

Weighted Overlay, Fuzzy Logic and Neural Networks for Estimating Vegetation Vulnerability within the Ecological Economical Zoning of Minas Gerais, Brazil

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Abstract. *This paper describes the research carried out within the framework of the Ecological Economical Zoning of Minas Gerais (ZEE-MG) to model vegetation vulnerability derived by a number of spatial inference methods. Methods based on weighted overlay, fuzzy logic, and neural networks were compared in terms of visual similarity between maps, the degree of restrictiveness concerning vulnerability, and the easiness of implementation. It was concluded that weighted overlay is the best approach to be used within the ZEE-MG.*

Resumo. *Este artigo descreve os estudos realizados durante os trabalhos do Zoneamento Ecológico Econômico de Minas Gerais para modelar a vulnerabilidade da vegetação derivada de vários métodos de inferência espacial. Métodos baseados em sobreposição ponderada, lógica fuzzy e redes neurais foram comparados em função da similaridade visual entre os mapas, do grau de restrição em relação à vulnerabilidade e da facilidade de operacionalização. Foi concluído que o método de sobreposição ponderada é a melhor alternativa para ser usada no ZEE-MG.*

1. Introduction

The growing concern with natural resources brought a number of mechanisms able to guide human activities and reduce environmental impacts. Environmental studies have been used as the basis for the definition of laws that regulate land use practices. Ecological Economical Zonings are examples of such mechanisms based on the proposal of zones, which are subject to a certain model of use according to degrees of natural vulnerability and social potentiality (MMA, 2005).

Among the various actions to be implemented by the Government of Minas Gerais State within the framework of its Structural Project PE 17, the Action nº P322 (Zoneamento Ecológico-Econômico do Estado de Minas Gerais – ZEE-MG) aims at

supporting policy making related to environmental management by means of a statewide diagnosis of economical, social, ecological and biophysical sustainability.

Indicators of natural vulnerability are used within the ZEE-MG to determine the susceptibility of natural systems to human impacts. Natural vulnerability is defined in the present study as the capacity that a certain land unit has to resist and or to recover from impacts caused by human activities considered normal, i.e. not subject to environmental licensing. It is assumed that if the land unit presents a certain level of vulnerability to human activities considered normal, it will also present the same or a higher level of vulnerability to an activity subject to licensing. The concept takes into account the present condition of biotic and physical aspects of the land unit, where already disturbed areas are less vulnerable than well preserved ones.

Due to the great importance of modeling vulnerable areas for the ZEE-MG, research on alternative methods for integrating the various indicators has been carried out. In this study, the approach implemented to combine the main factors driving vegetation vulnerability will be presented and compared to other methods. Vulnerabilities of flora and fauna form the biotic component of natural vulnerability within the ZEE-MG. Weighted overlay was initially selected by the ZEE-MG team and used for most map combinations in previous studies of the biotic (Carvalho and Louzada, 2007) and abiotic components. As a further development, our main objective in the present paper was to investigate alternative methods of spatial inference, viz. fuzzy logic and neural networks, to generate maps of vegetation vulnerability for the State of Minas Gerais, Brazil, and evaluate their suitability to be used instead of weighted overlay.

2. Study site and data sets

The study area comprises the whole State of Minas Gerais. The data compiled and included in the ZEE-MG were structured in a GIS using the raster data model (Burrough & McDonnell, 1998). Spatial resolution, determined by the pixel size, was defined for the ZEE-MG as 270x270 m, representing about 7 ha on the ground.

A set of specific indicators derived from variables that represent environmental aspects might determine different levels of vegetation vulnerability. In a higher hierarchical level, vegetation vulnerability of a certain region is one of the factors determining the natural vulnerability of this area. The variables used to derive indicators of vegetation vulnerability comprised a 30x30 m resolution land cover map for the State (Scolforo & Carvalho, 2006) and a map relative to areas of special ecological interest devised by a number of vegetation specialist from Minas Gerais (Drummond et al., 2005).

The following indicators of vegetation vulnerability were used in the present study: regional relevance of physiognomies, conservation degree, spatial heterogeneity of physiognomies and conservation priority.

2.1. Indicators 1 to 9: Regional relevance of physiognomies

Regional relevance of physiognomies (Figure 1) was defined for a pixel as the ratio between the actual area of a certain physiognomy (e.g. forest) in that pixel and the total

area of the same physiognomy in a certain region. The physiognomy area for a ZEE-MG pixel (270x270 m) is determined by simply counting the number of 30x30 m pixels within the ZEE-MG pixel. The regions considered in this study correspond to the administrative boundaries of the Regional Councils of Environment (COPAM). In this case, high values of regional relevance were obtained for areas of vegetation remnants in regions with very little vegetation representing that physiognomy.

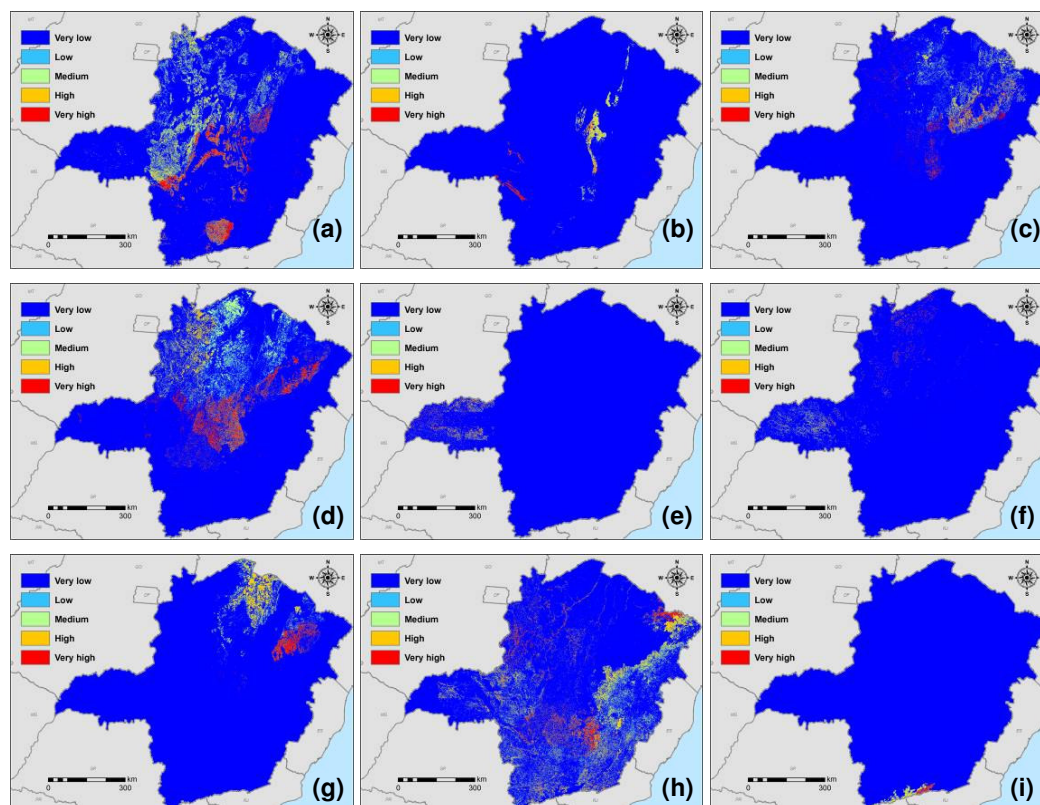


Figura 1. Regional relevance of (a) grass land, (b) rocky grass land, (c) open savanna, (d) savanna *stricto sensu*, (e) savanna woodland, (f) savanna palm land, (g) deciduous forest, (h) semi deciduous forest, and (i) evergreen forest.

2.2. Indicator 10: Degree of conservation

Following the same idea of the previous indicator, the degree of conservation (Figure 2a) was determined by counting the number of 30x30 m pixels covered by natural vegetation within each 270x270 m pixel of the ZEE-MG. Hence, well preserved areas are considered highly vulnerable to human impacts.

2.3. Indicator 11: Spatial heterogeneity

Again, this indicator (Figure 2b) was calculated by counting the number of different physiognomies that occur within each ZEE-MG pixel. This indicator captures transition areas between different physiognomies, which are thought to be highly important and, consequently, vulnerable as well.

2.4. Indicator 12: Conservation priorities

The last indicator of vegetation vulnerability (Figure 2c) was obtained by reclassifying and rasterizing vector maps relative to priority areas defined by expert knowledge. In the work of Drummond et al. (2005), vegetation specialists from all over Minas Gerais have indicated areas of relevant species endemism, the occurrence of rare or threatened species, areas of high biodiversity, ecological corridors, unique combinations of biotic and abiotic associations, and areas that lack floristic studies.

The reclassification scheme is presented in Table 1. Conservation priority classes were adjusted to fit the legend used within all outputs of the ZEE-MG project.

Table 1. Class correspondence between classification systems.

Conservation priority classes (Drummond et al., 2005)	ZEE-MG vulnerability classes
None	Very low
Corridor	Low
Potential	Medium
High	High
Very high	Very high
Extreme	Very high
Special	Very high

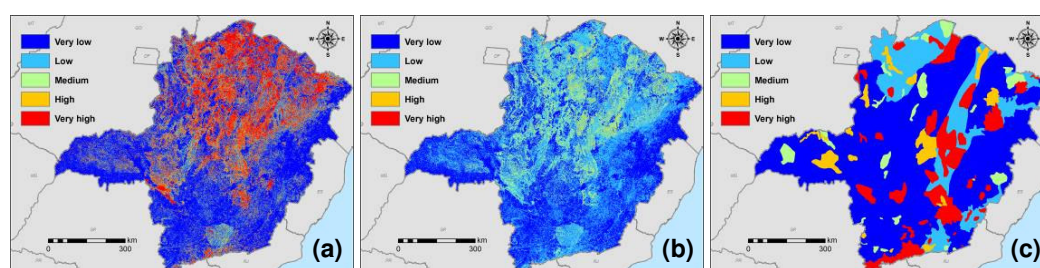


Figura 2. (a) Degree of conservation, (b) spatial heterogeneity, and (c) conservation priorities.

3. Methodology

All input data sets as well as the model outputs were registered to the Albers Conic Equal Area Projection (datum SAD-69) and resampled to 270x270 m using a nearest neighbor algorithm when necessary.

Spatial inference to come up with final maps of vegetation vulnerability was carried out by using weighted overlay, fuzzy logic, and neural networks, as detailed in the next sections. Vulnerability represented by the models outputs were classified as (1) Very low, (2) Low, (3) Medium, (4) High, and (5) Very high.

3.1. Weighted Overlay

Models based on overlay operations using weights allow a more flexible map combination when compared to operations based on Boolean logic. Modeling via Boolean logic, which has been for long used to analyze physical variables, involves the combination of binary maps generated by the application of operators (AND for

intersection, OR for union, and NOT for inclusion) that indicate two distinct conditions. Nevertheless, due to its crisp classification nature, the involved variables are considered to have the same importance to the problem at hand and the combination output will be described by a simple binary number, 1, vulnerable, or 0, not vulnerable, when vulnerability is the characteristic to be modeled.

Weighted overlay was used in this study because it is a simple and straightforward technique for spatial inference using multiple multi-class maps (ESRI, 2002). Furthermore, weights in the model represent the relative importance of each variable included in the analysis, as well as the relative importance of the classes of each variable according to a given objective. Meirelles et al. (2007a) state that the use of weighted overlay allows the inclusion of expert knowledge and the adjustment of intrinsic characteristics of each variable in the model. However, it must be highlighted here that the weights are considered constant for each variable and or class over the whole study area, which is not the case for most real world phenomena.

Following the framework of the ZEE-MG, all 12 indicators were input to the weighted overlay model with weights defined according to Table 2.

Table 2. Weights defined for each indicator of vegetation vulnerability.

Indicator	Indicator weight	Class	Class weight
Regional relevance	8	Very low	1
		Low	6
		Medium	10
		High	12
		Very high	12
Degree of conservation	12	Very low	1
		Low	6
		Medium	10
		High	12
		Very high	12
Spatial heterogeneity	4	Very low	1
		Low	6
		Medium	10
		High	12
		Very high	12
Conservation priority	12	Very low	1
		Low	2
		Medium	6
		High	12
		Very high	12

3.2. Fuzzy Logic

Methods based on fuzzy logic are very similar to weighted overlay, with the advantage that the combination rules are more flexible, thus promoting an improvement in the linear nature of the latter technique.

Instead of classifying geographical information in classes defined by exact boundaries and thereafter attributing weights to each class, one might reproduce the input data in a continuous scale using the assumption of continuous membership values. For each x value of the indicator variable, a $\mu(x)$ value is generated by a membership function, the so called fuzzyfication process, where the pair $(x, \mu(x))$ is known as the

fuzzy set. Membership functions are not necessarily linear; they can assume any analytical or arbitrary form that is appropriate to the problem under consideration.

Semantic models can be represented through various types of membership functions. The models of fuzzy classification used for environmental data are extensions of the functions that were generated by Kandel (1986). In the present paper, the symmetric fuzzy models were defined as followed:

$$FP_x = \mu A(x) = 1/\{1 + d(x-b)^2\} \quad \text{for } 0 \leq x \leq N$$

Where,

FP_x = Fuzzy membership function;

$\mu A(x)$ = Fuzzy membership level;

d = Parameter that is responsible for the function type;

b = Parameter that defines the domain of X according to the central concept.

After fuzzyfication of each variable through the membership functions, fuzzy operators were applied in order to combine the different layers. These operators allow distinct ways of manipulating simultaneously a set of layers containing fuzzy values through a process of fuzzy overlay.

Operator Fuzzy Gamma:

$$\mu_{combinação} = (SAF)^y * (PAF)^{1-y}$$

$$SAF = \mu_{combinação} = 1 - \prod(1 - \mu_i)$$

$$PAF = \mu_{combinação} = \prod \mu_i$$

Where,

SAF = Fuzzy Algebraic Sum;

PAF = Fuzzy algebraic product;

$\mu_{combination}$ = Membership value of the themes combination

μ_i = Fuzzy membership value for the map that stands in that order;

\prod = Theme maps (indicators) considered in the analyses of the phenomenon.

y = chosen parameter in the interval $[0,1]$

When y equals 1, the resulting map is identical to the result of fuzzy algebraic sum, and when y equals 0, the resulting map is identical to the result of fuzzy algebraic product. By varying the value of y , it is possible to obtain output values that assure certain flexibility between the tendency of growth of the fuzzy algebraic sum and the tendency of decrease of the fuzzy algebraic product. According to Meirelles et al. (2007b), modeling via fuzzy algebraic sum considers that if two evidences (e.g.

indicators of vulnerability) point to the same researched hypothesis, one will reinforce the other, and the resulting combination will have more support than the input evidences. Hence, the result of this operation is always a value greater or equal to the largest input value of fuzzy membership. On the other hand, the combination using the fuzzy algebraic product produces results that are always smaller or equal to the smallest input fuzzy membership value. As the goal of the present study is the maximization of vegetation vulnerability, two values of the parameter γ were used for the operator fuzzy gamma: $\gamma = 0.75$ and $\gamma = 0.95$.

Operator Fuzzy Convex Sum:

If A_1, \dots, A_k are subsets of X , and w_1, \dots, w_k are non negative weights then the convex combination of A_1, \dots, A_k is:

$$\mu_A \Delta \sum w_j \mu_{A_j}$$

Where, $\sum w_j = 1$

This procedure of defining weights is very similar to modeling via weighted overlay, but the class values are continuous in the interval $[0,1]$. The convex sum is generally used when the effects of the indicators are not equal. In the present study, weights were defined for the operator convex sum according to Table 2 as well.

3.3. Neural Networks

Neural networks are problem solving algorithms of the machine learning field. They use methods and techniques inspired on historical facts and models of biological neurons and networks. These biologically inspired models are extremely efficient when the pattern of classification is not a simple and trivial one (Barreto, 2002). Neural networks have shown to be helpful in the solution of practical problems as well as capable of classifying highly complex data (Kanellopoulos et al., 1997).

Self Organizing Maps

For the present work three different types of networks were used. Unsupervised neural networks called Self Organizing Maps (SOM) (Kohonen, 1990), were used to create vulnerability maps. SOM was implemented in two configurations: coupled and uncoupled with a k -means clustering algorithm. Unsupervised learning does not need input samples for pattern recognition. This perfectly fits the scope of this work since there was no collection of training data representing vulnerability classes.

The parameters presented in Table 3 were chosen after a number of trials and following empirical knowledge.

Table 3. SOM neural network parameters.

Parameter	SOM (without k -means)	SOM (with k -means)
Input layer neurons	12	12
Output layer neurons	9	36
Initial neighborhood radius	5.24	9.49
Minimum learning rate	0.5	0.5
Maximum learning rate	1	1
Iterations	874,080	628,992
Quantization Error	0.0241	0.0187

Fuzzy ArtMap

For Mather (1999) the use of soft classification paradigms with neural networks is adequate when we want to avoid errors of classification due to ambiguity of the generated classes. The third type of network considered in the present study was based on the ART (Adaptive Resonance Theory) (Carpenter et al., 1991), which exhibits a high degree of stability in order to preserve significant past learning, but remain enough adaptable to incorporate new information whenever it might appear (Carpenter, 1989). Fuzzy ArtMap is a clustering algorithm that operates on vectors with fuzzy analog input patterns (real numbers between 0 and 1) and incorporates an incremental learning approach which allows it to learn continuously without forgetting previous learned patterns. The Fuzzy ArtMap parameters used to estimate vegetation vulnerability in this study are summarized in Table 4. Again, the parameters were defined after a number of tests and according to previous expert knowledge.

Table 4. Fuzzy ArtMap neural network parameters.

Parameter	Fuzzy ArtMap
F1 layer neurons	24
F2 layer neurons	6
Choice parameter	0.01
Learning rate	1
Vigilance parameter	0.95
Iterations	48,923

4. Results and Discussions

The process of combining indicators of vegetation vulnerability generated a number of raster maps according to different inference models. For comparison purposes, the results for an example area within the State of Minas Gerais are illustrated in Figures 3 and 4.

4.1. Weighted overlay x Fuzzy logic

In Figure 3, models based on fuzzy logic are compared to the model generated via weighted overlay.

When comparing the maps of vegetation vulnerability generated by weighted overlay (Figure 3a) and the operator Fuzzy Gamma ($y=0,95$) (Figure 3b), it is observed that vulnerability classes are different for some regions. Some areas classified as medium and high vulnerability by the operator Fuzzy Gamma ($y=0,95$) were classified as low and very high vulnerability when using weighted overlay. Hence, the former seems to be less restrictive than the latter. This pattern might be due to the fact that weighted overlay uses a constant weight for the entire map extent. By decreasing the value of y , the output also shows a decrease in the values of fuzzy memberships probably due to the tendency of minimization that is characteristic when y approaches zero. Among all other fuzzy operators, the Fuzzy Gamma ($y=0,75$) is the most similar to the output generated by weighted overlay.

On the other hand, the Fuzzy Algebraic Sum (Figure 3c), maximized membership values when compared to the other operators used in the analysis. More

classes of very high vulnerability were obtained in this case showing that it is the most restrictive model.

Fuzzy Convex Sum (Figure 3d) showed results that are very close to the ones obtained with Fuzzy Gamma ($\gamma=0,95$), except for some areas that were classified as having medium vulnerability by Fuzzy convex sum and low vulnerability by Fuzzy Gamma. The other classes remained constant between the two operators. Weighting performed by Fuzzy Convex Sum probably caused this difference. This evidence shows the flexibility of this operator while using weights during the classification process.

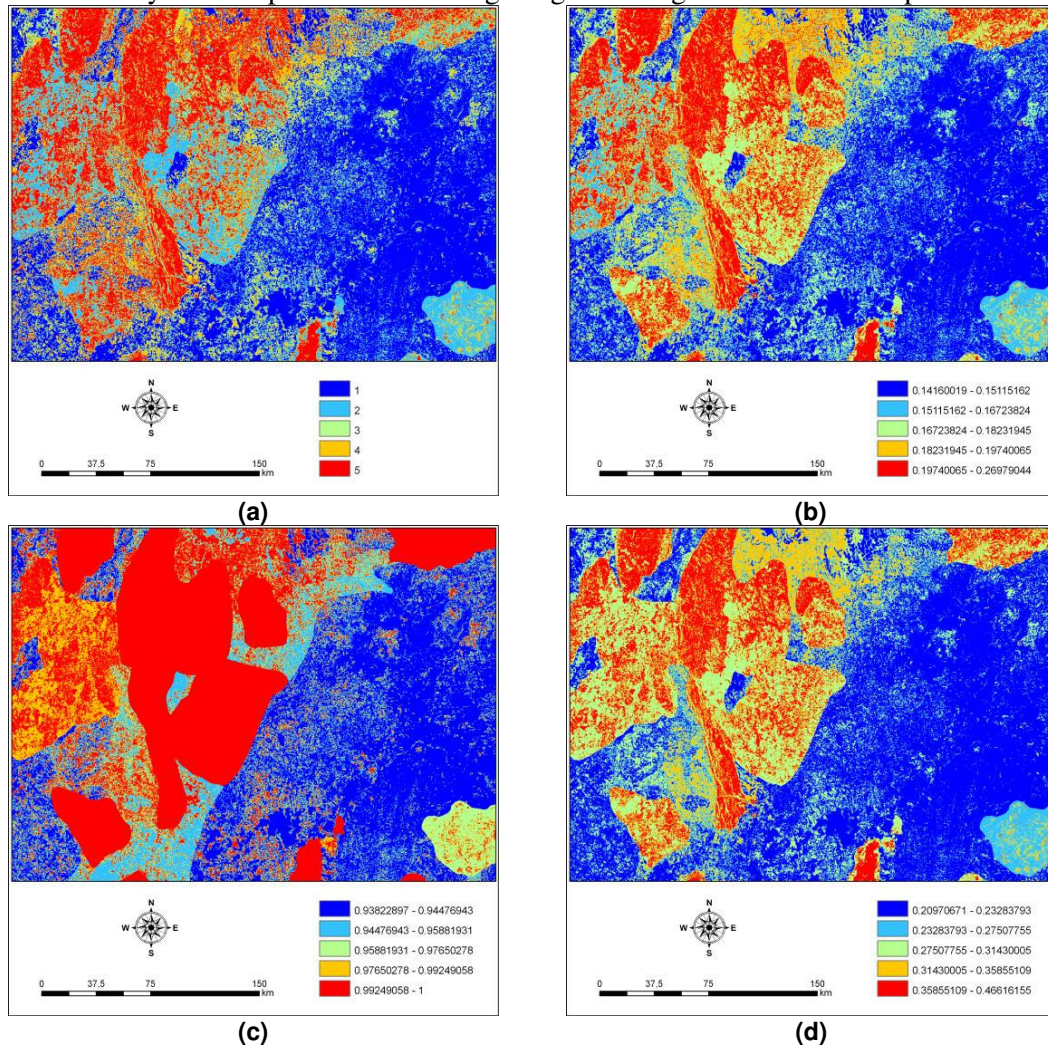


Figura 3. Vegetation vulnerability maps generated by the following models: (a) Weighted overlay, (b) Fuzzy Gamma ($\gamma = 0,95$), (c) Fuzzy Algebraic Sum, and (d) Fuzzy Convex Sum.

4.2. Weighted overlay x Neural networks

In Figure 4, models based on neural networks are compared to the reference model generated via weighted overlay (Figure 4a).

The map produced using Fuzzy ArtMap (Figure 4b) showed patterns similar to the results of Fuzzy Algebraic Sum maximizing most of the membership values and leading to a more restrictive scenario characterized by homogeneous zones. These patterns show a strong influence of the indicator related to conservation priorities. On the other hand, the map produced using SOM without k -means was not influenced by this indicator at all. It is noticed that the degree of conservation was the most important factor driving vegetation vulnerability when this model was implemented. Vulnerability was either very low or very high, with a few areas showing intermediate values.

Finally, the map produced using SOM with k -means clustering (Figure 4c) was similar to the reference map produced using weighted overlay (Figure 4a). It showed a better balance while representing the influence of each indicator. SOM with k -means also presented smoother transitions between classes. Nevertheless, neural networks have been criticized because of its “black box” nature. In fact, it is difficult for a non-expert to understand and set the network parameters, leading to an arbitrary result of vulnerability classes and less control of the indicators influences.

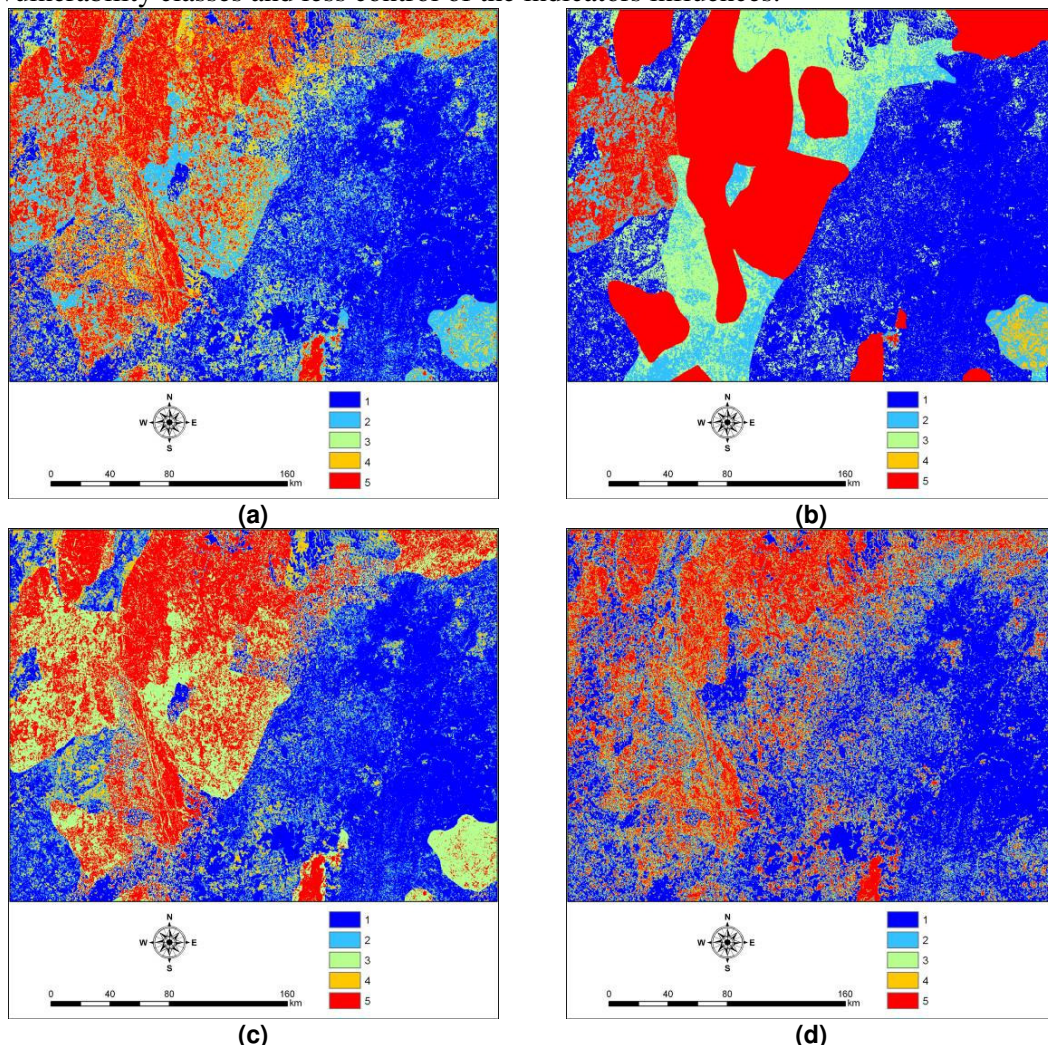


Figure 4. Vegetation vulnerability maps generated by the following models: (a) Weighted overlay, (b) Fuzzy Artmap, (c) SOM k -means, e (d) SOM.

4.3. Comparison criteria

As no reference data was available for estimating the accuracy of vegetation vulnerability maps, comparison criteria were empirically defined based on the visual similarity between maps, the degree of restrictiveness concerning vulnerability, and the easiness of implementation. Evaluation of these criteria led to the choice of weighted overlay as the most robust inference method considered in the present study, and thus kept within the framework of the ZEE-MG. SOM *k*-means, Fuzzy Gamma, and Fuzzy Convex Sum, showed similar results to the weighted overlay procedure, approaching patterns of vulnerability thought to be closer to reality according to the knowledge of experts involved in the project. Even so, weighted overlay was chosen because it is easier to be implemented with complete control over the involved indicators.

In Figure 5, the vegetation vulnerability map produced using weighted overlay is presented for the entire State of Minas Gerais.

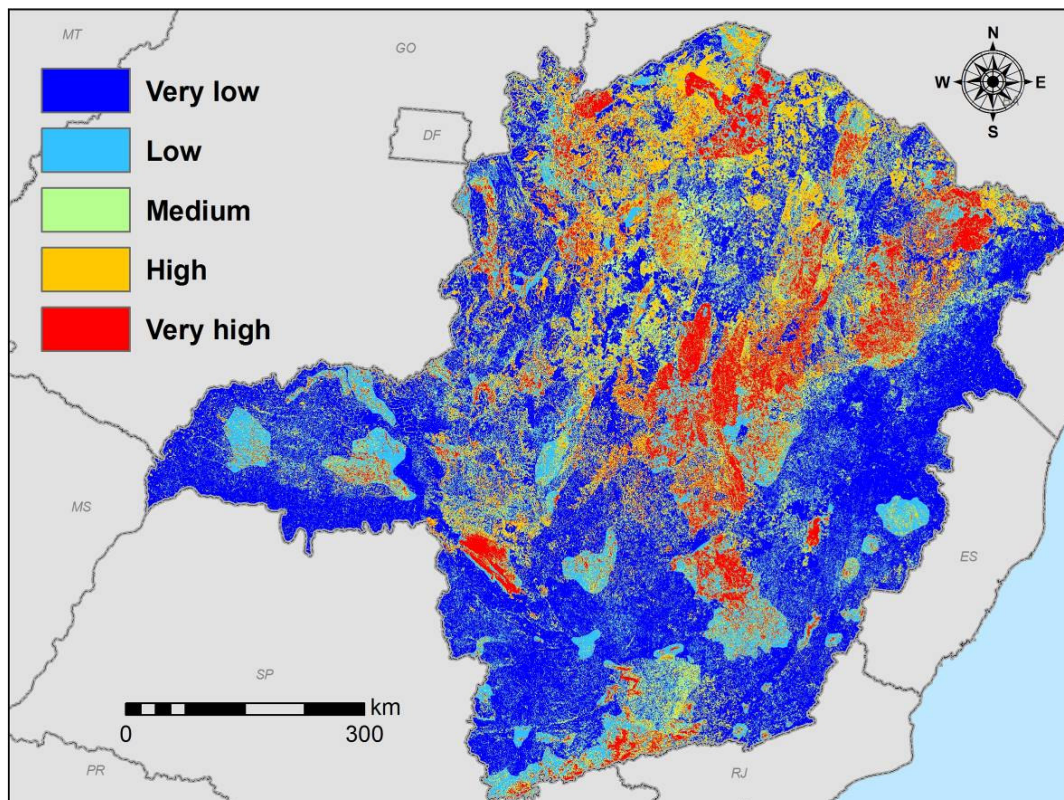


Figura 5. Vegetation vulnerability map obtained via weighted overlay and chosen according to the defined comparison criteria.

5. Conclusions

In this paper, a number of inference methods were implemented to produce maps of vegetation vulnerability. Methods based on fuzzy logic and neural networks were compared to weighted overlay, which was considered to be the reference map because it was already implemented during previous phases of the ZEE-MG.

We concluded that weighted overlay will not be replaced by any of the other tested methods. They are less intuitive, dependent on a number of arbitrary parameters, demand more computational power, and do not provide significant improvements when compared to the map produced using weighted overlay.

Nevertheless, fuzzy logic seems to be a promising approach and further research will be carried out in order to test different fuzzification methods, as well as different fuzzy operators to produce maps of vegetation vulnerability and to combine them with other biotic and physical components of natural vulnerability.

Neural networks provided interesting results, but due to the difficulties in setting the network parameters the method will be disregarded within the ZEE-MG.

Finally, a framework to collect field data concerning vegetation vulnerability classes will be developed to provide a robust base to carry out vulnerability map comparisons.

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