Revista Brasileira de Cartografia (2013) Nº 65/3: 431-439
Sociedade Brasileira de Cartografia, Geodésia, Fotogrametria e Sensoriamento Remoto
ISSN: 1808-0936

AN ASSESSMENT OF THE SUPPORT VECTOR MACHINE FOR A CBERS-2 CCD IMAGE CLASSIFICATION: A CASE STUDY OF A TROPICAL RESERVOIR IN BRAZIL

Uma Avaliação da Máquina de Suporte Vetorial para Classificação de Imagens CBERS-2 CCD: Estudo de Caso de um Reservatório Tropical no Brasil

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Recebido em 17 de março, 2012/ Aceito em 02 de junho, 2012
Received on march 17, 2012/ Accepted on june 02, 2012

ABSTRACT

The support vector machine (SVM) is a group of theoretically superior machine learning algorithms and has recently become an effective tool for pattern recognition. The aim of this work was to compare this newer classification algorithm against a traditional statistical classifier and to assess their accuracy. The area surrounding the Itumbiara reservoir in the State of Goiás, Brazil was selected as the study area. The classes were defined in accordance with the Cover Classification System of the Food and Agriculture Organization of the United Nations (FAO). Training sets were collected for each class, and the algorithms were then applied. A confusion matrix and Kappa coefficients were used to evaluate the classification algorithm. The computed accuracy was approximately 71%, and the Kappa coefficient was 0.64 for the SVM classification. For the maximum likelihood (ML) the overall accuracy was 49% and the Kappa coefficient was 0.36. According to these results, the optimal class separation by the SVM algorithm was considered to be appreciably better than the ML classification.

Keywords: Tropical Reservoir, CBERS, Support Vector Machine.

RESUMO

O Máquina de Suporte Vetorial (MSV) é um grupo teórico de algoritmos de aprendizagem de máquina e recentemente se tornou uma ferramenta efetiva para o reconhecimento de padrões. O objetivo deste trabalho foi o de comparar esse novo classificador contra os classificadores estatísticos tradicionais e avaliar sua acurácia. A área selecionada para realizar esse experimento foi a área de influência do reservatório hidrelétrico de Itumbiara (GO). As classes selecionadas foram obtidas pelo sistema de classificação de cobertura da FAO. Amostras de treinamento foram coletadas para cada classe e os algoritmos de classificação foram então aplicados. O coeficiente Kappa foi utilizado para avaliar os classificadores. Os resultados mostraram que para o algoritmo MSV a acurácia foi de 71% com um coeficiente Kappa de 0,64. Para o algoritmo de máxima verossimilhança a acurácia foi de 49% com Kappa de 0,36. De acordo com esses resultados, para a classificação da área de estudo selecionada, o algoritmo MSV apresentou melhor resultado na separação das classes propostas pela FAO.

Palavras chaves: Reservatório Tropical, CBERS, Máquina de Suporte Vetorial.

1. INTRODUCTION

Problems in remote sensing data processing are usually based on a specific identification of land cover, an estimation of biophysical parameters and features extraction. Moreover, the complexity of these problems increases with the complexity of the area analyzed. Land use and land cover mapping is one of the most important remote sensing applications. Briassoulis (1993) explained that the concepts of land cover and land use are similar, but not equivalent. Land cover is the physical, chemical and biological state of the terrestrial surface, represented by forests, water or built-up areas. Otherwise, land use is defined by the human activities associated with the land cover, such as cattle-raising, recreation, conservation and residential areas.

Over the last three decades, remote sensing has increasingly become a prime source of land cover information due to the advancements in satellite sensor technology and increases in the number of countries with Earth Observation Systems (FOODY and MATHUR, 2004). These technologies have enabled the acquisition of land cover information over large areas at various spatial, temporal, spectral and radiometric resolutions. One of the major approaches to derive land cover information from remotely sensed imagery is digital classification (HUANG et al. 2002).

Classification is the process that allows a correlation between pixels from satellite images and classes on the terrestrial surface. Most works with remotely sensed images involve the use of the reflectance and radiance of each pixel in order to assign it to a number of land cover classes (HUANG, et al. 2001). Spectral reflectance characteristics can identify the cover type if the sensor is able to measure data at several wavelengths (RICHARDS, 1993). For each pixel, the set of samples is analyzed to provide a label that associates the pixel with a particular land cover. The algorithms usually used for this process are known as image classifiers (MATHER, 1999). These classifiers can be separated into supervised and unsupervised classifiers. Among the unsupervised classifiers we can mention Isodata and K-means. Among the supervised classifiers are maximum likelihood, the minimum distance, spectral angle mapper, decision tress, neural networks and, more recently, the support vector machine (SVM).

Machine learning algorithms are designed to determine the location of decision boundaries that produce the optimal separation of classes with the fewest errors, thereby minimizing the confusion between classes (VAPNIK, 1995). The SVM classifier was introduced into statistical learning theory by Vapnik (1995) and is focused on the optimal separation between classes in the form of the training cases that are placed at the edge of the class descriptors. These training cases are called support vectors. Training cases other than the support vectors are discarded. This way, not only is an optimal hyperplane fitted, but fewer training samples are effectively used; thus, high classification accuracy is achieved with smaller training sets (MERCIER and LENNON, 2003).

Moreover, the SVM can be successfully applied to the problems of image classification with large input dimensionality (MELGANI and BRUZZONE, 2004). Several studies (HERMES et al. 1999; BROWN et al. 2000; PAL and MATHER, 2005) have shown that the SVM classifier presents better results in remotely sensed images classification than other classification methods such as neural networks and decision trees. In comparison with Artificial Neural Networks (ANNs), the SVM offers a solid mathematical foundation that provides a probabilistic guarantee of how well the classifier will generalize unseen data (PERKINS et al. 2001).

While ANNs are based on the idea of minimizing the errors in training data (i.e., empirical risk), the SVM operates on a principle known as Structural Risk Minimization (SRM) that minimizes the upper boundary of the generalization error or the errors in unseen data. A review about SVM method can be accessed at Mountrakis et al. (2011).

Images acquired by a multispectral sensor, such as the widely used Landsat Thematic Mapper (TM) sensor, are used in classification processes. Brazil and China jointly operate the China-Brazil Earth Resources Satellite (CBERS) program, which is a partnership between these two countries in the technical segment of space and science.

In this research, our objectives were to assess the classification by the SVM algorithm in its application for CBERS images, to compare this result against a traditional statistical classifier (ML) and to assess the accuracy of the combination of SVM/CBERS in remote sensing image classification. Further, we sought to assess the potential of CBERS data for image classification in general.

2. METHODS

2.1 Study area

To evaluate the efficiency of the SVM in CBERS-2 CCD images classification, the area surrounding the Itumbiara reservoir in the State of Goiás, Brazil was selected as our study area. This area was chosen due to the diversity of land use classes and the importance of these uses to the reservoir water quality. The reservoir (18° 25' S, 49° 06' W) is located in the Cerrado biome, between the states of Minas Gerais and Goiás (Figure 1).

It is formed mainly by the rivers Paranaíba, Araguari and Corumbá, and it has a dendritic shape, with 814,000 m^2 of flood area. The watershed of the Itumbiara reservoir features agriculture and husbandry as its main economic activities, with a great expansion of sugar cane plantations in the last years. These activities have an influence on water quality, because through them, organic and inorganic matter and pesticides drain into the reservoir.

2.2 Remote sensing data

For this study, two CBERS-2 CCD scenes were acquired (path/row 158/120 and 158/121) on September 2nd, 2007 from the image database of the Image Generation Division of the National Institute for Space Research (INPE), which contain images acquired by the LANDSAT 1-7, CBERS-2 and CBERS-2B satellites (http://www.dgi.inpe.br /CDSR/). All of the images were fully cost free when requested (via the Internet).

The bands used were band 2 (0.52–0.59 ìm), band 3 (0.63–0.69 ìm) and band 4 (0.77–0.89 ìm), which in combination cover the watershed area of the Itumbiara reservoir. A scene, available on the Global Land Cover Facility website (http:// glcf.umiacs.umd.edu/index.shtml), was used to geometrically correct the CBERS scenes that were restored in accordance with the procedures described by Fonseca et al. (1993) using instantaneous field of view (EIFOV) parameters described by Gouvea et al. (2007).

A mosaic with the CBERS scenes was made, and the area of interest around the reservoir was established. The classes to be identified by the classifiers were defined in agreement with the Land Cover Classification System of the Food and Agriculture Organization of the United Nations (FAO), version 2 (DI GREGÓRIO, 2005), as shown in Table 1.

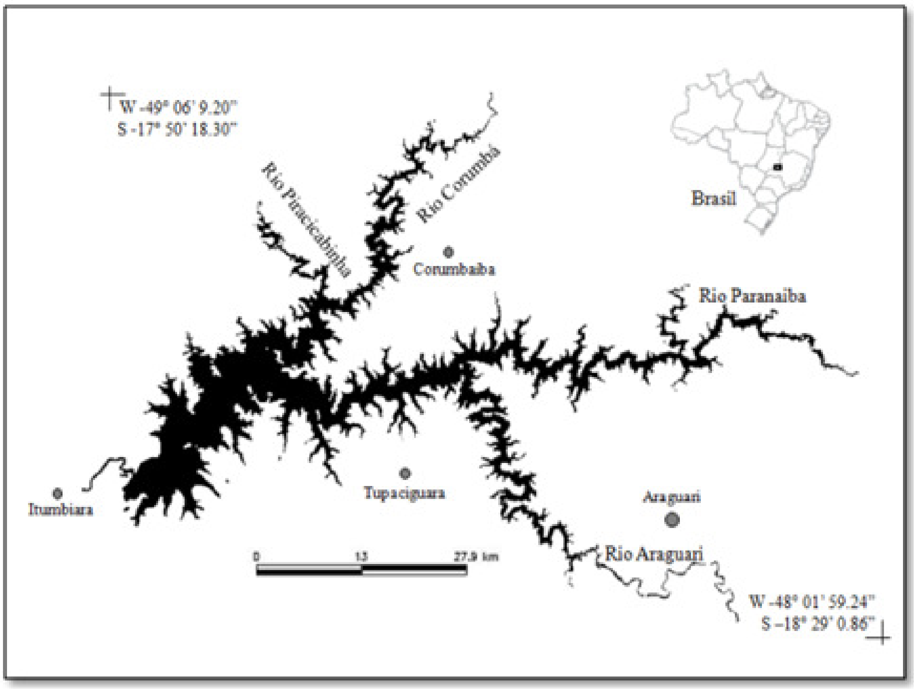

Fig. 1 - The location of the Itumbiara reservoir.

Table 1: Classes established for the CBERS-2 CCD images classification

Cultivated and Managed Terrestrial Areas	Areas where the natural vegetation has been removed or modified and replaced by other types of vegetative cover of anthropogenic origin. This vegetation is artificial and requires human activity to maintain it in the long term.
Natural and Semi-Natural Vegetation	Areas where the vegetative cover is in balance with the abiotic and biotic forces of its biotope. Semi-natural vegetation is defined as vegetation not planted by humans but influenced by human actions.
Artificial Surfaces and Associated Areas	This class describes areas that have an artificial cover as a result of human activities, such as construction (cities, towns, and transportation), extraction (open mines and quarries) or waste disposal.
Bare Areas	This class describes areas that do not have an artificial cover as a result of human activities. These areas include areas with less than 4% vegetation cover, like bare rock areas, sands and deserts.
Natural and Artificial Water Bodies	Areas that are naturally covered by water, such as lakes and rivers, or areas that are covered by water due to the construction of artefacts, such as reservoirs, canals or artificial lakes.

2.3 Training data selection

The training dataset used in this study consisted of 81,268 points (pixels). Small patches of homogenous pixels for each class were identified and labeled in the images. This process is a commonly used sampling method (CAMPBELL, 1996). These regions of interest were shaped irregularly and included numerous points. The distribution of classes in the training dataset is showed in Table 2. This training dataset was used as input for the ML and SVM.

Table 2: Distribution of classes in the training dataset.

Class	# of points
Natural and Artificial Water Bodies	39,879
Natural and Semi-Natural Vegetation	16,353
Artificial Surfaces and Associated Areas	6564
Cultivated and Managed Terrestrial Areas	9679
Bare Areas	8793

2.4 Maximum Likelihood Classifier (MLC)

The MLC is the most commonly used method of classification in remote sensing. This method assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. All pixels are classified through this method, unless a probability threshold is selected. Each pixel is assigned to the class that has the highest probability (i.e., the maximum likelihood).

A pixel with the maximum likelihood is classified into the corresponding class. If the highest probability is smaller than a threshold, the pixel remains unclassified. The equation 1 shows how the maximum likelihood classifies each pixel in the image (RICHARDS, 1993).

$$g_i(x) - \ln p(w_i) - \frac{1}{2}\ln\left|\sum{}_i\right| - \frac{1}{2}(x-m_i)^t \sum{}_i^{-1}(x-m_i) \qquad (1)$$

where i = class; x = n-dimensional data (where n is the number of bands); $p(w_i)$ = the probability that class w_i occurs in the image and is assumed the same for all classes; $\left|\sum{}_i\right|$ = the determinant of the covariance matrix of the data in class w_i; $\sum{}_i^{-1}$ = its inverse matrix; m_i = the mean vector. For a detailed explanation of MLC, refer to Mather (2001). The MLC is a classical parametric classifier that relies on second-order statistics of the Gaussian probability density model for each class (DUDA and HART, 1973). The equation for this classifier is given below:

$$D = \ln(a_c) - \left[0.51_n\left(\left|Cov_c\right|\right)\right] - \left[0.5(X-\mu_c)^T Cov_v^{-1}(X-\mu_c)\right] \qquad (2)$$

where D = likelihood; c = the particular class; X = the measurement vector of the candidate pixel; m_c = the mean vector of the sample of class c; a_c = the per cent probability (or a priori knowledge) that a candidate pixel is a member of class c; Cov_c = the covariance matrix of class c; $|Cov_c|$ = the determinant of Cov_c and Cov_c-1 = the inverse of Cov_c.

A pixel is assigned to class c for which the likelihood is the highest. A good estimation of the mean vector and covariance of the population is essential; hence a sufficient quantity of ground truth data should be sampled.

As a parametric classifier, ML relies heavily on a normal distribution of the data in each input band. In cases where there is high correlation between bands or in which ground truth data is homogeneous, the inverse of the variance-covariance matrix becomes unstable. ML training is long and time consuming because it involves two matrix multiplications for each pixel and for each class.

2.5 Support Vector Machine (SVM)

Recently, the SVM has become an important tool for the classification of remote sensed images. Many studies have shown that the SVM provides better classification results than other widely used methods, such as the MLC and neural network classifiers (THEODORIDIS)and KOUTROUMBAS, 2003). The SVM is based on statistical learning theory and is designed to determine the location of decision boundaries that produce the optimal separation of classes (VAPNIK, 1998).

One of the main results of statistical learning theory is that the error probability of a classifier is upper delimited by a quantity depending not only on the error rate achieved on the training set, but also on the intrinsic property of the classifier that serves as a measure of the "richness" of the set of decision functions the classifier can implement. The richer the set of decision functions, the higher the classifier's capacity.

The SVM is based on the SRM principle (Structural Risk Minimisation), which aims at reaching the minimum of the upper bound of the error probability of the classifier by achieving a trade-off between the training set and the capacity. The risk of a learning machine is bounded by the sum of the empirical risk estimated from training samples and a confidence interval. The strategy of SRM is to keep this empirical risk fixed and to minimize the confidence interval, or to maximize the margin between a separating hyperplane and the closest data points.

A separating hyperplane is a plane in a multi-dimensional space that separates the data samples of two classes. The optimal separating hyperplane is the one that maximizes the margin from the closest data points to the plane. It is discovered through the identification of the most representative training samples (i.e., the support vectors).

The SVM was initially designed for "two-class" problems. For multiple classes, an appropriate multi-class classifier is needed. Two strategies have been proposed for these problems. One compares one class with the others taken together. This strategy generates n classifiers, where n is the number of classes. The final output is the class that corresponds to the SVM with the largest margin; one class determines n hyperplanes. This method requires the solution of n quadratic programming optimization problems, each of which separates one class from the remaining classes ("one against the rest").

The other approach is to combine several classifiers ("one against one"), creating a binary classifier for each possible pair of classes. All of the possible two-class classifiers are evaluated from the training set of n classes, with each classifier trained on only two out of n classes, giving a total of n(n-1)/2 classifiers. Applying each classifier to the test data vectors gives one vote to the winning class. The data is assigned the label of the class with most votes.

If the training dataset is not linearly separable, a kernel method is used to simulate a non-linear projection of the data in a higher dimensional space, where the classes are linearly separable. According to the theoretical development of the SVM, the kernel function plays an important role in locating complex decision boundaries between classes.

The kernel functions convert non-linear boundaries in the original data space into linear ones in the high-dimensional space, boundaries that can be located using an optimization algorithm. The SVM has four kernel functions: (i) linear, (ii) quadratic, (iii) polynomial and (iv) radial base function (RBF). The selection of a kernel function and of the appropriate values for the corresponding kernel parameters may affect the performance of the SVM.

In addition, the SVM includes a penalty parameter (C) that allows a certain degree of misclassification, which is particularly important for non-separable training sets. This penalty parameter controls the trade-off between the permission of training errors and the requirement of rigid margins.

It creates a soft margin that permits some misclassifications, such as allowing some training points on the wrong side of the hyperplane. Increasing the value of the penalty parameter increases the cost of misclassifying points and forces the creation of a more accurate model that may not generalize well.

This study utilized the pair-wised classification strategy with the RBF kernel. This function was chosen because the others are variations of it. Further, in accordance with Melgani and Bruzzone (2004) the RBF shows the best results in the optimal separation between classes. The gamma (g) of the kernel function was 0.333, and the penalty parameter (C) was 100.

2.6 Testing dataset

An accuracy assessment was performed in order to evaluate the maps generated by the classifications. An equalized random sampling was used to generate ground truth points that were assigned reference values identified from a ground truth map. A total of 500 points (pixels), 100 pixels per class, were chosen from each classification map. The accuracy of these classifications was measured using the overall accuracy. The significance of the accuracy differences was tested using a confusion matrix and Kappa statistics in accordance with Hudson and Ramm (1987).

3. Results and discussion

The application of the restoration process using the EIFOV parameters described by Gouvea et al. (2007) resulted in an image with better visual quality. This procedure improved the use of CBERS images in the classification processes. The output map of the SVM classification is shown in Figure 2. The overall accuracy of this classifier was 71% with a Kappa coefficient of 0.64.

The confusion matrix of SVM classification (with producer's and user's accuracy) is shown in Table 3, and the commission and omission errors are shown in Table 4. The producer's and user's accuracies are ways of representing individual class accuracies that serve as replacements for the overall classification accuracy, and have been introduced by Story and Congalton (1986).

Producer's accuracy gives an indication of the accuracy of what the model was able to itself predict, whereas user's accuracy describes how well the training data was discerned. Errors of commission represent pixels (or percentage) that belong to another class that are labeled as belonging to the class of interest; errors of omission represent pixels (or percentages) that belong to the ground truth class for which the classification technique has failed to identify the right class.

Analyzing Table 3, it can be observed that

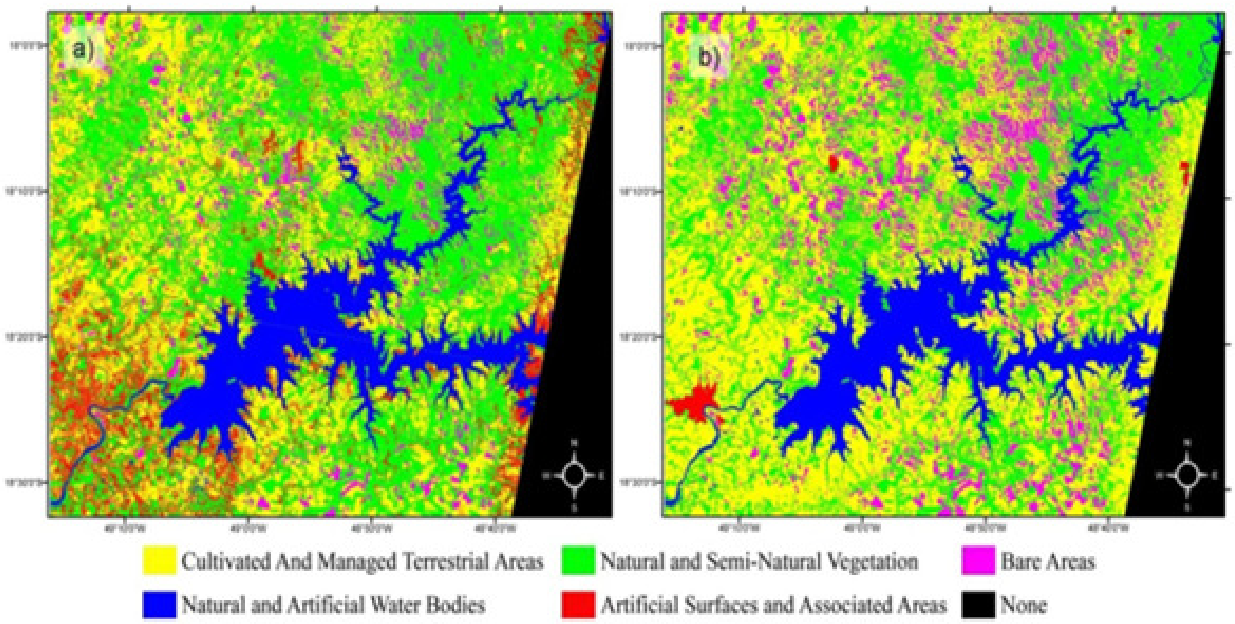

Fig. 2 - Comparison between the classification produced by the support vector machine classifier and the ground truth map.

Table 3: SVM's confusion matrix.

	WB	V	CMA	AS	BA	Total	User's accuracy (%)
Water bodies (WB)	**95**	0	0	0	0	95	100
Vegetation (V)	0	**43**	0	1	0	44	98
Cultivated and managed areas (CMA)	2	27	**91**	18	11	149	61
Artificial surfaces (AS)	3	30	5	**58**	19	115	50
Bare areas (BA)	0	0	4	0	**70**	97	72
Total	100	100	100	100	100	500	
Producer's accuracy (%)	95	43	91	58	70		

the class "water bodies" was the best classified, with high results in user's and producer's accuracies. All of the water bodies areas were correctly identified as water bodies, and 95% of the areas called water bodies on the map were actually water bodies on the ground. Vegetation presented a high user's accuracy, but a lower producer's accuracy.

Although 98% of the vegetation areas were correctly identified as vegetation, only 43% of the areas called vegetation on the map were actually vegetation on the ground. In general, all the classes showed a satisfactory classification. The algorithm was inadequate for classifying urban areas, which are represented by the artificial surfaces and associated areas class.

This inadequacy can be observed in table 4, which exhibits the commission and omission errors. The artificial surfaces class exhibited the highest error of omission; 42% of the pixels classified as not being of this class actually were. The Kappa coefficient determined in this calculation was 0.64. Coefficients between 0.61 and 0.8 represent moderate agreement, so that, in these terms, the classifier in this case obtained a satisfactory accuracy (LANDIS and KOCH, 1977).

Some classes presented as mismatching because of their similar spectral response. This mismatching can be associated with the spectral and radiometric resolutions of the CCD sensor and the presence of noise (POLIDORIO et al. 2006).

Table 4: The commission and omission errors of SVM classification.

	Errors of commission (%)	Errors of omission (%)
Water bodies	0.00	6.00
Vegetation	2.27	57.00
Cultivated and Managed Areas	38.93	9.00
Artificial surfaces	49.57	42.00
Bare areas	27.84	30.00

The ML Classifier presented an overall accuracy of 49%, with a Kappa coefficient of 0.36, which represents a poor agreement (MARÇAL et al. 2005). Figure 3 shows the comparison between the ML classification (Figure 3(a)) and the ground truth map (figure 3(b)). The confusion matrix of ML classification is shown in Table 5, and the commission and omission errors in Table 6.

The class that was best classified in the ML classification was water bodies (as in the SVM classification); this class presented with lower

Table 5: MLC's confusion matrix.

	WB	V	CMA	AS	BA	Total	User's accuracy (%)
Water bodies (WB)	**65**	2	3	0	0	69	94
Vegetation (V)	17	**74**	53	22	55	221	33
Cultivated and managed areas (CMA)	7	12	**27**	17	17	80	34
Artificial surfaces (AS)	10	8	14	**60**	8	100	60
Bare areas (BA)	1	4	4	1	**20**	30	67
Total	100	100	100	100	100	500	
Producer's accuracy (%)	65	74	27	60	20		

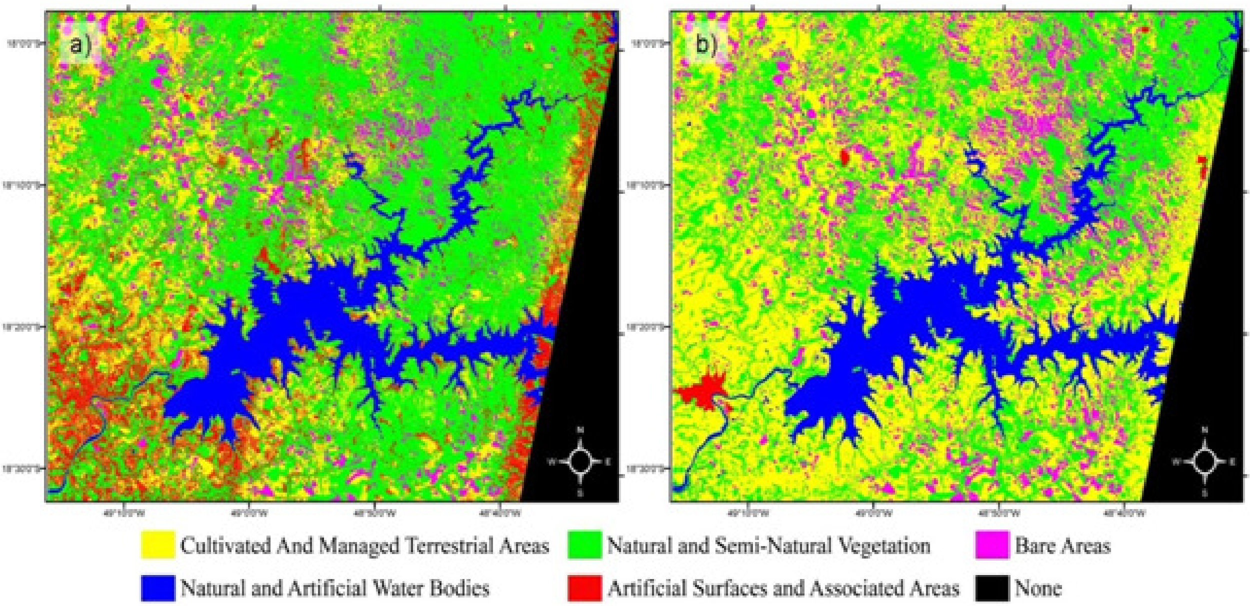

Fig. 3 - Comparison between the maximum likelihood classifier and the ground truth map.

accuracy than it did for SVM. Of the water bodies' areas, 94% were correctly identified as water bodies, but only 65% of the areas called water bodies on the map were actually water bodies on the ground. Although only 33% of vegetation areas were correctly identified as vegetation, 74% of the areas called vegetation on the map were actually vegetation on the ground.

The classifier was not efficient for classifying the classes of cultivated and managed areas and vegetation (see table 6). In these cases, there was a misclassification. The highest omission error was 80%, which was observed for the bare areas class.

Table 6: The commission and omission errors of maximum likelihood classification.

	Errors of commission (%)	Errors of omission (%)
Water bodies	6	35
Vegetation	66	26
Cultivated and Managed Areas	66	73
Artificial surfaces	40	40
Bare areas	33	80

The results show a better performance of the SVM approach and corroborate the results reported by several authors (i.e. Mathur and Foody, 2008; Dixon and Candade, 2008). The classifiers agreed in some cases, and the best fit in both classifications was that of natural and artificial water bodies. The better classification produced by the SVM affirms that CBERS images can be utilized in land use and cover classifications.

4. Conclusion

The aims of this study were to assess the classification by the SVM algorithm in CBERS images, to compare this result against a traditional statistical classifier (ML) and to assess the of SVM/ CBERS accuracy in remote sensing image classification.

Furthermore, we sought to assess the potential for CBERS data in image classification. The support vector machines classifier presented good results with minimum errors and presented better results than the maximum likelihood classifier. This result allows a more operational classification with less matrix addition.

For best results in CBERS-2 CCD classification, the authors suggest the testing of the other kernel functions for support vector machine classification and the comparison of the results with other classifiers. Despite the spectral and radiometric resolutions available for this study, the CBERS images showed a good potential for land use classifications.

ACKNOWLEDGMENTS

The authors would like to thank the Brazilian National Counsel of Technological and Scientific Development (CNPq) and the São Paulo Research Foundation (FAPESP) Project number 2007/ 08103-2.

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