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APPLICATIONS TO THE PUBLIC SECTOR SPECIAL ISSUE ARTICLES

DECISION SPATIAL MODEL TO EVALUATE HUMAN DEVELOPMENT IN THE STATE OF RIO GRANDE DO NORTE

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ABSTRACT. The present study applies a decision spatial model, previously developed, for the case of evaluating human development in the counties of the state of Rio Grande do Norte. The factors that encompass social, economic, health, education and territorial aspects of the counties were evaluated. The model makes use of decision rules and identification of spatial clusters to analyze the grouping of cities with better and worse performances. Three analyses were performed obtaining approximate results, verifying the robustness of the model employed. Additionally, the results were compared with the Human Development Index of the counties. In the case of the present study, the compensatory effect was not observed when compared to the original index, and the referred effect arises due to the calculation method used. Furthermore, the practical implication signifies the opportunity to develop public policies associated with the criteria showing poor performance and to visualize spatial patterns existing in municipalities with the same classification.

Keywords: spatial decision, human development, multiple-criteria.

1 INTRODUCTION

Evaluating the social good is a complex subject that necessitates a multidimensional approach due to the various variables involved in society. This evaluation is closely linked to human development. The Human Development Index (HDI), introduced by the United Nations Development Program (UNDP) in the 1990s, seeks to quantify human development through three core dimensions: health, education, and income (Sagar & Najam, 1998). This index underscores that

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improving the quality of life cannot be solely achieved by increasing income (McGillivray et al. 2023). Conversely, the HDI itself must expand to encompass other dimensions, including sustainable social development (Zaijun et al. 2022). Therefore, creating a composite of indicators that reflect the various dimensions within society proves practical and beneficial for informed decision-making. Public managers find this information invaluable in their pursuit of reliable insights (Leon-Castro et al. 2021).

According to McGillivray et al. (2023), the Human Development Index (HDI) is one of the most widespread representations to measure the development of the country, with many positive contributions and several criticisms. Considered as a strategic tool, reinforcing the importance of including aspects such as longevity and health, education and literacy of the population and not restricted only to the power of economic acquisition (income) (Yakunina & Bychkov, 2015). Although, even in the 1990s, criticisms emerged about the calculation used and the variables used in the representation of the dimensions (Sagar & Najam, 1998), in addition to other limitations as mentioned in Pereira & Mota (2016). In Brazil, the HDI measures the level of development of counties (HDI-M), with publications launched in 1998, 2003 and 2013 based on the census of counties (UNDP, 2022). Thus, using these indicators for the counties enables more strategies for actions that improve the quality of life of residents, in addition to portraying the development of the different regions of Brazil.

In the social sciences, the construction of indicators for measurement processes requires a connection between the dimensions used (Alaimo & Seri, 2023). For Mori & Christodoulou (2012), there is an inherent criticism of the construction of such indicators due to the subjectivity of the choice of variables and the weighting that may be used. In the case of Brazil, the Atlas of Human Development gives access to a platform containing information on the 5,565 Brazilian counties, with available data on education, housing, health, economy, employment, income and vulnerability (Castro et al. 2021). But they are limited until the last Census conducted in 2010, with an update expected for the year 2022.

In order to broaden the contextualization on HDI employment in response to contemporary practical problems, contributions that relate to social well-being should be emphasized. In the area of health, we seek to understand the relationship with HDI in what involves premature births of newborns (Chang et al. 2013); description of worldwide prevalence of physical inactivity (Dumith et al. 2011); and the relationship between cancer types and countries HDI level (Bray et al. 2012). They also extend to other dimensions to incorporate sustainability perspectives (Jin et al. 2020) and the relevance of measuring sustainable development (Strezov et al. 2017; Zaijun et al. 2022); the HDI in the composition of new indices to measure the risks of natural disasters (Debortoli et al. 2017) and in the evaluation of inequalities to develop strategies for the allocation of resources and services, encompassing criteria such as: poverty, inequality and segregation (Barrozo et al. 2020).

On the other hand, existing criticisms to reconsider the indices or new calculation formulas (Sagar & Najam, 1998; Pereira & Mota, 2016), there is a debate in the literature (Alaimo & Seri, 2023), including the way in which weights are used in the evaluation (McGillivray et al. 2023) or the fact that the methods proposed until 2010 do not consider the perspective of deprivation and do not include the deficiencies of countries in relation to the goals to be achieved (Mangaraj & Aparajita, 2020). Although Dervis & Klugman (2011) conclude that the HDI focuses on measures of inequality and deprivation. As the construction of the HDI is a multidimensional problem, due to the factors health, education and income, it becomes inherent to conduct the discussion of the problem within the scope of multicriteria decision models, due to the need to achieve several objectives. Although HDI has already been the subject of discussion with decision methods, including the perspective of ordered classification (Monteiro et al. 2018), the present study employs a more holistic approach to the problem, based on an approach that goes beyond the more usual concepts such as additivity and contribution of weights, usually mentioned as controversial in the literature (Alaimo & Seri, 2022). Furthermore, it includes spatial analysis as an important tool, as demonstrated in previous studies (Poleto et al. 2023). The Dominance-based Rough Set Approach (DRSA) was used in conjunction with a spatial analysis to verify clusters between the alternatives.

Then, a set of variables based on the HDI dimensions were chosen to explore and analyze the existence of possible development patterns based on these variables. Also, a set of three evaluation groups were used to verify possible changes and then a comparison was made with the HDI currently used. The performance evaluation was conducted in the counties of the state of Rio Grande do Norte and the results show the potential for the use of both the spatial decision approach and the use of alternative variables, aiming at the planning of public policies and replication to other Brazilian states.

The remainder of the article is divided into a review of the literature on the HDI, demonstrating past contributions to justify the motivation for employing a multiple criteria approach. Next, the methodology used is presented, consisting of two distinct sections. The first part involves presenting and explaining the procedures employed to develop the HDI evaluation index, while the second stage involves characterizing the research area, which comprises the counties within the state of Rio Grande do Norte. This is followed by the presentation of the results obtained by applying the methodology to analyze real data and discussing the findings. In the final section, we summarize key findings and suggest potential directions for future research.

2 THEORETICAL REVIEW

The HDI is a key reference for measuring quality of life and social well-being worldwide (Alaimo & Seri, 2022). It's calculated annually to rank countries and reported by the UNDP (Mangaraj & Aparajita, 2020; Pereira & Mota, 2016). There are ongoing efforts to enhance the index globally (Alaimo & Seri, 2022). In Brazil, the Municipal Human Development Index (MHDI) is used to plan local public policies, revealing regional disparities (Pereira & Mota, 2016; Sant'Anna et al. 2018). It assesses living standards through per capita income, quality of life via life expectancy, and education using average years of schooling and children's education. The HDI ranges from 0 (low human development) to 1 (high human development) and currently uses a geometric mean for calculation. In this section, we present an overview about HDI, decision models and spatial analysis that propose alternative approaches to measure human development, and that server as support to our research.

The characteristics of building an index that take into consideration the dimensions (health, education and income) to evaluate the alternatives (countries and counties) containing a respective numerical performance, also allow to evaluate as an MCDM problem. Including evidence of obtaining preferences with respect to the dimensions used (McGillivray et al. 2023) and the possibility of tradeoffs and rationality of choices (Lind, 2019). In this sense, the use of Multiple Criteria Decision Making (MCDM) allows dealing with the problem of the index, the ordering of alternatives or even the use of sorting (Basílio et al. 2022; Greco et al. 2016).

Within the scope of MCDM, emphasize some advantages such as allocating finite resources (Basílio et al. 2022), representing preferences from decision makers, including information on objectives, alternatives, and criteria (Eriskin, 2021), and supporting strategic actions (Mota et al. 2021; Figueiredo & Mota, 2019). Also, there are researches involving Composition Probabilistic Preferences to generate a global score, taking into account the HDI dimensions (Sant'Anna et al. 2018). In Recife, Brazil, the ELECTRE TRI-C decision method was applied to sectoral units, put alternatives into ordered classes. This approach yielded positive results, including reduced compensatory effects, fewer calculation problems, and the ability to make annual comparisons (Pereira & Mota, 2016). In Monteiro et al. (2018), a novel proposal using the ELECTRE-TRI classification model introduced Kernel Density Estimation to create country classes. This study contributes through a combined methodology, the inclusion of new dimensions, more realistic results, and the elimination of the compensatory effect.

In Tasabat, (2019), a new methodology was introduced, combining TOPSIS concepts with distance, correlation, and similarity measures. This approach utilized input information to generate positive-ideal and negative-ideal values while avoiding the geometric mean. Multiple experiments revealed variations in results based on different weights and index performances during the aggregation process. In the study conducted by Mangaraj & Aparajita (2020) a model combined with MCDM and Data Envelopment Analysis (DEA) generated a relative index, associated with two procedures of reference-dependent and optimization, including the perspective of deprivation. A flexible non-additive aggregative model (Choquet integral) was applied, which proposed a flexible approach, offering the decision-maker the ability to capture potential interactions between HDU dimensions (Pinar, 2022). Another way to measure HDI, was created using the PROMETHEE II - Preference Ranking Organization Method for Enrichment of Evaluations and the Global Innovation Index (GII) (Tunsi & Alidrisi, 2023). The analysis focused on the G8 countries, aiming to establish a benchmark for innovation in leading nations globally.

Although the term "multiple-criteria" is little used in the observed studies, other studies suggest changes in the way the three dimensions are aggregated, in order to make the indicators more realistic. The propose to the axiomatization of the HDI (Zambrano, 2014); new indicators tanking the other dimensions (Lind, 2019; Alaimo & Seri, 2022); expansion of the indicator to include environmental and public health aspects (Yang & Geng, 2022); and obtaining preferences from multiple decision-makers (McGillivray et al. 2023). Recently studies with spatial analysis were included, as in Herfort et al. (2023) which investigated the inequality in urban scenarios and spatial econometric models and HDI in China (Liu et al. 2023).

The HDI, MCDM and other propose theme is not exhausted and the opportunity for new subjects still persists. Recently the study Alaimo & Seri (2022) discuss through a review on HDI, obtaining some relevant findings. 1) the criticisms, although the definition of "human development" and the use of indicators are considered, little has been done in relation to the methodological concepts; 2) the importance of using clear elementary indicators that allow measurement through formal models; 3) the compensation between the dimensions exists and that the choice of such dimensions has a great impact on the results and, therefore, on the interpretations. The question of weights is complemented in McGillivray et al. (2023), in which the study showed the importance of varying the weights according to the countries. On the other hand, the use of weights or even additive functions can lead to greater cognitive effort of the decision-maker (Slowinski et al. 2012), when the same is present. Hence, although there are papers in the literature involving MCDM, they have not been verified considering past research with a holistic approach and examples of references, including spatial analysis to verify spatial patterns. Additionally, the proposed approach considers Brazilian municipalities that exhibit social and economic vulnerability.

3 METHODOLOGY

The Methodology is structured in two parts. The presentation and description of the steps used to create the index to evaluate HDI, considering the DRSA approach and spatial aspects. And in the second stage, characterization of the study site (counties in the state of Rio Grande do Norte) and description of the data used in the model.

3.1 DRSA-GIS Analysis

Multicriteria decision methods are widely known in the literature. With recent revisions in the area of additive approaches (Silva et al. 2022); in the financial sector (Almeida Filho et al. 2020); landfill suitability analysis (Bisneto & Figueiredo, 2022) and sustainable development (Kandakoglu et al. 2019; Bortuluzzi et al. 2021). Showing the potential applicability of exploring new themes. In the study of Silva et al. (2022) there is a special attention to decision models with partial information, in which the decision-maker does not need to spend his time to provide very complex information. Thus, holistic methods fall under this type of approach.

The Dominance-based Rough Set Approach (DRSA) offers an alternative approach by not requiring function tradeoffs or weights valuation for the criteria (Slowinski et al. 2012). Allowing the decision-maker to focus their tasks on holistic choices for classification issues. In addition, it can easily be used in the spatial context, aggregating information that improves the response of the model and allows a visualization of the information through maps instead of tables (Mota et al. 2021). It was also considered an adaptation for the present study, considering the DRSA and the spatial analysis of the results.

In DRSA, the basic fundamental is constituting of alternatives, which are evaluated by set of criteria and information given a four-tuple information system $S = \{A, Q, V, f\}$. Where: A is a finite set of objects; Q is a finite set of criteria; V_q is the domain of criterion $q; V = \bigcup_{q \in Q} V_q$, and $f : A \times Q \rightarrow V$ is a total function such that $f(a,q) \in V_q$ for each $q \in Q$ and $a \in A$. Also, the DRSA introduces the dominance relation. Let $P \subseteq C$ be a subset of condition criteria. The dominance relation D_p associate with P is defined for each pair of objects a_1 and a_2, such that $\forall (a_1, a_2) \in A \times A$ (Eq. 1):

$$D_p a_2 \Longleftrightarrow f(a_1, c) \succsim f(a_2, c) \forall c \in P \tag{1}$$

where: $f(a_1, c) \succsim f(a_2, c)$ means "a_1 dominates a_2 with respect to criterion c".

For each set of criteria Q is usually divided into set C of condition criteria and set D of decision attributes. The decision attributes d makes a partition in A into a finite number of preference-ordered classes $Cl = \{Cl_t,\ t \in T\},\ T = \{0, \ldots, n\}$, such that each $a \in A$ is classified to only class. For $r, s \in T$ and $r > s$, the alternatives from Cl_r prefer to the alternatives from Cl_s with respect to d.

The DOMLEM algorithm (Blaszczynski et al. 2013) generates decision rules for recommendations following an assessment of examples of references. The decision rules are categorized into two sections: conditional and decision. For this study, is considered the P-lower of decision classes $\underline{P}(Cl_t^{\geq})$ and $\underline{P}(Cl_t^{\leq})$ as it's assigned with certainty to the decision classes (Eq. 2):

if

$$f(a_i, c_1) \geq r_1 \wedge \ldots \wedge f(a_i, c_m) \geq r_t$$

Then $a_i \in Cl_t^{\geq}$ such that

$$(r_1 \ldots r_t) \in V_{c_1} \times \ldots \times V_{c_m} \tag{2}$$

where: $(a_i, c_1) \geq r_1$: represent the evaluation of alternative in related to the criteria for sort in $Cl_t^{\geq}$.

These rules are supported only by alternatives from P-lower approximations of the upward unions of classes $Cl_t^{\geq}$ (Eq. 3):

if

$$f(a_i, c_1) \leq r_1 \wedge \ldots \wedge f(a_i, c_m) \leq r_t$$

Then $a_i \in Cl_t^{\leq}$ such that

$$(r_1 \ldots r_t) \in V_{c_1} \times \ldots \times V_{c_m} \tag{3}$$

where: $(a_i, c_1) \geq r_1$: represent the evaluation of alternative in related to the criteria for sort in $Cl_t^{\leq}$.

The rules are only backed by options from the P-lower approximation of the downward unions of classes $Cl_t^{\leq}$. For the performance of those procedures, the software jMAF is available (Blaszczynski et al. 2013).

Also, the DRSA obtain the performance through of the quality of approximation of the classification ($\underline{P}(Cl_t^{\geq})$ and $\underline{P}(Cl_t^{\leq})$). To calculate is considered the ratio expressed by cardinality between the universe A and all P-correctly classified alternatives. For all minimal subset $P \subseteq C$ such that $\gamma_P(\mathbf{Cl}) = \gamma_C(\mathbf{Cl})$ is called a reduct of C with respect to **Cl** and is denoted by $RED_{Cl}(P)$. The core $CORE_P$ is formed by the intersection of all of the reducts (Eq. 4):

$$\gamma_P(Cl) = \frac{\left|A - \left(\bigcup_{t=1,..,n} Bn_P\left(Cl_t^{\leq}\right)\right) \cup \left(\bigcup_{t=1,..,n} Bn_P\left(Cl_t^{\geq}\right)\right)\right|}{|A|} \tag{4}$$

Then, the obtained decision classes are analyzed using a spatial statistical approach Getis-Ord Optimization (G_i^*) widely known in the literature (Getis & Ord, 1992). The importance of using this type of procedure is to seek spatial standards in relation to alternatives, a role not played by the DRSA, since the standards are observed criteria used in the creation of the rules.

The G_i^* is a value that refers to the assessment of the level of concentration, or dispersion, of a variable's values within a particular study area. Each alternative is given a weight and is associated with a set of sub-regions, and the calculation measures the proximity patterns between the variables based on the weights used, taking as the distance between these alternatives:

$$G_i^* = \frac{\sum_j w_{ij}(d)x_j}{\sum_j d_j}, \text{in which} j \neq i \tag{5}$$

where x_j is weight value for a given feature (in this study, HDI class) and $w_{ij}(d)$ is a symmetric one/zero spatial weight matrix, with ones of all links defined as being within distance d (or contiguous regions) of a given region i; all other links are zeros. Then, the result obtained is a new classification, in which the cold and red hotspots are obtained by measuring the significance of the analyzed areas. The results indicate the formation of more or less vulnerable groups and are useful for the process of formulating public policies. Finally, the results were compared with the MHDI. To perform the spatial analysis was used the software ArcGis 10.03 (ESRI).

3.2 Place of study

The study was conducted in the counties of the state of Rio Grande do Norte (Figure 1), located in the Northeast of Brazil. The state has most of its territory inserted in the semi-arid region, presenting challenges such as water scarcity and development in education and income, whose specific HDI indicators in these two dimensions are 0.597 (low) and 0.678 (medium) (UNDP, 2011), respectively. More recently, the last survey of the year 2017 made by Atlas Brasil, the global HDI of the state of Rio Grande do Norte was 0.731, considered as high, being in 16th place in relation to the other units of the federation (Radar IDHM, 2019). The economy focuses on family farming activities, mechanized fruit growing, salt industry, fabric production and expansion in the renewable energy sector (wind and solar) and industrial park in the metropolitan region of the capital Natal.

Currently the state has about 3.5 million inhabitants, distributed in 167 counties in an area of 52,809 km² (IBGE, 2020). Being the capital Natal with the largest population, 884,122 thousand

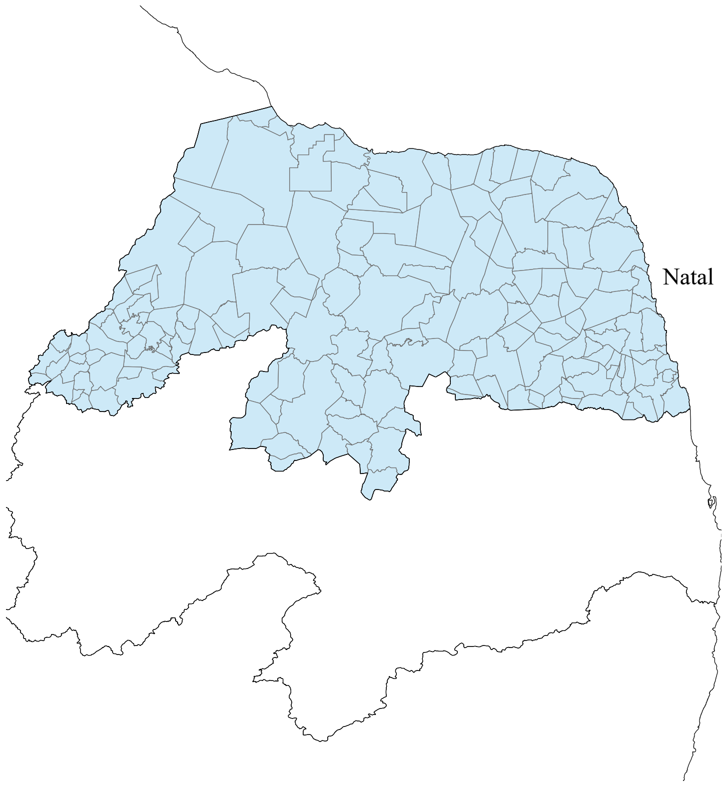

Figure 1 – Identification of the place of study.

inhabitants, then Mossoró (western region) with 297,378 inhabitants, Parnamirim with 261,469 inhabitants, São Gonçalo do Amarante 102,400 inhabitants and Macaíba 80,792 inhabitants. The last three are located in the Metropolitan Zone of the Capital. The average salary of the five most populous cities in RN is 3.1 in Natal, 2.4 in Mossoró, 1.8 in Parnamirim, 1.9 in São Gonçalo do Amarante and 2.1 in Macaíba (IBGE, 2020). A minimum wage equals US$ 250 at the most recent rate.

The objective of using a base with factors involving the three dimensions of the HDI (income, longevity and education) was to bring a comparison in the discussions. However, the longevity dimension was not available for more recent data, and other criteria that were closer were chosen. We used the data available on the website of the Brazilian Institute of Geography and Statistics (IBGE), containing various information on social, economic, demographic and collective health factors. Thus, a division was made for this study in the themes: Population, Economy, Health, Education and Territory. The latter was purposely included in order to achieve more efficient and representative results. In addition, it should be noted that most of the counties in the state analyzed have very small urban areas if we compare with the totality of their territory. There were 12 factors used and described in Table 1 below.

Table 1 – Factors used in the study.

Factors	Average	Standard deviation	Maximum	Minimum
Estimated population	20999	74454	884122	1718
Busy people	3913	24939	314728	199
Average salary	1.80	0.39	5.40	1.30
Proportion of employed persons (%)	0.11	0.05	0.36	0.04
Proportion of people on minimum wage (%)	0.49	0.04	0.61	0.36
Elementary Schools	16	32	356	1
Choose with High School	3	9	107	0
GDP per capita	13800	13519	106122	6536
Education rate (%)	1.0	0.0	1.0	0.9
SUS Establishments	9	14	149	1
Burnout (%)	0.27	0.24	0.97	0.00
Area (m²)	316.23	314.51	2099.33	26.10

Source: IBGE Cidades.

4 RESULTS

In this section we will present the results obtained with the use and application of the data in the spatial DRSA model. To obtain a representative analysis that shows in fact that there are patterns that can be obtained with decision rules for a human development problem, three groups of reference objectives were created. Another detail of the DRSA is to consider only one set of information (examples of references - counties) to obtain the decision rules. Here these subsets will be referenced as samples.

To investigate the performance of the proposed approach using DRSA and Getis-Ord optimization, an initial classification is required to establish reference examples. In some cases, the presence of a decision maker is useful to generate a subset with these examples. However, in this context, gathering pre-ordered classes of samples 1, 2, and 3 was defined based on the quartiles of the following factors: ”Average monthly salary of formal workers,” ”GDP per capita,” and ”employed population,” respectively.

Regarding the number of criteria applied in each sample, the following strategy was initially adopted. In the Sample 1 group, all criteria were maintained. In Sample 2, the criterion “Estimated population” was excluded. While in the third sample of reference objects it was decided to exclude the criteria related to population, GDP and the areas and densities of the county. Table 2 shows which criteria were used in each sample of the experiments conducted.

Table 2 – Criteria used in each sample.

Factors	Criteria	Sample 1	Sample 2	Sample 3
Estimated population	pop_estim			
Busy people	pes_ocup	***		***
Average salary	sal_mean	***	***	***
Proportion of employed persons (%)	Prop_ocu	***	***	***
Proportion of people on minimum wage (%)	Pe_pop_mei	***	***	***
Elementary Schools	nf	***	***	***
Choose with High School	em	***	***	***
GDP per capita	pib	***	***	
Education rate (%)	escol	***	***	***
SUS Establishments	sus	***	***	***
Burnout (%)	Esgot	***	***	***
Area (m²)	area	***	***	

Technically, one of the objectives of the DRSA is to extract the essential information, represented through the attributes/criteria that can respond with the same quality of information if all the criteria were used. And as a parameter use quality approximation to measure the quality of which the examples used can be applied to generate rules. Adequate percentages were found in Sample 1 (84.6%), Sample 2 (90.6%) and Sample 3 (83.3%). That is, the examples considered can generate good decision rules that will classify the other counties.

Decision rules use a set of criteria as constraints such as: If... So....; and classify all the objects considered in the problem. For the case of this study, in each of the samples almost all the available criteria were used with 15 rules (Sample 1), 20 (Sample 2) and 16 rules (Sample 3). It should be mentioned that in the first two samples the criteria referring to the population, population density and territory of the county were excluded, because in the first analyses there was an excess of information, which made it impossible to understand the patterns formed by the decision rules in relation to the dimension “income”, the conditioning criteria can be cited: “employed persons”, “proportion of employed persons”, “average minimum wage” “GDP”. For the dimension “education” it’s possible to obtain information on the number of high school and elementary schools and time of schooling. For the “life expectancy” axis, there was no direct relationship, as occurs in the measurement of the HDI for the estimated life span of the individual, but the % of basic sanitation available and the number of establishments that belong to the Unified Health System can be cited. Table 4 presents the criteria used in each sample.

Still regarding the rules, the conditions that lead to a “High” human development class of the counties are justified by few rules for each of the three samples analyzed, and represented by the criteria of “Occupied persons”, “Proportion of employed persons”, “Basic sanitation”, “Educational establishments” and “SUS establishments”. That is, several aspects of the dimensions of development can be used to indicate good developments, however few rules can be used, allowing a reduction of information with good qualification of the results. On the other hand, the "Moderate" and "Low" development has more rules, as shown in Table 3, possibly justified by the variability of the information contained in the counties used as references.

Table 3 – Division of development bands.

Sample	Rules used	Human Development
Sample 1	pes_ocup $\geq$ 1057 and esgot $\geq$ 0.639 pes_ocup $\geq$ 1418 & pro_ocup $\geq$ 0.138	High
	pes_ocup $\geq$ 918 nf $\geq$ 10.0 & esgo $\geq$ 0.602 nf $\geq$ 12.0 & esco $\geq$ 0.98 & sus $\geq$ 6.0 pro_ocup $\leq$ 0.105 & esgo $\leq$ 0.421	Moderate
	em $\leq$ 1.0 & esco $\leq$ 0.955 sus $\leq$ 2.0 & esgo $\leq$ 0.043 pro_ocup $\leq$ 0.057	Low
Sample 2	em $\geq$ 9.0 esgo $\geq$ 0.654 area $\geq$ 268.59	High
	pes_ocup $\geq$ 2833.0 sus $\geq$ 10.0 sal_mean $\geq$ 2.1 area $\geq$ 393.57	Moderate
	pib $\leq$ 7336.76 esco $\leq$ 0.954 sus $\leq$ 2.0 esgo $\leq$ 0.003 area $\leq$ 517.737	Low
Sample 3	pes_ocup $\geq$ 1960.0 pro_ocup $\geq$ 0.08 & esco $\geq$ 0.992	High
	sal_mean $\geq$ 2.1 & pro_ocup $\geq$ 0.058 esco $\geq$ 0.985 & sus $\geq$ 9.0 pib $\geq$ 9143.42 & esgo $\geq$ 0.237 pes_ocup $\geq$ 377 & sal_mean $\geq$ 1.9 & esco $\geq$ 0.984 pes_ocup $\leq$ 415 & pro_ocup $\leq$ 0.081	Moderate
	pib $\leq$ 7336.76 sal_mean $\leq$ 1.5 & esco $\leq$ 0.965 sus $\leq$ 4 & esgo $\leq$ 0.013 pes_ocup $\leq$ 415 & sal_mean $\leq$ 1.6 & pib $\leq$ 7534.35 esco $\leq$ 0.983 & esgo $\leq$ 0.14	Low

With the decision rules obtained by the DRSA, all counties in the state of Rio Grande do Norte were classified in relation to the HDI, as shown in Figure 2. The original HDI-M classification was also inserted. The visual results show that there are few variations between the samples selected to obtain the decision rules. In practice this means that there is good accuracy in the results, and that regardless of the counties used in the subset there is a classification pattern to be "discovered" with the data. It's possible to classify the other counties. Figure 2 shows the classifications of the samples and the HDI-M.

In addition, the discussion of the findings reveals another observation about the variances that exist among municipalities in Brazil. There are several discrepancies between demographic and economic performance data, for instance. The states of São Paulo, Minas Gerais, and Rio de Janeiro collectively house 39.9% of Brazil's population, making them the most populous regions in the country (IBGE, 2023). In Rio Grande do Norte, the situation is similar, with the capital, Natal, and Mossoró, the second-largest city in the state, together accounting for 34% of the population. Clearly, these variances emerge, and the DRSA (Decision Rule Set Analysis) may be employed to mitigate this issue through decision rules. Upon reviewing Table 3, it is noted that the "Busy people" criterion, represented as "pes_ocup," is used as a condition for classes "High" and "Moderate" but appears only once in class "Low" in Sample 3.

In the context of comparing with HDI-M values, we utilized a Natural breaks - Jenks classification directly obtained through ArcGIS 10.3. This particular classification optimizes the distribution of counties across different classes, minimizing mean deviations for each class. We chose to divide it into three classes, reflecting the same number of decision classes. Notably, when examining HDI-M, we observe similarity clusters among counties, likely attributed to the compensatory effect of the criteria used. Counties in close proximity tend to share similar characteristics, such as education and economics, for example. Conversely, certain similarities become apparent when analyzing maps, particularly in the metropolitan region of Natal.

Regarding the distribution of the quantities of counties in each class, a similarity was observed between the three samples analyzed. On the other hand, when compared, the results were distant in relation to the classification adopted (Natural Jenks). Observing the results among the samples, it was noted that Sample 1. Regarding the comparison with the HDI-M, the changes were more significant. Considering the division into Natural Breaks for the classes of lower development and moderate development, the distributions were close. For the counties classified as more developed, the amount was lower in relation to the data obtained by the DRSA samples (decision rules). In general, the results of the IBGE attribute counties in less developed, while in the HDI-M they are moderate. Table 4 summarizes this distribution.

Then, the analyses were made for the second stage of the model. The use of clusters through the optimized Get-Ord optimization tool has some advantages. First, it identifies the formation of precisely the clusters or hot areas. Second, it provides the decision maker with information about the similarities of the performances. In the case of this study, the results of the DRSA classifications. Third, the analysis for both sides of the information, that is, the counties with better performances (hot-spot) and also those with lower performance (cold-spot). Figure 3 shows this

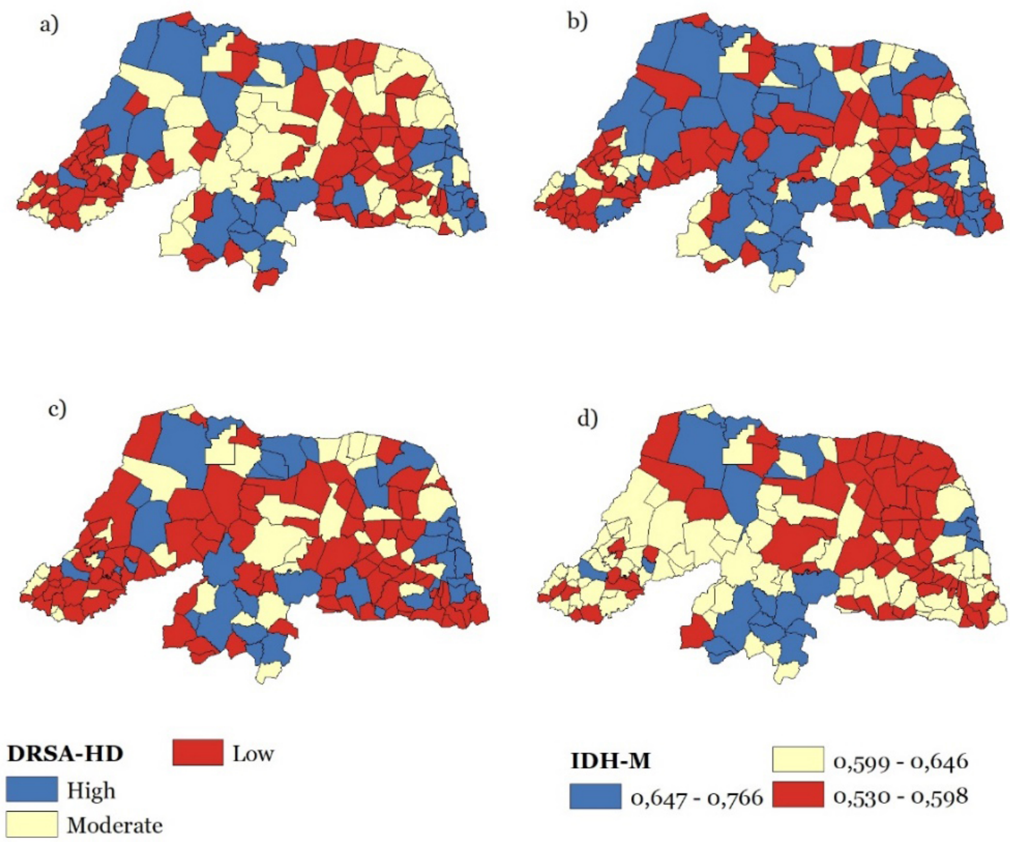

Figure 2 – Classification for the three samples and Jenks classification for HDI. a) Sample 1; b) Sample 2; c) Sample 3; d) HDI-M.

Table 4 – Division of development bands.

#	Low	Moderate	High
Sample 1	88	50	29
Sample 2	83	37	47
Sample 3	96	35	36
HDI-M	70 [0.530-0.598]	75 [0.599-0.564]	22 [0.647-0.766]

information. Counties in blue tones have the lowest performance. While those classified in red tones have similarity for the best performances, with respect to human development. The yellow color is neutral and has no similarity between nearby cities. Finally, when the results of the samples are compared with the HDI-M results, there is a proximity in the distributions of the counties ties for each hot or cold zone, as observed in Table 5.

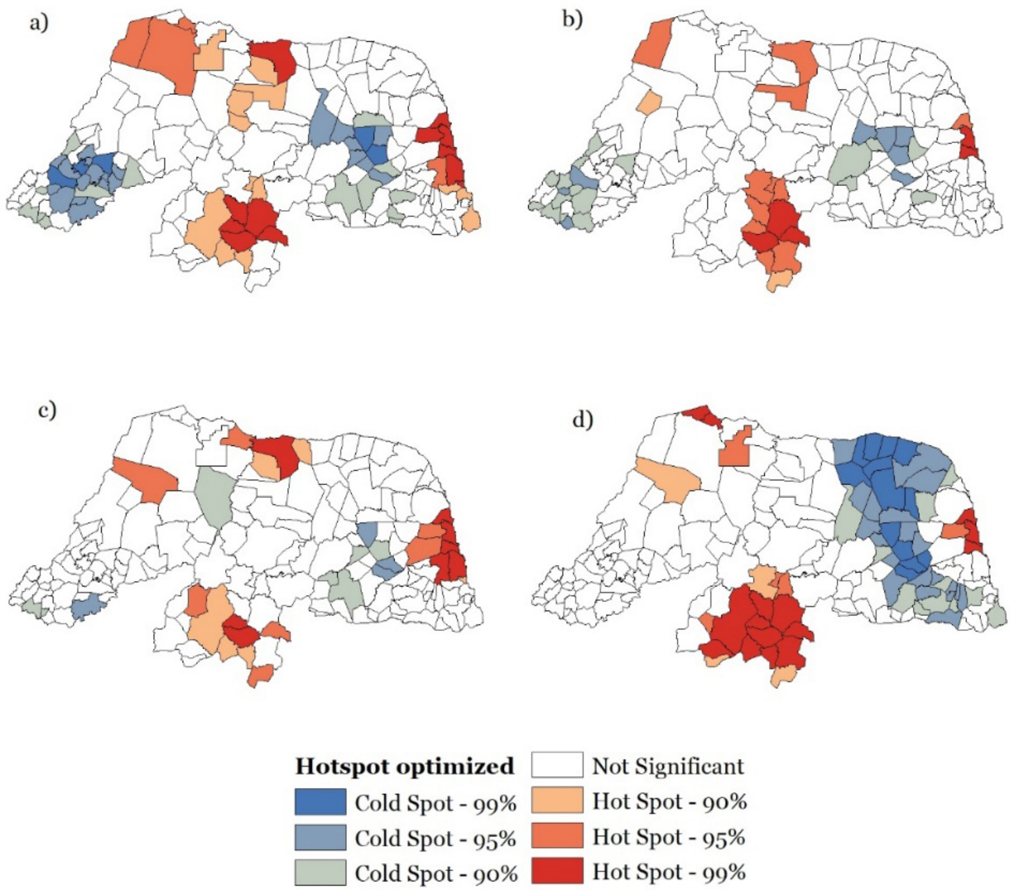

Figure 3 – Results using Get Ord optimized for cluster identification.
a) Sample 1; b) Sample 2; c) Sample 3; d) HDI-M.

Table 5 – Distribution of counties for spatial analysis.

	Reliable level	Sample 1	Sample 2	Sample 3	HDI-M
Hot zone	99%	12	5	8	15
	95%	4	11	7	5
	90%	13	2	6	4
	Not significant	98	124	135	99
Cold zone	90%	14	17	7	11
	95%	21	8	4	20
	99%	5	0	0	13

5 FINAL CONSIDERATIONS

The present research carried out an adaptation of a previous study on the exploration of preferences, for classification and formation of spatial clusters. For the application was considered the evaluation of human development in the counties ties of the state of Rio Grande do Norte, considering the factors related to Education, Economy, Population, Health and Territory. A multicriteria approach (DRSA) was used, which classified the counties in relation to development based on these aspects and adopting samples of different objects. Three analyses were performed with the factors employed, one being a control factor and the others varying the number of criteria for comparison purposes. In the end, decision rules classified all counties. Also, the cluster analysis added more information, allowing to identify where the groups of counties with better and worse performances in relation to the evaluations made are located.

The study conducted compared the results with the HDI-M of the state of Rio Grande do Norte. As mentioned before, the original HDI-M employs an additive function to determine the index values, and the compensatory effect is widely known. For example, one dimension with poor performance may be affected by another dimension with good performance. In the case of the results from DRSA, no compensation effect was found. This is justified because the alternatives with poor performance were allocated in the moderate or low classification. In case of the results from DRSA were not found the compensation, justified due the alternatives with bad performance were allocated in moderate or low classification. That is, the use of the rules allowed a more robust result, thus avoiding a better performance by effect of some criterion that compensates for the negative effect of another. A similar result was also found in Pereira & Mota (2016), Using another multicriteria approach. However, factors such as population, sanitation, health facilities and salary are essential to assess human development in counties. Similar to the HDI proposal that is currently used.

Finally, for future studies it's intended to expand the analyses to other Brazilian states and deepen the perspective of using other types of inputs that can be chosen. Here the territorial dimension of the counties was adopted. As limitations, it's noteworthy that the absence of more recent data for the analysis of smaller structures of space, such as census tracts and/or city neighborhoods.

Data Availability

The available data at paper comprises information on all alternatives and the reference examples utilized in the current study.

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