

Multidimensional poverty in the state of Bahia: a spatial analysis from the censuses of 2000 and 2010

Eli Izidro dos Santos

Universidade Estadual de Santa Cruz / Programa em Economia Regional e Políticas Públicas (Perpp)
Ilhéus / BA — Brazil

Ícaro Célio Santos de Carvalho

Fundação Getúlio Vargas / Escola de Administração de Empresas de São Paulo (FGV EAESP)
São Paulo / SP — Brazil

Ricardo Candéa Sá Barreto

Companhia de Água e Esgoto do Ceará (Cagece) / Diretoria Jurídica
Fortaleza / CE — Brazil

The article aims to collaborate with the analysis about poverty in the state of Bahia, studying the spatial behavior of poverty in the state in 2000 and 2010, using the Municipal Poverty Index (MPI). The MPI allowed the creation of a ranking of municipalities, which in comparison with the ranking based on the Municipal Human Development Index (MHDI) in the same years analyzed, was effective for measuring the spatial poverty in the state. The study found evidence of a pattern of spatialization as well as the existence of clusters of regional poverty. It is a multidimensional study using variables such as income, education, housing and health.

Keywords: cluster; spatial distribution; MHDI; poverty.

Pobreza multidimensional no estado da Bahia: uma análise espacial a partir dos censos de 2000 e 2010

Este artigo teve como intuito realizar uma análise do comportamento espacial da pobreza no estado da Bahia nos anos 2000 e 2010, a partir do cálculo do Índice Municipal de Pobreza (IMP), colaborando com as análises da pobreza já realizadas para o estado. O índice permitiu a criação de *rankings* municipais de pobreza, que em comparação com o *ranking* do Índice de Desenvolvimento Humano Municipal (IDHM), nos mesmos períodos em análise, mostraram-se eficientes para mensuração da pobreza espacial na região. Com isso, encontraram-se evidências de um padrão de espacialização, bem como a existência de *clusters* de pobreza regional. Para este estudo foram utilizadas, além da renda, outras variáveis como educação, habitação e saúde, o que caracteriza o trabalho como multidimensional.

Palavras-chave: *cluster*; distribuição espacial; IDHM; pobreza.

Pobreza multidimensional en el estado de Bahia: un análisis espacial de los censos de 2000 y 2010

Este trabajo tiene como objetivo colaborar con el análisis de comportamiento de la pobreza espacial en el estado de Bahia, en 2000 y 2010 a partir del cálculo del Índice de Pobreza Municipal (PIM), con el fin de colaborar con el análisis de la pobreza en el estado. El índice permitió la creación de *rankings* de pobreza municipales, que en comparación con el *ranking* del Índice de Desarrollo Humano (IDHM) durante los mismos periodos de revisión fueron efectivas para la medición de la pobreza espacial en la región. Por lo tanto, se encontraron pruebas de un patrón de espacio, así como la existencia de *clusters* regionales de pobreza. Para este estudio se utilizaron además de los ingresos, otras variables como la educación, la vivienda y la salud, que cuenta con el trabajo como multi-dimensional.

Palabras clave: *cluster*; distribución espacial; IDHM; pobreza.

DOI: <http://dx.doi.org/10.1590/0034-7612152341>

Article received on July 21, 2015 and accepted on March 22, 2017.

[Translated version] Note: All quotes in English translated by this article's translator.



1. INTRODUCTION

According to data collected by *Instituto Brasileiro de Geografia e Estatística* (IBGE, 2011), there is a slight fall on income inequality in the last few years, although there are great differences in income throughout Brazilian's territory, especially in big cities. According to 2010 Census, 25% of Brazilian have a per capita income of R\$ 188,00 per month, and 50% with a per capita income of R\$375,00, which means that 75% of Brazil's population were living with less than the minimum wage of 2010, which in that year was R\$510,00.

According to Lacerda and Neder (2010), the economic growth process in developing countries, especially from 1960, has showed some deformations in the interconnection between income's increase and poverty's end. Such deformations refer to the fact that many authors confuse economic growth and development. The process of development occurs when there is an increase in income's equality improving the life conditions of the poor. If there is only economic growth and no improvement or a decay in the life conditions of the poor, it is not possible to state that a development process has occurred. Therefore, poverty cannot be treated and analyzed by the unidimensional look of income. It is necessary to expand the studies on poverty, in order to understand the basic needs of individuals, such as nourishment, health, education, etc. In this sense, there is a new perception over poverty, which is attributed as multidimensional.

Despite the importance gained within specialized literature, especially in economic scene, this theme it is not new, since it has always been present in any historical frame. However, with the intensification of debates on economic growth and development in the 1960's, especially in third-world countries, the study on poverty received a great level of attention. Yet, according to *Superintendência de Estudos Socioeconômicos da Bahia* (SEI, 2008), it is necessary to develop more studies, especially focusing in other dimensions besides income.

Nevertheless, assuming that poverty does not limit itself to income is not enough to obtain good outcomes. If the object of analysis and its behavior are not properly known, any attempts to elaborate and evaluate politics against poverty and, mostly, understanding this reality in a consistent way become extremely limited, in order to intervene in a positive and long-lasting way. Thus, as a complex phenomena, the study of poverty needs an analysis that involves not only individual's income, but also other aspects that are related to its event and that are necessary to human's development such as health conditions, education, habitation, among others.

Therefore, in the search for identifying clusters of poverty in the state of Bahia, a municipal poverty ratio was calculated, with data collected in Demographic Census of 2000 and 2010, for all 417 cities, which analysis was developed using spacial methods. This study has as main goal developing a spacial analysis of poverty in the state of Bahia from 2000 to 2010. Its specific goals were: (1) measuring poverty in the state of Bahia from 2000 to 2010; (2) analyze spacially poverty in Bahia; (3) identify the regions in the state with biggest poverty concentration.

Thus, it is understood that the main contribution of this research relies in its approach. It is respected the great complexity of poverty, since it is unpredictable, and searching for ways to matematically determine this haziness. On the other hand, poverty is seen as an expression of the vulnerability level, not in a probability sense, but in the sense of a proximity to poverty's situation, of the unit of analysis (individual, Family, habitation, geographic unity). In this paper it was chosen to calculate a multidi-

mensional ratio of poverty, that allows comparisons of the outcomes, revealing some independence between multidimensional poverty and poverty by income.

Besides this introduction, the paper presents a literature review with the main theoretical approaches towards this theme, the methodological framework with the main methods used to measure poverty in the state of Bahia, as well as the data sources, the outcomes analysis with the rate of MPI, final considerations and references used in the conception of this study.

2. LITERATURE REVIEW

Understanding how poverty has behaved throughout the years leads to a comprehension on how its conception has been changing. In this sense, its history shows how the social context needed approaches that could better explain poverty. Thus, it was possible to understand the need of expanding the studies from an unidimensional look to studies with other variants on this theme.

Some conceptions on poverty were developed since the last century, although there is a complex conceptualization of the term, due to its subjective nature. Besides that, the study may be focused in two ways: the first one with an economic perspective in which only income is used, and the second one an analysis that incorporates other variants despite the economic ones, such as criminality that deprives citizens. Poor cities may have the same income, basic sanitation, piped water levels, among others. Yet, they may have different criminality levels. Violence in some poor cities is much superior to other with the same standard of living.

According to Crespo and Gurovitz (2002), in the last century it was developed three general ideas: (1) survival; (2) basic needs; and (3) relative deprivation. In the first case, the focus is more restrained and it has prevailed from the 19th to the 20th century, original from the work of english nutritionists, it showed that the income of the poor was not enough to maintain the individual's physical performance. The second case, it was expanded in the 1970's, in which other variables were incorporated, such as basic sanitation, piped water, health, education and culture to poverty studies. The third and last case received more attention from the 1980's on, in which the concept received a more rigid and broader focus, searching for a scientific formula and comparisons between international studies, especially those who emphasized the social aspect. This idea was strengthened by Amartya Sen, the main theorist of this new conception of poverty.

In this sense, according to Kageyama and Hoffmann (2006), the idea of poverty refers to some kind of deprivation, which can be material or include cultural and social elements, facing the available resources of the individual or of its Family. The distinction of deprivation's nature may be understood through conceptual discussions such as those of Feres and Villatoro (2013), who show absolute poverty as an irreducible core, which means, appart from people's income level. It is, therefore, in any context related to individual's survival. According to Vinhais and Souza (2006), the absolute poverty line refers to a given income level, despite its distribution. It has the advantage to allow comparisons between different time periods, in which is possible to follow poverty evolution, although it has as disadvantage the difficulty in measuring it economically with great growth ratios. The relative poverty line uses its concept of being related to a determined group considered poor, comparing it to the rest of population. It estipulates the amount of individuals with an income lower than a determined value such as an income average or median, as an example $\frac{1}{4}$ of minimum wage, as used in this study.

To Sen (2000), the characteristic of “absolute poverty” does not mean neither temporal or cultural invariability, neither a focus on nourishment and food, it being a focus to evaluate deprivation in absolute terms instead of more relative criteria.

Relative poverty contrasts to absolute conceptions and proposes the use of a perspective that refers to real deprivation conditions, especially in comparison with other individuals. According to Townsend (1962), “many people have been uneasily aware of the problems of defining necessities like housing, clothing, or fuel and light”. This means that individuals are in poverty situation when they do not have resources for daily activities in the society they belong, being excluded from the socially desirable lifestyle. Related to subjective poverty, according to Martini (2009:10),

[...] There are three present definitions in the studies. First of all, it can be considered poor the individuals who state they have less resources than what is enough to afford their basic needs. Secondly, this idea can be linked to the principle of *basic needs*, in a way that poverty is observed by the research, among each family of population, related to which are their basic needs and comparing it to their real income. Finally, it can be linked to the concept of relative poverty. In this case, being poor is extended to having an individual feeling of owning less than what is necessary to fulfill social commitments, in familiar, cultural, social and professional positions terms that each individual presents.

On the other hand, the studies on poverty were recently seen through a different look from those applied in the last century. The studies of Amartya Sen (2000) on the dynamic nature of poverty revealed a new horizon of research, in which other variables beyond income were incorporated to poverty analysis, which are described as studies on capabilities deprivation. To Crespo and Gurovitz (2002), “capability” means possible self-realizations. Therefore, capability is a kind of freedom: the freedom to be able to achieve self-realization or the freedom to have different lifestyles. As an example, a wealth person who decides to adhere to fasting by his/her choice, may have the same performance of someone poor who starves. However, the first person has a “capability set”, different from the second. The first may choose to eat well and be well nourished in an impossible way compared to the second (Crespo and Gurovitz, 2002).

According to Sen (2000), freedom narrows the idea of poverty under the lens of income, expanding and dinamizing new studies. The multidimensional concept of poverty was defined as an old idea with new arrangements, which characterizes the wideness of the term, in which the economic, social and structural dimensions are involved (Poggi, 2004; Conconi and Ham, 2007). According to IBGE (2011), the discussions on poverty indicators in Brazil still need to be deepened, because they still are very incipient. The federal government, as an example, uses many frames to implement social programs, such as the income distribution policy “Bolsa Família”, which considers poor the people who have a monthly income of R\$ 140,00 or less. However, there are other indicators such as *Pesquisa dos Orçamentos Familiares* (POF), which analyzes consumption, considering it less volatile than income and a representative of the real expenses in food and other goods.

While there are many conceptualizations, there is no consensus among authors, especially on the poverty lines used in the studies. Regarding multidimensional studies, this task becomes even harder,

because the choice of the dimensions that will be the object of study and which variants will be used depend on the working goal and on the concept of poverty used by the researcher.

To Lacerda (2009), the main difficulty is to find a good indicator capable of measuring the multidimensional nature of poverty. The author highlights that, unlike studies on the unidimensional light of income, there is not a set of established and solid measures in the multidimensional approach, in the form of a sole ratio that reflects all the multidimensional context.

While there is consensus among the researchers of poverty on how imprecise it is, there is no consensus on the nature of this imprecision and on how to capture it. Even among those who use the income poverty line, there is some concern related to how imprecise this measure is; however, such imprecision is attributed to the lack of information available to the researcher rather than to the nature of the studied phenomena.

As shown by Silva and Barros (2006), on the importance of scalar indicators of multidimensional poverty, it is worthy to note that there is not a single way for its construction. In each step of this process some dilemmas emerge, such as: which are the most relevant dimensions? Which variables and its weights should be adopted? Which method of aggregation of the poverty dimensions should be used? Among other questions.

This fact illustrates the importance of using the Municipal Poverty Index (MPI), that encompasses income, education, health and habitation. According to Ávila (2013), despite using quantitative data, this ratio focus on individual quality of life, not being restrained to monetary quantification of poverty. Thus, in applied studies, in particular reports of human development, the main indicator of multidimensional poverty used has been the *Índices de Pobreza Humana* (HPI – Human Poverty Index) proposed by Anand and Sen (1997), which inspired MPI. The HPI was incorporated to the Human Development Report of PNUD, from 1997, with the specific goal to measure poverty, using the same variants of Human Development Index (HDI). Nevertheless, it mainly focuses on the poor and adopts a perspective on individual deprivations. The HPI aims at measuring the size of the deficit in the same dimensions considered by HDI (Ávila, 2013; Lacerda, 2009).

Despite the limitations imposed by such methodology, it shows to be acceptable because it not only measures poverty as it tries to understand it, considering dimensions related to individuals' quality of life. Thus, the understanding of these indices allows the creation of public policies capable of meeting individual's needs, and reveal themselves much more efficient than methods that only adopts the income dimension (Ávila, 2013; Lacerda, 2009).

Therefore, the next section presents a short description of the steps needed to build a poverty index.

3. METHODOLOGY

3.1 BUILDING A MUNICIPAL POVERTY INDEX FROM THE METHODOLOGY OF HPI

The methodology adopted in this work was composed by techniques of spacial distribution based on the work developed by Ávila (2013), which structured the building of the municipal poverty index

from the methodology of the Human Poverty Index (HPI), created by Sudhir Anand and Amartya Sen (1997). The Exploratory Analysis of Spacial Data and the Global and Local Moran Index also compose this framework, which enable the spacement of poverty and inequality of cities in the state of Bahia under the multidimensional lens.

For the present research, a chart with the indicators of deprivation for each one of the cities of the state was created, in order to allow for the calculations for each index. Later, it was organized the *ranking* of the cities of Bahia for each calculated index. A comparative analysis of the hierarchies was made, searching the consistency of the indexes, as a way of explaining its use in spacial analysis. In verifying the consistency of the indexes it was used the ranking of the *Índice de Desenvolvimento Humano Municipal* (IDHM — Municipal Human Development Index) of 2000 and 2010, published on *Brazil's Human Development Atlas* (PNUD, 2013).

Therefore, as already highlighted, the methodology of HPI was initially proposed by Anand and Sen in 1997 and is part of the studies of the United Nations (UN) on human development and poverty fight in the world. According to Ávila (2013), while HDI analyzes average advances in poverty fight, the HPI measures the degree of deprivation of people. Nevertheless, it is important to highlight that, for Anand and Sen (1997), the fact that HPI uses three dimensions to measure deprivations — being one of them composed by three variables, and the other two by only one — may create a problem related to weighting dimensions.

The solution suggested by the authors was to measure the mean of the three variables that compose the economic dimension. According to Anand and Sen (1997), even recognizing the importance that these three components of human poverty have, it is not possible to assume that they equally affect it. Thus, to calculate HPI, they propose the use of a weighted average of the three dimensions as a way to highlight the influence of the dimension with highest value. However, the authors warn that the valuation of such influence should not be excessive, since it would cause a masking of the weight of the other dimensions.

Then, HPI measures the deprivations reflected in three dimensions of human life:

- poorness related to survival (P1) — percentage of people with life expectancy equal or below 40 years old;
- poorness related to knowledge (P2) — percentage of illiterate adults; and
- poorness related to life standards (P3) — composed by three variables: percentage of people with no access to healthcare (P31); percentage of people with no access to drinking water (P32); percentage of children with less than five years old in a undernourished situation (P33).

Thus, deprivation related to life standards is:

$$P_3 = (P_{31} + P_{32} + P_{33}) / 3 \quad (1)$$

And the formula for HPI is:

$$IPH = [1/3 (P_1^3 + P_2^3 + P_3^3)]^{1/3} \quad (2)$$

It is important to highlight that the indicators used to measure deprivations are percentuals, which makes the calculation of HPI easier, since these indicators are already standardized between 0 and 100, according to Technical Notes of the *Human Development Report* (PNUD, 2006). An important assumption is that all three deprivations that compose HPI have the same relative values and that they sum together. The final value of HPI indicates which proportion of the population is affected by the analyzed deprivations. The higher the percentage, the greater is the deprivation degree (Anand and Sen, 1997).

After data collection, it was calculated the Municipal Poverty Index (MPI) from the chosen variables, present in chart 1.

CHART 1 **DIMENSIONS AND VARIABLES THAT COMPOSE MPI**

DIMENSION (D)	DEPRIVATION (P)
Habitation and sanitation (HS)	5 or + people in one house (IBGE) No bathroom/toilette (IBGE) No drinking water (IBGE) No garbage collection (IBGE) No sewage treatment (IBGE)
Education (E)	No instruction/Sem instrução/basic education incomplete (IBGE)
Health (S)	Infant Mortality Index (PNUD; Ipea; FJP)
Income (R)	Until 1/4 minimum wage (SM) or no income (IBGE)

Fonte: Adapted from Ávila (2013).

Following the methodological framework, PMI is presented as follows:

$$D_i = \frac{1}{n} \left(\sum P_{ij} \right) \tag{3}$$

In which:

D_i = dimension to be calculate;

P_{ij} = deprivation that composes the derived variant;

i = number that indicates the dimension to be calculated ($i = 1, \dots, 4$);

j = number of the deprivation that composes the dimension to be calculated ($j = 1, \dots, 5$); e

n = amount of deprivations that compose the dimension.

Applying the weighted average to dimensions (D_i) and rewriting them: $HS = D_1$, $E = D_2$, $S = D_3$, e, $R = D_4$, the MPI assumes the following formula:

$$IMP = \left\{ \frac{1}{n} [D_1^\alpha + D_2^\alpha + D_3^\alpha + D_4^\alpha] \right\}^{\frac{1}{\alpha}} \quad (4)$$

Which means: $D = D_i; i = 1, \dots, n$

In general formula, there is:

$$IMP = \left[\frac{\sum D_i^\alpha}{n} \right]^{\frac{1}{\alpha}} \quad (5)$$

In which:

n = amount of dimensions that compose the index; and

α = weightening factor of the dimensions that compose the index.¹

This index can be presented in a more generic way, enabling a separate analysis of each dimension that compose it or even other dimensions or variables which are not study objects of this work. The three indexes used in this study are presented as it follows:

$$IMP_1 = \left\{ \frac{1}{n} [HS^\alpha + E^\alpha + S^\alpha + R_4^\alpha] \right\}^{\frac{1}{\alpha}} \alpha = n = 4 \quad (6)$$

$$IMP_2 = \left\{ \frac{1}{n} [HS^\alpha + E^\alpha + S^\alpha + R_4^\alpha] \right\}^{\frac{1}{\alpha}} \alpha = n = 3 \quad (7)$$

$$IMP_3 = \left\{ \frac{1}{n} [R^\alpha] \right\}^{\frac{1}{\alpha}} \alpha = n = 1 \quad (8)$$

And finally there is:

$$D_i = \frac{1}{n} \left(\sum P_{ij} \right) \quad n = 5 \text{ para } HS, \bar{n} = 1 \text{ para } E, S \text{ e } R \quad (9)$$

Since it was proposed to compare spacial distribution of multidimensional poverty in Bahia with poverty only measured through the income lens, it was used three indexes derived from general formula. The first (IMP 1) includes four dimensions previously defined (HS, E, Sd and R); the second (IMP 2) was calculated only with non monetary dimensions (HS, E and Sd); and the third (IMP 3) was measured only with monetary dimension (R)².

¹ To define the value of α , it was made a test with $\alpha = 3$ and $\alpha = 4$. The difference between the indexes was small, and it was arbitrarily chosen to use a $\alpha = n$. Although, there must be extra careful to avoid excessive weight on the more accentuated deprivations, if the number of dimension is high.

² More details, check Ávila (2013).

3.2 EXPLORATORY ANALYSIS OF SPATIAL DATA (EASD)

According to Anselin (1988), the Exploratory Analysis of Spatial Data (EaSd) uses georeferenced data and is usually used to test the existence of spacial patterns, such as spacial heterogeneity and spatial dependence, which indicates coincidence in similar values in neighboring regions. This technique considers distribution and data relationship in space. The EaSd is a useful methodology in the study of the processes of spatial propagation because it identifies the patterns of spatial self-correlation, that is, spatial dependence between geographic objects.

Thus, for spatial analysis of indexes, it was defined a matrix with two spatial weights (W), that according to Almeida (2008), is the way to express a given spatial arrangement of interactions resulting from the phenomena in study, as a first step for EaSd. However, considering the existance of spatial self-correlation, it was used the statistics I of Moran Global, which according to Almeida (2012), it is the most accepted way to identify and test it. However, when dealing with a great number of data, there is always the occurrence of spatial dependence. Therefore, it was used the statistics I of Moran Local, which enables the identification of spatial clusters where comparison was not made between cities, but between its local indicators and their neighbors, thus verifying if there are, or there are not, patterns of local concentrations.

To Almeida and partners (2008), the main goal of this method is to describe spatial distribution, the associated spatial patterns, the possible spatial clusters, verify the existence of different spatial regimes or other ways of spatial instability (non stationary) and identifying untypical spatial observations, the outliers. However, these authors highlight that for implementing EaSd it is necessary to define a matrix of spatial weights (W). According to Almeida and partners (2008), this matrix is the way to express a determined spatial arrangement of resulting interactions of the phenomena in study. According to these authors, it is likely to suppose that, in the study of several phenomena, neighboring regions have a stronger interaction among themselves than regions that are not contiguous. In a similar way, regions far from one another would have a smaller interaction. In this case, in which distance between regions matters in defining the strength of interaction, it would be possible to build a W matrix based on the inverse distance between regions, in order to capture such spatial arrangement of interaction. The authors highlight that choosing the matrix³ of spatial weights is very important in an EaSd, because the results of the analysis are sensible to such selection. Therefore, considering the idea presented in the contiguous matrix, there is a greater spatial interaction between neighbors than among those who are more distant. Ávila (2013) states that the outcome of this interaction is that poverty indexes influence and are influenced by poverty indexes of neighbor cities, and that this influence decreases according to the distance.

Thus, aiming at spatial self-correlation, Almeida (2012) highlights that the best way to identify and test is through statistics I of Moran, which presents values that range from -1 to 1 as a way of associating the dataset in analysis, which is quite helpful in studying the entire region. However, when

³ The queen and the tower are the main matrixes used. Thus, it is considered neighbors of the analyzed unity the areas that are at an inferior distance from the center of the sector related to the sice of the radius.

dealing with a great number of areas, it is common that different regimes in spatial crowding occur, emerging locals in which spatial dependence is evident (Almeida, 2012; Anselin, 1988).

Therefore, the matrix and the level of contiguity were initially defined, to later proceed to the analysis itself, through the creation of maps. Thus, the spatial self-correlation test was applied of the I of Moran, which indicated that the use of the Queen in the first order would be more suitable, since it presented a higher level of contiguity, closer to 1, for both periods and indexes, being in accordance with the methodological elements stated by Anselin (1988) and Almeida (2012).

The weight matrix is determined in an exogenous way. It can be defined using contiguity, distance or more complex specifications. According to LeSage (1999), the matrices of contiguity can be: linear, rook, bishop, double linear, double rook and queen. The queen weights matrix 1 was chosen by Esda for presenting a greater value in Moran's Index when compared to other matrices. The queen weights matrix 1 considers the regions that share sides and apexes with the region of interest.⁴

By calculating Municipal Poverty Index (MPI) it was comparatively analyzed the ranking of the cities. It was attempted to verify the consistency of calculated indexes as a way to explain its use in spatial analysis. To verify the consistency of indexes, as already mentioned, it was used the Municipal Human Development Index (IDHM in portuguese) of 2000 and 2010, published on *Brazil's Human Development Atlas* (PNUD, 2013).

This is an index ranging from 0 to 100; therefore, the final value of IMP indicates the proportion of poors in the city. This way, higher values mean greater degree of poverty. In this sense, the cities who obtained an index below 20% are considered low in poverty, those who obtained an index from 20% to 49,99% were considered intermediate in poverty, and those with an index beyond 49,99% were considered high in poverty (Ávila, 2013).

3.2.1 GLOBAL INDEX OF MORAN

Global Index of Moran (I) consists on a spatial self-correlation measure that shows the existence or non-existence of spatial groupments for a given variable, that is, the presence of poverty indexes with similar values among neighbors, according to an indicator of interest. This indicator, according to Almeida (2004) is convenient when it is desired a synthesis of spatial distribution of data, as proposed, being an alternative measure of segregation.

According to Almeida and partners (2008), this index enables to verify whether data are spatially correlated or not, indicating the level of linear association between vectors observed in time t (Z_t) and the weighted average of neighbor values, or the spatial lags (W_{ZT}). When the values of I are bigger than the expected value, represented by the formula $I > E(I) = -1/n - 1$, there is a positive self-correlation; on the other hand the formula $I < E(I) = -1/n - 1$, there is a negative self-correlation. The positive self-correlation demonstrates similarities between the variables of the studied characteristic and its spatial location. When the self-correlation is negative, there is heterogeneity between the variables of the studied characteristic and its spatial location (Almeida, 2004). Thus, Moran Index I is expressed in (10):

⁴ For further understanding of this subject, please see LeSage (1999).

$$I_t = (n / S_0)(z_t W z_t / z_t z_t) t = 1, \dots, n \tag{10}$$

in which: z_t represents the vector of n observations for the year t in the condition of deviation related to average; W is the matrix of spatial weight, whose elements in the main diagonal W_{ii} are equal to 0, while the elements W_{ij} point the way how region i presents itself spatially connected to region j ; and S_0 is the sum of all elements in the matrix of spatial weight W .

In the present work it is proposed to use statistics I of Moran calculating the matrix of spatial weights normalized in the line, which means, when the sum of elements in each line equals 1, the expression (11), can be written as follows:

$$I_t = (z_t W z_t / z_t z_t) t = 1, \dots, n \tag{11}$$

Thus, according to Almeida (2004), when the I of Moran results in a value < 0 , there is a positive self-correlation (clustering), revealing similarity between the data of the studied characteristic. If the value of I is > 0 there will be a negative self-correlation (spatial outlier) stating the dissimilarity between the values of the studied attribute and its spatial location. Finally, if the value of I of Moran equals zero (0), there is no self-correlation among the data.

Nevertheless, the index I of Moran is a global measure. In this sense, Almeida (2004) emphasizes that it is not possible to trust only in the global statistics, because they can hide or mask the local patterns of linear spatial association. In this case, the best way out is to use the Local Index of Moran, a measure that enables a complete evaluation of the studied region, enabling an observation of local patterns linearly significant to the study.

3.2.2 LOCAL INDEX OF MORAN

Local Index of Moran (ii) enables the identification of spatial clusters in the way exposed previously to the global index, with the difference of comparing local indicators and its neighbors instead of cities, verifying if there are patterns of local concentration or not. This is possible because the Moran Index presents a value for each region, enabling the identification of spatial patterns and creating clusters that would represent them.

Therefore, the Local Indicator of Spatial Association (Lisa) executes the dissolution of the global indicator of self-correlation in the local contribution of each observation in four categories, each one individually corresponding to a quadrant in the dispersion diagram of Moran. This way, Lisa is calculated through the Local Index of Moran, expressed as follows:

$$I_i = \frac{(y_i - \bar{y}) \sum_j w_{ij} (y_j - \bar{y})}{\sum_i (y_i - \bar{y})^2 / n} \tag{12}$$

Where: w_{ij} is the value of the neighbor matrix for the region i with region j in function of distance d , and y_i and y_j are the deviants related to the average.

Using the hypothesis of randomness, the expected value for local statistics I of Moran is given by $E(I_i) = -w_i / (n - 1)$, in which w_i is the sum of the line elements. In this context, the dispersion diagram of Moran is one of the ways to interpret the statistics I of Moran. According to Almeida and partners (2008), throughout the representation of regression coefficient, there is the possibility to check the linear correlation between z and W_z in the graph that considers both variables. Highlighting the specific case of statistics I of Moran, there is the graph of W_z and z . Therefore, the coefficient I of Moran is given by the declination of the regression curve of W_z against z , which will present its degree of adjustment. In this sense, the graph of dispersion of Moran is divided in four quadrants, which correspond to four patterns of local spatial association among regions and its respective neighbors.

The first quadrant exhibits regions with low values for the variable of interest, surrounded by neighbors who present high values, classified as Low-High (BA in portuguese). In the second quadrant are the regions who present greater values for the variable of analysis, surrounded by regions that equally present high values for the same variable, and it is classified as High-High (AA in portuguese). The third quadrant is named Low-Low (BB in portuguese), as it is formed by regions whose values of the variable of analysis are low and surrounded by regions in the same situation. The fourth quadrant is High-Low (AB in portuguese), composed by regions with high values for the variable of interest, which present themselves surrounded by regions of low values. In this sense, it is positively spatially self-correlated, that is, clusters of similar values to the regions located in AA (second) and BB (third) quadrants are created. On the other hand, the regions located in BA (first) and AB (second) quadrants have some negative spatial self-correlation, creating clusters with dissimilar values.

3.3 DATA SOURCE

In the present study, the regions used were cities from the state of Bahia. In this context, the unities are the amount of houses and number of inhabitants of each city to compose the analyzed dimensions. To habitation/sanitation and income dimensions, the unit of analysis is the residence. Regarding health and education dimensions, the unit of analysis is the individual.

It was used in this study data from the Census of 2000 and 2010, for each of the 417 cities in Bahia, obtained in the Sidra Bank of IBGE, available in: <www.sidra.ibge.gov.br/cd/cd2010Serie.asp?o=2&i=P>, as well as IDHM and Infant Mortality Index, whose data were obtained from *Brazil's Human Development Atlas*, created by the Development Program of the United Nations (PNUD, 2013).

It is highlighted the period of 2000 in which only 415 cities were used, since Barrocas and Luiz Eduardo Magalhães did not exist as oficial cities by then.

4. RESULTS AND DISCUSSIONS

This section aims to present and discuss the main results of this study, obtained through the calculation of indexes and the Exploratory Analysis of Spatial Data.

4.1 RANKINGS OF CITIES OF BAHIA RELATED TO POVERTY AND DEVELOPMENT

To analyze data, it was used a subsample of the 10 worst cities and the 10 best cities, according to the indexes calculated in this study, related to IDHM. This way, it was created rankings with the cities in a worse poverty situation, since the focus is poverty, for all the indexes used in this study.

In this sense, the city that presented the worst poverty situation was Buritirama, when evaluating IMP1, achieving the ratio of 63,93% and Pedro Alexandre for IMP2, with 63,71% in 2000. In 2010, the worst ratio achieved was on Mirante for IMP1, with 65,61% and the city of Caetanos with 66,99% for IMP2. Related to IMP3 the worst result obtained was in Buritirama in 2000 with IMP3 of 63,52% and in 2010 the worst result obtained was in Sitio do Mato, with 58,51%. However, related to IDHM the worst results were obtained in Monte Santo with 0,283 in 2000, and in Itapicuru with 0,486 in 2010. This data suggests that there was a great improvement on the levels of human development in a decade. Similar results were obtained by Lacerda (2009) and SEI (2008).

These results show the consistency of Municipal Poverty Indexes used in this study, simultaneously pointing that they can be used to study poverty in the state of Bahia, as well as its spatial distribution. It is clear that the similarity is bigger among cities with the 10 worst results, for every index, both in 2000 and 2010. Moreover, that the less developed cities are the ones with greater poverty indexes.

Regarding the descriptive analysis, it can be stated that more than half of the cities of Bahia have multidimensional poverty higher than the average of the state in 2000 (table 1), because it has a median greater than the average, both for IMP1 an IMP2. Analyzing IMP3, it is clear that there is a completely opposing situation, in which the average is greater than the median, showing that less than half of the cities in Bahia are poor.

TABLE 1 DESCRIPTIVE STATISTICS OF POVERTY AND DEVELOPMENT INDEXES IN BAHIA (2000)

		IMP1	IMP2	IMP3	IDHM
Number	Valid	415	415	415	415
	Absent	0	0	0	0
Average		50,51	49,74	33,82	0,426
Standard-error		0,39	0,37	0,41	0,002
Median		52	51	33	0,420
Standard-deviation		7,96	7,73	8,39	0,058
Variance		63,50	59,88	70,45	0,003
Confidence intervala (95%)		51	50	32	0,419
Minimum		18	18	14	0,283
Maximum		64	64	64	0,654

Source: Elaborated by the authors from the data of Sidra (2001) and *Brazil's Human Development Atlas* (PNUD, 2013).

The same can be verified in 2010, shown in table 2. It is clear, however, an increase of 2,68% in the average of multidimensional poverty of 2010 in relation to 2000. However, the IMP3 has decreased in 2,29%.

TABLE 2 DESCRIPTIVE STATISTICS OF POVERTY AND DEVELOPMENT INDEXES IN BAHIA (2010)

		IMP1	IMP2	IMP3	IDHM
N	Valid	417	417	417	417
	Absent	0	0	0	0
Average		53,19	52,92	31,53	0,594
Standard-error		0,39	0,36	0,40	0,002
Median		54,84	54,44	32,24	0,589
Standard-deviation		7,12	7,32	8,13	0,0413
Variance		50,68	53,54	66,11	0,002
Confidence interval (95%)		52,47	52,18	30,74	0,590
Minimum		22,77	22,23	10,20	0,486
Maximum		65,61	66,99	58,51	0,759

Source: Elaborated by the authors from the data of Sidra (2011) and *Brazil's Human Development Atlas* (PNUD, 2013).

These data reinforce what research institutes had already announced, a decrease in poverty. However, they demonstrate that income is not enough to study poverty and social inequality in Bahia and, in addition to confirming the statements of rankings, they also legitimate the use of indexes to study poverty in the state. According to Moura Jr. and partners (2014), in order for the strategies of poverty reduction to be efficient, they must advance towards acknowledging the specific needs of individuals inserted in a given social and cultural context, enabling the inclusion of new elements for a broader understanding of the poverty phenomena.

When cities are classified by poverty levels as high, intermediate or low, it seems that the results of indexes are in accordance with what rankings and descriptive analysis indicate: an underestimation of the number of cities in poverty situation, when observing the problem through the monetary lens (table 3). Yet, when other dimensions are considered, together with a high level of poverty in those cities whose index is 50% or more, results show 256 cities of Bahia in this situation in 2000. Cities with an average degree, from 20% to 49,99%, sum 158; Cities with a low poverty level, below 20%, is just 1. However, when only income is considered, the majority, 482 cities, are considered with an intermediate level of poverty, while only 19 are considered of low level and 15 of high level index.

TABLE 3 NUMBER OF CITIES OF BAHIA BY DEGREE OF POVERTY (2000 E 2010)

Index	Number of cities (2000)			Number of cities (2010)		
	Low	Intermediate	High	Low	Intermediate	High
IMP 1	01	158	256	0	90	327
IMP 2	01	173	241	0	98	319
IMP 3	19	382	15	35	379	03

Source: Elaborated by the authors.

Regarding 2010 (chart 3), it can be verified a similar structure of results when compared to the previous period. This confirms even more the consistency of the indexes used, as well as the results of previous analyses. However, it is clear the increase in multidimensional poverty in the state. Nevertheless, when comparing only income, there is a significant decrease in the high and intermediate poverty intervals, and consequently, an increase on the level of poverty from 19 to 35 cities in this condition. These results amplify even more the disparity between multidimensional and unidimensional indexes.

4.2 SPATIAL ANALYSIS OF POVERTY IN THE STATE OF BAHIA

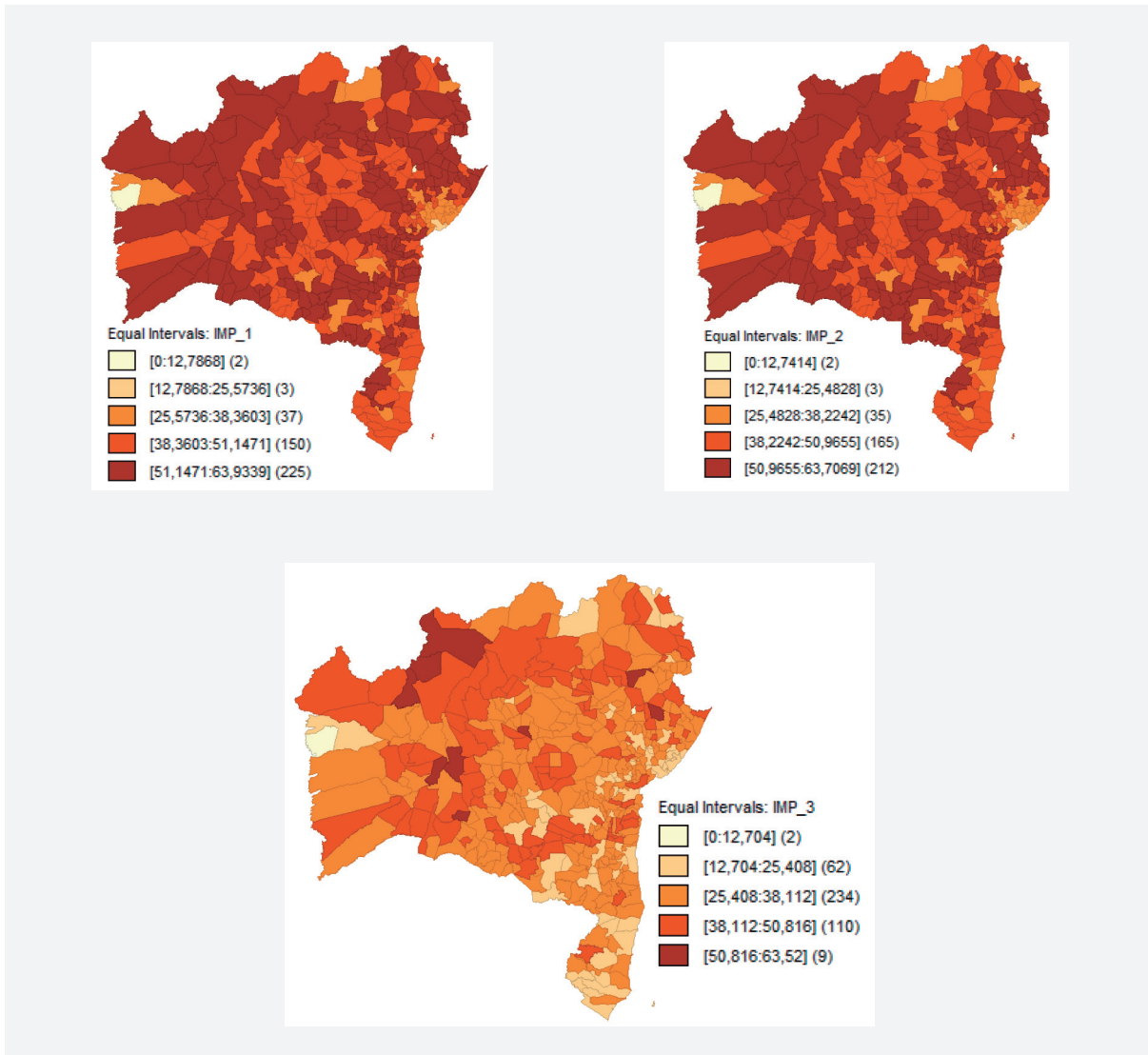
The following analysis enables a better look on how poverty, measured by the indexes here calculated, is distributed across Bahia, enabling it to proceed to a higher number of comparisons between poverty through the multidimensional lens and that based on income, unidimensional.

In this sense, the poverty distribution maps in the state of Bahia in 2000 (figure 1) demonstrate the existence of poor and not poor regions, where IMP1 and IMP2 have very similar results, and IMP3, who focuses on income, demonstrates a quite different format. The maps confirm what the rankings had already stated, but it differs since it shows the spatialization of poverty.

It can be verified the presence of clusters of poor and not poor cities, where the number of intervals in maps of multidimensional indexes are closer. It is highlighted that the GeoDa 9 software uses the maximum and minimum values of each ranking to determine the intervals of analysis, and is different from the ones used in the graduation rankings which range from 0 to 100. However, in the unidimensional poverty map there are 62 cities.⁵ This demonstrates a big disparity between this dimension and the multidimensional one. When observing the worst indexes, considering the 4th and the 5th intervals, disparity gets more clear. The IMP3 presents only 119 cities, while IMP1 and IMP2 register 375 and 377 cities, respectively.

⁵ The first chart, the clearest was not considered, since it refers to Barrocas and Luís Eduardo Magalhães which in 2000 were not official cities; however, they are present in the cartographic basis, which is more recent. Although their informations in the data basis are nuled.

FIGURE 1 POVERTY DISTRIBUTION MAPS IN THE STATE OF BAHIA (2000)



Source: Elaborated by the authors.

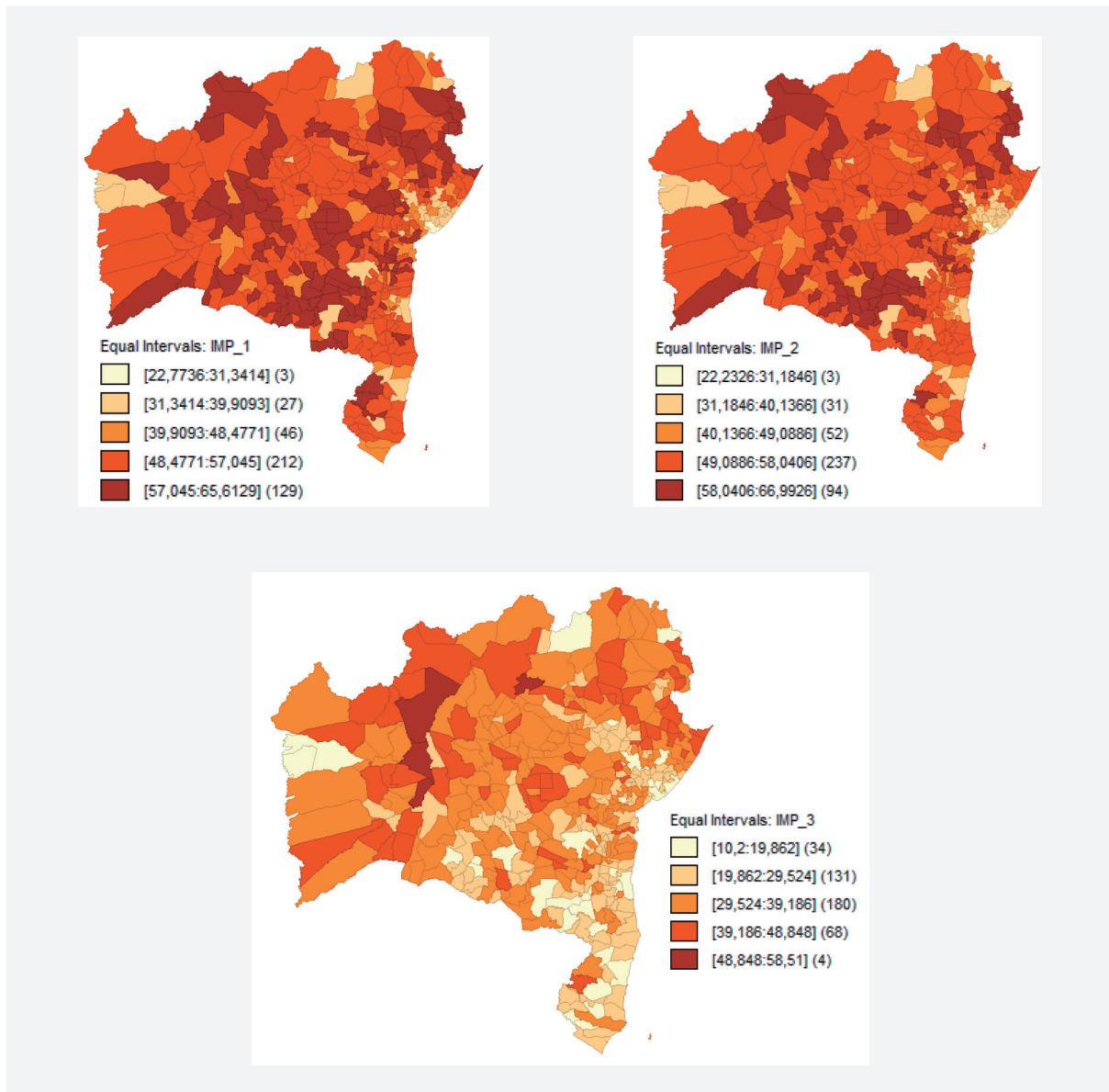
In 2010 (figure 2), the spatial distribution maps demonstrate how discrepancies between the multidimensional and unidimensional poverty indexes have increased even more in relation to 2000.

Observing the multidimensional maps, the equality on the intervals of cities with better poverty conditions is clear, in order that only three are registered. However, the unidimensional index is more expressive on the interval of cities with better poverty ratio, with 34 cities, pointing a substantial improvement on the unidimensional poverty indexes in relation to 2000.

When considering the intervals in which the cities with worst poverty condition are classified, using the two last intervals, 341 and 331 cities are ranked, considering the IMP1 and IMP2 indexes, respectively. Such data show a slightly decrease on the number of cities in this condition, around 9,55% when comparing to 2000, indicating an improvement on the levels of poverty. However, when

analyzing the unidimensional map, there are 72 cities in this category, representing an even more accentuated decrease, around 39% in the same period.

FIGURE 2 SPATIAL MAPS OF POVERTY IN THE STATE OF BAHIA (2010)



Source: Elaborated by the authors.

However, the spatial analyses conducted until the moment have considered a global measure as a basis, which according to Almeida (2012), could mask the existence of local associations. Thus, the search for statistically significant linear local associations can be done using the Local Indicator of Spatial Association (Lisa).

Considering the existence of spatial self-correlation, where the dispersion graph shows the existence or inexistence of spatial groupments, for a determined variable, the statistics I of Moran enables the author to verify if data is or is not spatially correlated, at the same time that it shows the intensity of this relation. In this sense, table 4 exhibits the outomes of each index calculated in this study.

TABLE 4 MORAN INDEX OF IMP1, IMP2 AND IMP3 TO THE STATE OF BAHIA (2000 AND 2010)

	IMP1	IMP2	IMP3
2000	0, 376	0,372	0, 376
2010	0, 462	0, 456	0, 439

Source: Elaborated by the authors.

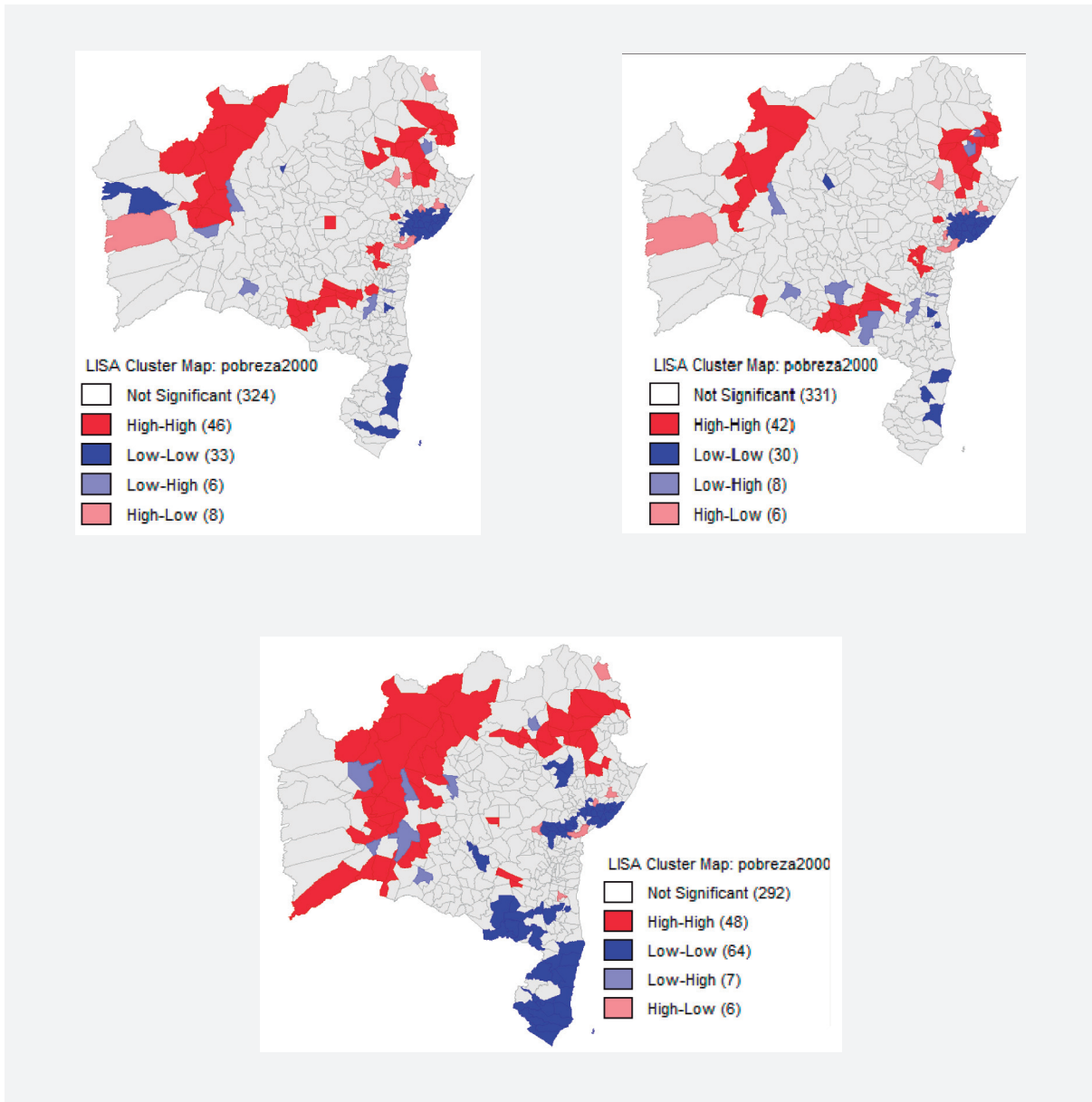
Generally, the indexes displayed have values closer to zero, pointing to a low spatial self-correlation for both periods, with more accentuated values in 2010. At the same time, there is an evidence of an increase on the spatial association degree in the dataset from one decade to another.

The results already presented indicate the presence of poverty clusters, in both periods of analysis for all indexes. However, the use of local index of Moran enables the identification of clusters (poverty spots) from the products in the first index; in this case, it is compared the indicator with their neighbors, verifying if there are local spatial concentrations or not. It is emphasized that it was considered a confidence interval of 99% with 99 disturbances in this study.

It should be highlighted the legend of the colors used in the maps: white means no statistical significance; dark red represents high poverty indexes surrounded by cities highly poor; dark blue represents cities with the lowest poverty index surrounded by cities with the same characteristic; light blue shows clusters of low poverty surrounded by cities of high poverty levels; and light red shows clusters of high poverty surrounded by cities of low poverty indexes.

By applying Local statistics I of Moran in IMP1, it can be noticed that the periods in analysis, 2000 (figure 3) and 2010 (figure 4), the cities who presented high poverty clusters surrounded by high poverty (High-High) have decreased from 39 to 36 regions. The low poverty clusters, surrounded by low poverty (Low-Low) have increased in the second period, 2010, which means there was an improvement on multidimensional poverty in Bahia. In the regions of low poverty surrounded by those of high poverty (Low-High) there was a slightly increase in the number of cities, and in the case of regions of high poverty surrounded by those of low poverty (High-Low) there was a decrease from eight to four regions, reinforcing the improvement that was registered in other three categories.

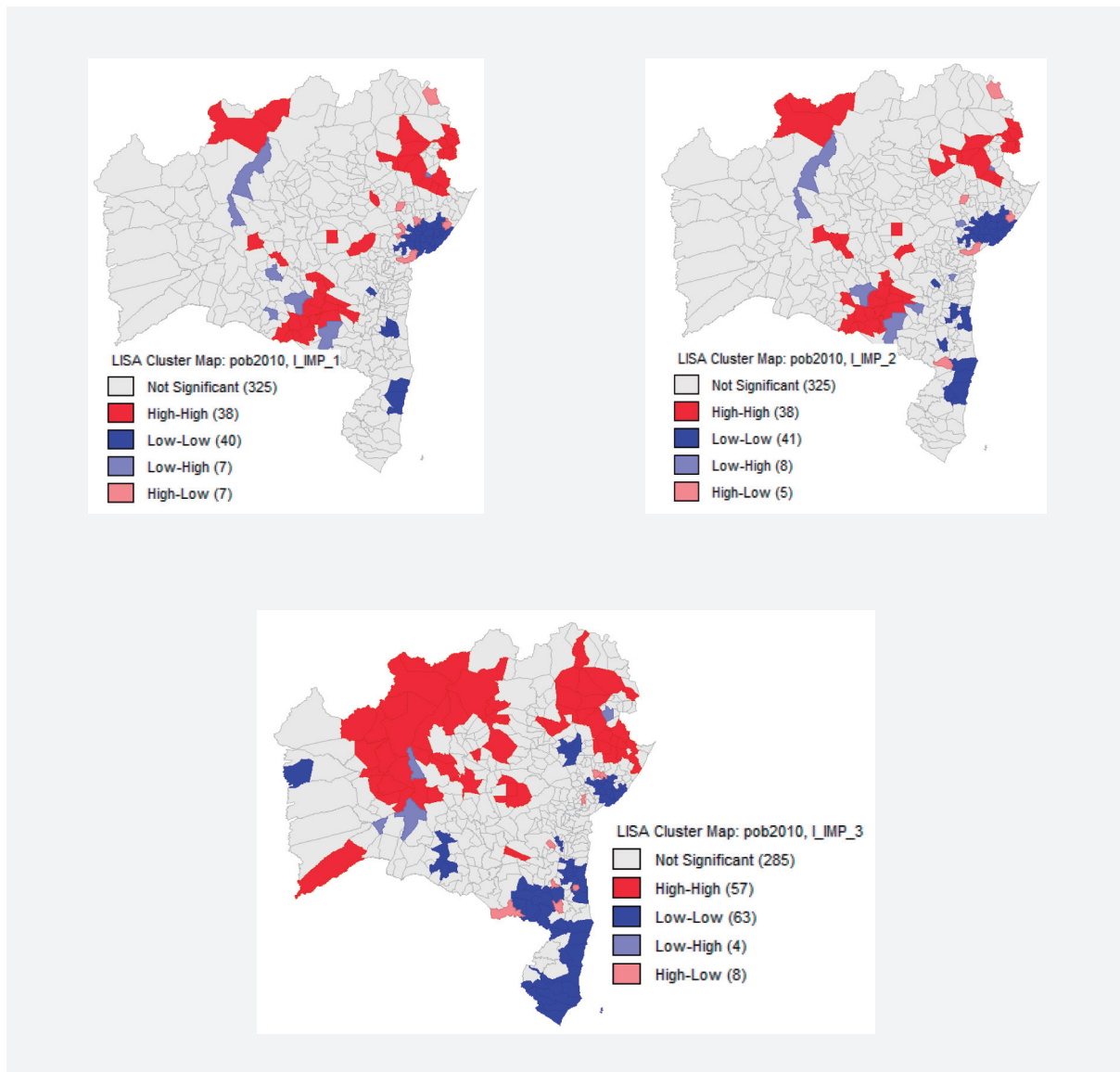
FIGURE 3 POVERTY CONCENTRATION MAP IN BAHIA (2000)



Source: Elaborated by the authors

About the IMP2 variable, as already mentioned, it does not include income in its scope. I can be noticed that the clusters of cities of high poverty surrounded by poverty also register a decrease from 44 to 34 cities in this condition. However, the regions with low poverty surrounded by cities of low poverty have increased significantly, emphasizing even more the improvement on multidimensional poverty in the state. The regions of low poverty surrounded by those of high poverty did not suffer any changes and kept the patterns of the previous index. In relation to regions of high poverty surrounded by those of low poverty indexes, there was a decrease in its amount.

FIGURE 4 POVERTY CONCENTRATION MAP IN BAHIA (2010)



Source: Elaborated by the authors

In relation to IMP3, the analysis reveal that the cities with high poverty indexes surrounded by those of high poverty indexes have increased from 49 to 60, concentrated on the north and northeastern regions of the state.

In the cities with low poverty index surrounded by cities of low poverty, there was a decrease of 10% in the number of cities in this condition. However, this does not mean that there was an increase of income poverty, but rather, a smaller interaction of cities in this category.

Those classified as low poverty surrounded by high poverty indexes there were no significant changes; yet, the regions with high poverty surrounded by low poverty had an increase due to the lack of interaction previously mentioned.

It is clear in this index the presence of bigger High-High clusters, especially on the outback of Bahia, and Low-Low clusters in the metropolitan and Southern region of the state, equal in both periods analyzed, with a slightly displacement of the outback cluster, which was already pointed by previous research, such as Lacerda (2009) and SEI (2008).

These data reinforce previous analyses that used the global index, at the same time it confirms the statement that poverty studies that take into account only the income variable are not enough to explain the reality of populations who suffer from deprivations in the state of Bahia, suggesting the need for many other multidimensional variables in the studies.

5. FINAL CONSIDERATIONS

Literature on social inequality, poverty and wealth has advanced a lot in the past years, especially regarding its determinants. It can be noticed that these themes have reached some expression in politics, and also caught the public's attention, contributing to an intensification of the studies that aim to understand the multidimensionality of the phenomena, searching for indicators strong enough to reproduce in an authentic way this problem, and so, to apply helping measures.

When considering the multidimensional nature of poverty, it is needed an indicator that corresponds to the multidimensional approach. Therefore, this study proposed to calculate an indicator of poverty that fits its multidimensional nature, whose methodological basis is similar to that used in HPI. It was also used the analysis of spatial data (Aede), which aimed at understanding the spatialization of poverty in the state of Bahia. Therefore, it was used data available in IBGE, through 2000 and 2010 Census, which were compared to IDMH of both periods, available in PNUD (2013), through *Brazil's Human Development Atlas*.

Regarding the spatial analysis, the outcomes confirmed the initial hypothesis of the study, reinforcing the existence of poverty concentrations in the state of Bahia, no matter the index used in its analysis. It was confirmed in the study that the number of concentration is higher when income analysis is used than when the multidimensional indexes is used, showing a spatial dependence. However, in the multidimensional maps, the clusters are more numerous and more diffuse throughout the state, indicating that poverty in this focus is more spatially distributed.

The analyses through this exploratory technique of spatial data evidenced that throughout the years there was an increase of positive self-correlation of poverty in the cities of Bahia, identifying greater High-High and Low-Low clusters in 2010. Another possible change to be observed is that, through the income lens, the majority of poverty clusters have presented a High-High set, indicating that the cities that presented a high index of monetary poverty suffered an influence from their neighbors in the same situation.

Thus, based on these outcomes, this study demonstrates that public policies that fight poverty, focused only on income, are not enough to win it, and in many cases, minimize the problem while underestimate poverty and the number of poors, when only the unidimensional focus is used. Therefore, it is necessary that the governments intensify their studies on programs that fight poverty using other dimensions that cause deprivation, beyond income, in order to enable the creation of more efficient public policies capable of eradicating this problem.

It is clear that Bahia must advance in creating and implementing public policies of development and poverty reduction, in a way to stimulate economic growth, especially those capable of generating jobs and income, as well as encouraging an improvement on poor people's life conditions, such as infrastructure of basic sanitation, better habitation, health and education. As long as these activities become more competitive, through policies developed by local agents, the effect of income generation will enable a greater local/regional development and, therefore, reduce poverty and social inequality. Even understanding that income should not be the only poverty indicator, it is possible to state that it remains as an important element to fight it.

As for future research, it is suggested to extend this investigation to habitation as a whole, since it is very expressive on the families' patrimony, including more than physical characteristics of habitation, such as access to infrastructure, social equipment, environment, criminality and other variables. The study must also be replicated in a neighborhood level in the same city, especially capitals and metropolitan areas, as well as for other states in Brazil.

REFERENCES

- ALMEIDA, Eduardo. Análise espacial da produtividade do setor agrícola brasileiro: 1991-2003. *Nova Economia*, v. 17, n. 1, p. 65-91, 2008.
- ALMEIDA, Eduardo. *Curso de econometria espacial aplicada*. Piracicaba: Esalq-USP, 2004.
- ALMEIDA, Eduardo. *Econometria espacial aplicada*. Campinas: Alínea, 2012.
- ALMEIDA, Eduardo S.; PEROBELLI, Fernando S.; FERREIRA, Pedro G. Existe convergência espacial da produtividade agrícola no Brasil? *Revista de Economia e Sociologia Rural*, v. 46, n. 1, p. 31-52, 2008. Available at: <www.scielo.br/scielo.php?script=sci_arttext&pid=S0103-20032008000100002&lng=en&nrm=iso>. Accessed on: 13 Jan. 2017.
- ANAND, Sudhir; SEN, Amartya. Concepts of human development and poverty: a multidimensional perspective. In: *Poverty and human development: human development papers*. New York: PNUD, 1997. p. 1-19. Available at: <<http://clasarchive.berkeley.edu/Academics/courses/center/fall2007/sehnbruch/UNDP%20Anand%20and%20Sen%20Concepts%20of%20HD%201997.pdf>>. Accessed on: 5 Feb. 2017.
- ANSELIN, Luc. *Spatial econometrics: methods and models*. Boston: Kluwert Academic, 1988.
- ÁVILA, José F. *Pobreza no Rio Grande do Sul: uma análise exploratória da sua distribuição espacial a partir de indicadores multi e unidimensionais*. Dissertação (mestrado em economia do desenvolvimento) — Faculdade de Administração, Contabilidade e Economia, Pontifícia Universidade Católica do Rio Grande do Sul, Porto Alegre, 2013.
- BAHIA. *Evolução e caracterização das manchas de pobreza na Bahia (1991-2000)*. Salvador: SEI, 2008.
- SILVA, Mirela de C. P. da; BARROS, Ricardo P. Pobreza multidimensional no Brasil. In: ENCONTRO NACIONAL DE ECONOMIA, 2006, Salvador. *Anais da Anpec*. 2006. p. 1-20.
- BRASIL. *Indicadores sociais municipais: uma análise dos resultados do universo do Censo Demográfico 2010*. Rio de Janeiro: IBGE, 2011.
- CONCONI, Adriana; HAM, Andrés. *Pobreza multidimensional relativa: una aplicación a la Argentina*. La Plata: Cedlas, 2007.
- CRESPO, Antônio; GUROVITZ, Elaine. A pobreza como um fenômeno multidimensional. *Revista RAE. RAE-eletrônica*, v. 1, n. 2, p. 1-12, 2002. Available at: <www.scielo.br/pdf/raeel/v1n2/v1n2a03>. Accessed on: 15 Feb. 2017.
- FERES, Juan C.; VILLATORO, Pablo. A viabilidade de se erradicar a pobreza: uma análise conceitual e metodológica. *Cadernos de Estudos — Desenvolvimento Social em Debate*, n. 15. Brasília, DF: Ministério do Desenvolvimento Social e Combate à Fome; Secretaria de Avaliação e Gestão da Informação, 2013.
- IBGE. Instituto Brasileiro de Geografia e Estatística. *Indicadores sociais municipais: uma análise dos resultados do universo do Censo Demográfico 2010*. Rio de Janeiro: IBGE, 2011.
- KAGEYAMA, Ângela; HOFFMANN, Rodolfo. Pobreza no Brasil: uma perspectiva multidimensional. *Economia e Sociedade*, Campinas, v. 15, n. 1 (26), p. 79-112, Jan./June 2006.
- LACERDA, Fernanda C. *A pobreza na Bahia sobre o prisma multidimensional: uma análise baseada na abordagem das necessidades básicas e na abordagem das capacitações*. Dissertação (mestrado em economia) — Universidade Federal de Uberlândia, Uberlândia, 2009.
- LACERDA, Fernanda C.; NEDER, Henrique D. Pobreza multidimensional na Bahia: uma análise fundamentada no indicador multidimensional de pobreza. *Revista Desenhavia*, v. 7, n. 13, p. 33-70, 2010.
- LESAGE, James P. *The theory and practice of spatial econometrics*. Ohio: University of Toledo, 1999.
- MARTINI, Ricardo A. *Um ensaio sobre os aspectos teóricos e metodológicos da economia da pobreza*. Belo Horizonte: UFMG/Cedeplar, 2009.
- MOURA JR., James. F. et al. Concepções de pobreza: um convite à discussão psicossocial. *Temas em Psicologia*, v. 22, n. 2, p. 341-352, 2014.
- PNUD. Programa das Nações Unidas para o Desenvolvimento. *Atlas do desenvolvimento humano do Brasil, 2013*. Brasília: PNUD; FJP; Ipea; ONU, 2013. Available at: <www.atlasbrasil.org.br/2013/pt/download/>. Accessed on: 25 Jan. 2017.

PNUD. Programa das Nações Unidas para o Desenvolvimento. *Relatório do desenvolvimento humano: a água para lá da escassez: poder, pobreza e a crise mundial da água*. New York: PNUD/ONU, 2006. Available at: <www.br.undp.org/content/brazil/pt/home/library/relatorios-de-desenvolvimento-humano/relatorio-do-desenvolvimento-humano-20006/>. Accessed on: 12 Feb. 2017.

POGGI, Ambra. *Social exclusion in Spain: measurement theory and application*. Tese (doutorado) — Universitat Autònoma de Barcelona, Barcelona, 2004.

SEI. Superintendência de Estudos Socioeconômicos da Bahia. *Evolução e caracterização das manchas de pobreza na Bahia (1991-2000)*. Salvador: SEI, 2008.

SEN, Amartya. *Desenvolvimento como liberdade*. Tradução de Laura Teixeira Mota. São Paulo: Companhia das Letras, 2000.

SIDRA. Sistema IBGE de Recuperação Automática. *Censo Demográfico 2000*. Brasília: Instituto Brasileiro de Geografia e Estatística, Brasília, 2001. Available at: <<https://sidra.ibge.gov.br/pesquisa/censo-demografico/demografico-2000/inicial>>. Accessed on: 10 Jan. 2017.

TOWNSEND, Peter. The meaning of poverty. *The British Journal of Sociology*, v. 13, n. 3, p. 210-227, 1962.

VINHAI, Henrique; SOUZA, André. Pobreza relativa ou absoluta? A linha híbrida de pobreza no Brasil. In: ENCONTRO NACIONAL DE ECONOMIA, 2006, Salvador. *Anais...* Salvador: Anpec, 2006. p. 1-18.

Eli Izidro dos Santos

Master degree in regional economics and public policies from State University of Santa Cruz (PERPP/UESC). E-mail: elyizidro@hotmail.com.

Ícaro Célio Santos de Carvalho

PhD candidate at Getulio Vargas Foundation, Business Administration School of São Paulo (FGV EAESP). E-mail: icarocelio@hotmail.com.

Ricardo Candéa Sá Barreto

PhD in economics applied at Federal University of Viçosa (UFV). Management analyst at Cagece. E-mail: ricardocandea@yahoo.com.br.