International Journal of Applied Earth Observation and Geoinformation 5 (2004) 173–186

INTERNATIONAL JOURNAL OF APPLIED EARTH OBSERVATION AND GEOINFORMATION

www.elsevier.com/locate/jag

Selection of imagery data and classifiers for mapping Brazilian semideciduous Atlantic forests

Luis M.T. de Carvalho [a], Jan G.P.W. Clevers [b,*], Andrew K. Skidmore [c], Steven M. de Jong [d]

[a] *Departamento de Ciências Florestais, Universidade Federal de Lavras, 37200-000 Lavras-MG, Brazil*
[b] *Centre for Geo-Information, Wageningen University, P.O. Box 47, NL-6700 AA Wageningen, The Netherlands*
[c] *Division of Agriculture, Conservation and Environment, ITC, Enschede, The Netherlands*
[d] *Department of Physical Geography, Utrecht University, Utrecht, The Netherlands*

Received 13 March 2003; received in revised form 3 February 2004; accepted 13 February 2004

Abstract

This paper presents a case study on the use of features derived from remote sensing data for mapping the highly fragmented semideciduous Atlantic forest in Brazil. Innovative aspects of this research include the evaluation of different feature sets in order to improve land cover mapping. The feature sets were defined based on expert knowledge and on data mining techniques to be input to traditional and machine learning algorithms for pattern recognition, viz. maximum likelihood, univariate decision trees, multivariate decision trees, and neural networks. The results showed that the maximum likelihood classification using temporal texture descriptors as extracted with wavelet transforms was most accurate to classify the semideciduous Atlantic forest. In this study, a special accuracy measure was used: the so-called class mapping accuracy. Maximum likelihood performed relatively well, with forest mapping accuracies ranging from 34.5 to 51.3%. In contrast, accuracies for neural networks ranged from 19.0 to 45.2%. Classification confusion occurred mainly with coffee and eucalyptus plantations. Univariate trees provided the most robust results for different feature sets, with accuracies ranging from 39.6 to 46.7%. Temporal information of vegetation indices was more important than image texture, terrain topography and raw spectral information for discriminating semideciduous Atlantic forest.

Keywords: Forest classification; Feature sets; Classifiers; Artificial intelligence

1. Introduction

July 2001 forests gained renewed interest at the world conference on global change in Bonn, Germany, mainly because of their role in important environmental matters such as carbon cycle, climate change, and biodiversity conservation. Data acquisition at appropriate spatial and temporal scales is the keystone to achieve the mapping accuracy needed for mentioned fields of application. In Brazil, ongoing initiatives have been producing valuable information on forest resources (INPE, 2000; Souza and Barreto, 2000; Alves et al., 1999). The Amazonian and the evergreen Atlantic forests have been subject of regular research in many scientific fields (Goldsmith, 1998), whereas only few studies have dealt with the semideciduous Atlantic forest (de Oliveira-Filho and Fontes, 2000). The semideciduous Atlantic forests of

* Corresponding author. Tel.: +31-317-474594; fax: +31-317-419000.
E-mail address: jan.clevers@wur.nl (J.G.P.W. Clevers).

0303-2434/$ – see front matter © 2004 Elsevier B.V. All rights reserved.
doi:10.1016/j.jag.2004.02.002

Brazil are in an advanced stage of fragmentation and biodiversity is seriously threatened. Accurate forest monitoring is of utmost importance for supporting incentives to stop these degradation processes.

It was acknowledged at the environmental conferences in Rio de Janeiro and Kyoto that satellite imagery will offer the most promising and probably the only feasible way for a detailed mapping and monitoring of forests over large geographical areas. The operational use of remote sensing for forest mapping at regional and local scales has many challenges that must be overcome in order to realise its potential. For example, there is a need for effective information extraction from a combination of different remotely sensed data sets. The preprocessing and analysis tools should be able to deal with a variety of data types to enhance our ability to distinguish between landscape features. This need is evident when considering the increasing availability of many remotely sensed data sets and our poor knowledge on basic information about forest extent and condition.

Coarse spatial resolution sensors such as the NOAA-AVHRR have been used widely for land cover mapping (Mücher et al., 2000; Lucas et al., 2000a). However, the results are also spatially coarse and, thus, unsuitable for analysing landscapes that are fragmented at a high spatial frequency (Foody et al., 1997; Lucas et al., 2000b). Recently, attempts to overcome the spatial constrains imposed by sensors such as AVHRR have explored the use of mixture models, fuzzy clustering and artificial neural networks (Atkinson et al., 1997; Tatem et al., 2001). Fine spatial resolution images (e.g., SPOT-XS and Landsat-TM imagery) have been used to map forests with the accuracy required by regional-scale models (Frohn et al., 1996). Significant operational limitations are due to spectral overlap, large data volumes, and consequently the computational costs needed for large area mapping (Kontoes and Rokos, 1996; Townshend et al., 1997; Suzen and Toprak, 1998). Still, fine spatial resolution images provide the most feasible way of dealing with situations where a sufficient level of detail is required over large geographical areas.

The issues discussed above are relevant in the mapping of the highly fragmented semideciduous Atlantic forest in southeastern Brazil. By estimating its actual cover using NOAA-AVHRR imagery, one would probably conclude that this ecosystem has been almost extinguished (Fig. 1). Spectral overlap affects the use of e.g., Landsat-TM imagery because of the co-occurrence of land cover types such as coffee and eucalyptus plantations (Varona, 2000; Raga, 2001).

1.1. Information sources

Since the first images from the Landsat satellite reached the scientific community, numerous studies have demonstrated the applicability of spectral information to discriminate among land cover types. Together with the capabilities of multispectral analysis, its limitations were also revealed. Scientists found that some objects on the Earth's surface reflect the electromagnetic energy in the same way when sensed with a multispectral scanner (Skidmore et al., 1988; Ma and Olson, 1989). In addition, objects' reflectance may vary according to growth stage, phenology, humidity, atmospheric transparency, illumination conditions etc. These drawbacks led to a search for alternative features to enable the discrimination of land cover classes with similar reflectance behaviour.

The developed approaches rely on the use of additional information mainly related to topography, geology, historical imagery, land cover data, image textural measures, and multisensor imagery. Skidmore (1989) successfully mapped different eucalyptus species in Australia by incorporating information on their preferred terrain positions based on a digital terrain model (DTM), whereas de Bruin and Gorte (2000) obtained better classification results by using geological stratification. Temporal information has been considered in an attempt to distinguish agricultural crops using their development stages within the yearly growth cycle (Clevers et al., 1999; Ortiz et al., 1997). For perennial plants (like trees) information over many years can be used instead of the temporal information within 1 year as for most agricultural crops. Temporal signatures are mostly treated in the same way as spectral signatures. An exception is a recent methodology developed by Vieira et al. (2000), the so-called spectral-temporal response surface (STRS), which characterises the pixel's reflectance over time for each waveband by means of analytical surface fitting. De Jong and Riezebos (1991) increased classification by 20% using agro-ecological zones and the probabilities of a land cover type to occur within certain zones. Xia (1996) was able to identify five additional classes

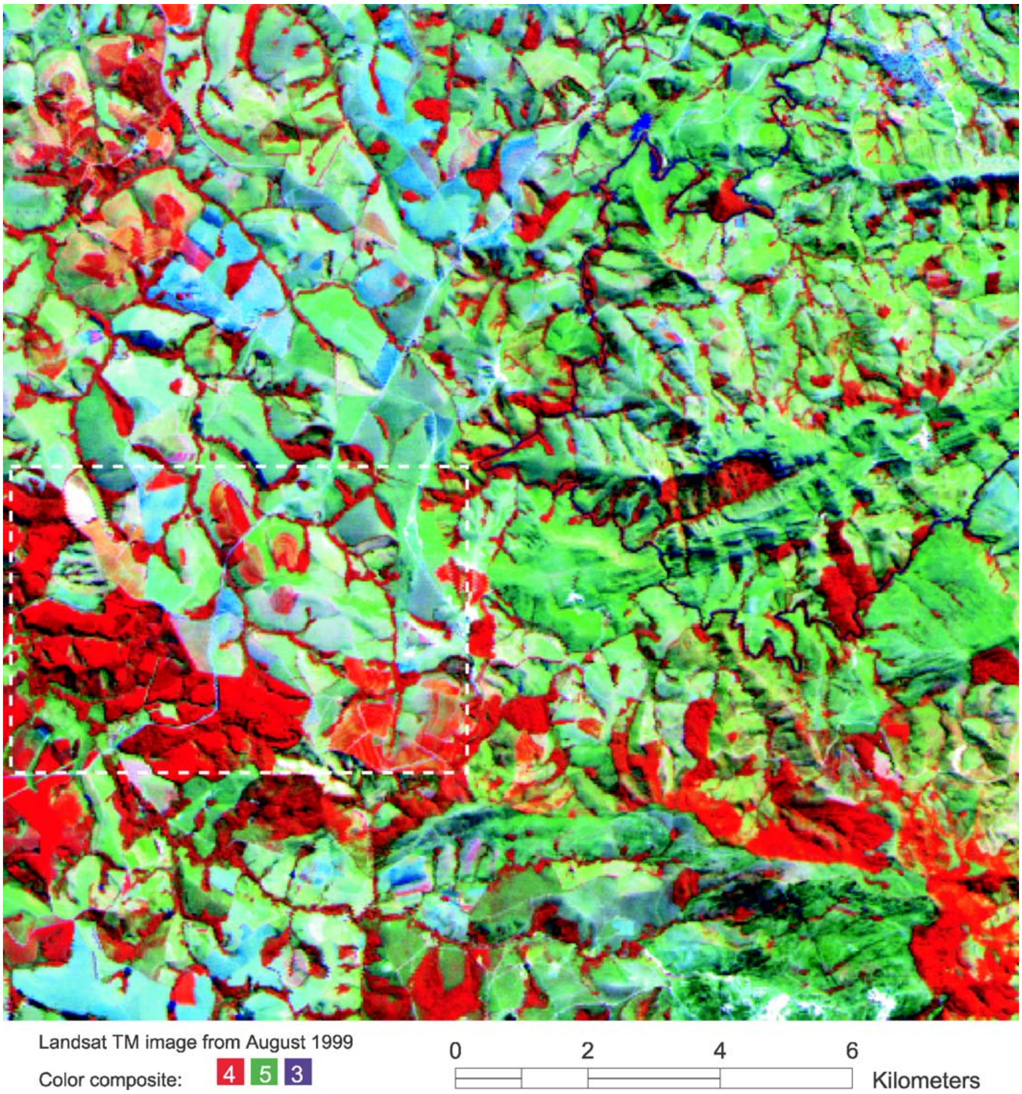

Fig. 1. Image used in the present study. The area within dashed lines is the subset shown in Fig. 2.

when information about objects' form was combined with spectral classification results. Image texture had little effect on increasing classification accuracy according to Dikshit (1996). In contradiction, Haralick (1979) obtained highly accurate results when using textural features derived from co-occurrence matrices. Manian et al. (2000) and Zhu and Yang (1998) reported promising results when texture features were extracted with logical operators and using wavelet transforms. Texture measures have been demonstrated to be of utmost importance for the analysis of SAR images (Soares et al., 1997; Fukuda and Hirosawa, 1999; Simard et al., 2000). The synergistic use of optical and radar remote sensing holds new opportunities for land cover classification (Clevers et al., 2000; Kuplich et al., 2000) since the latter provides additional data on vegetation structure and on areas frequently covered by clouds (Leeuwen et al., 1994).

Information sources for the present study were chosen as to evaluate the benefits provided by some of the features discussed above. The references cited in this section show evidences for the concomitant use of spectral and other sources of information to improve land cover mapping. Nevertheless, there is a lack of exploratory analyses comparing the accuracy achieved when using e.g., temporal instead of topographic information.

1.2. Classifiers

The above multisource information may be fed into a variety of classification schemes. The algorithms have evolved beyond the traditional probabilistic classifiers to deal with such heterogeneous data sets. Three approaches based on intelligent data analysis are being increasingly applied in the field of remote sensing. The first one, known as expert systems, works with encoded information termed knowledge base, which is generated by domain specialists. Unlike conventional mathematical models, the knowledge is stored in a separate file, which is evaluated within a set of rules defined by specialists (van den Eijkel, 1999). Some references cited above have used these models for land cover mapping (e.g., Skidmore, 1989; De Jong and Riezebos, 1991).

The second family of intelligent models is known as artificial neural networks. The most popular neural network model for classification of remotely sensed data is the multi-layer perceptron (MLP). Skidmore et al. (1997) used the backpropagation learning algorithm with a MLP model and reported no statistically significant improvement of classification accuracy for mapping forest types. New architectures have been developed in an attempt to improve over MLP, like the fuzzy ARTMAP (Carpenter et al., 1992), textural neural networks (Kaminsky et al., 1997) and combinations of neural networks and expert systems (Murai and Omatu, 1997).

Decision trees are the third family of 'intelligent' algorithms used for geographical analysis (Skidmore et al., 1996; Simard et al., 2000; Friedl et al., 2000; Gahegan, 2000). Induction of decision trees enables learning from pattern and is useful in selecting relevant features for classification (Borak and Strahler, 1999). It has been used extensively in other disciplines as a means of discovering knowledge for expert systems (Quinlan, 1986). Surprisingly, despite these attractive characteristics and investigations in the past (Swain and Hauska, 1977; Lee and Richards, 1985; Belward and de Hoyos, 1987), decision trees have only recently been considered for classification of remotely sensed images and not much work has been done up to now (Friedl and Brodley, 1997; DeFries et al., 1998; Friedl et al., 1999; Borak and Strahler, 1999). Finally, large-scale mapping projects using an increasing amount of remotely sensed data demand methods that are less dependent on human interventions and more capable of handling spectral, spatial, temporal and ancillary data from a variety of sources. In this context, decision trees have been regarded as one of the most important alternatives (DeFries and Townshend, 1999).

Artificial neural networks and decision trees were used in the present study because they have been regarded as the most promising approaches for automatic classification of large and heterogeneous datasets (DeFries and Townshend, 1999). Furthermore, they were compared to the traditional maximum likelihood classifier in terms of classification accuracy.

1.3. Objective

The operational use of fine spatial resolution images for forest mapping is still premature, especially within complex and fragmented agricultural systems. There is a need for an effective classification procedure that: (a) distinguishes between natural forest and classes that spectrally overlap with it, (b) gets the most from available features for classification, and (c) requires the least human intervention, if reliable estimates of forest cover are to be made frequently over large geographical areas.

Based on the statement above, the general objective of this study is to evaluate suitable methods of classifying forest cover in a representative study area in the semideciduous Atlantic forest in Brazil. This study intends to evaluate the suitability of a multisource classification approach by testing the following features for distinguishing natural forest from coffee and eucalyptus plantations.

- Multispectral remote sensing (RS) data within 1 year.
- Multispectral RS data over many years.
- Monotemporal RS data combined with DTM information.
- Spatial image texture.

- Temporal image texture.
- Spectral-temporal response surface method.
- Combination of all features (“data mining”).

Classification performance is evaluated by using maximum likelihood, neural network, and decision tree (univariate and multivariate) classifiers in combination with each feature set.

2. Material and methods

2.1. Study site and data

It is supposed that the Brazilian Atlantic forests have once covered about one million square kilometres, corresponding to almost 12% of the country’s area (de Oliveira-Filho and Fontes, 2000). Nowadays, estimated figures indicate that it has been reduced to less than 5% of the original cover and has become one of the most important examples of the radical destruction of tropical forests reported. An area in the “*Vale do Alto Rio Grande*”, southeastern Brazil, representing a complex and fragmented land cover pattern, was chosen as study area (Fig. 1). The occupation of this region was characterised by four economic cycles. Gold mining in the 18th century was the first important activity in the region. Mining was soon abandoned giving room to ranching and agriculture. In the nineteenth century, the region was the main furnisher of cattle and working animals to the market of Rio de Janeiro, which was by that time the capital of Brazil. Later in this century, the culture of coffee was introduced and increased very fast to become one of the main causes of deforestation in the region. Nowadays, besides the increasing industrialisation, coffee and milk production form the main economical activities in the region.

The “*Vale do Alto Rio Grande*” is characterised by gentle hills, with altitudes ranging in most of the region between 700 and 1000 m. However, altitudes between 100 and 1400 m occur on the steeper ridges of some mountain chains. Additionally, flat areas are mainly represented by flood plains at the river’s margins and by a few localised plateaus. The main land cover types in the study area are perennial crops like coffee, eucalyptus and pasture, enclosing remnants of semideciduous Atlantic forest and savanna-related formations. Both natural formations are often confused with planted crops because of their similar reflectance characteristics. Thus, the potential of variables derived from time series of reflectance data, spatial and temporal texture, and terrain topography were assessed to define a mapping strategy for the semideciduous Atlantic forests.

Table 1
Acquisition dates (day/month/year) of Landsat-TM images used in this study

12/10/84	04/06/89	05/06/95
09/06/85	22/07/89	31/01/96
15/10/85	26/10/89	07/06/96
16/11/85	25/07/90	28/07/97
14/07/86	23/04/91	01/11/97
03/11/86	14/09/91	16/08/98
17/07/87	30/07/92	29/04/99
13/03/88	01/07/93	19/08/99
03/07/88	05/08/94	23/11/99

The input data set consisted of spectral bands 3–5 from 27 Landsat-TM images of the study area acquired between 1984 and 1999 (Table 1). In addition, digitised contour lines with 20 m vertical resolution were used to derive a digital terrain model (DTM) of the study area. Land cover maps were obtained by combining the information of a field campaign in 1999 with available aerial photographs of the study area. Carvalho (2001) gave an extensive description of the study area and the data collection procedures.

2.2. Data preprocessing

Image registration was performed using a first order polynomial function and a nearest neighbour resampling method. Ten ground control points were selected for each image and the root mean square errors (RMSE) were less than one pixel for all registrations. The resulting time-series was declouded using the method developed and described in Carvalho (2001).

2.3. Development of feature sets

Seven sets of attributes were input to four classification algorithms. Descriptions of derived features, as well as the motivation for construction of each feature set, are listed further.

2.3.1. Set 1—yearly cycle of multispectral data

Bands 3–5 of TM data acquired in August 1998, April 1999, August 1999, and November 1999 were combined to form a set of 12 features. This data set was motivated by the assumption that different land cover types exhibit different dynamics throughout the year, which might aid the discrimination of spectrally similar land cover types.

2.3.2. Set 2—15 years of NDVI data

The normalized difference vegetation index (NDVI) images were calculated from TM images acquired yearly from 1985 till 1999. NDVI was chosen because it is thought to represent not only phenological variation but also rotation and management practices in perennial crops. It is assumed that natural forests exhibit a relatively constant temporal profile in relation to eucalyptus and coffee plantations.

2.3.3. Set 3—topography

From the digitised contour lines, a regular grid of elevation data with a spatial resolution of 30 m was generated using Delaunay triangulation with linear interpolation. This grid was then used to derive slope and aspect information. Elevation, slope and aspect features were combined with all TM bands (except for the thermal channel) of an image acquired in August 1998, thus forming a set with nine features. The assumption here was that topography determines agricultural land use and might provide discriminating information for forest classification.

2.3.4. Set 4—spatial texture

Multiscale texture descriptors were extracted in the spatial domain using a 2D discrete wavelet transform (Carvalho, 2001). Using this transform, four high-frequency images, representing textural variation at increasing spatial frequencies, were obtained for three TM bands (3–5) from 1999. Thus, 15 features (12 texture features and three TM bands) composed this set. The '*à trous*' algorithm with linear spline basis (Holschneider et al., 1989; Carvalho et al., 2001) was used for the wavelet decomposition.

2.3.5. Set 5—temporal texture

The 1D discrete wavelet transform was applied to extract temporal texture descriptors from the NDVI time series. Temporal profiles were decomposed pixel-wise using the Haar wavelet basis and pyramidal decomposition (Carvalho, 2001). Different from the 'à trous' algorithm, the pyramidal algorithm is non-redundant, i.e., generates two transformed vectors with half of the elements in the original vector, one representing low-frequency components and the other high-frequency components. One-level decomposition was applied to 14 NDVI images resulting in seven high-frequency texture features. These were stacked with TM bands 3–5 from 1999 generating a set with 10 features for classification.

2.3.6. Set 6—the spectral-temporal response surface (STRS)

Bands 3–5 from 27 images acquired from 1984 to 1999 were used to calculate coefficients of the spectral-temporal response surface (Vieira et al., 2000). The coefficients of the fitted analytical surface describe pixels as a function of time and wavelength, and represent the spectral-temporal relations. In two dimensions, i.e., spectral (x-coordinate) and temporal (y-coordinate), polynomials derived by multiple regression for each pixel in the image are surfaces $[f(x, y)]$ of the form (Burrough and McDonnell, 1998):

$$f(x, y) = b_0 \quad \text{(zero order)}$$

$$f(x, y) = b_0 + b_1x + b_2y \quad \text{(first order)}$$

$$f(x, y) = b_0 + b_1x + b_2y + b_3x^2 + b_4xy + b_5y^2 \quad \text{(second order)}$$

$$f(x, y) = b_0 + b_1x + b_2y + b_3x^2 + b_4xy + b_5y^2 + b_6x^3 + b_7x^2y + b_8xy^2 + b_9y^3 \quad \text{(third order)}$$

As suggested by Vieira et al. (2000), a polynomial fit of third order was used to generate a set of 10 coefficients (i.e., features) for each pixel in the subset scene.

2.3.7. Set 7—mined features

The 59 features described previously (in some of the previous sets the same features occur) were fed into a data mining package called classification and regression trees (CART) (Breiman et al., 1984) for exploratory analysis with decision trees (Carvalho, 2001). The top 10 discriminating features were selected to compose the last set for classification. The automatically selected features were six NDVI images from 1985 till 1987 and from 1992 till 1994, band 5 from April 1999 and the second, fourth and seventh coefficient images of the STRS.

In this way, sets 1–6 reflected expert knowledge on how different information might contribute to class discrimination, whereas in set 7, this knowledge was automatically generated based on relationships not always clear to domain experts. For the purpose of mapping semideciduous Atlantic forests, we hypothesise that feature sets 2 and 5–7, which include long time series, should be more relevant than the other feature sets that represent yearly cycles or have no temporal information included.

2.4. Classification procedures

2.4.1. Maximum likelihood

This algorithm has been the most popular for classification of remote sensing imagery. As a parametric classifier, it assumes that a hyper-ellipsoid decision volume can approximate the shape of the data clusters. For a given unknown pixel, described by a vector of features, the probability of membership in each class is calculated using the classes' mean feature vector, covariance matrix and prior probability (Duda and Hart, 1973). The unknown pixel is considered to belong to the class with maximum probability of membership.

2.4.2. Artificial neural networks

This algorithm has spread in the remote sensing literature as a promising technique for a number of situations such as non-normality, complex feature spaces and multivariate data types, where traditional methods fail to give accurate results (Atkinson and Tatnall, 1997). All feature sets were normalised before input to the neural network. The MLP model with a back-propagation learning algorithm (Carvalho, 2001) was used in the present case. The network architecture was set as follows: two hidden layers with 18 nodes each using the sigmoid function as the activation method, a fixed learning rate set to 0.9 and learning momentum set to 0.7.

2.4.3. Decision trees

Inductive learning is another approach for artificial intelligence. The rationale behind it is very simple and intuitive: starting from a set of examples (e.g., training pixels) described by a set of features, a binary decision rule is defined to split the data into subsets more homogeneous than the original. Each subset is then subject to a new split generating even more homogeneous subsets. Theoretically, the procedure iterates until 'pure' subsets are obtained. Decision rules at each split are normally obtained by thresholding the best discriminant attribute (univariate tree) or by defining the best discriminant function based on linear combinations of attributes (multivariate tree) (Brodley and Utgoff, 1995). The choice of attributes to be used in each split is guided by a quality measure applied to the generated subset. Decision trees share the same advantages of neural networks compared with traditional probabilistic algorithms because they are strictly nonparametric, free from distribution assumptions, able to deal with nonlinear relations, insensitive to missing values, and capable of handling numerical and categorical inputs. CART was used in this study to generate univariate and multivariate classification trees (Carvalho, 2001).

We expect neural networks and decision trees to be more accurate than the maximum likelihood classifier because of the advantages mentioned above and the complex land cover pattern in the study site.

Classifiers were trained with a set of 700 sample pixels equally distributed over seven main land cover types: natural forest, savanna, coffee, eucalyptus, annual crops, grassland and bare land. In addition, decision trees were pruned with another set of 700 sample pixels different from the training set. A class-oriented approach was chosen and all classes, except forest, were merged in a single class named non-forest.

2.5. Accuracy measures

Each forest/non-forest output map was tested for accuracy using a unique set of 2000 pixels selected with simple random sampling. Training, pruning and testing pixels were checked during field campaigns in 1999 aided by visual interpretation of small-format aerial photos and Landsat-TM images. Only 162 out of 2000 testing pixels were forest pixels, indicating that forest was only a minor class in the study area.

The chosen accuracy measure for classification comparisons was the class mapping accuracy proposed by Kalensky and Scherk (1975):

Table 2
Forest mapping accuracy with 99% confidence interval according to Thomas and Allcock (1984) with omissions and commissions for each combination of feature set/classifier evaluated in this study

Feature sets	Classifiers			
	Maximum likelihood		Neural network	
	Forest accuracy (%)	Omissions/commissions (pixels)	Forest accuracy (%)	Omissions/commissions (pixels)
One year cycle	46.9 ± 2.4	16/149	44.2 ± 2.2	16/168
NDVI time series	44.2 ± 2.2	16/168	20.8 ± 0.8	9/574
Topography	34.5 ± 1.7	16/261	33.8 ± 2.4	29/231
Spatial texture	39.8 ± 1.6	11/217	40.2 ± 5.2	68/72
Temporal texture	51.3 ± 3.0	21/113	35.1 ± 2.2	23/234
STRS	34.7 ± 1.0	6/287	45.2 ± 2.7	22/148
Mined features	42.8 ± 1.5	8/198	19.0 ± 0.6	6/658
	Univariate Tree		Multivariate Tree	
One year cycle	41.8 ± 3.1	32/149	38.4 ± 2.4	23/200
NDVI time series	43.3 ± 1.9	13/182	36.0 ± 1.4	10/260
Topography	41.8 ± 3.1	32/149	44.0 ± 2.9	26/147
Spatial texture	39.6 ± 3.4	40/146	40.1 ± 4.6	59/95
Temporal texture	42.0 ± 2.5	21/174	32.1 ± 1.8	19/283
STRS	44.4 ± 2.5	23/182	43.4 ± 2.7	23/158
Mined features	46.7 ± 4.3	43/93	35.8 ± 1.7	14/251

$$A_i = \frac{N_i}{N_i + E_i} 100\%, \quad (1)$$

where, A_i is the percentage mapping accuracy of class i, N_i the number of correctly classified pixels in class i, and E_i the sum of omissions and commissions in class i. This measure was chosen instead of the overall classification accuracy or the κ-statistics because the former might overestimate positional class accuracy (Skidmore, 1999) and the latter lacks probabilistic interpretation due to adjustments for hypothetical chance agreement (Stehman, 1997). Although included in the calculations of A_i, the number of omissions and commissions are also presented along with A_i in Table 2 because they provide meaningful indicators of classification performance. In addition, the entire confusion matrices are shown for the three best combinations of classifier and feature set.

3. Results and discussion

Table 2 shows an overview of the results of the classification into forest and non-forest for each combination of classifier and feature set. The forest mapping accuracy was highest when using the temporal texture as input for the maximum likelihood classification (Table 2). Some classifier-feature set combinations omitted less forest pixels than the most accurate ones, whereas others classified fewer non-forest pixels as forest. For example, when mined features were input to neural networks, only six forest pixels were omitted from this class, but 658 non-forest pixels were classified as forest. On the other hand, neural networks with spatial texture showed a few commissions but more omissions than the best combination. The third most accurate combination, the univariate tree with mined features, provided a balance between omissions and commissions, similar to the multivariate tree with spatial texture, but yet with high accuracy. The least accurate classification result (19%) was provided by the combination of neural networks with mined features mainly due to the large number of commissions.

Maximum likelihood performed relatively well with all input feature sets (Table 2) with accuracies ranging from 34.5 to 51.3%. In contrast, neural networks showed the greatest variation, with accuracies ranging from 19.0 to 45.2%. Commissions made by this type of classifier range from 72 to 658 pixels

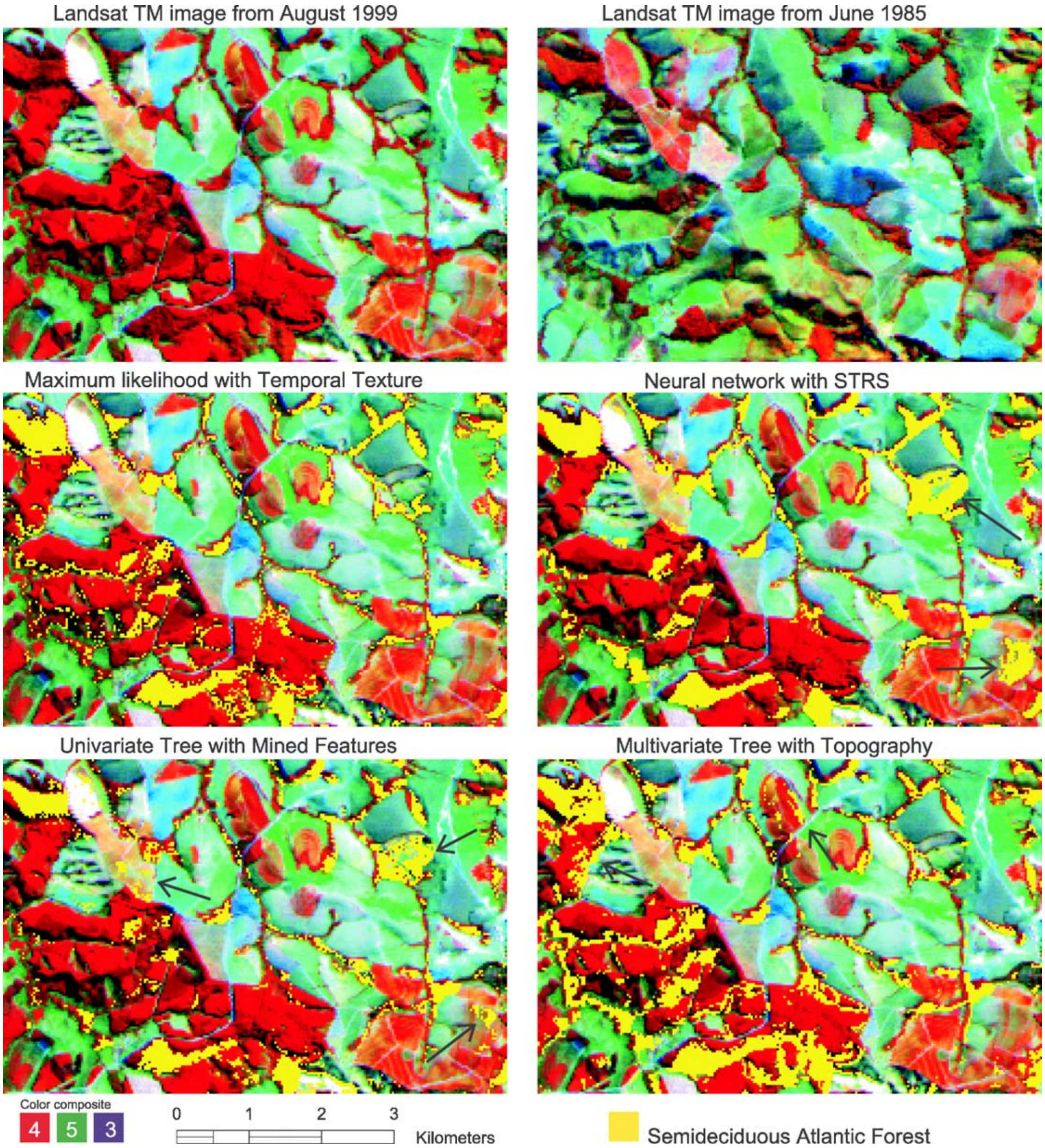

Fig. 2. Illustration of two Landsat-TM images and the best feature set for each of the four classifiers. Black arrows indicate misclassifications.

(out of 2000 pixels), the lowest and highest commission values in Table 2. Univariate trees provided the smallest range of variation for different feature sets, with classification accuracies ranging from 39.6 to 46.7%.

As expected, classification confusion (arrows in Fig. 2) occurred mainly with coffee and eucalyptus plantations, but neural networks and univariate trees also misclassified deforested areas currently covered with pasture. Table 3 provides a schematic overview of the classification results, combining the mapping accuracy and the errors of omission and commission in a somewhat subjective way, but helping in making the results more transparent.

Table 3
Schematic overview of the classification results of this study

Feature sets	Classifiers			
	Maximum likelihood	Neural network	Univariate tree	Multivariate tree
One year cycle	++	++	+	+
NDVI time series	++	−	++	0
Topography	0	0	+	++
Spatial image texture	+	++	+	++
Temporal image texture	+++	0	+	0
STRS	0	++	++	++
Mined features	++	−	++	0

(−) Unsuitable; (0) neutral; (+) suitable; (++) very suitable; (+++) most suitable.

3.1. Feature sets and classifiers

The information provided by the high frequency components extracted from temporal profiles was relevant in this study, probably because of the different dynamics exhibited by natural forests and managed land cover types with similar reflectance characteristics. Considering that temporal information provides discriminating features for a given application, we suggest that these findings could be applied to other areas as well, and high frequency coefficients as extracted with pyramidal wavelet transforms might provide data reduction and yet enough information for class discrimination. The Haar wavelet was chosen for this study because it is equivalent to subtracting subsequent years and, thus, represents differences in land cover characteristics between the considered years. Wavelet coefficients were able to capture land cover dynamics, thus enabling change information to be used effectively during classification. Note that this feature set provided more accurate results than the NDVI time series from which wavelet coefficients were extracted. This fact may be explained by the so-called curse of dimensionality: provided that the number of training samples per class is fixed, the classification accuracy decreases as the number of input features increases (Bishop, 1995). In contrast to the results presented here, Borak and Strahler (1999) concluded that features representing time had minor importance for class discrimination, but their temporal data set included only images from a one-year cycle. Long time series (e.g., over decades) can be very effective for class discrimination if the goal is comparisons between natural and managed land cover types, since the latter are mostly more dynamic. Another reason for this different conclusion could have been the pronounced spectral overlap of forests with perennial crops in our study site, preventing the efficient use of spectral features for class separation. Neural networks combined with STRS coefficients and univariate trees combined with mined features misclassified deforested areas currently covered with pasture (black arrows in Fig. 2), probably because temporal information was not effectively used. The fact that forests once covered these areas might have been more important for the mentioned combinations of classifiers-feature set.

From the seven feature sets evaluated, only sets three (topography) and four (spatial texture) represented static information. Probably because of the explicit combination of features to define discriminant functions, multivariate trees performed well when sets three and four were supplied for classification. For example, when a multivariate tree was grown using topographic information, a relationship between slope, near-infrared reflectance (NIR) and the occurrence of forest was found, which could have been hidden for other classifiers hampering their ability to use topographic features for classification. Another indication for the lesser importance of topography and spatial texture comes from the fact that they were rarely selected during data mining and hence considered to have low discriminating power. Data mining with decision trees provided an effective feature selection and reduction, but classification accuracy increased only when the mined features were used to grow another decision tree. Eighty-one features were reduced to ten coefficients of the STRS, which kept most of the relevant information and showed good accuracy when

Table 4
Accuracy measures for the map produced with the maximum likelihood classifier applied to feature set 5 (temporal texture)

Mapped class	Ground truth			Commission error (%)	User accuracy (%)
	Forest	Non-forest	Total		
Forest	141	113	254	44.49	55.51
Non-forest	21	1725	1746	1.20	98.80
Total	162	1838	2000		
Omission error (%)	12.96	6.15			
Producer accuracy (%)	87.04	93.85			

Values in the contingency table are the number of pixels. Overall accuracy = 93.30%, κ-coefficient = 0.6425, Z-statistic = 7.90.

input to neural networks, univariate and multivariate decision trees. Although preprocessing with data mining decreased the neural network's accuracy, the most accurate results provided by feature reduction with the STRS show the benefit of using data transformations and preprocessing before neural network classification.

It is important to mention that equal prior probabilities were provided to the maximum likelihood classifier, whereas neural networks and decision trees learned the different prior probabilities from training data distributions. Still, maximum likelihood was the best classifier in this study and an increased accuracy may still be achieved by provision of prior probabilities for each land cover class. On the other hand, the unpredictable behaviour of neural networks could be a reflection of its lack of interpretability, demanding careful experimentation before use in particular situations.

Univariate trees were more accurate than multivariate trees whenever temporal information was used. Classifiers with learning capabilities generally provide better results when more examples (i.e., training samples) are provided. In this study, only 100 pixels for each of the seven original classes were used for training and that could have limited the accuracy levels obtained with decision trees.

3.2. Mapping accuracy

As for the choice of classifiers, decision of what should be considered the most appropriate in terms of accuracy depends largely on the objectives of the mapping project (Stehman, 1997). Because the aim of this study was to evaluate classification of forests as a whole, the total number of misclassifications was the chosen indicator. As opposed to measures based on indicators of type I and type II errors (e.g., user and producer accuracy), the class mapping accuracy proposed by Kalensky and Scherk (1975) takes omissions and commissions into account generating an unbiased estimator of positional class accuracy (Skidmore, 1999) (compare Tables 4 and 5). The combination shown in Table 6 would be considered the best for forest mapping if one used producer accuracy as indicator. Considering the class-oriented approach and the binary

Table 5
Accuracy measures for the map produced with the neural network classifier applied to feature set 4 (spatial texture)

Mapped class	Ground truth			Commission error (%)	User accuracy (%)
	Forest	Non-forest	Total		
Forest	94	72	166	43.37	56.63
Non-forest	68	1766	1834	3.71	96.29
Total	162	1838	2000		
Omission error (%)	41.98	3.92			
Producer accuracy (%)	58.02	96.08			

Values in the contingency table are the number of pixels. Overall accuracy = 93.00%, κ-coefficient = 0.5351, Z-statistic = 5.26.

Table 6
Accuracy measures for the map produced with the maximum likelihood applied to feature set 1 (yearly cycle)

Mapped class	Ground truth			Commission error (%)	User accuracy (%)
	Forest	Non-forest	Total		
Forest	146	149	295	50.51	49.49
Non-forest	16	1689	1705	0.94	99.06
Total	162	1838	2000		
Omission error (%)	9.88	8.11			
Producer accuracy (%)	90.12	91.89			

Values in the contingency table are the number of pixels. Overall accuracy = 91.75%, κ-coefficient = 0.5968, Z-statistic = 7.81.

classification problem presented in this study, the overall accuracy would yield similar results, but still, the combination of a neural network with the spatial texture (overall accuracy of 93%) would be misinterpreted as giving the second best result even omitting a large number of forest pixels. Stehman (1997) criticised the lack of probabilistic interpretation when using coefficients like Kappa and conditional Kappa, but in the present study they did not lead to misinterpretation of the case mentioned above (compare Tables 5 and 6). In all three cases the obtained Z-statistic was highly significant.

4. Conclusions

Considering the study set up and its outcomes, the following statements could be drawn about mapping the semideciduous Atlantic forest.

- Temporal information from vegetation indices was more important than image texture, terrain topography and raw spectral information for discriminating semideciduous Atlantic forest in the present study. Nevertheless, spatial texture and topographical features were still important when neural networks and multivariate trees were used for classification.
- The choice of classifier is dependent on the data, objectives, resources, and expertise available for a given mapping project. Aiming at accurate mapping of semideciduous Atlantic forest in the “Vale do Alto Rio Grande”, using the data set available for this study and considering the other factors given, one is advised to use maximum likelihood classification and temporal texture descriptors of NDVI time series as input data.

References

Alves, D.S., Pereira, J.L.G., De Souza, C.L., Soares, J.V., Yamaguchi, F., 1999. Characterizing landscape changes in central Rondônia using Landsat TM imagery. Int. J. Remote Sens. 20, 2877–2882.

Atkinson, P.M., Tatnall, A.R.L., 1997. Neural networks in remote sensing—Introduction. Int. J. Remote Sens. 18, 699–709.

Atkinson, P.M., Cutler, M.E.J., Lewis, H., 1997. Mapping sub-pixel proportional land cover with AVHRR imagery. Int. J. Remote Sens. 18, 917–935.

Belward, A.S., de Hoyos, A., 1987. A comparison of supervised maximum likelihood and decision tree classification for crop cover estimation from multitemporal Landsat MSS data. Int. J. Remote Sens. 8, 229–235.

Bishop, C.M., 1995. Neural Networks for Pattern Recognition. Clarendon, Oxford.

Borak, J.S., Strahler, A.H., 1999. Feature selection and land cover classification of a MODIS-like data set for a semi-arid environment. Int. J. Remote Sens. 20, 919–938.

Breiman, L., Friedman, J.H., Olsen, R.A. and Stone, C.J., 1984. Classification and Regression Trees. Wadsworth, Belmont.

Brodley, C.E., Utgoff, P.E., 1995. Multivariate decision trees. Machine Learning 19, 45–77.

de Bruin, S., Gorte, B.G.H., 2000. Probabilistic image classification using geological map units applied to land-cover change detection. Int. J. Remote Sens. 21, 2389–2402.

Burrough, P.A., McDonnell, R.A., 1998. Principles of Geographic Information Systems. Oxford University Press, New York.

Carpenter, G.A., Grossberg, S., Markuzon, S., Reynolds, N., Rosen, D.B., 1992. Fuzzy ARTMAP: a neural network architecture for incremental supervised learning of analog multidimensional maps. IEEE Trans. Neural Networks 3, 698–713.

Carvalho, L.M.T., 2001. Mapping and monitoring forest remnants: a multiscale analysis of spatio-temporal data. Ph.D. Thesis, Wageningen University, Wageningen, The Netherlands.

Carvalho, L.M.T., Fonseca, L.M.G., Murtagh, F., Clevers, J.G.P.W., 2001. Change detection at multiple spatial scales with the aid of multiresolution wavelet analysis. Int. J. Remote Sens. 22, 3871–3876.

Clevers, J.G.P.W., Vandysheva, N.M., Mücher, C.A., Vassilenko, G.I., Filonov, S.V., Zhoukova, G.A., Izotova, V.P., Gurov, A.F., Nieuwenhuis, G.J.A., Addink, E.A., 1999.

Agricultural Land Use Monitoring with Improved Remote Sensing Techniques. Report LUW-GIRS-199902, Wageningen University, Wageningen, The Netherlands.

Clevers, J.G.P.W., Vonder, O.W., Schok, H.A., Addink, E.A., 2000. Applications of Multisensor Remote Sensing Satellite Sensors. CGI Report 2000-03, Wageningen University, Wageningen, The Netherlands.

DeFries, R.S., Townshend, J.R.G., 1999. Global land cover characterization from satellite data: from research to operational implementation? Global Ecol. Biogeogr. 8, 367–379.

DeFries, R.S., Hansen, M., Townshend, J.R.G., Sohlberg, R., 1998. Global land cover classifications at 8 km spatial resolution: the use of training data derived from Landsat imagery in decision tree classifiers. Int. J. Remote Sens. 19, 3141–3168.

De Jong, S.M., Riezebos, H.T., 1991. Use of a GIS database as “a priori” knowledge in multispectral land cover classification. In: Proceedings of the Second European Conference on Geographical Information Systems. Brussels, pp. 503–508.

Dikshit, O., 1996. Textural classification for ecological research using ATM images. Int. J. Remote Sens. 17, 887–915.

Duda, R.O., Hart, P.E., 1973. Pattern Classification and Scene Analysis. Wiley, New York.

Eijkel, G.C. van den, 1999. Rule induction. In: Berthold, M., Hand, D.J. (Eds.), Intelligent Data Analysis: An Introduction. Springer-Verlag, Berlin, pp. 195–216.

Foody, G.M., Lucas, R.M., Curran, P.J., Honzak, M., 1997. Mapping tropical forest fractional cover from coarse spatial resolution remote sensing imagery. Plant Ecol. 131, 143–154.

Friedl, M.A., Brodley, C.E., 1997. Decision trees classification of land cover from remotely sensed data. Remote Sens. Environ. 61, 399–409.

Friedl, M.A., Brodley, C.E., Strahler, A.H., 1999. Maximizing land cover classification accuracies produced by decision trees at continental to global scales. IEEE Trans. Geosci. Remote Sens. 37, 969–977.

Friedl, M.A., Woodcock, C., Gopal, S., Muchoney, D., Strahler, A.H., Barker-Schaaf, C., 2000. A note on procedures used for accuracy assessment in land cover maps derived from AVHRR data. Int. J. Remote Sens. 21, 1073–1077.

Frohn, R.C., McGwire, K.C., Dale, V.H., Estes, J.E., 1996. Using satellite remote sensing analysis to evaluate a socio-economic and ecological model of deforestation in Rondonia, Brazil. Int. J. Remote Sens. 17, 3233–3255.

Fukuda, S., Hirosawa, H.A., 1999. Wavelet-based texture feature set applied to classification of multifrequency polarimetric SAR images. IEEE Trans. Geosci. Remote Sens. 37, 2282–2286.

Gahegan, M., 2000. On the application of inductive machine learning tools to geographical analysis. Geograph. Anal. 32, 113–139.

Goldsmith, F.B., 1998. Tropical Rain Forest: a Wider Perspective. Chapman and Hall, Padstow.

Haralick, R.M., 1979. Statistical and structural approaches to texture. Proc. IEEE 67, 786–804.

Holschneider, M., Kronland-Martinet, R., Morlet, J., Tchmitchian, P., 1989. A real time algorithm for signal analysis with the help of the wavelet transform. In: Combes, J.M., Grossman, A., Tchmitchian, P. (Eds.), Wavelets: Time Frequency Methods and Phase Space. Springer-Verlag, New York, pp. 286–297.

INPE, 2000. Monitoramento de Floresta Amazônica por Satélite 1998–1999. Instituto Nacional de Pesquisas Espaciais, São José dos Campos, Brazil.

Kalensky, Z.D., Scherk, L.R., 1975. Accuracy of forest mapping from Landsat CCTs. In: Proceedings of the 10th International Symposium on Remote Sensing of Environment. ERIM, Ann Arbor, pp. 1159–1163.

Kaminsky, E.J., Barad, H., Brown, W., 1997. Textural neural network and version space classifiers for remote sensing. Int. J. Remote Sens. 18, 741–762.

Kontoes, C.C., Rokos, D., 1996. The integration of spatial context information in an experimental knowledge-based system and the supervised relaxation algorithm: two successful approaches to improving SPOT-XS classification. Int. J. Remote Sens. 17, 3093–3106.

Kuplich, T.M., Freitas, C.C., Soares, J.V., 2000. The study of ERS-1 SAR and Landsat TM synergism for land use classification. Int. J. Remote Sens. 21, 2101–2111.

Lee, T., Richards, J.A., 1985. A low-cost classifier for multitemporal applications. Int. J. Remote Sens. 6, 1405–1417.

Leeuwen, H.J.C. van, Clevers, J.G.P.W., Rijckenberg, G.J., 1994. Synergy between optical and microwave remote sensing data using models and specific features with respect to the sugar beet crop. In: Proceedings of the IGARSS’94 Symposium, Pasadera, California, 8–12 August 1994, Vol. 2, pp. 827–831.

Lucas, R.M., Honzak, M., Curran, P.J., Foody, G.M., Ngueles, D.T., 2000a. Characterizing tropical forest regeneration in Cameroon using NOAA AVHRR data. Int. J. Remote Sens. 21, 2831–2854.

Lucas, R.M., Honzak, M., Curran, P.J., Foody, G.M., Milne, R., Brow, T., Amaral, S., 2000b. Mapping the regional extent of tropical forest regeneration stages in the Brazilian Legal Amazon using NOAA AVHRR data. Int. J. Remote Sens. 21, 2855–2881.

Ma, Z., Olson, C.E., 1989. A measurement of spectral overlap among cover types. Photogrammetric Eng. Remote Sens. 55, 1441–1444.

Manian, V., Vásquez, R., Katiyar, P., 2000. Texture classification using logical operators. IEEE Trans. Image Proces. 9, 1693–1703.

Mücher, C.A., Steinnocher, K.T., Kressler, F.P., Heunks, C., 2000. Land cover characterization and change detection for environmental monitoring of pan-Europe. Int. J. Remote Sens. 21, 1159–1181.

Murai, H., Omatu, S., 1997. Remote sensing image analysis using a neural network and knowledge-based processing. Int. J. Remote Sens. 18, 811–828.

de Oliveira-Filho, A.T., Fontes, M.A.L., 2000. Patterns of floristic differentiation among Atlantic forests in southeastern Brazil and the influence of climate. Biotropica 32, 793–810.

Ortiz, M.J., Formaggio, A.R., Epiphanio, J.C.N., 1997. Classification of croplands through integration of remote sensing, GIS, and historical database. Int. J. Remote Sens. 18, 95–105.

Quinlan, J.R., 1986. Induction of decision trees. Machine Learn. 1, 81–106.

Raga, D.O., 2001. Using neural network and temporal information to improve land cover separability. MSc Thesis, Wageningen University, Wageningen, The Netherlands.

Simard, M., Saatchi, S.S., De Grandi, G., 2000. The use of decision tree and multiscale texture for classification of JERS-1 SAR data over tropical forest. IEEE Trans. Geosci. Remote Sens. 38, 2310–2331.

Skidmore, A.K., 1989. An expert system classifies eucalypt forest types using Thematic Mapper data and a digital terrain model. Photogram. Eng. Remote Sensing 55, 1449–1464.

Skidmore, A.K., 1999. Accuracy assessment of spatial information. In: Stein, A., Van Der Meer, F., Gorte, B. (Eds.), Spatial Statistics for Remote Sensing. Kluwer Academic Publishers, Dordrecht.

Skidmore, A.K., Forbes, G.W., Carpenter, D.J., 1988. Non-parametric test of overlap in multispectral classification. Int. J. Remote Sens. 9, 777–785.

Skidmore, A.K., Gauld, A., Walker, P., 1996. Classification of kangaroo habitat distribution using three GIS models. Int. J. Geograph. Inform. Sys. 10, 441–454.

Skidmore, A.K., Turner, B.J., Brinkhof, W., Knowles, E., 1997. Performance of a neural network: mapping forests using GIS and remotely sensed data. Photogram. Eng. Remote Sens. 63, 501–514.

Soares, J.V., Renno, C.D., Formaggio, A.R., Yanasse, C.D.C.F., Frery, A.C., 1997. An investigation of the selection of texture features for crop discrimination using SAR imagery. Remote Sens. Environ. 59, 234–247.

Souza Jr., C., Barreto, P., 2000. An alternative approach for detecting and monitoring selectively logged forests in the Amazon. Int. J. Remote Sens. 21, 173–179.

Stehman, S.V., 1997. Selecting and interpreting measures of thematic classification accuracy. Remote Sens. Environ. 62, 77–89.

Suzen, M.L., Toprak, V., 1998. Filtering of satellite images in geological lineament analyses: an application to a fault zone in central Turkey. Int. J. Remote Sens. 19, 1101–1114.

Swain, P.H., Hauska, H., 1977. The decision tree classifier: design and potential. IEEE Trans. Geosci. Electron. 15, 142–147.

Tatem, A.J., Lewis, H.G., Atkinson, P.M., Nixon, M.S., 2001. Super-resolution target identification from remotely sensed images using a Hopfield neural network. IEEE Trans. Geosci. Remote Sensing 39, 781–796.

Thomas, I.L., Allcock, G.M., 1984. Determining the confidence interval of a classification. Photogram. Eng. Remote Sens. 50, 1491–1496.

Townshend, J., DeFries, R., Dubayah, R., Goward, S., Kearney, M., Tucker, C.J., Vermonte, E., 1997. Land cover characterization at regional and global scales: lessons learnt and prospects. In: Proceedings of the 23rd Annual Conference of the Remote Sensing Society on Observations and Interactions. The Remote Sensing Society, Nottingham, UK.

Varona, L.D., 2000. Applying remote sensing and GIS for monitoring fragmentation in an area of Atlantic forest of Southeastern Brazil. MSc Thesis, Wageningen University, Wageningen, The Netherlands.

Vieira, C., Mather, P., McCullagh, M., 2000. The spectral-temporal response surface and its use in the multisensor, multitemporal classification of agricultural crops. In: Proceedings of the 19th Congress of the ISPRS. Amsterdam, pp. 582–589.

Xia, L., 1996. A method to improve classification with shape information. Int. J. Remote Sens. 17, 1473–1481.

Zhu, C., Yang, X., 1998. Study of remote sensing image texture analysis and classification using wavelets. Int. J. Remote Sens. 19, 3197–3203.