2023, Volume 46, Issue 91, 1-21 / ISSN 2304-4306

ECONOMÍA

revistas.pucp.edu.pe/economia

FONDO EDITORIAL

www.fondoeditorial.pucp.edu.pe

Altitude and Distance Relationships with the Multidimensional Poverty Index: The case of Peru

Augusto Delgado[a]

[a]Waseda University, Tokyo, Japan

✉ adelgado@tiu.co.jp

Abstract

This paper studies the potential association between two geographic indicators, distance and altitude, with the Multidimensional Poverty Index (MPI) for 1,874 district in Peru by using the National Census of 2017. We investigate whether higher altitude or longer distance is associated with higher MPI values. For this purpose, we use the distance of each district to three different potential spaces of reference. First, we use the shortest distance to the metropolitan area of Lima; second, the shortest distance to the capitals of coastal departments; third, and finally, the shortest distance to the sea. We obtain three relevant results. First, we find evidence that altitude is statistically significant and positive associated with variation of MPI among districts. Second, the distance with respect to the sea appears to be more relevant to explaining differences in MPI than the distance to the Metropolitan area or coastal departmental capitals. Finally, we find evidence of spatial externalities of MPI across districts which also seem to be stronger than the direct effect of altitude and distance.

Article History: Received: 01 February 2022 / Revised: 15 July 2022 / Accepted: 02 September 2022

Keywords: Altitude; Distance; Multidimensional Poverty Index

JEL Classification: C13, C21, I32, P25, R10

https://doi.org/10.18800/economia.202301.001

1. Introduction

There are probably few topics that attract the interest of scholars in different areas as much as poverty and its policy implications. For decades, poverty has been defined, measured, and vastly studied from different perspectives but mainly focused on income measures or their deviation to the average within a population. In 1976, Amartya Sen redefined how we should understand and study poverty. He sustained that rather than focus on income, we must focus on capabilities (Sen, 1976). Considering all the new approaches and influence of this new view, in 1997, the United Nations introduced the Human Development Index (HDI). This HDI is calculated by the average of three indicators that capture three development dimensions, education (measured by years of schooling), health (measured by the life of expectancy), and living conditions (measured by the GNI). Later, in 2010, after concluding that HDI has limitations, Sabina Alkire and Maria Emma Santos designed the Multidimensional Poverty Index (MPI), which, in its simple form, uses ten indicators to capture the exact three development dimensions as the HDI (Alkire et al., 2014).

In 2002, poverty topic gained another impulsed with the adoption of the Millennium Development Goals (MDG) that compromised countries on eight goals to be achieved by 2015. Recently, studies related to poverty received a new impulse with the arise of more sophisticated data, methodologies, and software, especially those related to the spatial dimension of poverty. Regarding this spatial or geographical dimension of poverty, the extensive literature suggests that there is heterogeneity of poverty between rural and urban areas and the effect of the natural geographical environment over poverty (Barbier, 2010; Gallup et al., 1999; Olivia et al., 2011; Gray and Moseley, 2005).

Considering the increasing presence of poverty analysis by using spatial data and methodologies, this research aims to contribute on the literature by analyzing the relationship between space and poverty with the usage of the MPI as proxy. Our contribution is the employment of distances respect to three alternative points of reference to analyze their relationship with the MPI; also, we use altitude and the interaction between altitude and distances. Altitude and distances works as a sort of "remoteness" and their impact over MPI may allow us to discuss the effect of disconnection among districts respect to our references. Nevertheless, we may have heterogeneous interaction between altitude and distances, for example, taking the metropolitan city as point of reference, there are districts with high altitude but close in distance; conversely, there are districts which are far located from the metropolis but with low altitude. Thereby, the interaction between these two variables allow us to deal with those previously mentioned cases.

To carry our analysis, firstly, we calculate the MPI by following Odekon (2015) focusing on five dimensions, i.e., Education, Childhood and Youth, Health, Employment, and Household. The data is obtained from the Census 2017 in Peru. Later and with the purpose of obtaining robust results, we employ three estimation strategies. First, we estimate the MPI at district level (1,874 in total) versus the coordinate values, longitude and latitude, and their squared terms. These first regressions let us to identify the possibility of having clusters. Second, we regress the MPI versus the three alternative distances (1, the distance to Metropolitan Lima (the capital);

2, distance to the capital of coastal departments; and 3, distance to the sea.), altitude, and their interaction. These regressions allow us to identify which distance has a significant impact over poverty. In the third strategy, we use spatial models to incorporate the possibility of having spatial spillovers among districts with altitude and distances as main covariates.

Certainly, distance and altitude are not the cause of the heterogeneity on the development differences among areas; on the contrary, they allow us to identify the areas where other underlying variables may be causing the gap. Considering these reasons, we investigate the potential association of distance and altitude over the development status among Peruvian districts. We use the MPI as a proxy of development degree in each district.

Succeeding our methodology, the main results may be summarized as follows. First, by using the first strategy, there is no clear evidence of clusters. Second, distances, altitude, and their interaction seem to be significant to explain the spatial behavior of the MPI; however, among those distances, the distance respect to the sea give us the most robust and significant estimators. Finally, by using the third estimation strategy, there is evidence of spatial spillovers of the MPI across districts, which is sustain the idea that poverty has an interactive spatial component.

In order to develop and contrast our hypothesis, this article is divided as follow. Section 2 presents a brief literature review while in Section 3, Methodology, we explain the calculation of the MPI, the definition of the variables, and the model we use for our further analysis. Then, in Section 4, we explain our empirical results by using OLS and spatial econometric models. Finally, in Section 5, we present our main results and the conclusions.

2. Brief Literature Review

Taking into consideration the effect of space over poverty, the empirical evidence suggests the existence of disparities of poverty along the space, even within countries. Therefore, the introduction of spatial econometrics methodologies is justified by the empirical evidence. Among the international literature, we have Gräb (2009) and Gräb and Grimm (2011), who study the source of income variance in Burkina Faso, which mainly comes from heterogeneity among households rather than provinces and communities. Similarly, Akinyemi and Bigirimana (2012) studies the living conditions in Kigali, Rwanda, by analyzing income, health, education, and access to services through 10 indicators and using the Geographic Information System (GIS) as the main tool of analysis. With this geographic analysis, the author can identify areas where poverty is agglomerated and the disparities among those areas. On the other hand, Aklilu Zewdie (2015) uses spatial econometrics to study the spatial interaction of poverty among 105 districts in Java Island, Indonesia, finding that education and working hours are statistically significant once spatial interaction is controlled in the model. Related evidence, where space is considered relevant to explain poverty, are available to study poverty in China (Chen et al., 2015; Tan et al., 2021), and USA (Brunn and Wheeler, 1971; Crandall and Weber, 2004; Holt, 2007; Rupasingha and Goetz, 2007).

In Latin America and Peru, studies in regional and urban economics have been rapidly increasing in the last decades; the main characteristics of these studies are the usage of space as a central variable in the analysis of poverty or development issues (Palomino, 2020). In particular, Torres et al. (2011) study the spatial patterns of poverty at the municipal level in Brazil; they identify hot-spots and clusters of municipalities' poverty close to the São Francisco River. Combining Census and Survey in Ecuador, Hentschel et al. (2000) predicts poverty and studies the impact of space on poverty prediction. Specifically, in the case of Peru, Clausen and Flor (2014) study and criticize the election of dimensions and the methodologies used to analyze poverty; in their findings, they highlight the lagged situation of the north of Peru regarding the MPI, which is not conclusive under a monetary analysis. From a similar perspective, Urbina and Quispe (2016) study the relevance of specific dimensions over the multidimensional poverty analysis. Palomino and Sanchez (2021), from a spatial analysis perspective, evaluates and identifies the spatial heterogeneity of the factors that influence monetary poverty among Peruvian districts.

The literature shrinks once we look for an analysis of the interaction between the MPI and space. In this regard, Dong et al. (2021) explore the spatio-temporal behavior of the MPI by using a panel vector autoregressive of Chinese provinces between 2007 to 2017. Among their results, the provincial MPIs have strong spatial dynamics and an increasing trend toward central provinces. With similar objectives of the analysis, Liu and Xu (2016) propose an alternative MPI for Chinese provinces, i.e., the Multidimensional Development Index. In their findings, they sustain that poverty is focused in Tibetan areas, and there is evidence of clusterization in rural provinces. The results obtained are consistent with alternative measurements such as MPI.

Similarly, for Chinese provinces as well, Zhou et al. (2022) calculates the MPI using machine learning, and they find evidence of clusterization among provinces in concordance with previously cited papers. Outside Asia, we have the research of Haddad et al. (2022), which analyzes the MPI in Morocco from 2004 to 2014 at the provincial level using spatial models. In their outcomes, they find evidence of hot spots in the northeast provinces associated with poor infrastructure. On the other hand, Dhongde and Haveman (2022) analyze the spatial and temporal regularities of the MPI across states in the US from 2008 to 2019. They find evidence of agglomeration of MPI in the south and western states; also, the hot spots are concentrated on young adults and immigrants, particularly Hispanics. In the case of Latin America, we have the investigation of Santos et al. (2017), who studied the spatial behavior of poverty in the Bahia state between 2000 to 2010 by calculating the MPI; similarly to previously listed results, they found signs of clusters of poverty among areas inside the state. Finally, in Colombia, Turriago-Hoyos et al. (2020) using the Unsatisfied Basic Needs index since 2005 at the municipal level, they confirm the presence of clusters, especially in municipalities located in Pacific regions. Considering all this evidence, and as far as we are aware, there is no evidence of analysis made by including different types of distances, interaction with altitude, and later comparing it with spatial models.

Distance and altitude are relevant geographical characteristics that open the possibility of further studies since they are related to poverty persistence across areas. In this sense, Bigman and Fofack (2000) and Webb (2013) study the relevance of geographic location and economic connectivity among subnational areas. In this sense, these authors emphasize the connection between high and less developed areas within a country. The main reasons for these development gaps among areas are, first, low quality of public services such as health and education; second, poor infrastructure in rural or distant areas (e.g., roads and railroads); and finally, the inhibition of internal economic transactions, access to financial products, and economic complexity across regions. The underlying variables that help us to explain connectivity are distance and altitude. In both cases, when the subnational areas along the country suffer from poor economic and infrastructure connection, distance and altitude work as a good proxy of the connectivity among those areas. In the case of a country without much elevation heterogeneity along its territory, distance itself might work alone as a good proxy of connectivity; however, in Peru's case, the Andean mountains' presence difficult the connection even between close districts. In this sense, altitude also works as a good proxy of economic and infrastructure connectivity.

3. Methodology

3.1 Multidimensional Poverty Index

To calculate the "Multidimensional Poverty Index", we obtain the data from the National Institute of Statistics and Informatics (INEI, in Spanish) corresponding to the National Census 2017. From the census, and to construct the MPI, three kinds of indicators are used; first, Housing Characteristics and Services; second, Households' characteristics; and finally, Population Characteristics. Following Odekon (2015), the MPI is built by using five dimensions: Education, Childhood and youth, Health, Employment, and Household. These dimensions are weighted in the following way:

$$\texttt{MPI} = 0.2(\texttt{edu}) + 0.2(\texttt{child}) + 0.2(\texttt{health}) + 0.2(\texttt{employ}) + 0.2(\texttt{house}). \tag{1}$$

Regarding the first dimension, the variable `edu` stands for Education. This dimension is crucial since it allows households to adapt to social changing conditions. This dimension is composed of two indicators:

1. Educational achievements (`edu1`). This indicator is calculated by taking the average years of schooling for all household members older than 15 years old since the first grade in elementary school. If the average years of schooling is less than nine, the household is considered deprived.

2. Illiteracy (`edu2`). This indicator counts the number of household members older than 15 years old who cannot read or write. If households with at least one member fall into this condition, then it is considered deprived.

For the second dimension, the variable `child` refers to the "Childhood and youth" dimension. The importance of this dimension is because it allows to development crucial capabilities and skills to have self-sufficient citizens. On the other hand, during this stage of life, individuals have a higher probability of getting infected with some diseases or being forced to work to raise the household income. Considering the relevance of these elements, this dimension is composed of four indicators:

1. Educational lag (`child1`). We filter members between 7 and 17 years old in each household. Then, we build the indicator by using the following condition: seven years old and do not have at least one year of schooling; eight years old and do not have at least two years of schooling, nine years old and do not have at least three years of schooling; up to 17 years old and do not have at least 11 years of schooling. Finally, we count the number of members who fall under this condition; if there is at least one member under this condition, the household is deprived.

2. School absenteeism (`child2`). We count the members between 6 and 16 years old that are currently attending a school. In this indicator, the household is considered deprived if at least one of these members is not attending any school.

3. Childhood Care (`child3`). In this indicator, we count the members younger than five years old who do not have any insurance (public or private) and do not go to any educational institution to get care support. If there is at least one member under this condition, the household is considered deprived.

4. Child labor (`child4`). We count the members below 14 who are currently working to collaborate with household income. If at least one member falls under this condition, the household is deprived.

"Health" dimension is captured in the variable `health`, which is crucial to allow people's conditions to follow their goals. The dimension is composed of a unique indicator.

1. Healthcare insurance (`health`). We count the number of members aged above five who are not affiliated with any health insurance system (public or private). If at least one member falls under this condition, the household is deprived.

The fourth dimension, "Employment", is crucial by providing an adequate income and avoiding lying on poverty or non-adequate job. The variable that captures this dimension is `employ`, and it is composed of the following factors:

1. Employment (`employment1`). We count the members older than 14 years old who currently do not have a job and are looking actively for one. If at least one member falls under this condition, the household is deprived.

2. Informality (`employment2`). We count the members working in a company with five or fewer employees. If at least one member falls under this condition, the household is deprived.

Variable `house` refers to the "Housing" dimension, which is important because it represents the minimum conditions where household members develop their daily-life activities to build their capabilities. This dimension is composed of seven elements:

1. Water access (`house1`). A household is deprived if it does not have water service inside the house, inside the building, or from a public sink. Additionally, it is deprived if they do not have access to water less than three days per week.

2. Sewage access (`house2`). We consider a household is deprived if it does not have access to any sewage service inside the house or the building.

3. Floor (`house3`). We consider a household is deprived if the house's floor material is other than parquet, tiles, vinyl, or cement.

4. Walls (`house4`). The household is deprived if the house's wall material is other than bricks, stones, mud bricks, or wood.

5. Roof (`house5`). We consider a household is deprived if the house's roof material is other than concrete, wood, or tiles.

6. Public lighting (`house6`). We consider a household is deprived if the house does not have access to any public lighting.

7. Overcrowding (`house7`). We consider a household is deprived if the house has more than three members per room.

Consequently, the `MPI` is built by using the previously defined indicators and dimensions and following equation (1). Regarding each dimension, they are calculated as follows:

$$\mathtt{edu} = \frac{\mathtt{edu1} + \mathtt{edu2}}{2} \tag{2}$$

$$\mathtt{child} = \frac{\mathtt{child1} + \mathtt{child2} + \mathtt{child3} + \mathtt{child4}}{4} \tag{3}$$

$$\mathtt{health} = \mathtt{health} \tag{4}$$

$$\mathtt{employ} = \frac{\mathtt{employment1} + \mathtt{employment2}}{2} \tag{5}$$

$$\mathtt{house} = \frac{\mathtt{house1} + \mathtt{house2} + \mathtt{house3} + \mathtt{house4} + \mathtt{house5} + \mathtt{house6} + \mathtt{house7}}{7} \tag{6}$$

3.2 Preliminary Analysis

After the calculation of the MPI at district level, we can make some preliminary analysis, first at departamental level and second at district level. In Figure 1 we present the distribution of the MPI by region at departamental level. Peru is naturally divided in three main natural regions: *Costa* (Coast) composed by 12 departments,[1] *Sierra* (Highlands) composed by 10 departments, and *Selva* (Jungle) composed by 4 departments. Also the figure shows some important statistics.

From the figure we observe that, in average, Coastal departments have lower MPI while Jungle ones have slightly higher than Highlands departments. Additionally, we notice a more heterogeneity among the MPIs of the areas located in the highlands. In the case of departments located on the Coast, we notice less heterogeneity but there is some evidence of asymmetry on the distribution since the mode and the mean are not aligned each other. Finally, in all the cases, the distribution is unimodal showing the presence of normal distribution in all cases, this is noted since all violin graphics are grouped around the mean value.

[1] Notice that Lima department is divided into three: Callao, Metropolitan Lima, and Lima provinces.

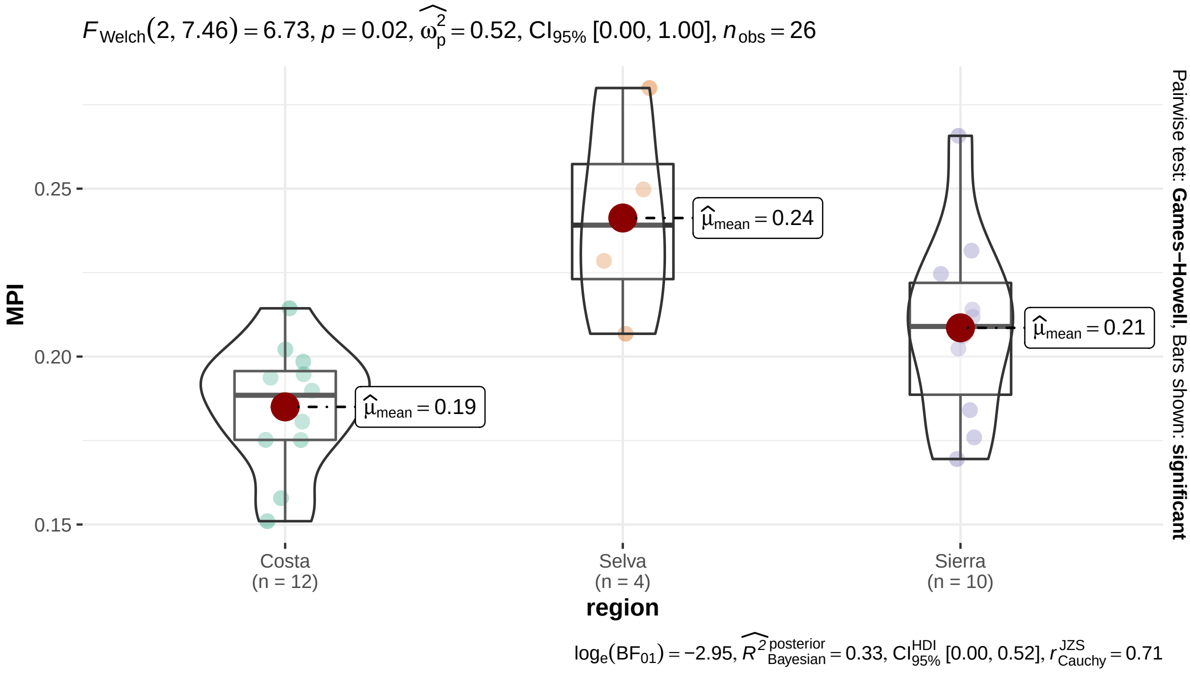

Figure 1. Distribution of the MPI across Natural Regions

Another interesting analysis is the detection of clusterization behavior of the MPI variable among the 1,874 districts along Peru. For this purpose we estimate the local Moran's I based on the following equation:

$$I_i = \frac{x_i - \bar{x}}{\frac{\sum_{j=1,j\neq i}^{n} w_{ij} - \bar{x}}{n-1}} \sum_{j=1,j\neq i}^{n} w_{ij}(x_i - \bar{x}) \tag{7}$$

where x_i is the value of MPI for each district, $\bar{x}$ is the mean of the variable MPI, w_{ij} is the spatial weight matrix between two districts i and j where the sum of those weights is 1, and n is the total number of districts, i.e. 1,874.

In particular, the local Moran's I examines the relationship between the districts and their neighbors, which can occur in the following four situations: High-High, when both the district and their neighbors have positive values of the local Moran's I; in other words, these areas determine the presence of hot-spots since those areas have positive spatial autocorrelation and their neighbors as well. High-Low, when the district has positive spatial autocorrelation but their neighbors have negative values. Low-High, when the spatial autocorrelation of the district is negative and their neighbors is positive. Finally, Low-Low, when both, the district and its neighbors have negative spatial autocorrelation, these areas are also called cold-spots.

In Figure 2 we present the results of the local Moran's I calculation for all Peruvian districts. In the figure is also shown the location of the departamental capitals and the boundaries of those departments. We observe that most of red highlighted areas (High-High) are located on the jungle and part on the highlands of Peru, which implies that the multidimensional poverty is clusterized on jungle districts which may be related with the distance of those areas respect

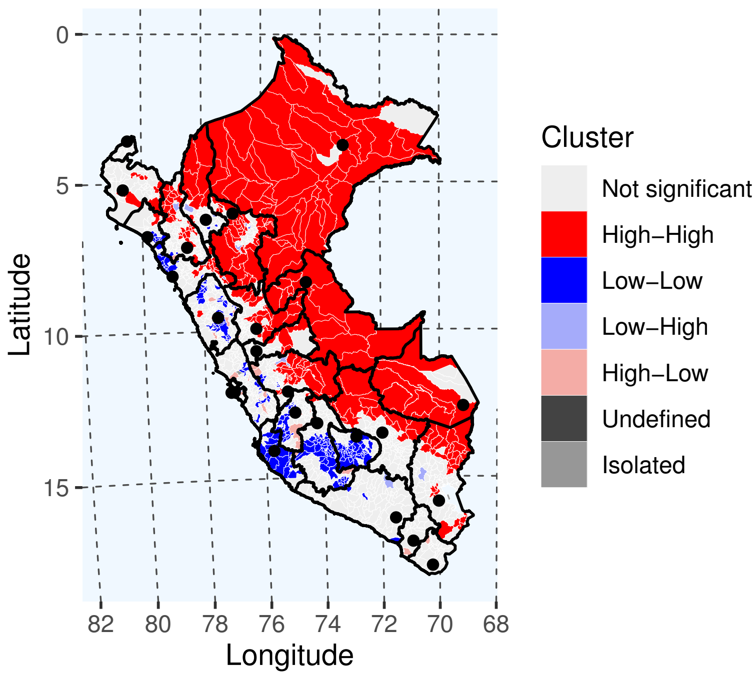

Figure 2. Hot and Cold Spots for the Multidimensional Poverty Index

to the coast or the metropolis. In other words, poverty seems to be spatially concentrated in some areas and those districts have positive and significant spatial autocorrelation with their neighbors. From another side, we observe that the cold-spots (Low-Low) or blue highlighted areas are located mostly on the coast and south departments, which implies that those districts have low levels of spatial autocorrelation; similarly to their neighbors.

Another fact that is relevant to mention is that those districts where the capital is located in each department are those that have, in most of the cases, no significant spatial autocorrelation with their neighbors. In other words, departamental capitals seem to be islands respect to their neighboring areas.

3.3 The Econometric Model

We propose three models to study the association of space and altitude with the previously defined MPI. The geographic information is obtained from the INEI and the United Nations Environment Programme (UNEP) as polygons, which allow us to calculate the distance between two coordinate points. It is important to notice that the distance we use are the euclidean distance between two points based in this equation: $d_{(i,j)} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$. Another valid alternative to measure distance is the time that it takes going from one point to another. Nevertheless, it is not used since no terrestrial routes connect all districts in Peru; therefore, no data are available. Regarding the altitude distance, the data is obtained from the UNEP as raster information and transformed to polygons to process all the information and extract the dad included in it.

The first type of model investigates how clustered are the values of MPI at district level over the space or how much is associated the districts' MPI values with their geographic location. For this purpose, we estimate a regression between the MPI values at district level versus their longitude and latitude coordinates. Therefore, the equations are defined as:

$$\mathtt{MPI}_i = \alpha_0 + \alpha_1 \mathtt{long}_i + \alpha_2 \mathtt{lat}_i + \varepsilon_i, \tag{8}$$

$$\mathtt{MPI}_i = \alpha_0 + \alpha_1 \mathtt{long}_i + \alpha_2 \mathtt{lat}_i + \alpha_3 \mathtt{long}_i^2 + \alpha_4 \mathtt{lat}_i^2 + \varepsilon_i, \tag{9}$$

where $\mathtt{long}_i$ is the average longitude of district i, $\mathtt{lat}_i$ is the average latitude of district i, and ε_i are the errors to be assumed *iid*.

The second type of models studies the association of MPI values at district level versus altitude and three types of relevant distances. Distances are defined as follow:

1. Distance between each district centroid and Metropolitan Lima's centroid.[2] The metropolitan area is conformed by 42 districts[3] plus Callao.
2. Distance between each district's centroid and the capital of each coastal department.[4]
3. Distance between each district's centroid and the Sea.

Considering the three types of distances, the estimation equations are:

$$\mathtt{MPI}_i = \beta_0 + \beta_1 \mathtt{dtoX}_i + \beta_2 \mathtt{alt}_i + \varepsilon_i, \tag{10}$$

$$\mathtt{MPI}_i = \beta_0 + \beta_1 \mathtt{dtoX}_i + \beta_2 \mathtt{alt}_i + \beta_3 \mathtt{dtoX}_i^* \mathtt{alt}_i + \varepsilon_i, \tag{11}$$

where $\mathtt{alt}_i$ stands for average altitude of district i, $\mathtt{dtoX}_i$ stands for distance from district i to X_i, where X_i may be Metropolitan Lima, Coastal Capitals, or Sea. Finally, ε_i are the errors, assumed to be *iid*.

Now, the main limitation with the models described above is that they ignore the space and its potential effects. To solve this issue, we can include those potential effects by using spatial

[2] Bakhvalov (2015) defines the centroid by considering the set of points of a closed polygon $\{(x_i, y_i)\}_{i=0}^{N-1} \in \mathbb{R}^2$, and letting the vertices to be organized clockwise. Then the polygon encloses the area:

$$A = \frac{1}{2} \sum_{i=0}^{N-1} (x_i y_{i+1} - x_{i+1} y_i),$$

and its centroid is given by:

$$\text{centroid} = \frac{1}{6A} \Big(\sum_{i=0}^{N-1} (x_i + x_{i+1})(x_i y_{i+1} - x_{i+1} y_i), \sum_{i=0}^{N-1} (y_i + y_{i+1})(x_i y_{i+1} - x_{i+1} y_i) \Big)^T \in \mathbb{R}^2.$$

[3] Ancón, Ate, Barranco, Breña, Carabayllo, Cercado de Lima, Chaclacayo, Chorrillos, Cieneguilla, Comas, El Agustino, Independencia, Jesús María, La Molina, La Victoria, Lince, Los Olivos, Lurigancho, Lurín, Magdalena del Mar, Miraflores, Pachacámac, Pucusana, Pueblo Libre, Puente Piedra, Punta Hermosa, Punta Negra, Rímac, San Bartolo, San Borja, San Isidro, San Juan de Lurigancho, San Juan de Miraflores, San Luis, San Martín de Porres, San Miguel, Santa Anita, Santa María del Mar, Santa Rosa, Santiago de Surco, Surquillo, Villa el Salvador, and Villa Maria del Triunfo.

[4] The capitals of each departments are: Tumbes (Tumbes), Piura (Piura), Chiclayo (Lambayeque), Trujillo (La Libertad), Huaraz (Ancash), Lima (Lima), Ica (Ica), Arequipa (Arequipa), Moquegua (Moquegua), and Tacna (Tacna).

models. There are three basic types how the space can be included into a model; first, we include the possibility of spatial effect into the endogenous variable (i.e. Spatial Autocorrelation Models); second, spatial effects into part or all the set of exogenous variables (i.e. Spatial Durbin Models); and third, spatial effects into the errors (i.e. Spatial Error Models). Naturally, the types of spatial models can be increased by mixing the previous three types. Theoretically, the three types have a purpose on their usage, the Spatial Autocorrelation Models captures the presence of spillovers when they born on the endogenous variable; similarly the Durbin Spatial Models captures the spillovers generated by the set of exogenous variables; however, when the origin of the spillovers cannot be determined by using the endogenous or exogenous variables, they are included into the errors which may capture the spillovers generated in omitted variables.

Considering the potential spatial correlation of MPI across space and to correct spatial heteroskedasticity, by following LeSage and Pace (2009), Arbia and Baltagi (2009), LeSage and Pace (2014), and Arbia (2016), we extend equation (11) and employ three alternative specifications:

1. **Spatial Autocorrelation (SAR) Models**, which includes the spatial lag of the endogenous variable to capture any spatial spillovers of the endogenous variable across the space:

$$\texttt{MPI}_i = \beta_0 + \rho W \texttt{MPI}_i + \beta_1 \texttt{dtoX}_i + \beta_2 \texttt{alt}_i + \beta_3 \texttt{dtoX}_i^* \texttt{alt}_i + \varepsilon_i, \tag{12}$$

   where ρ captures the spatial autocorrelation originated on the endogenous variable, MPI. W is the spatial weight matrix, which identifies the contiguous neighbors of district i.[5] Intuitively, the model states that MPI in each district is related to the average MPI from neighboring districts.

2. **Spatial Error (SEM) Models**, which includes the spatial lag of the errors to capture spatial spillovers of omitted variable across the space and the spatial interaction works through the error term:

$$\begin{aligned} \texttt{MPI}_i &= \beta_0 + \beta_1 \texttt{dtoX}_i + \beta_2 \texttt{alt}_i + \beta_3 \texttt{dtoX}_i^* \texttt{alt}_i + \varepsilon_i, \\ \varepsilon &= \lambda W \varepsilon_i + \mu_i, \end{aligned} \tag{13}$$

   where λ is the scalar spatial error coefficient and μ_i is the disturbance term. The main purpose of λ is correct potential heteroskedasticity across the space generated by omitted variables; therefore, the intuition remain the same for βs, but they are corrected for potential heteroskedasticity.

3. **Spatial Autocorrelation and Error (SARAR) Models**, which includes the spatial lag of the endogenous variable and the error term. In other words, this especification combines SAR and SEM models.

$$\begin{aligned} \texttt{MPI}_i &= \beta_0 + \rho W \texttt{MPI}_i + \beta_1 \texttt{dtoX}_i + \beta_2 \texttt{alt}_i + \beta_3 \texttt{dtoX}_i^* \texttt{alt}_i + \varepsilon_i, \\ \varepsilon &= \lambda W \varepsilon_i + \mu_i. \end{aligned} \tag{14}$$

[5] In this case, we use the nearest neighbor weight matrix. For more details, see LeSage (2008).

Note that we do not include the case of Spatial Durbin Models because, reasonably, we are assuming that altitude and distance do not have spatial spillovers or they do not have spatial autocorrelation with altitude and distance in neighboring districts. This is not the case of MPI or the errors.

4. Results

This section presents the estimation results of the previously detailed models. We divide this section into three parts, the first one corresponding to the results when the set of covariates are longitude and latitude. In the second part, we use distances and altitude as covariates. Finally, in the last part, we use spatial models.

4.1 Longitude and Latitude

Table 1 presents ordinary least squares (OLS) estimates of equations (8) and (9) in which we use longitude and latitude for each district as covariates. Column (1) shows the results of the base model, which correspond to equation (8). Column (2) presents the results of equation (9), which includes the squared terms of longitude and latitude. We observe that the higher longitude and latitude are, the higher the values of MPI; in other words, the values of the multidimensional poverty index are concentrated on the south and west districts of Peru. In this regard, we notice that districts located in west areas are associated with higher MPI values than areas in the south of Peru. All the estimated coefficients are statistically significant at 1%.

On the other hand, once we incorporate the squared values of the longitude and latitude coordinates, we observe that the original association between location and MPI changes. First,

Table 1

OLS estimation results.

	Dependent variable: `MPI`	
	(1)	(2)
`long`	0.011***	0.030*
	(0.0005)	(0.015)
`lat`	0.009***	0.006***
	(0.0004)	(0.002)
`long`^{2}		0.0001
		(0.0001)
`lat`^{2}		−0.0002**
		(0.0001)
Constant	1.137***	1.831***
	(0.037)	(0.571)
Observations	1,874	1,874
R^2	0.277	0.279
Adjusted R^2	0.277	0.278
Residual Std. Error	0.033	0.033
F Statistic	359.2***	181.0***

Note: *p<0.1; **p<0.05; ***p<0.01.

we observe that similarly to the above results, MPI values increases on the north (`lat`) and east (`long`) located districts; however, the association between west locations and MPI is reduced until being lower than the association between north locations and MPI. In other words, north-located districts are more associated with higher MPI than east-located districts. Second, even though northern districts are associated with higher MPI values, the association level increases at diminishing rates. In other words, districts in north areas are associated with higher MPI values, but the differences among districts decrease as north coordinates go. Third, districts located in east areas are associated with higher MPI values. Also, the association level tends to change constantly as far as east coordinates go since the squared values of `long` are not statistically significant. To sum up, districts located in the northern departments of Peru or those located in east departments (jungle region) are associated with high MPI values. These results are analogous to those obtained by Clausen and Flor (2014) and Palomino and Sanchez (2021).

4.2 Distance and Altitude

In this subsection we present the estimation results when we use distances and altitude as covariates. In this sense, Table 2 shows the estimation results for equations (10) and (11) and their variations once we use different types of distances previously defined. Those type of distances are: distance from each district to Metropolitan Lima (`dLima`) in column (1) and (2); distance from each district to coastal capitals (`dCoast`) in column (3) and (4); finally, distance from each district to the sea (`dSea`) in column (5) and (6).

Regarding the results, we observe that the association of the altitude (`alt`) with the MPI values is not stable across specifications. The altitude is associated with lower MPI values when there is no interaction between distances and altitude covariates. However, these results change once the interaction is incorporated. In all the cases, the estimation results with the interaction term have higher R^2 and lower Akaike criterion value, which makes those results preferred over the non-interaction term equations.

Concerning our estimation results, we observe that in the first set of outcomes (columns (1) and (2)), in which we use distance to Metropolitan Lima as a covariate, the association between altitude with MPI values, and distance with MPI values are the same. Intuitively a district located 1% further from Metropolitan Lima is associated with 0.023 higher MPI points, which describes districts with higher multidimensional poverty levels. Similarly, a district located 1% higher than Metropolitan Lima is also associated with 0.023 higher MPI values. Therefore, altitude and distance have similar semi-elasticities with respect to MPI, so districts at higher places are equivalent to districts at further locations. An interesting result we find in Table 2 is that the interaction terms have statistically significant and negative signs across specifications; intuitively, these results mean that districts located in far and high areas are associated with lower MPI values than those districts located close and low areas.

On the second (columns (3) and (4)) and third (columns (5) and (6)) set of results, we also observe that equivalence on the association between distances and altitude changed. In more detail, in both cases, distance from the reference point changes to be associated with higher MPI

Table 2
OLS estimation results.

	Dependent variable: MPI					
	(1)	(2)	(3)	(4)	(5)	(6)
`alt`	−0.002**	0.023***	−0.005***	0.025***	−0.011***	0.010**
	(0.001)	(0.005)	(0.001)	(0.004)	(0.001)	(0.005)
`dLima`	0.011***	0.023***				
	(0.001)	(0.003)				
`alt*dLima`		−0.002***				
		(0.0004)				
`dCoast`			0.014***	0.033***		
			(0.001)	(0.002)		
`alt*dCoast`				−0.003***		
				(0.0004)		
`dSea`					0.020***	0.030***
					(0.001)	(0.002)
`alt*dSea`						−0.002***
						(0.0004)
`Constant`	0.071***	−0.080**	0.084***	−0.110***	0.048***	−0.064**
	(0.010)	(0.035)	(0.007)	(0.026)	(0.008)	(0.026)
Observations	1,874	1,874	1,874	1,874	1,874	1,874
R^2	0.105	0.115	0.215	0.240	0.259	0.267
Adjusted R^2	0.105	0.114	0.214	0.239	0.258	0.266
Residual SE	0.036	0.036	0.034	0.033	0.033	0.033
F Statistic	110.33***	81.04***	255.97***	196.69***	327.10***	226.81***
AIC	-7109	-7127	-7353	-7412	-7462	-7480

Note: *p<0.1; **p<0.05; ***p<0.01.

values than those districts in upper places. Additionally, comparing the three sets of regressions based on alternative definitions of distances, we observe that distance of districts to the sea (`dSea`, which correspond to columns (5) and (6)) show higher R^2, higher adjusted-R^2, and lower AIC. Therefore, distance to the sea gives us more robust results than the distance to Metropolitan Lima or the Coastal capitals. Considering this evidence, we present the results in the following subsection by using spatial models based on the distance to the sea as the main definition of distance.

4.3 Spatial Model Results

Table 3 shows the estimation results using distance from each district to the sea and altitude as covariates. Also, the table presents three types of spatial models, based on equations (12), (13), and (14); additionally, in order to get robust results, we grouped the estimation results into three sets, each of those corresponding to different spatial lags. Each lag follows the number of k nearest neighbors to each district. In particular, in Table 3, we use k = 3, 6, and 9 nearest neighbors. Notice that we do not identify neighbors based on contiguities such as *Rook* or *Queen* because, in the results, some districts without neighbors invalidate the estimation of the spatial effects due to the no invertibility of the matrix W.

Table 3

Spatial Models Estimation Results.

	Dependent variable: Multidimensional Poverty Index (MPI)								
	Spatial Lags ($k = 3$)			Spatial Lags ($k = 6$)			Spatial Lags ($k = 9$)		
	(SAR)	(SEM)	(SARAR)	(SAR)	(SEM)	(SARAR)	(SAR)	(SEM)	(SARAR)
`alt`	0.011***	0.009	0.008***	0.005**	0.004	0.006**	0.008**	−0.004	0.008**
	(0.004)	(0.008)	(0.003)	(0.004)	(0.009)	(0.003)	(0.004)	(0.009)	(0.004)
`dSea`	0.014***	0.023***	0.009***	0.010***	0.016***	0.008***	0.009***	0.010**	0.009***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)	(0.000)	(0.005)	(0.002)
`alt*dSea`	−0.001***	−0.001*	−0.001***	−0.001**	−0.001	−0.001***	−0.001**	−0.000	−0.001**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.009)	(0.000)
ρ	0.640***		0.788***	0.743***		0.788***	0.796***		0.803***
	(0.018)		(0.022)	(0.018)		(0.021)	(0.020)		(0.033)
λ		0.639***	−0.360***		0.756***	−0.287***		0.817***	−0.024
		(0.018)	(0.047)		(0.018)	(0.073)		(0.016)	(0.100)
`Constant`	−0.069***	−0.032	−0.052*	−0.053**	0.025	−0.044**	−0.052**	0.082*	−0.052**
	(0.025)	(0.049)	(0.018)	(0.024)	(0.050)	(0.019)	(0.024)	(0.049)	(0.024)
Observations	1,874	1,874	1,874	1,874	1,874	1,874	1,874	1,874	1,874
Log Likelihood	4061	4051	4080	4120	4113	4126	4125	4119	4125
σ^2	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026	0.026
AIC	−8111	−8090	−8147	−8227	−8214	−8238	−8238	−8227	−8236
Wald Test	1291***	1268***	989***	1661***	1815***	1234***	1961***	2376***	1416***
LR Test	846.5***	825.7***	884.5***	962***	948.8***	975***	973***	962***	973***
Hausman Test		53920***			7760***			7377***	

Note: *p<0.1; **p<0.05; ***p<0.01.

Regarding the set of covariates, the first covariate, `alt`, refers to the natural logarithm of altitude; therefore, the estimation coefficients are interpreted as semi-elasticities. The second covariate, `dSea`, refers to the natural logarithm of the shortest distance in kilometers between the centroid of each district to the sea or the coastline; its coefficients may also be interpreted as semi-elasticities. Finally, the third covariate, `alt*dSea`, captures the interaction between the natural logarithm of the altitude and the distance. On the other hand, we have the spatial effects, which are captured onto two estimators. The fourth estimated coefficient, ρ, captures the spatial autocorrelation of the endogenous variable MPI with their nearest neighbors. Intuitively, for the 3-nearest neighbors, this coefficient measures the relationship that MPI has in district i with the averages of their three nearest neighbors, similarly to the other neighbors ($k = 6$ and 9). λ, in the same way, captures the spatial interaction of the error terms with their k-nearest neighbors. Since the error terms capture the effect of any omitted variable in the proposed model, λ captures the spatial interaction of any omitted variables; therefore, it helps to correct heteroskedasticity in the original model. Finally, the sixth estimated coefficient captures the constant term.

The estimation results in Table 3 shows mixed results. First of all, in the case of the variable of altitude, `alt`, results are significant in all the cases except when the spatial effects are only established for the errors. In particular, we observe that the effect of altitude in the significant cases goes from 0.005 to 0.011, which implies that with an increment of 1% on altitude, the multidimensional poverty index (MPI) increases between 0.005/100 to 0.011/100 points. On the contrary, the semi-elasticity of `dSea` is more stable in its results, and it is statistically significant across spatial models with values that go from 0.008 to 0.023; similarly to altitude, an increment of 1% on distance with respect to the sea implies an increment on the MPI between 0.008/100 and 0.023/100 points. Similarly to altitude and distance, the interaction term between these two covariates is negative and statistically significant in most cases. The negative coefficient `alt*dSea` intuitively sustains that districts far from the sea with high altitude are associated with slightly less MPI than other districts.

Regarding the spatial terms, ρ, results are statistically significant and positive in all models. The coefficient shows that MPI is spatially autocorrelated, which implies that districts are spatially autocorrelated with their neighbors. Additionally, we observe that the spatial effect increases once the number of spatial lags increases and when the possibility of spatial interaction on the error terms is included. In other words, the spatial effects of MPI across districts are sensitive to the number of neighbors included in the analysis and the incorporation of spatial effects on the errors. In this sense, regarding the spatial externalities on the error terms, λ, shows coefficients on SEM models similar to the ρ coefficients on SAR models; these results mean that once the spatial lag of the endogenous variable is omitted, its whole effect goes to the error terms and it is captured on the spatial lag of the error terms λ.

Furthermore, when we incorporate both variables into the same equation, spatial lag on the endogenous variable and lag in the error terms, we observe that ρ remains statistically significant, and its value does not change dramatically. Nevertheless, the λ coefficient changes drastically until be negative and statistically significant for the two first sets (3 and 6 nearest neighbors), and it is not statistically significant in the case of 9 nearest neighbors. In other words, in the case of having more lags, the spatial externalities are fully captured by the lag of the endogenous variable, and there are no spatial effects of omitted variables.

Furthermore, in Table 3, considering the Wald and LR tests, the spatial effects are significant since the null hypothesis of the non-spatial model is rejected in all the cases. Also, the Hausman test rejects the null hypothesis in favor of using the SEM models (Pace and LeSage, 2008). Also, comparing the models by using the Akaike Criterion, we observe that, among SAR models, that one with $k = 9$ is preferred; second, similarly to the SAR models, among SEM models, $k = 9$'s is chosen; finally, among the SARAR models, the model with six lags is preferred. Notice that, generally, a model with more lags is preferred since it allows us to capture the spatial effects more clearly.

Following Golgher and Voss (2015), we estimate the Direct, Indirect, and Total effects. Considering the endogenous variable y and the exogenous variable x, district i and its neighbors. The *direct impact* estimate the effect of x over the variable y in the district i. On the other hand, the *indirect impact* estimates the effect of the variation on the variable x on neighbor districts over the variable y in the district i. When there are no spatial effects from the set of covariates (i.e., no Durbin Spatial model), the *indirect impact* is also called *Global impacts*. Furthermore, in Table 4, we observe that all direct and indirect impacts have the same signs, which implies that their impacts reinforce each other.

In the SAR model, altitude has a direct impact of 0.0087, which indicates that an increment on 10% on the altitude in district i is associated with an increment of the MPI on 0.00087 points. On the other hand, the indirect impact is 0.0286, which implies that an increment on 10% on the altitude of neighbors increases the MPI on district i in 0.00286 points. We obtain similar results for distance with respect to the sea and similar results for the SARAR model. It is important to notice that the indirect impact is larger than the direct one in all cases. This fact suggests that the spatial spillovers on poverty across districts are larger than the effects generated within the district; in other words, the spillover generated by neighbor districts located at a further distance or higher altitude is stronger onto the district i than if this district itself is located in higher or further location.

Finally, the realization of a similar analysis using different distance measures and weight matrices remains on the research agenda. For example, we can re-estimate the model using distance measured in time rather than physical distance, also, we can use distance by routing through-

Table 4
Spatial Impacts.

	Dependent variable: Multidimensional Poverty Index (MPI)					
	SAR ($k = 9$)			SARAR ($k = 6$)		
	Direct	Indirect	Total	Direct	Indirect	Total
`alt`	0.0087**	0.0286*	0.0373**	0.0081**	0.0305**	0.0386**
`dSea`	0.0104***	0.0343***	0.0448***	0.0096***	0.0360***	0.0456***
`alt*dSea`	−0.0009**	−0.0030**	−0.0039**	−0.0009***	−0.0032***	−0.0041***

Note: *p<0.1; **p<0.05; ***p<0.01.

out available roads. On the other hand, in the case of weigh matrices, it may be interesting to analyze the model sensitivity by using neighbor matrix identifying them by considering the routes connections (roads, railroads, flight routes, and other transportation infrastructures) that districts may have among them.

5. Final Discussion and Conclusions

Certainly, as the vast literature sustains, geography itself is not the cause of poverty; however, geography is highly correlated with underlying characteristics that make poverty spatially grouped. In this sense, geography, and distance or altitude, as we proposed, are variables that work as a sort of connection-level among districts. In general Bigman and Fofack (2000) highlights that poverty may be related to location because it is correlated with low quality of public services, poor conditions of rural infrastructure, low level of social capital, and low flow of trade among subnational areas. These reasons agree with Webb (2013), which in particular, argues that in Peru, there is a significant disconnection between urban and rural areas due to inadequate infrastructure and low level of essential public services in distant areas.

Considering that distance and altitude are variables that help us understand the level of connection among districts, we studied the level of association between the MPI at the district level versus the altitude and different types of distances. Initially, on non-spatial models, we observe that distance and altitude are relevant to understanding the differences of MPI among districts. Second, altitude is initially negatively associated with MPI, which results counter-intuitive; however, these results are reverted once the interaction of altitude and distance is included in each case. Third, we observe that the distance of each district concerning the sea gives us more robust estimators than the distance to Metropolitan Lima or Coastal departmental capitals.

On the other hand, when we use spatial models to study the presence of spatial externalities, firstly, we observe that altitude, similarly to non-spatial models, remains to be statistically significant, i.e., districts located in higher altitude places is associated with higher multidimensional poverty index. Second, the distance to the sea remains positive and significant across models. In other words, districts located further from the sea tend to have higher MPI or poorer from a multidimensional perspective. Third, there is evidence of spatial externalities associated with MPI between districts; in other words, multidimensional poverty presents a spatial behavior. Similar results were obtained in Palomino and Sanchez (2021). These results open the possibility of new studies that explore the spatial dimension of poverty.

References

Akinyemi, F., and Bigirimana, F. (2012). A Spatial Analysis of Poverty in Kigali, Rwanda using indicators of household living standard. *Rwanda Journal 26(1)*, 3-22.

Aklilu Zewdie, M. (2015). Spatial Econometric Model of Poverty in Java Island. *American Journal of Theoretical and Applied Statistics 4(6)*, 420-425.

Alkire, S., Conconi, A., and Seth, S. (2014). Multidimensional Poverty Index 2014: Brief Methodological Note and Results. University of Oxford.

Arbia, G. (2016). Spatial Econometrics: A Rapidly Evolving Discipline. *Econometrics 4(1)*, 18.

Arbia, G., and Baltagi, B. H. (Eds.). (2009). *Spatial Econometrics: Method and Applications*. Heidelberg: Physica-Verlag.

Bakhvalov, N. S. (2015). On the approximate calculation of multiple integrals. *Journal of Complexity 31(4)*, 502-516.

Barbier, E. (2010). Poverty, development, and environment. *Environment and Development Economics 15(6)*, 635-660.

Bigman, D., and Fofack, H. (2000). Geographical Targeting for Poverty Alleviation: An Introduction to the Special Issue. *The World Bank Economic Review 14(1)*, 129-145.

Brunn, S. D., and Wheeler, J. O. (1971). Spatial Dimensions of Poverty in the United States. *Geografiska Annaler. Series B, Human Geography 53(1)*, 6-15.

Chen, X., Pei, Z., Chen, A. L., Wang, F., Shen, K., Zhou, Q., and Sun, L. (2015). Spatial Distribution Patterns and Influencing Factors of Poverty - A Case Study on Key Country From National Contiguous Special Poverty-stricken Areas in China. *Procedia Environmental Sciences 26*, 82-90.

Clausen, J. A., and Flor, J. L. (2014). Sobre la naturaleza multidimensional de la pobreza humana: propuesta conceptual e implementación empírica para el caso peruano. Documento de Trabajo No. 387, Departamento de Economía, PUCP.

Crandall, M. S., and Weber, B. A. (2004). Local Social and Economic Conditions, Spatial Concentrations of Poverty, and Poverty Dynamics. *American Journal of Agricultural Economics 86(5)*, 1276-1281.

Dhongde, S., and Haveman, R. (2022). Spatial and Temporal Trends in Multidimensional Poverty in the United States over the Last Decade. *Social Indicators Research 163*, 1-26.

Dong, Y., Jin, G., Deng, X., and Wu, F. (2021). Multidimensional measurement of poverty and its spatio-temporal dynamics in China from the perspective of development geography. *Journal of geographical sciences 31(1)*, 130-148.

Gallup, J. L., Sachs, J. D., and Mellinger, A. D. (1999). Geography and Economic Development. *International Regional Science Review 22(2)*, 179-232.

Golgher, A. B., and Voss, P. R. (2015). How to Interpret the Coefficients of Spatial Models: Spillovers, Direct and Indirect Effects. *Spatial demography 4(3)*, 175-205.

Gräb, J. (2009). *Econometric Analysis in Poverty Research: With Case Studies from Developing Countries* (NED - New edition). Frankfurt am Main: Peter Lang AG.

Gräb, J., and Grimm, M. (2011). Inequality in Burkina Faso—to what extent do household, community and regional factors matter? *Journal of the Royal Statistical Society: Series A (Statistics in Society) 174(3)*, 759-784.

Gray, L. C., and Moseley, W. G. (2005). A geographical perspective on poverty-environment interactions. *The Geographical Journal 171(1)*, 9-23.

Haddad, E. A., Araujo, I. F., Idrissi, Z. S., Ihezagire, C., and Bouazzaoui, Y. E. (2022). Multidimensional Poverty in Morocco: An Exploratory Spatial Approach. Working Paper Series No. 2022-12, Department of Economics, FEA-USP.

Hentschel, J., Lanjouw, J. O., Lanjouw, P., and Poggi, J. (2000). Combining Census and Survey Data to Trace the Spatial Dimensions of Poverty: A Case Study of Ecuador. *The World Bank Economic Review 14(1)*, 147-165.

Holt, J. B. (2007). The Topography of Poverty in the United States: A Spatial Analysis Using County-Level Data From the Community Health Status Indicators Project. *Preventing Chronic Disease 4(4)*, A111.

LeSage, J. (2008). An introduction to spatial econometrics. *Revue d'économie industrielle 123 (3)*, 19-44.

LeSage, J., and Pace, R. K. (2009). *Introduction to Spatial Econometrics.* Boca Raton: CRC Press.

LeSage, J. P., and Pace, R. K. (2014). The Biggest Myth in Spatial Econometrics. *Econometrics 2(4)*, 217-249.

Liu, Y., and Xu, Y. (2016). A geographic identification of multidimensional poverty in rural China under the framework of sustainable livelihoods analysis. *Applied Geography 73*, 62-76.

Odekon, M. (Ed.). (2015). *The SAGE Encyclopedia of World Poverty.* Thousand Oaks, CA: SAGE Publications, 2nd ed.

Olivia, S., Gibson, J., Rozelle, S., Huang, J., and Deng, X. (2011). Mapping poverty in rural China: how much does the environment matter? *Environment and Development Economics 16(2)*, 129-153.

Pace, R. K., and LeSage, J. P. (2008). A spatial Hausman test. *Economics Letters 101(3)*, 282-284.

Palomino, J. (2020). Development of Regional Economics Studies in Peru: Contributions and Criticisms. *Economía 43(86)*, 39-56.

Palomino, J., and Sanchez, T. (2021). Where Are the Poor Located? A Spatial Heterogeneity Analysis of Monetary Poverty in Peru. *Economía 44(87)*, 89-114.

Rupasingha, A., and Goetz, S. J. (2007). Social and political forces as determinants of poverty: A spatial analysis. *The Journal of Socio-Economics 36(4)*, 650-671.

Santos, E. I. d., Carvalho, I. C. S. d., and Barreto, R. C. S. (2017). Multidimensional poverty in the state of Bahia: a spatial analysis from the censuses of 2000 and 2010. *Revista de Administração Pública 51(2)*, 240-263.

Sen, A. (1976). Poverty: An Ordinal Approach to Measurement. *Econometrica 44(2)*, 219-231.

Tan, X., Yu, H., An, Y., Wang, Z., Jiang, L., and Ren, H. (2021). Spatial Differentiation and Influencing Factors of Poverty Alleviation Performance Under the Background of Sustainable Development: A Case Study of Contiguous Destitute Areas in Hunan Province, China. *Chinese Geographical Science 31(6)*, 1029-1044.

Torres, M. d. O., Vosti, S. A., Maneta, M. P., Wallender, W. W., Rodrigues, L. N., Bassoi, L. H., and Young, J. A. (2011). Spatial patterns of rural poverty: an exploratory analysis in the São Francisco River Basin, Brazil. *Nova Economia 21(1)*, 45-66.

Turriago-Hoyos, A., Martínez Mateus, W. A., and Thoene, U. (2020). Spatial analysis of multidimensional poverty in Colombia: Applications of the Unsatisfied Basic Needs (UBN) Index. *Cogent Economics & Finance 8(1)*, 1-19.

Urbina, D., and Quispe, M. (2016). La pobreza monetaria desde la perspectiva de la pobreza multidimensional: el caso peruano. *Enfoque 2-3*, 77-98.

Webb, R. (2013). *Conexión y Despegue Rural*. Lima: Fondo Editorial, Universidad San Martín de Porres.

Zhou, Q., Chen, N., and Lin, S. (2022). A Poverty Measurement Method Incorporating Spatial Correlation: A Case Study in Yangtze River Economic Belt, China. *ISPRS International Journal of Geo-Information 11(1)*, 50.