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FLORISTIC DIVERSITY AND EQUITABILITY IN FOREST FRAGMENTS USING ARTIFICIAL NEURAL NETWORKS

DIVERSIDADE FLORÍSTICA E EQUABILIDADE EM FRAGMENTOS FLORESTAIS USANDO REDES NEURAIS ARTIFICIAIS

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ABSTRACT

This study aimed to evaluate the predictive efficiency of Shannon index (H') and Pielou Equitability index (J) in forest fragments from the Brazilian Cerrado biome, from the vegetation indices and landscape metrics using artificial neural networks (ANN). Feedforward networks were used and they were trained through a back propagation error algorithm. The variables used as ANN input for simultaneous estimation of indices were: the categorical (H' and J) and the numbers related to the mean and standard deviation of vegetation indices (NDVI, SAVI, EVI, and MVI5, MVI7) and landscape metrics (AREA, GYRATE, SHAPE, CONTIG, CORE and ENN). It was generated five models of ANN from the functional relationships between numerical variables inherent to vegetation indices in two seasons, a dry season (June) and a rainy season (February). The architecture of the networks was the Multilayer Perceptron (MLP), to estimate simultaneously the H' and J: 500 using vegetation indices in the wet season (100 for each vegetation index) and 500 in dry (100 for each vegetation index). The precision, accuracy and realism of biological ANN were assessed. The nets built during the rainy season and dry season that used vegetation indices MVI5 (Moisture Vegetation Index) and SAVI (Soil Adjusted Vegetation Index), respectively, were more appropriate, accurate and biologically realistic to estimate both indices H' and J. The ANN modeling demonstrated to be adequate to estimate the diversity index.
Keywords: biological diversity; Brazilian Cerrado; MLP.

RESUMO

Este estudo teve como objetivo avaliar a eficiência da predição dos índices de diversidade de Shannon (H') e de Equabilidade de Pielou (J) em fragmentos florestais do Cerrado brasileiro a partir de índices de vegetação e métricas da paisagem empregando redes neurais artificiais (RNA). Utilizaram-se redes anteroalimentadas (*feedforward*), treinadas por meio do algoritmo da retropropagação do erro (*back propagation*). As variáveis utilizadas como entradas das RNA para a estimação simultânea dos índices foram: as categóricas (índices H' e J) e as numéricas relacionadas às médias e desvios padrão dos índices de vegetação (NDVI, SAVI, EVI, MVI5 e MVI7) e métricas da paisagem (AREA, GYRATE, SHAPE, CONTIG, CORE e ENN). Foram gerados cinco modelos de RNA a partir das relações funcionais entre as variáveis numéricas inerentes aos índices de vegetação em duas épocas, uma seca (junho) e outra chuvosa (fevereiro). A arquitetura das redes foi a Multilayer Perceptron (MLP) para estimar simultaneamente H' e J: 500 utilizando os índices de vegetação na época úmida (100 para cada índice de vegetação) e 500, na seca (100 para cada índice de vegetação). Foi avaliada a precisão, acurácia e realismo biológico das RNA. As redes construídas na época chuvosa e seca que utilizaram os índices de vegetação MVI5 (Moisture Vegetation Index) e SAVI (Soil Adjusted Vegetation Index), respectivamente, foram mais adequadas, precisas e realistas biologicamente para estimar, simultaneamente, os índices de H' e de J. A modelagem por RNA demonstrou-se adequada para estimar os índices de diversidade e equabilidade.
Palavras-chave: diversidade biológica; Cerrado; MLP.

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INTRODUCTION

Biodiversity is often estimated using remote sensing images through basic vegetation indices such as NDVI (Normalized Difference Vegetation Index) and traditional statistical techniques such as regression (FOODY; CUTLER, 2006; SCRINZI et al., 2007). Among the vegetation indices, NDVI provides an estimate of "greenness" of vegetation or biomass per pixel and is commonly used in remote sensing studies (INGRAM et al., 2005; MAEDA et al., 2009).

Relationship between spectral data and forest attributes are usually complex and nonlinear, and may vary between different bands (INGRAM et al., 2005). Even under these conditions, linear regression establishing relationships between the variables of interest is common in studies that utilize remote sensing (BRADSHAW et al., 2002; INGRAM et al., 2005). These approaches are not always appropriate, being recommended methods that do not rely on assumptions about the statistical distributions of variables (or nonparametric). In the search for new options for a safe and efficient characterization of diversity indices, what stands out is artificial intelligence. Artificial neural networks (ANN) represent a new approach to the development of predictive models, capable of learn complex patterns and trends in data, even if not normal, or linear, are dynamic, flexible and adaptable (HAYKIN, 2001; SCRINZI et al., 2007).

The ANN computer systems are structured in similarity to the human brain's design and information processing (MAEDA et al., 2009). Made up of simple processing units (or artificial neurons), its training consists in providing to pre-established architecture a pair of patterns: a standard input and the desired, corresponding to output pattern (MONJEZI et al., 2010). Several algorithms can be used in training a neural network model. The back propagation algorithm is the most versatile, robust technique and provides more efficient learning in multilayer networks (MLP) (TAWADROUS; KATSABANIS, 2009). This architecture builds global proximity, consisting in an input layer, one or more hidden layers and an output layer (SOARES et al., 2011).

The efficiency of ANN can be evaluated using a type of cross-validation commonly referred to as holdout method (HAYKIN, 2001). Based on the separation of a set of data into mutually exclusive subsets, in which part of the data is used in training and the other remaining data in validation. This procedure is important to test the ability to correctly classify patterns not included in the training, and therefore the definition of the network with better generalization ability (FERNANDES et al., 2004).

The networks are being increasingly used in environmental sciences. Recent applications include the prediction of severe events using meteorological data (PESSOA et al., 2012). Ingram, Dawson and Whittaker (2005) demonstrated the potential use of ANN integrating satellite data (Landsat ETM +) in the spectral bands 3, 4, 5 and 7, to estimate the basal area of Madagascar's southeastern tropical forests. Foody and Cutler (2006) found a strong correlation between the biodiversity indices estimates derived from remote sensing and field research while working on mapping the richness of species and composition of tropical forests in ANN.

Remote sensing can provide useful information on biodiversity (CABACINHA; CASTRO, 2009; FOODY; CUTLER, 2006; INGRAM et al., 2005; KALACSKA et al., 2007). The ANN associated with remote sensing can be a viable alternative in research on sustainability and establishment of practical criteria for the characterization and classification of sites for the assessment of environmental impacts and recovery of degraded areas. In this article, the following hypotheses are being tested: (i) ANN is suitable to estimate the Shannon Index and Pielou Equitability Index and (ii) ANN can provide biologically accurate and realistic estimates for the Shannon Index and Pielou Equitability Index. This study aimed to evaluate the efficiency of the prediction of the Shannon diversity index and Pielou Equitability Index in fragments the Brazilian Cerrado biome, from vegetation indices and landscape metrics employing ANN.

MATERIAL AND METHODS

Study area

The study area where data were collected is located in the extreme southwest of Goiás state, in Mineiros region, and the south of Mato Grosso state, in Alto Araguaia region, near the frontier of these two states and Mato Grosso do Sul (Figure 1). It is located in the quadrant formed by the coordinates, 17^{o}49´12”S and 53^{o}15´00”, 18^{o}03´36”S and 52^{o}57´00”W, covering 52,214.70 ha area. According to the Köppen climate classification the region presents a climate type Aw, characterized by being; tropical rainy, with hot summers and dry winters and annual mean temperatures between 18 and 32 ^{o}C and the annual precipitation varies between 1500 and 1600 mm (OLIVEIRA et al., 2003). Further details can be seen in Cabacinha and Castro (2009).

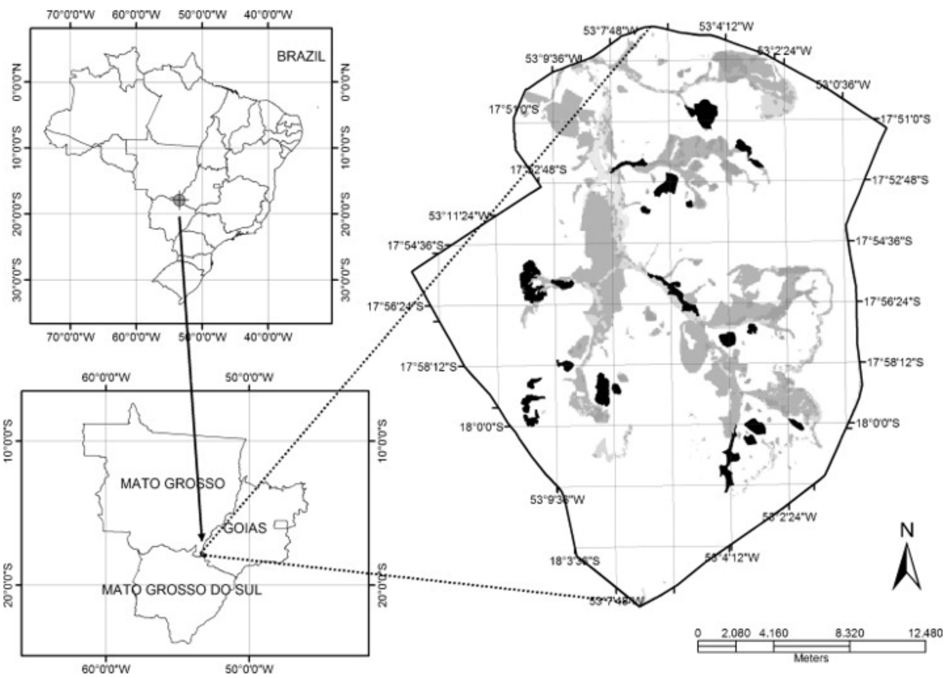

FIGURE 1: Localization of the study area and location of forest fragments (black) studied. Brazil. Using lat/long unit. Font: Cabacinha and Castro (2009).

FIGURA 1: Localização da área de estudo e locação dos fragmentos florestais (preto) estudados. Brasil. Usando unidades de latitude e longitude. Fonte: Cabacinha and Castro (2009).

Artificial neural network model

The data used in the training of artificial neural networks relates to each fragment evaluated. This training, also called learning, consists in adjusting network parameters (weights and biases) through a learning algorithm (MAEDA et al. 2009). In this process, the training data set (examples) are submitted to a pre-set architecture, i.e. a number of neuron arrangements in layers and the training algorithm extracts features in order to represent the information and to perform a given task. The variables used as input of ANN for simultaneous estimation of diversity indices were: a categorical index (H’: 1 and J: 2) and the number related to the medium (M) and standard deviations (D) of vegetation indices (NDVIM, NDVID, SAVIM, SAVID, EVIM, EVID, MVI5N, MVI5D, MVI7M and MVI7D) and landscape metrics (AREA, GYRATE, SHAPE, CONTIG, CORE and ENN). Further details can be seen in Cabacinha and Castro (2009).

For the prediction of diversity (ID) 5 models were generated from ANN from the functional relationships between numerical variables inherent vegetation indices in two seasons, a dry season (June) and a rainy season (February):

$$ID_x = f(Indice_x, NDVI, SAVI, EVI, MVI5, MVI7)$$

When *x* equal 1 and 2 refer to H’ and J, respectively. Ten ANN were constructed (Table 1).

TABLE 1: Identification and inputs used in artificial neural networks (ANN) to estimate the diversity index due to the season.
TABELA 1: Identificação e *inputs* utilizados nas redes neurais artificiais (RNA) para estimar os índices de diversidade em função da época.

Season	ANN	n	-------------------------- Inputs --------------------------	
			Numerical	Categorical
Rainy (February)	1	44	*NDVIM, NDVID, A, G, S, CONTIG, CORE, ENN*	Índice
	2	44	*SAVIM, SAVID, A, G, S, CONTIG, CORE, ENN*	Índice
	3	44	*EVIM, EVID, A, G, S, CONTIG, CORE, ENN*	Índice
	4	44	*MVI5M, MVI5D, A, G, S, CONTIG, CORE, ENN*	Índice
	5	44	*MVI7M, MVI7D, A, G, S, CONTIG, CORE, ENN*	Índice
Dry (June)	6	44	*NDVIM, NDVID, A, G, S, CONTIG, CORE, ENN*	Índice
	7	44	*SAVIM, SAVID, A, G, S, CONTIG, CORE, ENN*	Índice
	8	44	*EVIM, EVID, A, G, S, CONTIG, CORE, ENN*	Índice
	9	44	*MVI5M, MVI5D, A, G, S, CONTIG, CORE, ENN*	Índice
	10	44	*MVI7M, MVI7D, A, G, S, CONTIG, CORE, ENN*	Índice

Em que: *A* = ÁREA. *G* = GYRATE. *S* = SHAPE. When "Índice" equal 1 and 2 refer to H' and J, respectively. n = number of observations.

Training and validation

The networks were fed and trained through the error back propagation algorithm, i.e. during training, calculations were performed from the input layer to the network output and the error propagated to previous layers. In all of the pre-processing, it was performed a normalization and equalization of data thus enhancing the sensitivity to the variation of the same network to better capture their behavior. In accordance with Bradshaw et al. (2002) and Pessoa et al. (2012), the data were divided into groups of training and of validation using random sampling method. That is, 80% of samples were taken for the first group and the remainder in the second.

Thousand ANN of the type Multilayer Perceptron (MLP) were trained to estimate simultaneously the H' and J: 500 using vegetation indices in the wet season (100 for each vegetation index) and 500 in the dry season (100 for each vegetation index). We adopted a heuristic model as described by backward elimination Cerqueira, Andrade and Poppi (2001). Of these ANN, were selected one of each type based on the deviation of the observed and estimated values. One of the most common problems observed in the training of the ANN is overfitting. Seeking to avoid it, the training of the networks was stopped when the error began to increase, as Bradshaw et al. (2002), and Maeda et al. (2009).

The optimal number of hidden layers and neurons per layer is not generally known, a priori. Once defined the architecture and training parameters of the artificial neural network, it is trained in an interactive form (BLACKARD; DEAN, 1999). Therefore, the definition of the network architecture was optimized by the tool Intelligent Problem Solver (IPS) from the software 'Statistica 7.0' (STATSOFT, 2007). The number of neurons is data dependent, and the following formula was applied as by Ingram, Dawson and Whittaker (2005):

$$N = 2i + 1$$

Where ***N*** is the number of neurons in the input layer *i* is equal to the number of inputs of the network. There were nine inputs formed by numerical and categorical variables.

Model performance

The evaluations of the accuracy and precision of the training of ANN were performed using the $Error_{\%}$, $RMSE_{\%}$ test, $Bias_{\%}$ test and a graphical analysis to observe the magnitude and distribution of error percentage and detect systematic discrepancies. The estimates were compared using the paired *t*-test probability to 5.0 % with the observed values as Gorgens et al. (2009). The errors (residuals) were defined as follows:

$$error_{\%} = ((\hat{y} - y)/y)100$$

Where and are the observed and predicted values, respectively.

The root mean square error ($RMSE_{\%}$) and tendencies ($Bias_{\%}$) were determined according Mabvurira and Miina (2002):

$$RMSE_{\%} = 100\left(\sqrt{\sum(y_i - \hat{y}_i)^2/n-1}\right)/\left(\sum \hat{y}_i/n\right)$$

$$BIAS_{\%} = 100\left(\sum(y_i - \hat{y}_i)\right)/\left(\sum \hat{y}_i/n\right)$$

Where and are the observed and predicted values, respectively.

The points that extrapolated the general trend of diversity indices were not eliminated in order to verify the ability of artificial neural networks to deal with outliers or noises. It was used the Pearson correlation coefficient ($\alpha = 0.05$) to assess the relationship between number of neurons, cycles and statistical precision of ANN. To verify that the estimated data meet the assumptions for performing the analysis of variance, normality was tested, as by Shapiro Wilk and homogeneity of variances by graphical analysis and Cochran test. All statistical analyzes were performed using the software Statistica 7.0 (STATSOFT, 2007).

RESULTS AND DISCUSSION

Most networks presented nonlinear activation functions in hidden and output layers (Table 2). The networks that used vegetation indices NDVI and EVI as numerical input presented a pure logistic and linear approximation, respectively in the hidden layer, followed by sigmoidal activation functions in the next layer. By the training of ANN, the largest number of neurons in hidden layer resulted in greater complexity for ANN 4 and 7. The networks that integrated NDVI, EVI and MVI7 presented a simpler architecture. The number of cycles and the neurons in the hidden layer showed a correlation coefficient of 0.52^{ns}. The correlation coefficients for the training of networks built during the wet and dry seasons were strong (above 0.99). The difference between the correlation coefficients of the training and validation were, on average, of 0.04, being smaller in the networks that integrated the SAVI and MVI5. It was noticed fewer cycles (median 87 cycles) in the training the networks that were based on EVI.

Residuals of the networks 4, 5 and 7 followed a homogeneous distribution in accordance with Cochran test and Figure 2. These networks had little noise as outliers by taking the data lines that, after processing showed higher levels of diversity than 2.0 standard deviation units compared to the corresponding observed data. This criterion was used by Maeda et al (2009). Estimates of these ratios tended to normality by the Shapiro Wilk test ($p_W = 0.34$ for ANN 4, $p_W = 0.64$ for ANN 5 and $p_W = 0.47$ for ANN 7).

Network predictions 4, 5 and 7 did not generate estimates similar (Figure 2), and the ANN 5 showed less symmetrical distribution (Figure 2).

Despite the loss of accuracy verified when the area of the fragments was smaller, the use of vegetation index and landscape metrics associated with artificial intelligence provided accurate estimates of the diversity of fragments in Cerrado, both in the rainy season (MVI5) and in the dry one (SAVI).

Network ability with MLP architecture to establish nonlinear relationships between dependent and independent variables may have been impaired by activation functions of the type identity in the middle tier, considering that the largest $RMSE_{\%}$ (average 9.5 %) during learning networks were observed in EVI used as numeric entry (Table 3). The inherent ability of MLP in making nonlinear approximations in the hidden layer is important because it allows the composition of functions in successive layers to solve

TABLE 2: Characteristics of artificial neural networks (ANN) constructed to estimate the diversity index as a function of season.
TABELA 2: Características das redes neurais artificiais (RNA) construídas para estimar os índices de diversidade em função da época.

ANN	Architecture	Correlation coefficient		Cycles	Activation function	
		Training	Validation		Hidden	Output
1	MLP 10-6-1	0.9982*	0.9509*	902	Logistic	Tangential
2	MLP 10-8-1	0.9986*	0.9454*	385	Logistic	Logistic
3	MLP 10-5-1	0.9906*	0.8975*	64	Identity	Logistic
4	MLP 10-12-1	0.9999*	0.9835*	1029	Exponential	Logistic
5	MLP 10-6-1	0.9994*	0.9637*	660	Logistic	Identity
6	MLP 10-4-1	0.9970*	0.9416*	187	Logistic	Logistic
7	MLP 10-13-1	0.9999*	0.9837*	449	Exponential	Exponential
8	MLP 10-5-1	0.9742*	0.9534*	109	Identity	Tangential
9	MLP 10-9-1	0.9993*	0.9610*	671	Logistic	Exponential
10	MLP 10-4-1	0.9978*	0.9522*	315	Logistic	Tangential

Where in: Wet season: ANN from 1 to 5; Dry Season: ANN from 6 to 10. $^{*}p < 0.05$.

TABLE 3: Artificial neural networks (ANN) precision constructed to estimate the diversity index as a function of season.
TABELA 3: Precisão das redes neurais artificiais (RNA) construídas para estimar os índices de diversidade em função da época.

ANN	Phases	$RMSE_{\%}$	$Bias_{\%}$	Relative errors (%)			*t*-test
				Maximum	Medium	Minimum	*p*
1	Training	3.2	0.3	5.2	-0.1	-5.2	0.5339
	Validation	16.7	0.2	17.2	0.1	-16.9	0.9688
2	Training	2.9	0.3	9.1	-0.1	-6.6	0.4938
	Validation	18.0	2.2	18.9	-1.8	-18.2	0.7402
3	Training	7.2	0.7	13.5	-0.6	-10.3	0.5866
	Validation	25.3	4.1	21.1	-3.8	-32.2	0.6568
4	Training	0.8	0.1	4.0	-0.1	-6.3	0.5442
	Validation	11.6	-3.5	14.7	1.6	-13.5	0.4020
5	Training	1.8	0.0	7.6	0.1	-5.0	1.0000
	Validation	14.8	-1.7	16.8	1.1	-13.6	0.7521
6	Training	4.2	0.4	10.8	0.1	-6.9	0.5848
	Validation	18.3	0.7	20.1	-0.3	-19.2	0.9120
7	Training	0.7	0.0	4.8	0.1	-3.8	0.8859
	Validation	9.6	0.0	8.9	-0.4	-14.0	0.9938
8	Training	11.8	0.5	24.7	0.2	-19.1	0.8184
	Validation	17.2	0.9	17.2	-3.2	-30.1	0.8859
9	Training	2.0	-0.3	11.9	0.6	-4.3	0.4373
	Validation	14.9	-0.1	18.8	0.1	-14.4	0.9909
10	Training	3.5	0.4	6.5	-0.2	-5.6	0.4677
	Validation	16.3	-0.2	17.9	-18.0	-18.0	0.9696

the problems of higher order in the input space, even if the classes are not linearly separable (HAYKIN, 2001). Even if the EVI is an enhanced vegetation index that considers the effect of soil (SAVI) and the atmosphere (ARVI, *Atmosphere Resistance Vegetation Index*) (CABACINHA; CASTRO, 2009), a good training was not observed. This may be associated with an under fitting (the network does not converge during training) generated by a small number of cycles (Table 1), preventing the network from reaching its optimum performance.

Networks complex was not necessarily caused by a greater number of times that training set was presented to the architecture, because the ANN 7 had more neurons in the hidden layer and fewer cycles when compared to network 1 and 5 (Table 2). However, the performance during the training and validation phases may have been influenced by both the number of neurons as by the number of cycles (Table 2 and 3) (CERQUEIRA et al., 2001; HAYKIN, 2001; MAEDA et al., 2009). Even though the slightest error during the training of validation suggests an excessive storage of data during teach (MAEDA et al., 2009), overfitting was not verified. This phenomenon can occur when there is an excessive number of neurons in

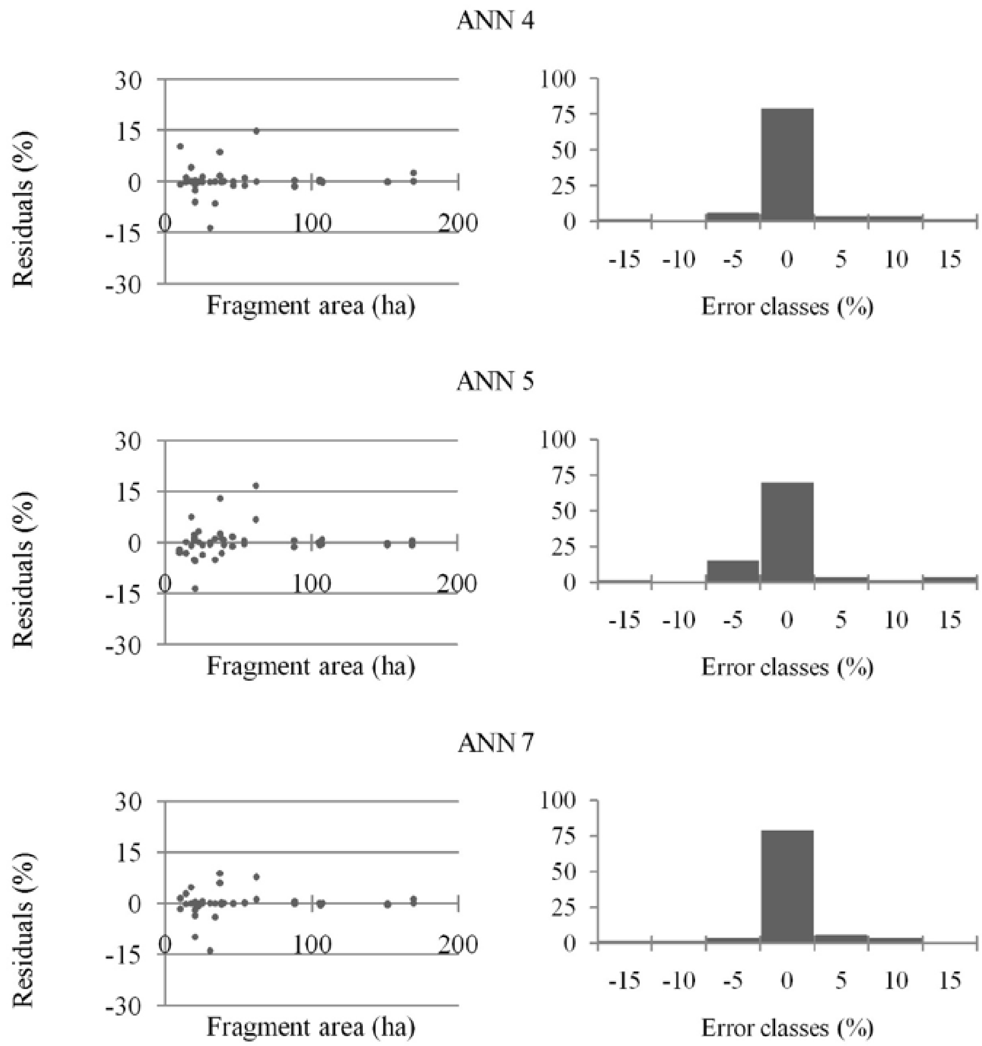

FIGURE 2: Residual dispersion (%) in function of fragment area and histogram of frequencies of the error classes for artificial neural networks (ANN) constructed to estimate the diversity index in function of the rainy season (ANN 4; ANN 5) and dry season (ANN 7).

FIGURA 2: Dispersão dos resíduos (%) em função da área do fragmento e histograma de frequências das classes de erros para as redes neurais artificiais (RNA) construídas para estimar o índice de diversidade em função da estação chuvosa (RNA 4; RNA 5) e estação seca (RNA 7).

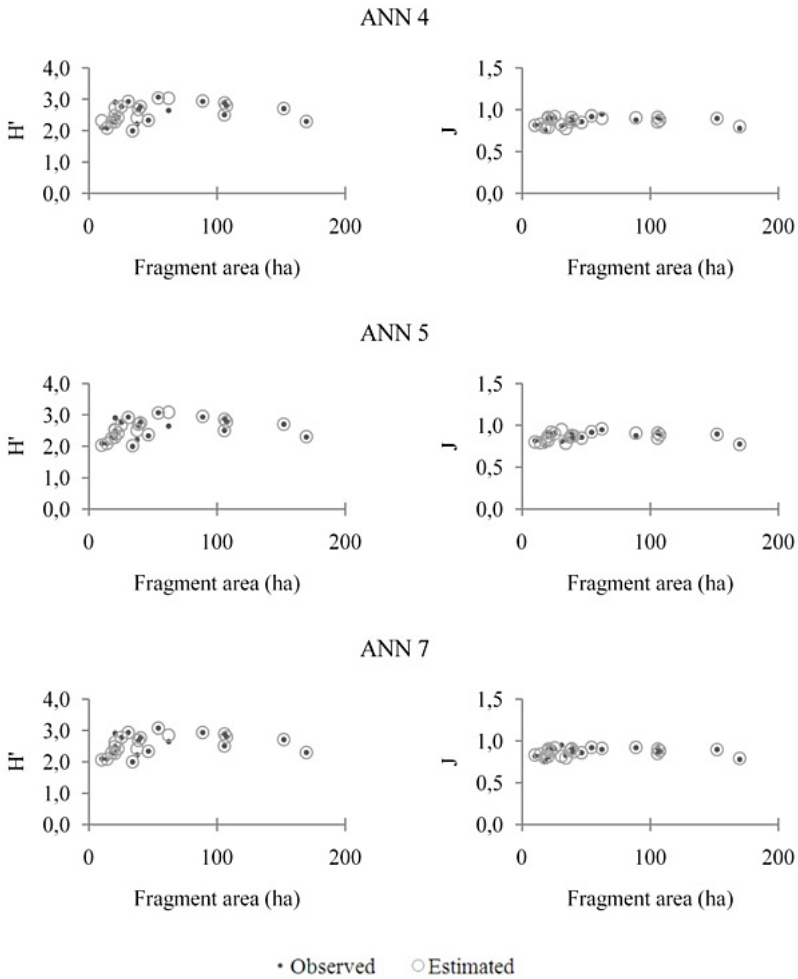

FIGURE 3: Diversity index and Pielou Equitability index estimation due to the rainy season (ANN 4; ANN 5) and dry season (ANN 7).

FIGURA 3: Estimativa dos índices de diversidade e equabilidade de Pielou em função da estação chuvosa (RNA 4; RNA 5) e estação seca (RNA 7).

the hidden layer (CERQUEIRA et al., 2001), which is not observed in networks and corroborated by the lack of significance in the paired t test. Furthermore, a high number of cycles were not used by the networks (Table 2). Kuplich (2006) found greater accuracy using around 2500 iterations in his training networks during his work on the classification of stages of forest regeneration in the Amazon using remote sensing images. We applied the technique of early interruption and data normalization as heuristics. The heuristic provides an approximation of the optimal solution (SOARES et al., 2011; STATSOFT, 2007).

Networks 4, 5 and 7 showed minor deviations in the phases of training and validation (Table 3). Even though little noise was observed in these networks, the ability to handle outliers during the process of adjusting their weights through a learning algorithm was proved (Figure 2). It is noteworthy that the total variance of experimental tests is partly attributable to controlled factors of known and independent causes and other factors not controlled, so are not free of errors. Estimates of these networks that may be used in the majority of statistical techniques that are based on the central limit theorem, did not generate estimates similar to each other (Figure 2 and 3).

Residual distribution in errors classes was less symmetrical in ANN 5 (Figure 2). The training set estimates were not exactly the same in all points (Figure 2), mischaracterizing an overffiting as by Statsoft (2007). Although the actual number of cycles used to train the network based on MVI5 in the rainy season presented approximately the ratio 2:1 compared to SAVI in the dry season, and both were superior and appropriate for the estimation of diversity indices. For the networks built under the dry season, better results were expected due to the reduction of visibility with increasing humidity. The decreases in visual conditions may be caused by the intensification of drizzle, fog and atmospheric pollution. The best vegetation index to estimate H' and J in the wet season was MVI5, which, by nature, was developed on the basis of vegetation and humidity (CABACINHA; CASTRO, 2009).

The networks 4 and 7 were able to learn and generalize the assimilated knowledge to all fragments of the validation set, i.e., for a set of unknown data not employed during training (Figure 3). Thus, demonstrated that they can grasp the biological realism. The generalization capability and connectivity allowed for one network to perform the simultaneous estimation of Shannon index and Pielou Equitability index. In contrast, the use of traditional methods would imply performing regression analysis for each individual diversity index.

Diversity indices are the basis for the assessment of environmental impact and development of programs for the recovery of degraded areas.

The Statistical method proposed by this paper provided accurate estimates, and furthermore obtaining these results related to biodiversity in a much faster, less laborious and less costly way due to the possibility of using orbital data, independently of local climatic conditions.

It is recommended a constant measurement of diversity indices due to variations that can occur in one fragment due to anthropogenic factors, edge effect and other soil and climatic conditions, thus, the artificial neural networks reduce operational activities for the obtaining of diversity indices.

CONCLUSION

The modeling by artificial neural network Multilayer Perceptron showed to be appropriate for estimating the Shannon and Pielou Equitability indices.

Artificial neural networks constructed in the rainy and drought season that used vegetation indices MVI5 (Moisture Vegetation Index) and SAVI (Soil Adjusted Vegetation Index), respectively, were more appropriate, accurate and biologically realistic to estimate, simultaneously, the Shannon and Pielou Equitability indices in forest fragments of Brazilian Cerrado biome.

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