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Research Article

A Classification Model to Evaluate the Security Level in a City Based on GIS-MCDA

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The aim of this paper is to map the most favorable locations for the occurrence of robberies in the Brazilian city through the multicriteria method Dominance-Based Rough Set Approach. Considering the city divisions with alternatives and evaluating by several spatial criteria, a decision-maker is building a preference model with based previous knowledge. Next, decision rules induced from preference information are introduced to the spatial environment to get the results. The decision rules can be seen as conditional part (represented by criteria) and decision part (assignment to decision classes). The rules classify all the alternatives according to security level. Moreover, the rules help to understand the social dynamics of the city and to assist in the proposition of strategies against violence.

1. Introduction

The issues of public safety and violence are often discussed because they directly affect each person living in society. In general, understanding and explaining the occurrence of violence require significant efforts to collect information on the issue. Information such as crime rates and socioeconomic variables associated with the population is important for the development of new research [1, 2]. Then the data can be used to create strategic options that will help to combat violence.

For Andresen [3], field studies of violence require more than discrete data. It is necessary to assess the evolution of violence over time and space for decision-making in public security. According to Elmes and Roedl [4], the Geographic Information System (GIS) is an important tool to support this decision-making process and formulate strategies to combat crime.

In the literature, the use of GIS in the field of criminality has already been reported in several different contexts. Various studies show themes and applications such as the identification of crime spatial patterns [4], spatial diversity of crimes [5], spatial correlation between crime and inequality [2, 6], and simulation and agent-based models for exploring crime patterns [7]. However, our intention is to provide an alternative technique, using GIS within the context of crime. This technique explores several factors that can help to understand violence.

Therefore, by evaluating different areas as alternatives and the impact of the multiple criteria with respect to violence, we used Multicriteria Decision-Making (MCDM). The primary objective of MCDM is to assist a decision-maker (DM) in choosing, ordering, or sorting a given set of two or more alternative criteria [8]. Moreover, several studies demonstrate the importance of the MCDM in many research fields [9–11]. In our case, we also considered the features of the spatial information supported by GIS. In the literature, there are very few studies of the combined use of MCDM and GIS to criminality. Gurgel and Mota [12] presented a GIS-MCDM model to prioritize regions for allocation resources considering several criteria; and in [13] a multicriteria approach was proposed aimed at setting police patrol sectors.

The focus of this study is to build a GIS-MCDM model to assess the level of security (increase in crime) in a city. The present study can be divided into two main contributions. First, we discuss the classification of the spatial alternatives to evaluate the level of security and its relationship to criminality using a GIS-MCDM approach. Second, we discuss how the

results of the model can be used in the formulation of security policies and which criteria are most important.

The rest of the paper is divided as follows. Section 2 presents background information illustrating the importance of GIS-MCDM. Section 3 presents the MCDM method used in the application. In Section 4, we present a model of the problem and describe the procedures used. In Section 5, we apply and discuss the results that were obtained. In Section 6, we present our conclusions and perspectives for future studies.

2. Background on GIS-MCDM

The MCDM approach assists in building an aggregation model based on the preference information sourced by the DM [14]. For Dyer et al. [15], since the 1980s MCDM methods have been implemented in computer systems to support the decision-making process and have subsequently been called Decision Support Systems (DSS). In recent years, authors have explored MCDM methods in different applications [16–18].

Specifically, there has been a growth in the use of GIS with MCDM because of the development computerized systems and improved access by users [19]. This combination is important because spatial decision problems typically involve several alternatives assessed by conflicting multiple criteria. Also, the evaluation is conducted by a DM or group of decision-makers [20]. Afterwards the concept of GIS-based Multicriteria Decision-Making (GIS-MCDM) emerged [19].

In the recent literature, several studies have combined the decision process using GIS and MCDM such as choosing a better route for vehicles [21], identifying sustainable sites for environmental conservation [20, 22], sorting regions to implement energy mixes [23], allocating industries [24], and suitable land use [25].

We also observed that authors have evaluated specific combination MCDM methods with GIS. The adaptation of GIS-MCDM needs to create a synergy that might facilitate the aggregation of information. In this sense, [20, 26, 27] have presented studies using the importance of scales to assess alternatives based on DM preferences or situations involving uncertainty.

On the contrary, authors have shown more traditional methods including both compensatory and noncompensatory methods. In the compensatory methods, AHP was integrated into the GIS environment [28, 29]. Noncompensatory methods present practical applications with ELECTRE and other outranking methods [22, 30]. Also, there are software packages to facilitate the generation of recommendations to decision-makers [30].

Thus, the possibilities are extensive for combining the GIS-MCDM approach to support decision-making processes that directly involve the spatial use. However, there are a few studies that use GIS-MCDM for the public security field [12, 13]. Thus, the gap related with GIS-MCDM and criminality becomes a motivator for building a model to solve specific problems in public safety.

3. DRSA Method

In this section, we present Dominance-Based Rough Set Approach (DRSA) method that was integrated with GIS. We choose a method that allows using the set of reference examples (real or fictitious) for aggregating the information from preference obtained with the DM. Thereafter, each reference alternative of the set is allocated in preordered classes [31, 32]. To arrive in results, the DRSA method consider the preference model in the form of a set of "IF…THEN…" decision rules discovered from the data by inductive learning [14, 32].

Highlighted DRSA method, the absence in weights, and preference thresholds used by DM avoiding a high cognitive effort are required. The reference examples are used as input to get DM's preference information. Moreover, there is an interactive construction between the DM and the analyst. The rules are transparent and easy to interpret for the DM and give arguments to justify and explain the decision.

3.1. Notations Used. Let set of alternatives be finite, discrete, and nonempty n, $A = \{a_1, a_2, \ldots, a_n\}$.

Let a finite, discrete, and nonempty set of alternatives $A^* = \{a_1^*, \ldots, a_k^*, \ldots\}$ assuming $A^* \subseteq A$, called the set of reference examples where the DM wishes to express his/her preferences for a given problem.

Also, let a collection of finite and nonempty set of criteria $m, C = \{c_1, c_2, \ldots, c_m\}$, and each alternative has an evaluation criterion $c_m(a_k^*)$ for all $a_k^* \in A^*$. Thus, for two alternatives a_1^* and $a_2^* \in A^*$, we have $c_m(a_1^*) \gtrsim c_m(a_2^*)$ which means that "a_1^* is at least as good in relation to a_2^* when compared with criteria c_m", representing a weak preference relation between both alternatives pairs [32]. We also assume that these criteria are preference ordered with two types: cost criteria (the smaller the better) and gain criteria (the greater the better).

In addition $\mathrm{Cl} = \{\mathrm{Cl}_t,\ t \in T\}$, with $T = \{1, \ldots, j\}$, such that $a_1^* \in A^*$ must belong to one and only one class $\mathrm{Cl}_t \in \mathrm{Cl}$. Each class is called decision class. Assuming too that these classes are ordered for all and any r and $s \in T$, such as $r > s$, the actions included in Cl_r are preferred over the actions contained in Cl_s. The sets to be approximated are called upward and downward unions of decision classes, respectively (see (1) and (2)). Consider

$$\mathrm{Cl}_t^{\geq} = \bigcup_{s \geq t} \mathrm{Cl}_s, \tag{1}$$

$$\mathrm{Cl}_t^{\leq} = \bigcup_{s \leq t} \mathrm{Cl}_s, \quad t = 1, \ldots, j. \tag{2}$$

It is assumed that for each evaluation of the alternatives with respect to criteria having a strictly monotonicity relationship with decision class, we can define the dominance relation according to [32]. Let $P \subseteq C$ be a subset of condition criteria; we can say that a_1^* *dominates* a_2^* in the condition criteria space (denoted by $a_1^* D_p a_2^*$) if $a_1^* \gtrsim a_2^*\ \forall c \in P$. Assuming, without loss of generality, that the domains of the criteria are numerical and that they are ordered so that the preference increases with the value, we can say that $a_1^* D_p a_2^*$

is equivalent to $a_1^* \geq a_2^* \ \forall c \in P$, $P \subseteq C$. The analogous definition holds in the decision class space [32].

In DRSA, the granules of knowledge used for approximation are dominance cones that are defined as follows in objects that are dominating and dominated, respectively, with respect to P:

$$D_P^+ a_1^* = \{a_2^* \in A^* : a_2^* D_P a_1^*\}, \quad (3)$$

$$D_P^- a_1^* = \{a_2^* \in A^* : a_1^* D_P a_2^*\}. \quad (4)$$

Finally, the upper and lower approximations of unions of decision classes with respect to P are calculated as follows:

(i) The P-upper approximation of $\mathrm{Cl}_t^{\geq}$: $\overline{P}(\mathrm{Cl}_t^{\geq}) = \{a_1^* \in A^* : D_P^-(a_1^*) \cap \mathrm{Cl}_t^{\geq} \neq \emptyset\}$.

(ii) The P-lower approximation of $\mathrm{Cl}_t^{\geq}$: $\underline{P}(\mathrm{Cl}_t^{\geq}) = \{a_1^* \in A^* : D_P^+(a_1^*) \subseteq \mathrm{Cl}_t^{\geq}\}$.

(iii) The P-upper approximation of $\mathrm{Cl}_t^{\leq}$: $\overline{P}(\mathrm{Cl}_t^{\leq}) = \{a_1^* \in A^* : D_P^+(a_1^*) \cap \mathrm{Cl}_t^{\leq} \neq \emptyset\}$.

(iv) The P-lower approximation of $\mathrm{Cl}_t^{\leq}$: $\underline{P}(\mathrm{Cl}_t^{\leq}) = \{a_1^* \in A^* : D_P^-(a_1^*) \subseteq \mathrm{Cl}_t^{\leq}\}$.

Finally, the P-boundaries (doubtful regions) of the unions $\mathrm{Cl}_t^{\geq}$ and $\mathrm{Cl}_t^{\leq}$ are defined, respectively, as follows:

$$Bn_P\left(\mathrm{Cl}_t^{\geq}\right) = \overline{P}\left(\mathrm{Cl}_t^{\geq}\right) - \underline{P}\left(\mathrm{Cl}_t^{\geq}\right), \quad (5)$$

$$Bn_P\left(\mathrm{Cl}_t^{\leq}\right) = \overline{P}\left(\mathrm{Cl}_t^{\leq}\right) - \underline{P}\left(\mathrm{Cl}_t^{\leq}\right). \quad (6)$$

To evaluate the results using the sample of the reference examples, the DRSA apply the accuracy of approximation. For any $t \in T$ and for any $P \subseteq C$ the accuracy is defined as $\mathrm{Cl}_t^{\geq}$ and $\mathrm{Cl}_t^{\leq}$ by P as the respective ratios (see (7) and (8)). Consider

$$\alpha_P\left(\mathrm{Cl}_t^{\geq}\right) = \frac{\mathrm{card}\left(\underline{P}\left(\mathrm{Cl}_t^{\geq}\right)\right)}{\mathrm{card}\left(\overline{P}\left(\mathrm{Cl}_t^{\geq}\right)\right)}, \quad (7)$$

$$\alpha_P\left(\mathrm{Cl}_t^{\leq}\right) = \frac{\mathrm{card}\left(\underline{P}\left(\mathrm{Cl}_t^{\leq}\right)\right)}{\mathrm{card}\left(\overline{P}\left(\mathrm{Cl}_t^{\leq}\right)\right)}. \quad (8)$$

From the accuracy approximation we can obtaining the quality approximation (see (9)). It expresses the ration of all P-correctly sorted reference examples to all reference examples in the table. For every minimal $P \subseteq C$ we define such that $\gamma_P(\mathrm{Cl}) = \gamma_C(\mathrm{Cl})$ is called a reduct of Cl and denoted by $\mathrm{RED}_{\mathrm{Cl}}(P)$. The intersection of all of the reducts is called the core and denoted by $\mathrm{CORE}_{\mathrm{Cl}}$:

$$\begin{aligned}\gamma_P(\mathrm{Cl}) &= \frac{\mathrm{card}\left(A^* - \left(\bigcup_{t\in T} Bn_P\left(\mathrm{Cl}_t^{\leq}\right)\right)\right)}{\mathrm{card}\left(A^*\right)} \\ &= \frac{\mathrm{card}\left(A^* - \left(\bigcup_{t\in T} Bn_P\left(\mathrm{Cl}_t^{\geq}\right)\right)\right)}{\mathrm{card}\left(A^*\right)}.\end{aligned} \quad (9)$$

The decision rules are the final of the DRSA method and are divided in two parts: condition and decision, where the condition part specifies the values assumed by one or more criteria and the decision part specifies an assignment to one decision class [33].

4. Development of GIS-MCDM Model for Public Safety

The present study shows the usefulness of the GIS-MCDM approach, using DRSA method. In this the section we expose the steps of the GIS-MCDM model for public safety and application performed on a real problem.

4.1. Steps of the GIS-MCDM. The integration between the DRSA method with spatial data is made in two systems. All evaluations for choosing the reference examples are prepared in a GIS environment, which avoids the decision table to realize the same procedure. Moreover, the visualization of data becomes better understood by the DM. However, to execute DRSA, we used the free software called jMAF (available at http://idss.cs.put.poznan.pl/).

The construction of the model comprises two integrated processes. The first is the selection of the reference examples using the maps, which contains the numeric values for each criterion (layers). Each layer is a set of alternatives evaluated by one criterion. The DM chooses the same subset of alternatives considering all criteria. Next, each alternative is allocated to only one predefined class. These procedures are performed in ArcGis 10.1 and exported to the second step.

In second procedure, the alternatives are evaluated for each criterion and each alternative is allocated in only one decision class [34]. Furthermore, we may get the results in relation to $\overline{P}(\mathrm{Cl}_t^{\geq})$ and $\underline{P}(\mathrm{Cl}_t^{\geq})$, as well as $\overline{P}(\mathrm{Cl}_t^{\leq})$ and $\underline{P}(\mathrm{Cl}_t^{\leq})$ for decision classes, and we may obtain the decision rules that are used to map the alternatives. Thereafter, the rules that are exported come back to ArcGis 10.1 and are implemented on the Python environment to classify all the alternatives. The decision rules are divided in the condition criteria part (IF) and decision classes part (THEN). This permits the interactive decision process to be with the DM. Because if the DM does not agree with the results, he/she can change the $A^* \subseteq A$ set. Figure 1 shows the flowchart with the procedures.

5. An Application with Real Data

In this section, we present the results of the application using real data. As follows, the model is performed with other subsets of the reference examples. Finally, we bring a discussion about the impact on the security policies.

5.1. Results of the Model GIS-MCDM. We performed an application using real data in the city of Recife, the state capital of Pernambuco, the second most populous city in Northeastern Brazil. According to Ratton et al. [35], Recife was very violent, but the violence decreased because of to the Pact for Life program, which was established in 2007 by the Government of Pernambuco. The Pact for Life program aimed to suppress the violence that plagued the state by using laws to punish crime and strategies to the violence. However,

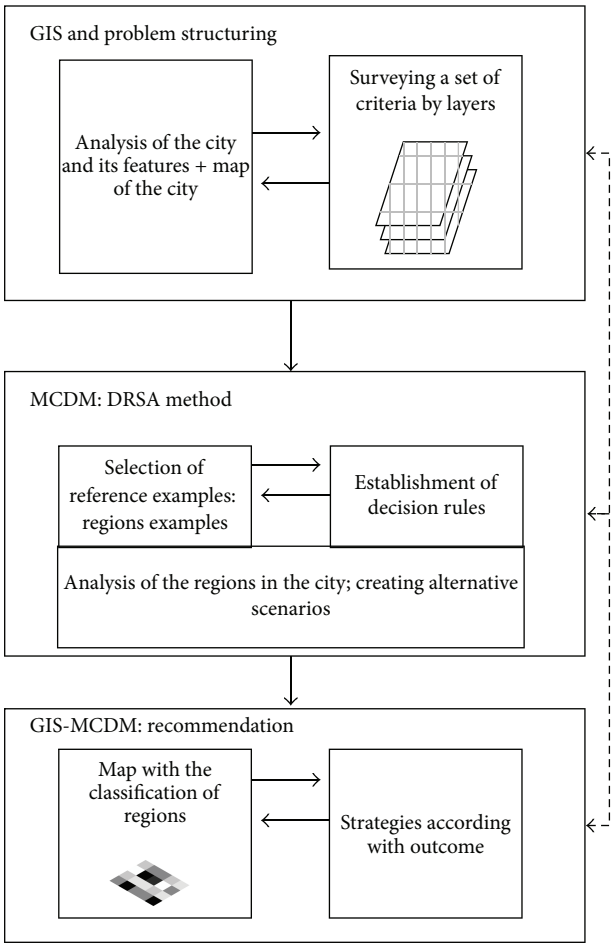

Figure 1: Flowchart used in the construction of the GIS-MCDM model.

there are still many challenges to be overcome in the program to improve it before it can fully benefit society [35].

Recife city has a spatial division called the Human Development Units (HDUs). Each unit is an alternative and is evaluated according to the criteria used in this problem. The territory that was used to perform this application is composed of 62 alternatives. Figure 2 shows the localization of Recife city.

To apply the proposed approach, different criteria were built with the base in factors that have been indicated by authors of specialized literature that explain how there are the increases in violence. In our case, these criteria explain how the increase or decrease in the occurrence influence robbery. About the issue, Andresen [3] and Levitt [36] provided detailed discussion of how related factors such as unemployment and low income affect the occurrence of crimes. For instance, a person who had no chance of working becomes motivated to commit crime in terms of disadvantaged conditions in which he or she lives. On the other hand, Fajnzylber et al. [37] and Frank et al. [5] state that there are many different factors that influence the occurrence of robbery, such as socioeconomic factors, physical environment, and demographic density, and that these factors end up being disaggregated into various peices of information related to these features.

We also check that the issue of crime is treated directly within spatial context [4, 6]; therefore, there is a motivation to use the factors that can be used to map areas that are more or less secure. In this sense, there are studies that aggregate information about the occurrence of crime to evaluate the safety level as expressed above. However, there is no preference aggregation of the DM or other criteria built by DM, with [12, 13] being an exception. Consequently, this study serves to identify areas where there are more crimes. Then, we select the approach GIS-MCDM to create results-based preference model.

Based on these factors exposed, we raised criteria that can be taken into account to evaluate the city in relation to the safety level. In our case, the criteria have a relation with robbery and are presenting a preference ordered. For the city of Recife, we consider a total of five criteria that influence the occurrence of this type of crime; these are described in Table 1, and the 2005 Atlas of Human Development in Recife was used as the data source.

When applying MCDM methods there is a difficulty in determining the contribution of each criterion in the problem (or even the relative importance). Therefore, in the DRSA method, this step of inserting information concerning the criteria is not used, and every criterion has equal importance. However, as this is a classification problem, it is necessary to assign each class a level of preference, and, in our case, this reflects the level of safety with which it is associated.

Given the criteria, five classes (Cl) were determined according to the preferences of the DM: $\mathrm{Cl}_{\text{Very high}} > \mathrm{Cl}_{\text{High}} > \mathrm{Cl}_{\text{Moderate}} > \mathrm{Cl}_{\text{Low}} > \mathrm{Cl}_{\text{Very low}}$. Thus $\mathrm{Cl}_{\text{Very high}}$ is a place with a low incidence of robberies and a very high level of security while $\mathrm{Cl}_{\text{Very low}}$ is a place with a high incidence of robberies and a very low level of security.

The exploration of the map in the initial model phase enables the choice of reference examples in the map of Recife city. Each alternative has information about the criteria and is displayed on the map to DM. In Figure 3 we present alternatives evaluated by each criterion. The values were grouped by ArcGis (this function can be called Natural breaks). Next, the data is exported in table format (.txt). We established the initial classification decision table, where the rows contain the alternatives chosen by the DM and columns contain the criteria. A decision class evaluated by the DM is listed in the final column. In Table 2, we list reference examples that were used.

Firstly, DRSA method was applied using the data from Table 2. After the quality of the results was evaluated. According to the definition in Section 3.1, an accuracy of approximation was equal to 1 in both $\mathrm{Cl}_t^{\geq}$ and $\mathrm{Cl}_t^{\leq}$ for all the decision classes. The quality of approximation was also equal to 1. Consequently, the reference examples are suitable to obtain precise classification and have a strong ability that will be used in the classification of the other alternatives.

The outcomes reveal two reducts: $\mathrm{RED}_{\mathrm{Cl}}$ (Gini, Infrastructure, Demographic density, and Education); $\mathrm{RED}_{\mathrm{Cl}}$ (Gini, Income, Infrastructure, and Demographic density). Therefore, the $\mathrm{CORE}_{\mathrm{Cl}}$ is represented by the following criteria: Gini

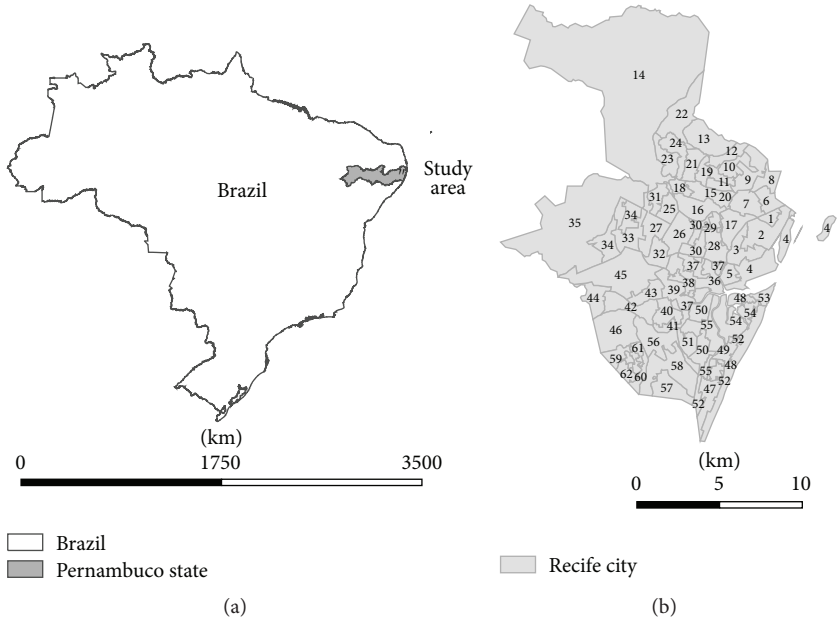

Figure 2: (a) Brazil and Pernambuco state and (b) Recife city with alternatives.

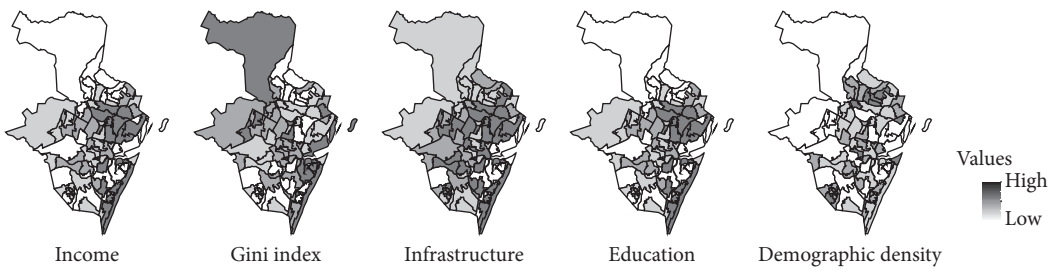

Figure 3: Alternatives considering each criterion.

Table 1: Criteria used with descriptive values.

Criterion	Maximum value	Minimum value	Mean	Standard deviation	Preference	Definition
Income, R$* (by person)	1863.64	86.15	378.66	400	Gain	The lower the income of the person the greater the chances of the person committing a crime
Gini index	0.72	0.40	0.52	0.05	Cost	Measuring the distribution of the income; if less, then people have equal distribution
Infrastructure (bathroom and piped water%)	99.59	48.53	83.57	12.40	Gain	The precarious condition makes the place prone to crime
Education (years)	13	4	7.36	2.36	Gain	The better education conditions decrease the chances of people getting involved in crime
Demographic density per km^2	28422	355	12390	6617	Cost	The population increase makes the environment more propitious for making off after the crime

*For each US$1.00 equal R$3.80.

Table 2: Reference examples evaluated by criteria and decision class.

HDU code	Gini	Income	Infrastructure	Demographic density per km^2	Education	Decision class
16	0.50	1353.42	94.74	6436	11.73	1
19	0.47	126.0	75.00	23956	5.51	1
21	0.45	141.47	78.81	18506	5.97	1
15	0.52	902.38	97.31	10888	10.58	2
20	0.47	158.00	78.00	28220	6.12	2
7	0.50	893.13	94.45	8796	11.09	3
35	0.55	187.10	78.24	1516	6.55	3
45	0.50	143.00	89.00	1930	5.52	3
2	0.50	616.00	98.00	3927	10.27	4
3	0.50	868.60	99.00	6577	11.20	4
48	0.61	1,864.00	96.00	9887	11.77	4
4	0.60	169.00	67.00	1893	5.64	5
50	0.47	571.00	95.00	6739	10.09	5

Table 3: Decision rules generated by the DOMLEM.

Rule ID	Rule description	Class	Number of supporting objects
Rule 1	IF (gini ≤ 0.47) THEN	At least very high	2
Rule 2	IF (inc ≥ 1353.42) THEN	At least very high	1
Rule 3	IF (gini ≤ 0.47) THEN	At least high	3
Rule 4	IF (inc ≥ 902.38) THEN	At least high	2
Rule 5	IF (inc ≥ 893.13) THEN	At least moderate	3
Rule 6	IF (demog ≤ 1516) THEN	At least moderate	1
Rule 7	IF (gini ≤ 0.50) & (demog ≤ 1930) THEN	At least moderate	1
Rule 8	IF (edu ≥ 10.27) THEN	At least low	6
Rule 9	IF (infr ≥ 89) & (demog ≤ 1930) THEN	At least low	1
Rule 10	IF (infr ≤ 67.00) THEN	At most very low	1
Rule 11	IF (gini ≥ 0.47) & (demog ≥ 6739) & (edu ≤ 10.09) THEN	At most very low	1
Rule 12	IF (gini ≥ 0.60) THEN	At most low	2
Rule 13	IF (gini ≥ 0.50) & (inc ≤ 868.6) & (demog ≥ 3927) THEN	At most low	3
Rule 14	IF (gini ≥ 0.47) & (inc ≤ 571.00) & (demog ≥ 6739) THEN	At most low	2
Rule 15	IF (gini ≥ 0.47) & (inc ≤ 893.13) THEN	At most moderate	8
Rule 16	IF (gini ≥ 0.50) THEN	At most high	6
Rule 17	IF (demog ≥ 28220) THEN	At most high	1

Index, Infrastructure, and Demographic density. These are the three criteria that are adequate to explain the decision, according to the DRSA method.

Then, we performed the jMAF system to create the decision rules by the DOMLEM algorithm. Using the algorithm we can obtain 17 deterministic certain decision rules from 13 reference examples in total. Those decision rules represent the certain knowledge. The certain rules are originated from P-lower approximation of $\underline{P}(\mathrm{Cl}_t^{\geq})$ and $\underline{P}(\mathrm{Cl}_t^{\leq})$ of the union class. The decision rules can be implanted directly into a GIS environment to generate the results to all the alternatives and those presented in Table 3.

Given the decision rules, we can compare the remaining alternatives that do not belong in Table 2. The results are presented in the form of map, where the darker alternatives need more attention, because they have a lower level of security. In Figure 4 the following are the classification in the all alternatives for the Recife city.

Therefore, we can draw some conclusions about the results:

(i) HDU 52 is classified as *at most very low*. Therefore, it is a place with high chances for robbery occurrence. When we compare criteria evaluations with Rules 10 and 11, we can see that the alternative complies with both rules. Also, HDU 52 has a Gini Index equal to 0.72, demonstrating a high social inequality among its inhabitants.

(ii) The alternatives 10 and 11 are encircled by other alternatives that were classified as being more prone

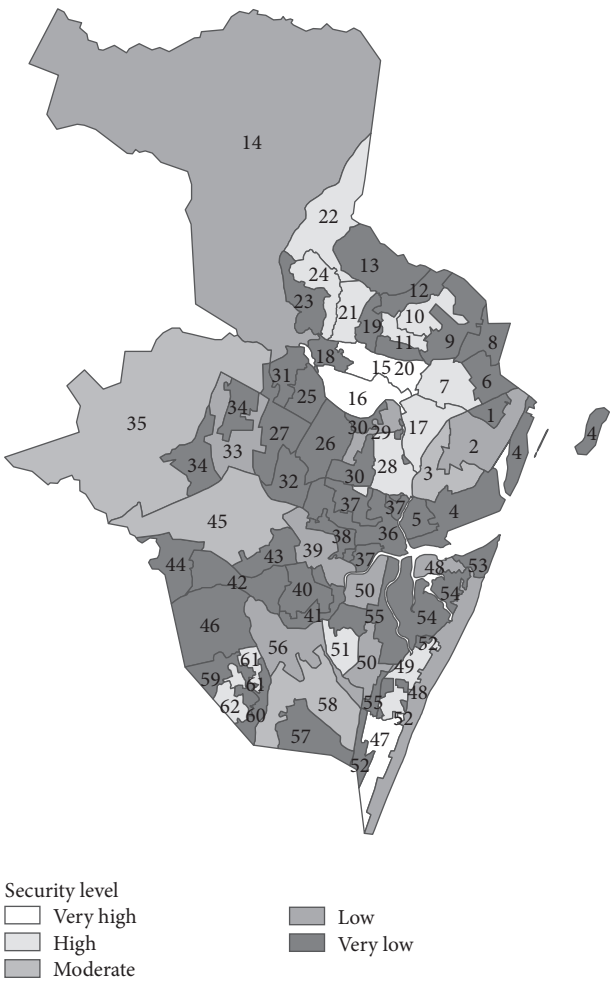

Figure 4: The classification using GIS-MCDM model for security public.

to robbery, because the criminal proliferation varies over space and time. Some alternatives fit certain rules while other alternatives are explained by other kinds of rules.

(iii) The spatial proximity of the alternatives is also highlighted. The HDUs that present darker color are neighboring other alternatives with the same color, because of the proximity along the criteria values.

5.2. Discussion. Let us now consider the change in the reference examples as an option for DM and discuss the results in the case involving a security problem. Each alternative is described in terms of the decision rules and rules have both representation and recommendation tasks. Then, we modified the data presented in Table 2 resulting in new decision rules, but these alterations maintain the readiness to interpret the results according to the DRSA method [14]. We also kept the same number of the reference examples. Either some examples that belong in Table 2 were changed by new examples or they just altered the class. Consequently, we want to check the impact presented by the new results.

The most important argument for the proposal of several rules is the fact that these rules may be applied in different results. However, it is important to discover if the alternatives swapped their security level. For instance, HDU 33 was allocated in Cl_{Low}, as can be seen in Figure 4, which takes into account Rules 8, 12, and 13. After the new application of the model, this alternative was assigned to $Cl_{Very\ low}$ class. Now, the rules that are classified in Cl_{Low} modified their values and HDU 33 complies with condition rules that classify $Cl_{Very\ low}$. On the contrary, for HDUs 17 and 28, both changed from Cl_{High} to $Cl_{Very\ high}$ class. Now, these alternatives can be considered of high level of security. The results are presented in Figure 5, which shows that some alternatives changed to new classes.

Moreover, the other remarks consider the decision rules and the remaining results. In the second result, there was only reduct and only $CORE_{Cl}$ (Gini, Infrastructure, and Demographic density). The number of rules decreased to 15, while the quality and accuracy were kept with the same values. Therefore, the examples were also suitable to explain all the data of the problem. That decision rule highlighted other combinations. For instance, IF (gini $\geq$ 0.47) & (inc $\leq$ 893.13) THEN *At most Moderate* passed to IF (income $\geq$ 893.13) & (demog $\leq$ 1516) THEN *At most Moderate*.

The second part of the section is about the problem of public security and GIS-MCDM. Reference examples in which the DM is given options by MCDM models have been widely reported [31, 38–40]. A multicriteria approach with predefined information enables the DM to know which examples give him/her the opportunity to be more secure. In our case, using the map is most favorable because the DM does not look for alternatives in a table which may represent your preference information. We also avoid other MCDM methods that use weights and preference thresholds to aggregate the preference.

The results of this study can be used to propose strategies to help the police and to enhance public security. The DM may be interested either in increasing police effectiveness or in planning public polices for improvements in certain regions (i.e., a specific set of the HDU). In the second situation, the DM may have a focus on building new schools and developing infrastructure. However, such situation would involve more than one DM, implying the problem of aggregation of group preferences; this situation is not investigated in this paper.

The criteria that are socioeconomic indicators show the discrimination of the values with respect to the security level. Alternatives allocated into Cl_{Low} have a mean year of education of 6.47 and 6.97 for first and second results for the Education criteria, respectively. However, HDUs classified in Cl_{High} and $Cl_{Very\ high}$ have a mean year of education of 8.63. These mean years present the following results: places more prone to robbery have citizens with little education. The same situation occurs for the criteria: Gini index, Income, and Infrastructure. HDUs with security decreased also present adverse values with relation to all the alternatives (Table 1). The most interesting is the Gini index (means of 0.54 for the alternatives allocated in $Cl_{Very\ low}$) because it serves as inequality indicator.

Figure 5: Comparing two results: (a) first results and (b) results using other reference examples.

Another interesting point is to observe how a modification in the reference examples may affect the result. In other words, the DM might want to check how the preference information affects the results through a more general outcome. With respect to the DRSA method, a HDU passing from one class to another is because of the new decision rules. However, we may also see the sensibility of the alternatives and use the results within security strategies. For instance, an alternative that passed to a better class no longer receives attention from the Government. Instead, there was just a change into another class, which yet requires resources to establish a secure place. Therefore, the comparison between changes of the classes is an important consideration. Figure 6 shows each situation.

Still, the second results of the model allow making two conclusions: the intention of the DM to change the set of the reference examples to apply the DRSA method or the participating of more DMs. In the first case, the DM is interested in using the other examples motivated by preference information. This fact will be necessary in case he/she does not agree with the decision rule. The second case will be the participating new DM. However, there is a problem in how to aggregate the preference for a specific situation in public security.

6. Conclusion

In this paper, we discuss the use of a GIS-MCDM approach in order to get a simple and intuitive explanation of the results. We integrate the DRSA method with the GIS tool to evaluate the safety level in Recife, Brazil. The connection in GIS-MCDM was motivated because the spatial information is available, which encourages processes that select soft reference examples. Also, the construction of the model was performed in two steps: (1) selection and evaluation of the reference examples analyzed on the spatial shape using DRSA method and (2) applying the decision rules in GIS tool to generate the final recommendation.

The two contributions expected as the study's objectives were achieved. Firstly, the feasibility of adapting the GIS-MCDM system and creating a classification problem in a georeferenced environment for the final decision was determined. These results are useful for decision-making and planning to solve public security problems through a proper implementation of the results obtained, which can give a final recommendation for the current decision problem. Then, we checked the impacts caused by the reference examples chosen and they are useful in security policies. Also, alternatives

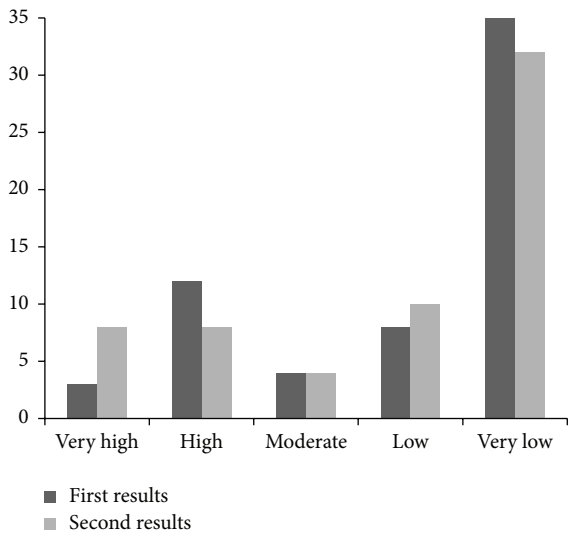

Figure 6: Distribution of HDUs class for the two results.

classified as having low level of security have the worst condition based on relation of the criteria.

Finally, the work in view of the junction between GIS and MCDM does not exhaust the possibilities of study in the field of public safety. Other studies would result in group decision-making using methodologies presented in [33, 41, 42] or adopt other multicriteria approach that use combined methods to facilitate the preference aggregation [14].

Competing Interests

The authors declare that there are no competing interests regarding the publication of this paper.

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