043/DYS.85.3

Gonzales de Olarte, E. (2003). Decentralization for human development in Peru. United Nations Development Programme, 1(1), 1–61.

Journal of Ecohumanism
2024
Volume: 3, No: 8, pp. 6953 – 6965
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v3i8.5297

http://propuestaciudadana.org.pe/sites/default/files/sala_lectura/archivos/Descentralizaci_n_para_el_desarrollo_humano._Cap_II_1.pdf

Gonzales de Olarte, E. (1986). Options for regional development in Peru. Economy, 9(17–18), 201–216. https://doi.org/10.18800/economia.198601.009

Gonzales de Olarte, E., & Del Pozo, J. M. (2018). Space Matters for Human Development: The Peruvian Case. In PUCP Working Paper (Document, Issue 462). Pontificia Universidad Católica del Perú. https://doi.org/10.18800/2079-8474.0462

Guerra Carrillo, J. C., & Castañeda Núñez, E. S. (2020). Impact of municipal investment management on the human development index in the Mantaro Valley (Peru). Revista Visión Contable, 0104(21), 143–165. https://doi.org/10.24142/rvc.n21a5

Hernández Mota, J. L. (2016). Public Expenditure and Productive Complementarity: An Analysis of the Mexican Economy, 1980-2012. Cuadernos de Economía, 35(67), 315–352. https://doi.org/10.15446/cuad.econ.v35n67.52459

Herrera, M. (2017). Fundamentals of Applied Spatial Econometrics. Munich Personal RePEc Archive MPRA, 1, 1–34. https://mpra.ub.uni-muenchen.de/80871/

Hong, Y., Liu, W., & Song, H. (2022). Spatial econometric analysis of effect of New economic momentum on China's high-quality development. Research in International Business and Finance, 61(February), 101621. https://doi.org/10.1016/j.ribaf.2022.101621

Hurtado, A. V, & Pinchi, W. R. (2019). Crecimiento económico, pobreza y desarrollo humano en el Perú Economic growth, poverty and human development in Peru. Revista Pakamuros, Año, 7, 68–79.

IPE. (2021). Human Development Index - HDI (p. 179). Peruvian Institute of Economics. http://hdr.undp.org/en/content/2019-human-development-index-ranking

Kogan, J., & Bondorevsky, D. (2016). Infrastructure in the development of Latin America. Economics and Development, 156(1), 168–186. https://www.redalyc.org/articulo.oa?id=425547537012

LeSage, J. P., & Pace, R. K. (2010). Handbook of Applied Spatial Analysis. Software Tools, Methods and Applications. In M. M. Fischer & A. Getis (Eds.), Handbook of Applied Spatial Analysis (Issue 2007). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-03647-7

Li, B., Li, T., Yu, M., & Chen, B. (2017). Can equalization of public services narrow the regional disparities in China? A spatial econometrics approach. China Economic Review, 44, 67–78. https://doi.org/10.1016/j.chieco.2017.03.010

Liu, C., Nie, F., & Ren, D. (2021). Temporal and Spatial Evolution of China's Human Development Index and Its Determinants: An Extended Study Based on Five New Development Concepts. Social Indicators Research, 157(1), 247–282. https://doi.org/10.1007/s11205-021-02639-1

Paelinck, J., Mur, J., & Trivez, J. (2015). Models for spatial data with cross-sectional or panel structure. A review. Studies in Applied Economics, 33(1), 7–30.

Pérez, J. A. (2006). Spatial econometrics and regional science. Economic Research, 65(258), 129–160.

Pinilla-Rodriguez, D. E., Jimenez Aguilera, J. D. D., & Montero-Granados, R. (2014). Fiscal decentralization in Latin America. Social impact and determinants. Economic Research, 73(289), 79–110. https://doi.org/10.1016/S0185-1667(15)30004-7

UNDP. (2019a). The challenge of equality. A reading of territorial dynamics in Peru. In United Nations Development Programme (Vol. 53, Issue 9, p. 118). https://www.pe.undp.org/content/dam/peru/docs/Publicaciones poverty/UNDP Peru - The Challenge of Igualdad.pdf

UNDP. (2019b). Human Development Report 2019. Beyond income, beyond averages, beyond the present: Inequalities in human development in the twenty-first century. In United Nations Development Programme. https://www.co.undp.org/content/colombia/es/home/library/human_development/informe-sobre-desarrollo-humano-2019.html

Tapia Martínez, A. P. (2020). The Determination of the Spatial Factor in Human Development: An Analysis for the Peruvian Case [Pontificia Universidad Católica del Perú]. http://hdl.handle.net/20.500.12404/17048

Zubia-Mendoza, B. S. (2021). Social progress, human development and regional competitiveness in Peru. Comparative study disaggregated by regions. Waynarroque – Journal of Applied Social Sciences, 1(1), 73–80. https://doi.org/10.47190/rcsaw.v1i1.7