APPLICATION OF ARTIFICIAL NEURAL NETWORK IN THE CLASSIFICATION OF COFFEE AREAS IN MACHADO, MINAS GERAIS STATE

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ABSTRACT: The coffee is extremely important activity in southern of Minas Gerais and techniques for estimating acreage, seeking reliable crop forecasts are being intensely investigated. It is presented in this study, an application of Artificial Neural Networks (ANN) for the automatic classification of remote sensing data in order to identify areas of the coffee region Machado, Minas Gerais. The methodology for developing the application of RNA was divided into three stages: pre-processing of data, training and use of RNA, and analysis of results. The first step was performed dividing the study area into two parts (one embossed busiest and least busy one with relief), because this region has a strong emphasis smooth wavy, causing a greater difficulty of automatic mapping of use earth from satellite images. Masks were also created in the drainage network and the urban area. In the second step, various RNA's were trained from several samples representative of the classes of images of interest and was made to classify the rest of the image obtained using the best RNA. The third step consisted in analyzing and validating the results, performing a cross between the classified map and the map visually classified by neural network chosen. We used the Kappa index to evaluate the performance of the RNA, since the use of this coefficient is satisfactory to assess the accuracy of a thematic classification. The result was higher than the results reported in the literature, with a Kappa index of 0.558 to 0.602 relief busiest and least busy for relief.

Index Terms: Artificial Neural Networks, automatic classification, coffee.

APLICAÇÃO DE REDES NEURAIS ARTIFICIAIS NA CLASSIFICAÇÃO DE ÁREAS CAFEEIRAS EM MACHADO-MG

RESUMO: *A cafeicultura é atividade de fundamental importância na região sul de Minas Gerais e técnicas de estimativa da área plantada, visando previsões de safra confiáveis, estão sendo intensamente pesquisadas. Apresenta-se,no presente estudo, uma aplicação de Redes Neurais Artificiais (RNA) para a classificação automática de dados de sensoriamento remoto, objetivando identificar áreas cafeeiras da região de Machado, MG. A metodologia para desenvolvimento da aplicação da RNA foi dividida em três etapas: pré-processamento dos dados; treinamento e uso da RNA; e análise dos resultados. Na primeira etapa foi realizada a divisão da área em estudo em duas partes (uma com relevo mais movimentado e outra com relevo menos movimentado), isso porque a região apresenta relevo suave ondulado a forte ondulado, o que acarreta maior dificuldade do mapeamento automático do uso da terra a partir de imagens de satélite. Foram também criadas máscaras na rede de drenagem e área urbana. Na segunda etapa, diversas RNAs foram treinadas a partir de várias amostras de imagens representativas das classes de interesse e foi feita a classificação do restante da imagem utilizando a melhor RNA obtida. A terceira etapa consistiu na análise e validação dos resultados, realizando um cruzamento entre o mapa classificado visualmente e o mapa classificado pela Rede Neural escolhida. Utilizou-se o índice Kappa para avaliar o desempenho da RNA, uma vez que o uso desse coeficiente é satisfatório na avaliação da precisão de uma classificação temática. O resultado obtido foi superior aos resultados encontrados na literatura, com um índice Kappa de 0,558 para o relevo mais movimentado e 0,602 para o relevo menos movimentado.*

Termos para indexação: *Redes Neurais Artificiais, classificação automática, cafeicultura.*

1 INTRODUCTION

Mapping and dynamics of use and occupation of land, as uses and covers are concerned, have important impacts in socioeconomics and environmental systems, presenting significant strategic measures for coffee productive chain.

When coffee plantations are targeted, it is needed to notice that these are inserted in an environmental context, so, there are multiple interferences, as much as from the adjacent objects as from the variations of their own features. Thus the soil, for example, influences the reflectance of surfaces composed by vegetation and soils. Another factor to consider is the exposure of this surface to light, due to the orientation of the vertent

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causing different shading effects (relief with a lot of movement provides shaded regions) and increase or reduction of the diffuse radiation component. Besides that, studies have shown that coffee shows a complex and varied spectral response, which is related to culture parameters. Allied with that there is the fact that coffee trees with over three years of planting age show a spectral response similar to forests (EPIPHANIO; LEONARDI; FORMAGGIO, 1994; VIEIRA et al., 2006).

Due to these factors, in mapping of coffee areas the classification methods based os statistic concepts have not reached the desired objectives, once human interaction is necessary, which means that visual interpretation performs an expresive role. In view of the difficulties observed in the process of recognizing image patterns, applications in the field of remote sensory image classification have been recorded in literature, showing that Artificial Neural Networks (Redes Neurais Artificiais or RNAs) used to classify agricultural cultures have displayed superior results when compared to conventional automatic classification methods (CHAGAS et al., 2009; VIEIRA; LACERDA; BOTELHO, 2009).

Neural networks have been applied successfully in the image processing and pattern recognition areas (GONÇALVES et al., 2008). RNAs use elements of non linear computing (called neurons) organized as networks, in a similar way as it is believed that brain cells are interconnected inside the human brain (BRAGA; CARVALHO; LUDERMIR, 2007; GONZALES; WOODS, 2008). In the particular case of remote sensory image classification applications, many works (CHAGAS et al., 2010; LIU; XIAO, 1991; RUHOFF; FANTIN-CRUZ; COLLISCHONN, 2010) have used RNA, applying a network of Multi-Layer Perceptrons (MLP - *Multi Layer Perceptron*) to solve the classification problem. This type of network is characterized by taking decision regions similar to those formed by a statistic calculator, however with non-related entries and different data distribution (LIPPMANN, 1987).

So, the objective of this work is to define an automatic clasification procedure usin RNAs to identify coffee areas in satellite images in the Machado-MG region, where there is one of the most important coffee producing regions of Southern Minas Gerais state.

2 MATERIAIS AND METHODS

Study area is in Southern Minas Gerais state, in the municipality of Machado, geographic coordinates 21º42’05” and 21º31’10” South and 46º02’38” and 45º47’30” West. The environment is characterized by elevated areas, with altitudes from 780 to 1260 m, mild climate, subject to frosts, moderate hidric deficiency, smooth wavy to strongly wavy relief, with great possibility of production of fine beverages, medium to high technological level production systems. Coffee produced in Machado is internationally remarked. Recently the city received the award of World Capital of Organic Coffee due to the pioneering in this culture.

In the present work were used multispectral images for automatic RNA classification, which referr to the 3, 4 and 5 bands of Landsat 5 satellite, TM senson, passage date 16/08/2007 (Figure 1), made available by the National Space Research Institute (Instituto Nacional de Pesquisas Espaciais – INPE), and the map of land use Machado-MG (EMPRESA DE PESQUISA AGROPECUÁRIA DE MINAS GERAIS - EPAMIG, 2009) (Figure 2), rated visually from the same image. Geographic information systems SPRING version 4.3.3 and software IDRISI were used.

The diagram in Figure 3 shows all the stages of work.

Pre-processings

An image restoring process was used to improve data’s spatial quality (PAPA et al., 2008). The restoring process turned pixels which had spatial resolution from 30m to 10m. Boggione and Fonseca (2003) explain that the image restoring techniques are oriented for degrading and recovery modelling of the original signal which was degraded during the process of image formation.

During the image generation process, spatial resolution is degraded due to optic diffraction, at detector size, to the limitations of electronic filter, transmission channel etc. that degradation makes the images to show a blurry aspect, which characterizes loss of details. With

restoring techniques, it is posible to increase the effective resolution of image to a certain level (BOGGIONE; FONSECA, 2003).

Following that, a mask was created along the draining network (Figure 4), using the Spatial Language for Algebric Geoprocessing (Linguagem Espacial para Geoprocessamento Algébrico - LEGAL), of SPRING, in each of the three bands.

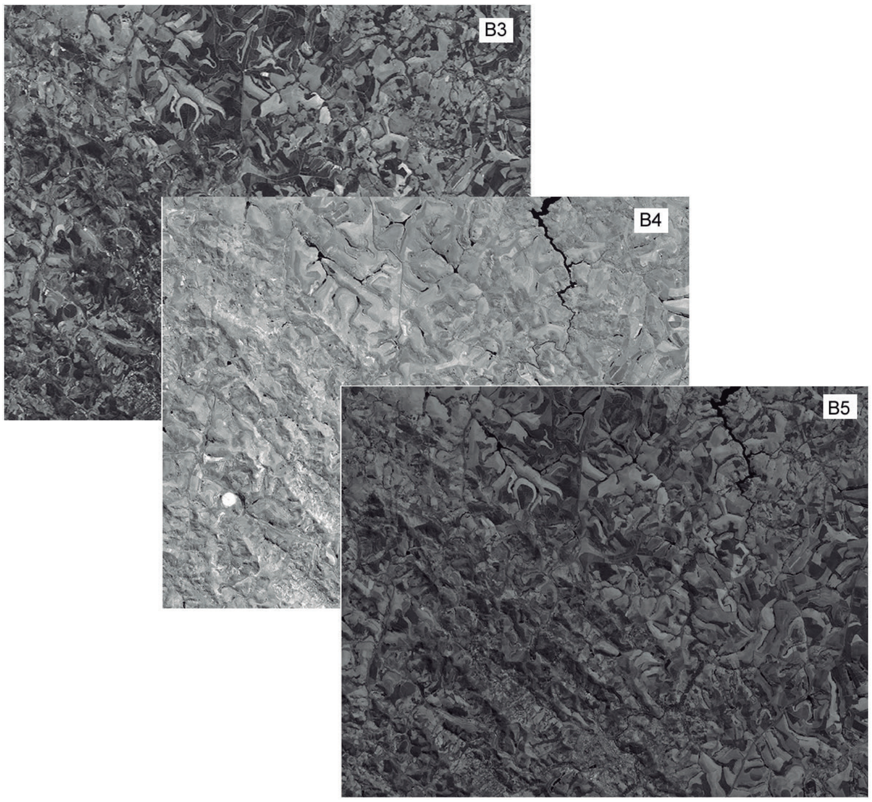


FIGURE 1 - Images TM/Landsat 5, bands 3, 4 and 5.

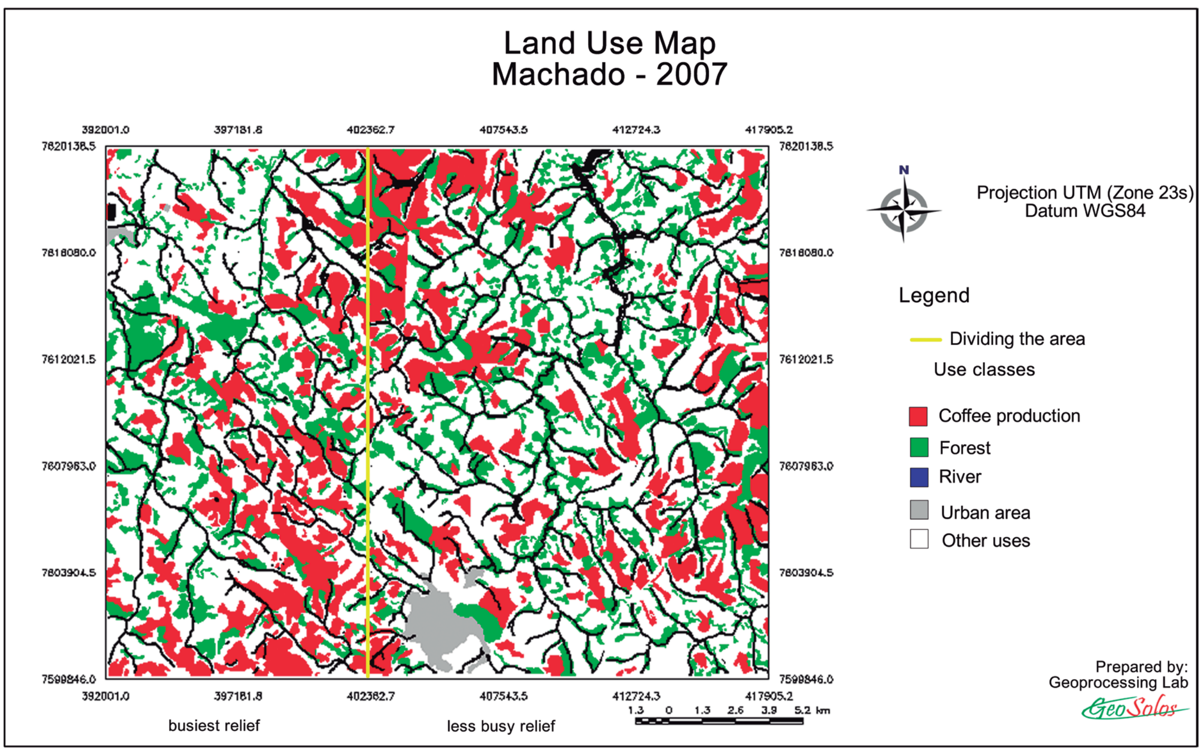


FIGURE 2 - Land use map visually clasified with the draining mask.

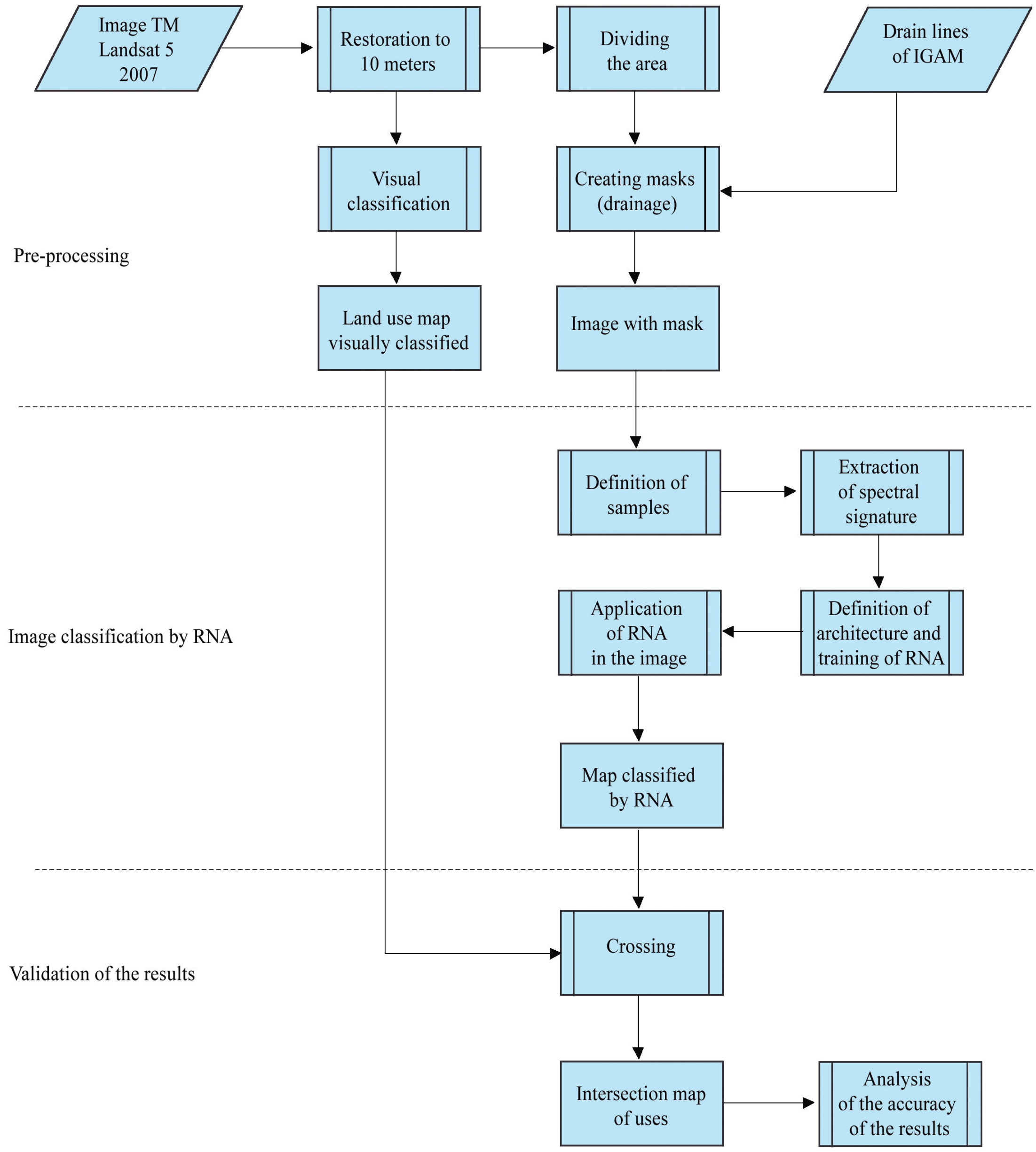
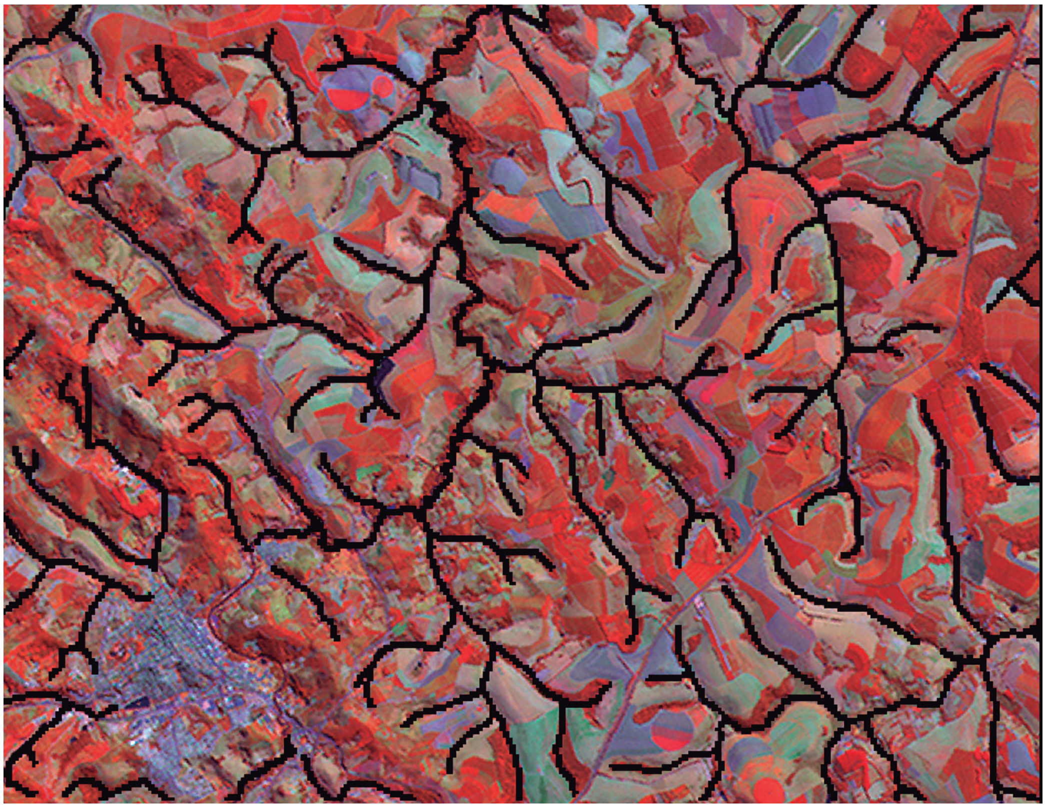


FIGURE 3 - Work methodology.

Digital draining lines were used from the Minas Gerais Water Management Institute (Instituto Mineiro de Gestão das Águas - IGAM), and, over them, created a buffer of 50m and given a 10 value to the pixels that were on these areas. This processing was performed in order to attempt to eliminate the error caused by RNA classification, once along the draining there are small vegetation areas which can be mistaken for coffee trees or any other use class.

Also was created a mask in the urban area of Machado and given the value of the pixels in 255.

After the creation of the mask, the image was divided in two parts, one with the more rugged relief and other with the less rugged relief. SPRING software was used to perform image division, as the separation of environments occurred in straight line (for simplification reasons), as seen in RGB image shown on Figure 4.



(a) relevo mais movimentado (b) relevo menos movimentado

FIGURE 4 - RGB composition image with draining mask: (a) more rugged relief (b) less rugged relief.

According to Lacerda et al. (2001), in Machado region there are two geomorphic environments: Geomorphic environment N-NE-E, with mainly flat to wavy relief, occurring in the North, Northeast and East region to the urban core; and WNW Geomorphic Environment, with mainly wavy to mountainous relief in the West and Northwest region to the urban core. The most rugged environment shows shading in some areas, which makes it more difficult to classify the image through neural network, while the less rugged environment is less likely to shading occurrance. Environment separation allows the neural network to better identify classes, for, if applied over the entire image, it could not show good results, for the bad performance of one environment could influence on the results of the other.

RNA training

Obtaining areas for the RNA training was carried out by extracting areas in the form of polygons of the image for each class to be classified. To aid in the definition of training samples we used a thematic map of land use in the region selected, classified visually. Were selected between 45 and 50 polygons of varying sizes and spaced at random for each class, composed as follows: coffee in production: crops over three years old; forest: dense woods formations and gallery woods on small river margins; urban area: area with large concentration of buildings; water: lagoons, dams and the mask in the draining network; and other uses: areas of coffee in formation (under three years), areas with annual cultures in diverse stages of development, grazing areas and other types of vegetation.. the class “other uses” had many diverse areas so that these areas did not interfere in RNA classification, since the main objective of the work was to identify the coffee areas existing in the image.

After the training areas were obtained, the *Makesig* module of IDRISI was used in order to perform the extraction of spectral signature of the sample set. For RNA architecture definition for image classification, the classification module was executed by neural network of the *multi layer perceptron* (MLP) type, of IDRISI software, under supervised training.

The number of elements of the output layer was defined based on the number of classes to be classified in the image, being five knots with identified values on the creation of samples.

RNA was trained with *backpropagation* algorythm, performing thte followeing changes in RNA architecture: set number of pixels for the training set and testing, number of layers, number of neurons in layers; momentum factor and learning rate. Then, the best trained network was applied to the study area, automatically identifying the classes defined during the collection of the samples, resulting in a thematic map.

Validation of the results

A thematic mapping based on satellite images needs to be validated so that the information generated can be trusted. Using the LEGAL language of the software SPRING, crosses were performed between the maps classified visually and the ones classified automatically by the best trained neural network. The result of these crosses is a confusion matrix, from which is possible to obtain the concordance coefficients to validate the classification precision.

The confusion matrix is a square matrix of numbers that express the amount of sample units associated with a given category during the classification process performed, and the actual category they belong to these units (CONGALTON, 1991; SOUSA et al., 2010).

The Kappa index (GÓES; MELLO FILHO; CARVALHO, 2006) was used to assess RNA performance. The use of this coefficient is satisfactory in assessing the accuracy of a thematic classification, because they take into account all the confusion matrix in their calculation, including the elements outside the main diagonal, which account for disagreements in the classification (FRANCA; SANO, 2011).

The Kappa index is a measure of actual agreement (indicated by the diagonal elements of the confusion matrix) unless the agreement by chance (indicated by total product of row and column) (SMITH, 2005), as follows:

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+}\, x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+}\, x_{+i})}$$

being: K = Kappa index; N = total amount of sample points; r = number of rows of error matrix; xii = value on row i and column i; xi+ = sum of row i; x+i = sum of column i. The levels used to assess the quality of classification, based on Kappa value are those proposed by Nanni et al. (2010).

The analysis of RNA performance was also assessed through a map, formed by three parts: Correctly classified areas: Coffee pixel areas classified by RNA and the visual method; Incorrectly classified areas: pixels that RNA classified as coffee however they were not coffee areas and Not classified areas: pixels that RNA failed to classify as coffee, classifying them something else.

3 RESULTS AND DISCUSSION

To set the number of hidden layers and number of neurons in each layer several implementations were performed with different network architectures and verified the performance of each trained network. The number of hidden layers and the number of elements in these layers have been defined experimentally evaluated architectures have been one and two hidden layers. Some of the results are shown in Table 1.

The test configuration and training used on the neural network were the same for the more rugged relief as for the less rugged relief. Table 1 shows the configurations used, and highlights those which showed the best results.

The network that showed the best results for the less rugged relief had 18 neurons in one single hidden layer and 5 neurons in output, being each sample with 70 pixels of image, learning rate of 0,02; momentum factor of 0,53 to speed convergence in network; and sigmoid constant of 1. For the more rugged relief, the RNA that had the best result also had only one hidden layer, however with 14 neurons, learning rate of 0,01 and momentum factor of 0,5. As training stop criteria was established, for both parts, quadratic average error (EMQ) of 0,0001 or 10.000 iteractions (whatever came first). The RNA training stop occurred by the number of iteractions of backpropagation algorythm, resulting in a final EQM value for all of the training and test data.

According to Table 1, the neural network performed better with a hidden layer. The intermediate layers work with error estimates for adjustments of the weights of the input neurons, which, in larger quantities, lead to problems of network convergence (overscaling).

TABLE 1 - Configurations used in training.

Conf.	Pixel[1*]	Nº of internal layers	Neurons		Learning rate	Mom.	Iteractions	EMQ (less rugged relief)		EMQ (more rugged relief)	
			1ª layer.	2ª layer.				Train.	Test	Train.	Test
1	60	1	16	-	0,01	0,5	10000	0,005661	0,005841	0,00501	0,005715
2	60	2	20	14	0,01	0,5	10000	0,004914	0,005907	-	-
3	**65**	**1**	**14**	**-**	**0,01**	**0,5**	**10000**	**-**	**-**	**0,005491**	**0,005474**
4	65	1	18	-	0,01	0,5	10000	-	-	0,005231	0,005599
5	65	1	18	-	0,01	0,5	10000	0,004861	0,005471	0,005231	0,005599
6	65	2	24	18	0,01	0,53	10000	0,005129	0,005137	-	-
7	70	1	16	-	0,01	0,5	10000	0,005062	0,005216	0,004369	0,005332
8	70	2	16	10	0,01	0,5	10000	0,00497	0,005185	-	-
9	70	1	18	-	0,01	0,5	10000	0,004771	0,005381	0,005116	0,00514
10	**70**	**1**	**18**	**-**	**0,02**	**0,53**	**10000**	**0,00472**	**0,004984**	0,00465	0,005073

Observing the results in relief less rugged, it was noticed that increasing the number of pixels in the samples of training sets and testing, the network produced better results with a number of neurons of the first layer ranging between 16 and 18. Busiest in relief, the network achieved better results had also a small number of neurons in the hidden layer. The good performance in the use of only one hidden layer can also be seen in the work of researchers Boschi and Galo (2007) who applied a MLP type network the classification of land cover in urban Presidente Prudente and obtained satisfactory results in the discrimination of changes in urban land cover.

The better neural network performance was tested obtaining the Kappa index between the RNA classified map and the visually classified land use map. Figure 5 shows the classification performed by RNA on both environments.

The global accuracy index of the map classified by RNA was 73.33% for the less rugged relief and 70.42% for the more rugged relief. the Kappa accuracy index was of 0,558 for the more rugged relief and 0,602 for the less rugged relief which, according to Nanni et al. (2010) are good and very good indexes. The indexes obtained in the RNA classification could have been impaired by environmental factos which interfere in the image's spectral pattern, such as variations in phenological stage, vegetative vigor, the spacing of plants in fields and cultural managements used, existance of interpolate cultures, more shading due to rugged terrain and low spatial resolution of the used Landsat images. However, when compared to the results obtained by Marques (2003) and Santos et al. (2007), who used Battacharya and Maxver automatic classification algorythms, in the same coffee region for land use mapping, RNA showed better results.

Marques (2003) applied the automatic classifiers Battacharya (classifier by region) and Maxver (pixel by pixel classifier) in Landsat 7 ETM+ images in 2000 and, despite the low Kappa accuracy indexes, Maxver with 0,39 and Battacharya with 0,42, the author concluded that the classifiers had a moderate performance, for the area has a relief that makes classification more difficult. Santos et al. (2007) used the same automatic classifiers in Landsat 5 TM images in 2005, on the same area and obtained low Kappa accuracy indexes, being 0,202 for Battacharya and 0,25 for Maxver. The authors concluded that the low classification performance could be explained for the fact that this region has a very rugged relief, providing shaded regions and coffee crops contiguous to fragments of native vegetation, which presents spectral response similar to the coffee plantation.

In Table 2 is presented the confusion matrix between the maps of reference and the one classified by RNA. The matrix contains the omission and commission errors, consumer and producer accuracy for each class. The highlighted values in grey are those of the areas with less rugged relief.

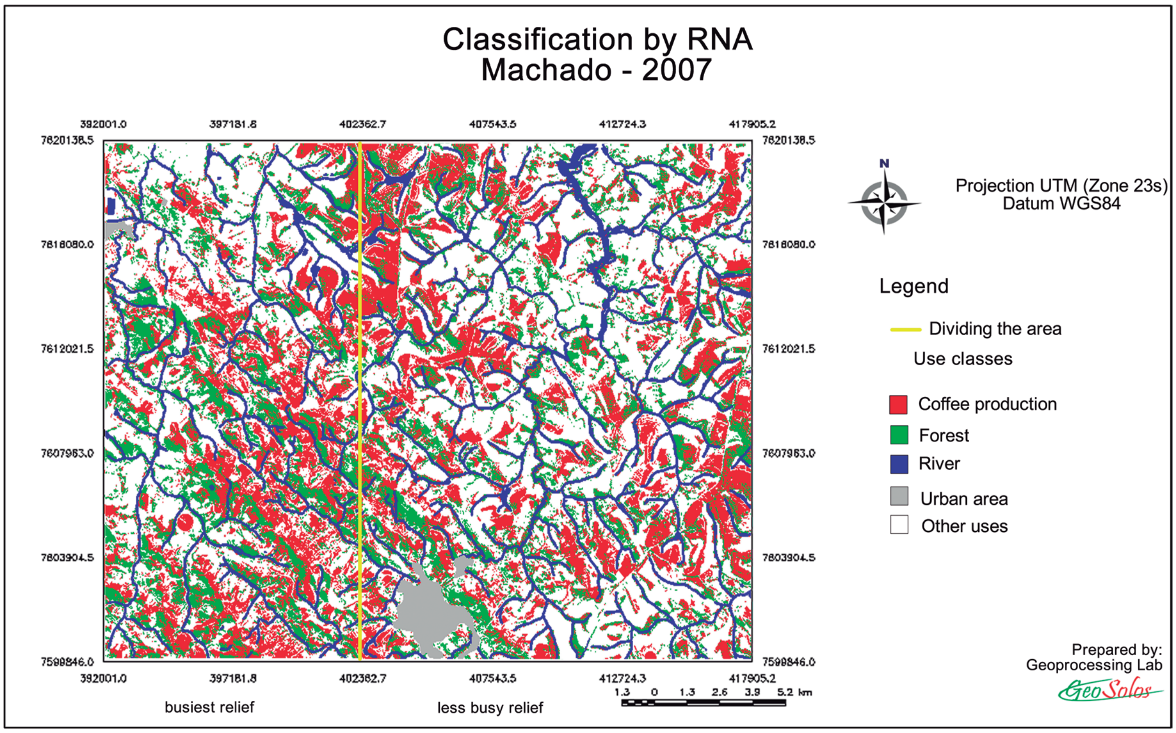


FIGURE 5 - RNA classified land use mapping.

Analysing the confusion matrix, it is possible to observe that in the less rugged relief the network classified better the coffee producing areas, with a 63,60% correct percentage (producer accuracy), which corresponds to approximately 55% of the real coffee are, represented by the consumer accuracy. Approximately 44% of the mapped area as coffee did not correspond spatially to the real, which matches the commission errors for that class. In the more rugged relief, the network achieved a slightly lower hit, 59,06%. As expected, the less rugged relief showed better results due to the lower interference of shading in the reflectance of the coffee tree canopy. Another important factor was the creation of thematic classes forest and coffee along drains, and, therefore, improving the RNA classification results.

The other uses class which encompasses coffee in formation, annual cultures in different stages of development, grazing areas and other types of vegetation, could also be considered as a good classification, varying between 75% and 82%, showing low confusion with coffee and forest areas.

Yet another classification difficulty showed by RNA could be observed in the forest class, which had an accuracy of 42% and 50% respectively for the less rugged and the more rugged reliefs.

The forest classification had large confusion with coffee areas, due to the very close spectral pattern (VIEIRA et al., 2006), and showed large confusion with areas of other uses as well, due to factors already discused.

The water class showed accuracy superior to 90%, for during the creation of the mask was attributed value 10 to the pixels which were found in the areas covered by the buffer and in water areas. The urban area had a good classification, with indexes superior to 95%, for it was also created a mask with pixels with the value of 255.

The reference map and the one generated by RNA classification were crossed on SPRING, using LEGAL language. From this crossing the thematic map presented on Figure 6 was obtained, in which there is, spatially, the performance of RNA, and shows the following thematic classes: correctly classified areas, incorrectly classified areas and not clasified areas.

The total map area is 520 km^2, being 110,13 km^2 of coffee areas. The maps show an RNA performance over the coffee class, in which correctly classified coffee is 67,95 km^2, incorrectly classified is 50,58 km^2 and the not classified areas 42,18 km^2. Analyzing the areas separately, the less rugged terrain has 69,34 km^2 of coffee areas, being correctly classified by RNA 40,80 km^2, and 28,54 km^2 in areas that were incorrectly classified. As for the more rugged relief, it has 49,20 km^2 of coffee areas, being 27,15 km^2 correctly classified and 22,04 km^2 incorrectly classified.

TABLE 2 -Confusion matrix with omission and comission errors, consumer and producer accuracy, global and Kappa accuracy index, obtained between the reference and RNA clasified maps.

Mapa Classificado Visualmente (km^2)	RNA classified map(km^2)							
	Coffee in production	**Forest**	**Water**	**Urban area**	**Other uses**	**TOTAL**	**Omission errors**	**Producer accuracy**
Coffee in production	**40.801**	9.0397	0.205	0.01	14.0987	64.1544	36%	63.60%
	27.1553	9.4697	0.0001	0.0054	9.3493	45.9798	40.94%	59.06%
Forest	14.875	**22.3209**	1.2182	0.0134	14.2844	52.7119	58%	42.35%
	9.5603	**17.254**	0.0051	0.0006	7.4564	34.2764	49.66%	50.34%
Water	0.4812	0.8532	**33.9702**	0.2273	1.5846	37.1165	8%	91.52%
	0.0001	0.0002	**21.3333**	0	0.0015	21.3351	0.01%	99.99%
Urban area	0.0215	0.0313	0.0069	**6.0838**	0.08	6.2235	2%	97.76%
	0	0	0	**0.516**	0.0001	0.5161	0	99.98%
Other uses	13.1591	11.913	1.6071	0.1669	**127.4844**	154.3305	17%	82.60%
	12.4853	12.6592	0.014	0.011	**79.0199**	104.1894	24.16%	75.84%
Total	69.3378	44.1581	37.0074	6.5014	157.5321	314.5368		
	49.201	39.3831	21.3525	0.533	95.8272	206.2968		
Comission error	44.48%	41.43%	8.18%	6.71%	19.47%			
	47.95%	64.56%	0.09%	3.29%	16.13%			
Consumer accuracy	55.52%	58.57%	91.82%	93.29%	80.53%			
	52.05%	35.44%	99.91%	96.71%	83.87%			
Global accuracy index	73.33%			**Kappa**	0.602			
	70.42%				0.558			

* each cell in the table contains two values, referring to the two areas classified by the neural network (less rugged relief, more rugged relief).

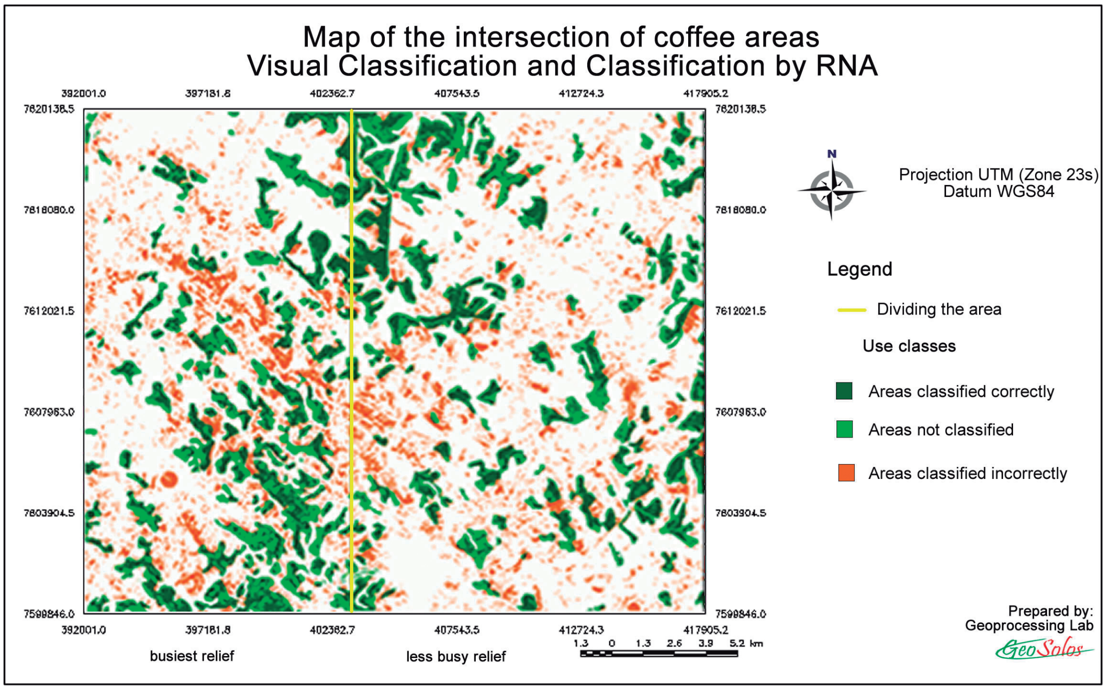


FIGURE 6 - Crossing map of the coffee areas between the reference map and the RNA classified map.

4 CONCLUSIONS

This work showed the potential of artificial neural networks in automatic satellite image classification for identifying coffee areas, obtaining classification accuracy indexes superior to the ones found in literature.

Separation of geomorphic environments and the inclusion of masks on the draining network and urban area during pre-processing enabled lower variability of observed targets in images.

Future works proposing the division of different geomorphic environments by means of slope mals, derived from a Digital Elevation Model, could be performed separating more precisely the areas with different reliefs. Also as future proposition, incorporate to RNA structure attributes such as form and target texture, since these are the used atributes by visual interpretation, in moments in which only the spectral response is not enough.

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