A NEW PROCEDURE FOR FORESTRY DATABASE UPDATING WITH GIS AND REMOTE SENSING

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ABSTRACT: The aim of this study was to develop an automated, simple and flexible procedure for updating raster-based forestry database. Four modules compose the procedure: (1) location of changed sites, (2) quantification of changed area, (3) identification of the new land cover, and (4) database updating. Firstly, a difference image is decomposed with wavelet transforms in order to extract changed sites. Secondly, segmentation is performed on the difference image. Thirdly, each changed pixel or each segmented region is assigned to the land cover class with the highest probability of membership. Then, the output is used to update the GIS layer where changes took place. This procedure was less sensitive to geometric and radiometric misregistration, and less dependent on ground truth, when compared with post classification comparison and direct multidate classification.

Key words: wavelets, segmentation, classification, raster, change detection, remote sensing

UM NOVO PROCEDIMENTO PARA A ATUALIZAÇÃO DE BANCO DE DADOS FLORESTAL COM SIG E SENSORIAMENTO REMOTO

RESUMO: O intuito deste estudo foi desenvolver um procedimento automático, simples e flexível para a atualização de base de dados florestais em formato matricial. Quatro módulos compõem o procedimento: (1) localização das áreas que sofreram modificações, (2) quantificação da área modificada, (3) identificação das novas classes de ocupação do solo e (4) atualização da base de dados. Primeiramente, uma imagem diferença é decomposta usando a transformada ondaleta para extrair os locais onde ocorreram modificações. Posteriormente, a imagem diferença é segmentada nestes locais. Num terceiro estágio, cada pixel ou cada região que sofreu modificação é classificada. Por fim, o resultado é usado para atualizar a base de dados. Este procedimento mostrou-se menos sensível a distorções nos registros geométricos e radiométricos e menos dependente de informações coletadas em campo quando comparado com dois procedimentos tradicionalmente usados para detecção de mudanças.

Palavras-chave: ondaletas, segmentação, classificação, raster, detecção de mudança, sensoriamento remoto.

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1 INTRODUCTION

Remote sensing and GIS are being increasingly used in combination. GIS databases are used to improve the extraction of relevant information from remote sensing imagery, whereas remote sensing data provide periodic pictures of geometric and thematic characteristics of terrain objects, improving our ability to detect changes and update GIS databases (Janssen, 1993). In a previous work, a method to extract change information at varying spatial scales was presented and discussed (Carvalho et al., 2001). This paper incorporates multiscale change analysis in an operational environment to, automatically, detect changes and to update GIS databases, using multitemporal remote sensing imagery.

Most research efforts for monitoring land cover change with remote sensing have dealt with localised case studies of experimental nature (Wyatt, 2000). Considering monitoring of forests, the PRODES project (Estimate of Amazon gross deforestation) from the Brazilian Institute for Space Research (INPE) is one of the few examples of operational application of high spatial resolution remote sensing data for change analysis over large geographical areas. It has been providing valuable estimates of deforestation since 1974. Until 2003, the methodology used by PRODES relied on manual delineation of deforested areas, involving for each assessment approximately 50,000 man-hours with a team of 70 remote sensing specialists supervised by 15 researchers (INPE, 2000). Such a framework would be inapplicable for complex fragmented landscapes, as in the case study presented in this paper, unless automation of some tasks is achieved. The Landsat Pathfinder project (deforestation in the humid tropics) is another relevant attempt to monitor land cover at large scales with high spatial resolution imagery, which gave strong evidence for the need of automated approaches as well (Townshend et al., 1997).

The difficulties of dealling with land cover change detection are further complicated, when compared to land cover mapping, imposing limits to automation. In fact, as change analysis with remote sensing compares image snap shots acquired at intervals of time, they, inevitably, inherit problems of single-date image analysis and rise new ones related to the integration of multitemporal data sets. The first difficulty while handling time-series of remotely sensed data is (1) the geometric transformation of each image in the series to match a reference image or map. Errors result from this process and part of detected changes is caused by misregistration (Townshend et al., 1992). Another important spatial aspect is related to (2) the size of changes to be observed. Change detection is limited by the nominal spatial resolution of the sensor, the degree of fragmentation of the landscape and the nature of boundaries between objects. They influence land cover mixture in a pixel, which may vary from one date to the other, even if no land cover change occurs. (3) Temporal scales in which changes occur must be considered as well, and the choice of sensors to provide data should be guided by the nature of processes under investigation. (4) Atmospheric conditions by the time of image acquisition vary considerably and might weaken the signal that reaches the sensor or even obstruct it completely, generating differences that can be misinterpreted as land cover change. (5) Remote sensing-based land cover studies rely on the premise that the radiometric response of objects on the Earth's surface must differ in the spectral region covered by the sensor. Finally, (6) some changes are gradual and their detection is difficult. Forest degradation and regeneration, for instance, are much harder to quantify with remote sensing when compared to forest removal. Advances on hyper-spectral and temporal data analysis may help to study such

cases, but their use for change detection is still premature (Wyatt, 2000).

Automation has been one of the early goals of geoinformation processing due to the potential of performing unsupervised tasks provided by computer-aided analysis (Tzschupke, 1976; Dobson, 1983). In digital change detection, little work has been carried out in this direction and the few established procedures are related to image classification (Tou & Gonzales, 1974). Automated change detection using remote sensing data is reported by a few recent studies (Chavez & Mackinnon, 1994; Michener & Houhoulis, 1997; Pristnall & Glover, 1998; Hamë et al., 1998; Kwartenge & Chavez 1998; Salvador et al., 2000). Even so, the term 'automated' is causing confusion in the literature, considering that the process of change detection is very broad and should not be misinterpreted as the simple act of automatically producing, for instance, a difference or ratio image.

The approach proposed by Priestnall & Glover (1998) for updating vector-based GIS databases represents an effective step towards automation of change detection. Yet, they concluded that the project is still in the beginning and many challenges are still to be met. This is because their aim is on cartographic-quality updating of high spatial resolution databases involving increased complexity of contextual information, which in turn makes the approach complex. Hamë et al. (1998) described an interesting procedure (called "AutoChange") as a change detection and recognition system that could be considered automatic. The procedure is also complex and though the term 'recognition' was used to describe it, the outputs only provide changes and their magnitudes, but not labels. Furthermore, its best reported performance was below 66% of correct distinction between changed and unchanged pixels. Machine learning techniques are potential tools for automatic change detection, which were evaluated in studies by Abuelgasim et al. (1999) using fuzzy neural networks and Dai & Khorram (1999) using multi-layer perceptron (MLP).

The aim of this study was to develop an automated, simple and flexible procedure for updating raster-based forestry databases. Automated in the sense that changes are detected, segmented, classified, and the GIS layers updated without human interaction, though ground-truth for changed sites and spectral signatures of the new land cover classes must be known in advance. Note that this is also the case with the so-called unsupervised classification algorithms, where the analyst still has to label clusters. Flexibility relates to the possibility of accommodating various segmentation and classification schemes (e.g., machine learning algorithms, parametric classifiers), of taking into consideration knowledge on the changes of interest (i.e., denoising), and of using pixel - or object-oriented approaches during classification.

2 MATERIALS AND METHODS

2.1 A compound procedure for automatic GIS updating

The procedure proposed and illustrated in this paper (figure 1) uses as input two remotely sensed (RS) images acquired at different points in time (t1 and t2), GIS layers representing the land cover types under investigation, and a set of ground-truth data (GT) for the present land cover pattern and for changed sites. The most recent image is used to update the GIS layers based on radiometric differences with the oldest image. This latter should have been acquired near the map production date to give a representative picture of the land cover pattern by that time.
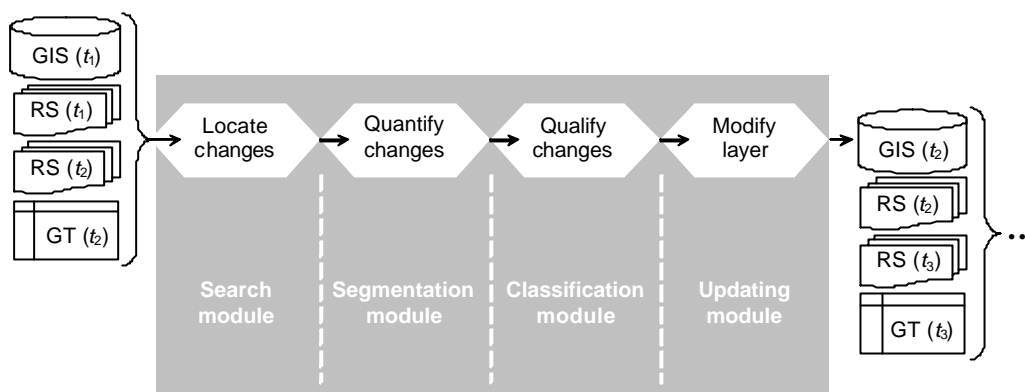
Figure 1. Flow diagram illustrating the main modules of the procedure.

Figura 1. Fluxograma ilustrando os principais módulos do procedimento.

Four modules compose the procedure according to the main tasks performed: (1) location of changed sites, (2) quantification of changed area, (3) classification of the new land cover type, and (4) updating the database. First, the difference image is decomposed with wavelet transforms and the maxima of multiscale products, representing significant singularities, are extracted at changed sites. Secondly, segmentation is performed on the difference image based on a decision rule to check if the pixels surrounding each detected maximum are spectrally similar. Thirdly, each changed pixel or each segmented region is assigned to the land cover class with the highest probability of membership. Then, the output is used to update all the GIS layers where changes took place. Each module is explained in more detail in the following sections.

2.1.1 Search module

The extraction of meaningful information from noisy, high-dimensional and multi-modal data sets is a complex task, which requires new and appropriate tools for tackling the problem. For the present algorithm, feature extraction is performed with the aid of multiresolution wavelet analysis and the so-called multiscale products (Sadler & Swami 1999; Carvalho et

al., 2001), where maxima points are extracted at changed sites. Small area changes and geometric misregistration are captured in the fine wavelet scales whereas overall changes, such as variations due to phenology, are captured at the coarse wavelet scales and at the smoothed representation of the original difference image. Thus, multiscale products are calculated using only intermediate wavelet scales to filter out spurious effects of misregistration and to reduce the search space (Carvalho et al., 2001). At this stage, maxima points are located in the filtered multiscale product if the value of a pixel is greater than its eight immediate neighbours. In this study, the difference image was produced by subtracting images of different dates.

2.1.2 Segmentation module

For abrupt radiometric changes (e.g. deforestation, burnings, geometric misregistration etc) the decision of what represents change is easily taken by level slicing the difference image. In this experiment, segmentation of changed areas was performed with a simple region-growing algorithm, where neighbouring pixels of the detected maxima were sequentially evaluated by a decision rule until no more neighbours of the grown region

meet the defined criterion. The decision threshold used was empirically extracted from groundtruth as 1.5 standard deviations from the mean value of the difference image. For example, if some neighbours of the pixel under consideration are greater than a threshold, they are stored sequentially in a temporary array. The first one is now turned into the pixel under consideration and its neighbours, greater than the threshold, are stored at the end of the same temporary array. This process iterates until the pixel under consideration has no neighbours greater than the threshold. Then, the next pixel in the temporary array is considered. The segmentation stops when the end of the temporary array is reached. Alternatively, the module may use adaptive thresholding with parametric or non-parametric rules applied to the spatial context surrounding each seed pixel (i.e., detected maximum) in single band or multispectral difference images.

2.1.3 Classification module

The classification of changed areas may be performed according to any desired decision rule (e.g., maximum likelihood, minimum distance, neural networks, decision trees etc) or even by an unsupervised procedure. If classification is unsupervised, the output clusters will have no label. In the supervised case, groundtruth for land cover classes of the most recent image must exist with which to compare the segmented areas. The comparison might be performed pixel-by-pixel or assuming homogeneity within the segmented regions. In the first case, each pixel is assigned to the class that has the largest probability of membership. The second case can be viewed as an object-oriented approach, where each segmented area is considered a single object, which is assigned to the class that has the largest probability of membership. The output of this module is a thematic change layer where pixels that did not change are zero-valued. For this study a supervised scheme with maximum likelihood

decision rules was used in a pixel-by-pixel base.

2.1.4 Updating module

This module assumes that GIS layers are input to the procedure as binary raster-based masks. Then, updating is straightforward with two simple conditional statements. (1) If a given location (i.e., pixel) in the change layer and in the GIS input layer are different from zero, then the land cover at this position has changed and the corresponding pixel in the GIS layer is assigned a value of zero. (2) If the changed pixel belongs to the land cover class represented by the input GIS layer, then a value of one is assigned to that location in the GIS layer under consideration. In this way, an updated binary mask representing the new land cover configuration is generated for each input GIS layer.

2.2   Other approaches to automatic change detection

Two other methods for change detection and identification were applied in this study: post classification comparison and direct multidate classification using artificial neural networks. The post classification comparison was chosen because it is the most popular in an operational context and a standard reference in change detection studies, whereas the neural network approach was chosen because it has been regarded as a promising tool for various automated tasks concerning geoinformation processing.

2.2.1 Post-classification comparison

This simple approach consists of comparing the properly coded results of two separate classifications. Normally, the map from time t1 is compared with the map produced at time t2, and a complete matrix of categorical changes is obtained. For comparison purposes, the post classification approach could be illustrated as in the diagram of figure 2.

2.2.2 Artificial Neural networks

Neural network based change detection follows the same principles of traditional image classification, but includes the land cover classes of both times. The direct multidate classification procedure proposed and described in Dai & Khorran (1999) for change detection was implemented in the present study. The authors used the MLP neural network model to classify a single data set composed by 12 Landsat TM bands, six from time t1 and six from time t2. Slightly different from the procedure used by Dai & Khorran (1999), our architectural settings were defined as follows: a four-layer fully interconnected network with back-propagation learning algorithm was used. The network had six nodes in the input layer because only three image bands were available for each date. The output layer had one node for each of the 16 change classes (i.e., direct output encoding) and the two intermediate (hidden) layers had 6 nodes each. The selected activation method was the sigmoid function with a fixed learning rate set to 0.001 and learning momentum set to 0.00005. The use of neural networks for change detection is illustrated in Figure 3.

2.3 Test site and data

The case study comprised subsets of 187 x 250 pixels of co-registered Landsat TM images (path 218, row 75) from October 1984 and August 1999 (figure 4), for which detailed ground truth was available. Two raster layers from a GIS database concerning semi-natural areas of forest and rocky-fields were used as the subjects to be updated (figure 5). Note that illumination and phenological conditions are distinct within the imagery set. The image from 1999 has more relief shadows and the overall reflectance of vegetated areas in 1984 is notably higher. Yet, no attempt was made to correct these differences, as the proposed method is less sensitive to them (Carvalho et al., 2001). It is important to mention that the proposed method is also considered to be less dependent on accurate image registration (Carvalho et al., 2001). Thus, only five ground control points (GCPs) were used to register a large image of 6500 x 4000 pixels, which was subset afterwards for this study. The root mean square error was 0.64 pixel, but visually evaluated displacements ranged from one to three pixels. TM band 3 was input to the search and segmentation modules whereas bands 3, 4 and 5 to the classification module.
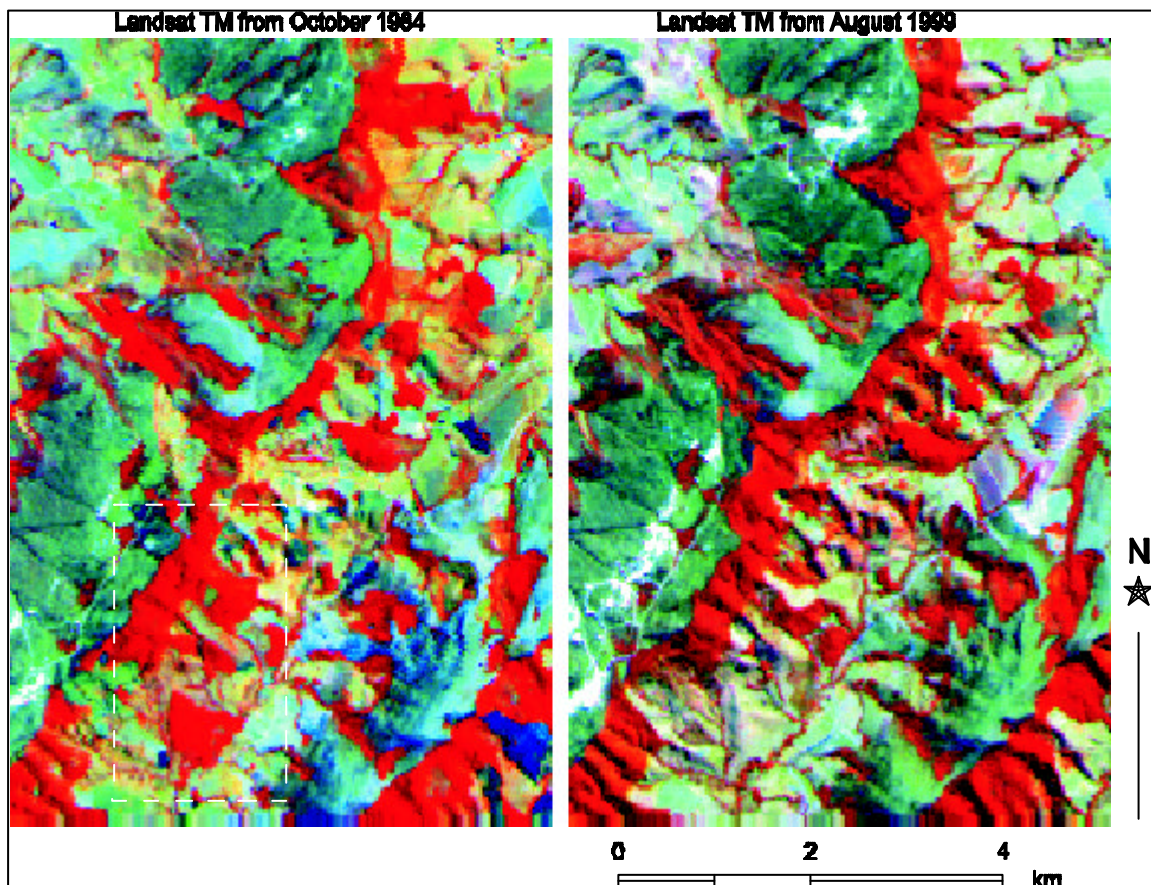

Figure 2. Flow diagram illustrating post classification comparison.

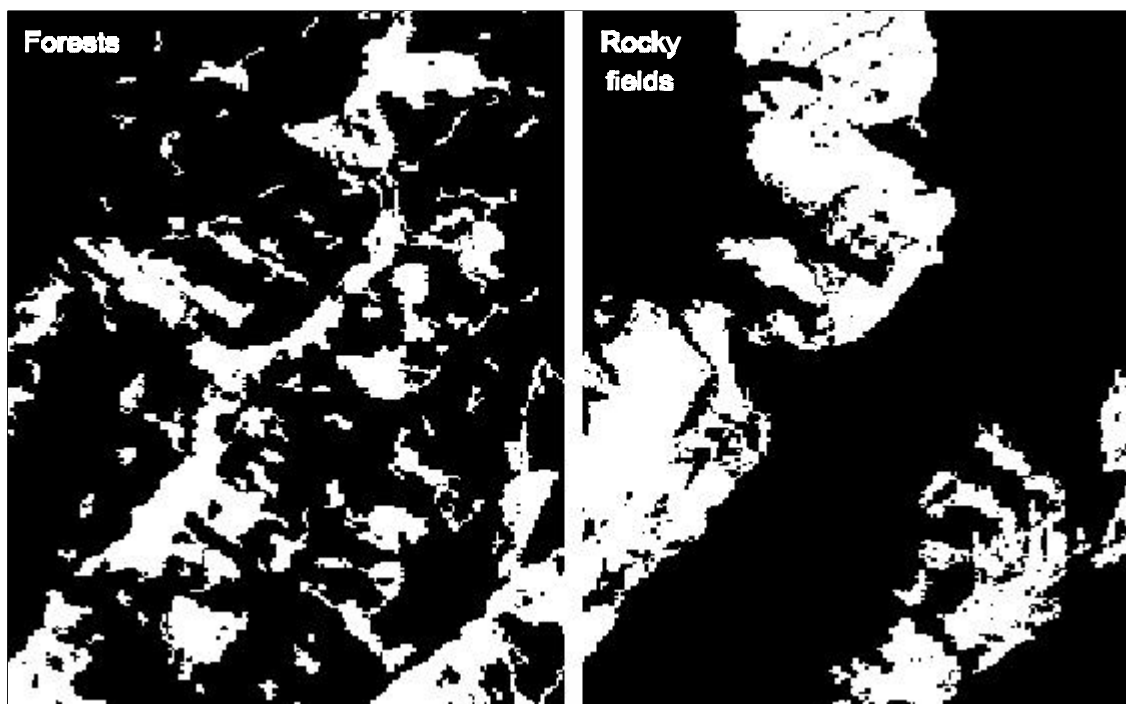*Figura 2. Fluxograma ilustrando o método de comparação pós-classificação.*
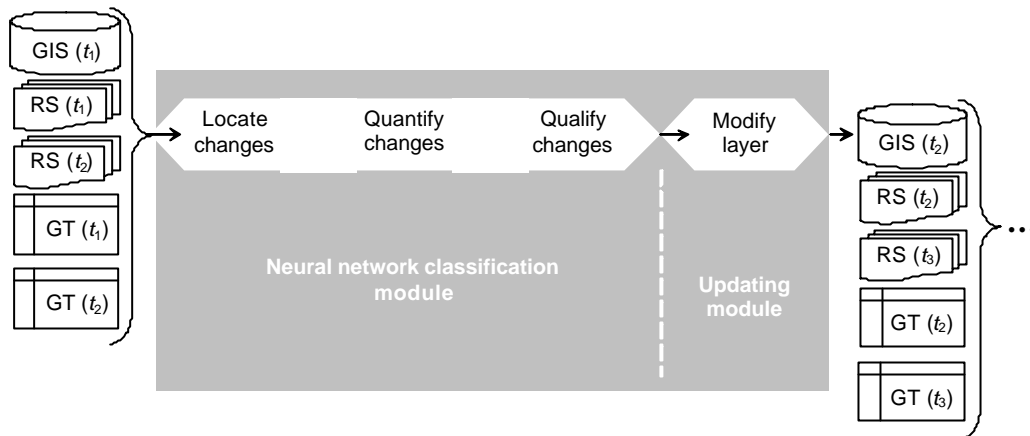
Figure 3. Flow diagram illustrating the neural network approach for change detection.

Figura 3. Fluxograma ilustrando a abordagem de redes neurais para detecção de mudanças.

Figure 4. Images used in this study.

Figura 4. Imagens usadas neste estudo.

Figure 5. GIS database to be updated.

Figura 5. Banco de dados a ser atualizado.

Ancillary data comprised a complete orthophoto mosaic (1:10,000) from 1984, small-format aerial photos, and GPS measurements on the ground acquired during field campaigns in 1999. Orthophotos were used during field surveys to locate ground-truth samples. Thirty sample pixels of forest, rocky-field, grass land and rock exploitation sites were used to train the classifiers. In the neural network approach, training samples included all possible combinations of changes, whereas the other two approaches required only samples representing the four land cover classes occurring in the area. For accuracy assessment, deforestation and new rock exploitation sites were identified within a random set of 200 forest pixels and 200 rocky-field pixels. The change maps obtained with the proposed procedure, post-classification comparison, and neural networks were organised in contingency tables from which standard per pixel error estimates were extracted.

3 RESULTS AND DISCUSSION

Figure 6 (a) and (b) illustrates the local maxima (arrows) found in the multiscale product image. They correspond to sites where land cover has changed in the GIS layers under consideration. The multiscale product image presented in figure 6(a) and (b) is almost flat everywhere except for changed sites facilitating their automatic location. The detected maxima are then located in the data set that will be subject to the region growing algorithm, which, in the present case corresponds to a single band difference image (figure 6c). The regions segmented with the region growing algorithm are illustrated in figure 6 (d). Pixels surrounding the detected maxima were

considered to have changed and included in the region if they exceeded the threshold value. In this study, the threshold value was empirically determined because enough groundtruth data were available. Yet, this threshold might be automatically defined by considering the standard deviation of immediate neighbours of all detected maxima and by applying statistical significance tests. Finally, figure 6 (e) shows the segmented regions classified on a pixel-by-pixel basis. These results were then used to update the GIS layer representing forest areas.

Tables 1, 2, and 3 show the calculated change detection accuracy for the method proposed in this paper, the neural network-based change detection, and for the classification comparison method, respectively. Although not significantly different (z = 0.1992) (Cohen, 1960), artificial neural networks performed slightly better than our approach. On the other hand, post classification comparison results were far worse than the other approaches, confirming the expected error propagation of separate classifications.
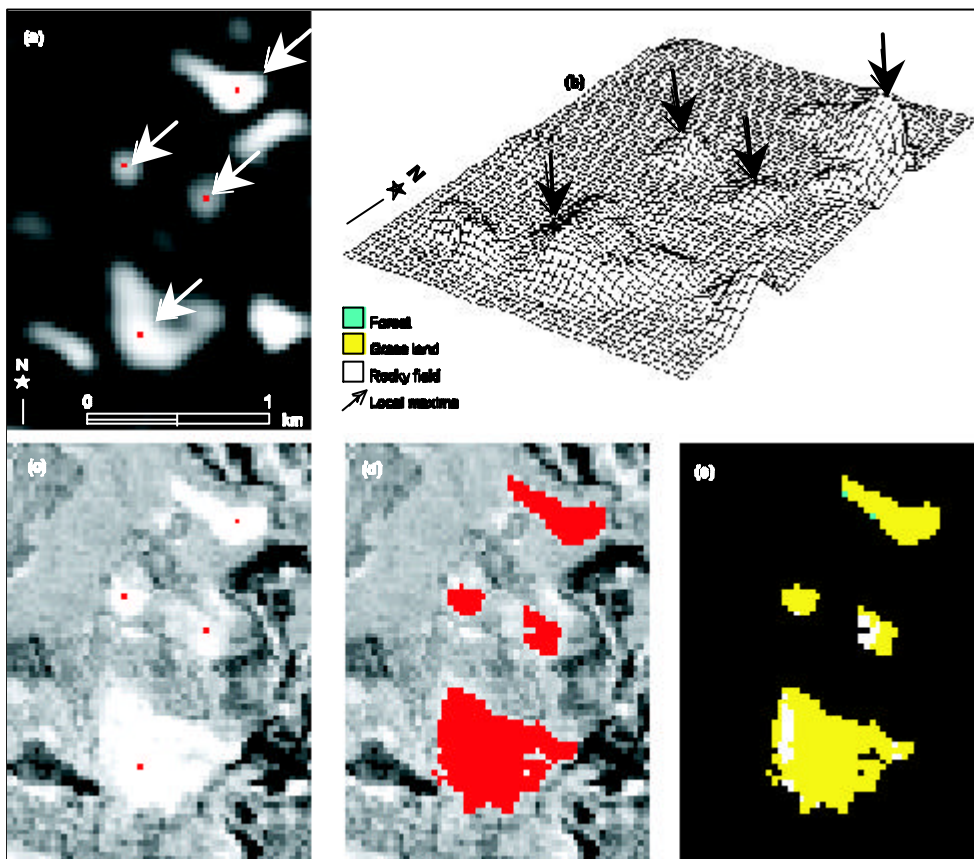
Figure 6. Sequence of the results produced by the first three modules of the procedure proposed in this work. Identification of maxima points (a and b), output from search module (c), output from segmentation module (d), and output from classification module (e).

Figura 6. Seqüência de resultados produzidos pelos três primeiros módulos do procedimento proposto neste trabalho. Identificação de pontos de máxima (a e b), resultado do módulo de busca (c), resultado do módulo de segmentação (d) e resultado do módulo de classificação (e).

Table 1. Confusion matrix of the change detection results produced by the method proposed in this work.

Tabela 1. Matriz de confusão dos resultados de detecção de mudança produzidos pelo método proposto neste trabalho.

Mapped class	Ground truth (pixels)				
	Rock exploitation	Grass	Rocky field	Forest	Totals
Rock exploitation	14	0	0	0	14
Grass	1	21	0	3	25
Rocky field	4	1	181	1	187
Forest	0	4	0	170	174
Totals	19	26	181	174	400

Overall Accuracy = 96.5% (386/400)   Kappa Coefficient = 0.9410

Table 2. Confusion matrix of the change detection results produced by the neural network-based change detection.

Tabela 2. Matriz de confusão dos resultados de detecção de mudança produzidos pelo método de redes neurais.

Mapped class	Ground truth (pixels)				
	Rock exploitation	Grass	Rocky field	Forest	Totals
Rock exploitation	15	0	0	0	15
Grass	0	21	0	3	25
Rocky field	4	0	181	1	186
Forest	0	5	0	170	175
Totals	19	26	181	174	400

Overall Accuracy = 96.75% (387/400)   Kappa Coefficient = 0.9452

Table 3. Confusion matrix of change detection results produced by the post classification comparison method.

Tabela 3. Matriz de confusão dos resultados de detecção de mudança produzidos pelo método de comparação pós-classificação.

Mapped class	Ground truth (pixels)				
	Rock exploitation	Grass	Rocky field	Forest	Totals
Rock exploitation	15	0	1	1	17
Grass	0	21	16	7	44
Rocky field	4	2	142	8	156
Forest	0	3	22	158	183
Totals	19	26	181	174	400

Overall Accuracy = 84.0% (336/400)   Kappa Coefficient = 0.7400

Field surveys revealed that changed patches were converted to only one new cover type. Forest areas were replaced by grassland, and rocky-field areas by rock exploitation. Thus, the results provided by our approach might be further improved if an object-oriented approach is used. Each segmented region would then be treated as a single entity and assigned to a unique class. This would reduce the problem of speckled misclassification, which was not well represented in the test samples but visually detected as a considerable problem in changes from rocky-field to rock exploitation areas, mainly at the segments' edges. On the other hand, classification of deforested areas was well described by the confusion matrix, since visual evaluation showed just a few misclassifications.

Figure 7 shows the change maps produced by each method evaluated in this study to update the GIS layer representing forest cover. Note the strong effect of geometric misregistration represented by many small and linear change patterns depicted with post classification comparison (figure 7c) and the neural network-based change detection (figure 7b). The method proposed here (figure 7a) was more effective in depicting important changes.
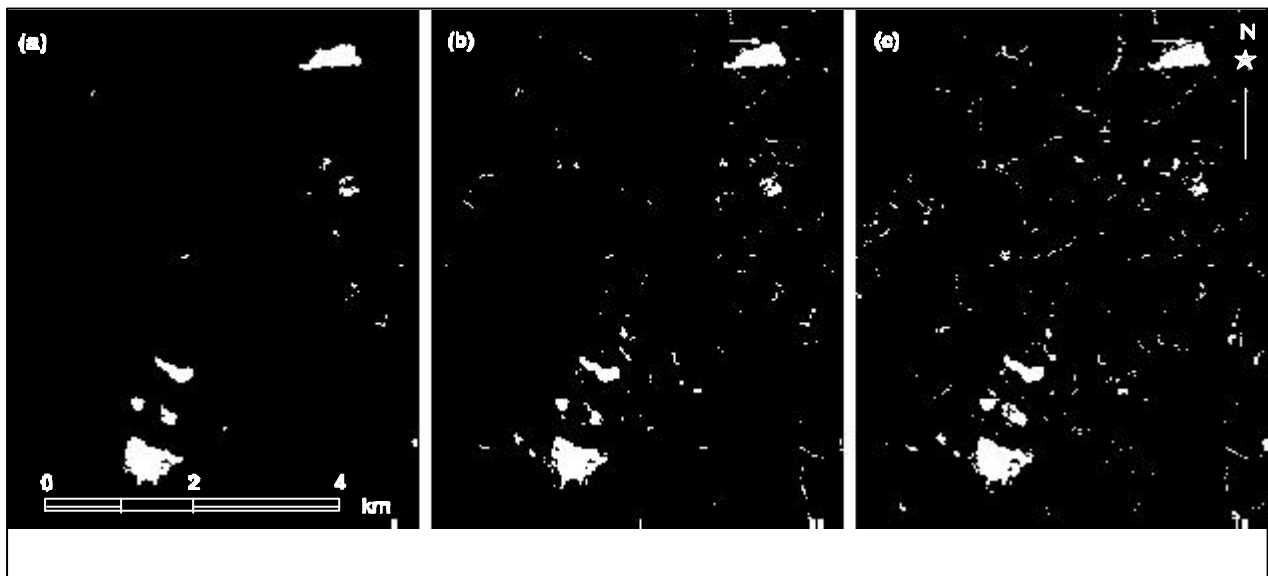
Figure 7. Change maps produced with our compound procedure (a), with artificial neural networks (b), and with post classification comparison (c).

Figura 7. Mapas de mudanças produzidos usando o nosso procedimento (a), usando redes neurais (b) e usando comparação pós-classificação (c).

The techniques currently available for detecting changes on remotely sensed data are dependent on accurate radiometric and geometric rectification (Dai & Khorram, 1998; Schott et al., 1988), which are difficult tasks in most situations (e.g. poor quality of old sensors). The method proposed here detected changes using TM band 3, which is the one most influenced by atmospheric effects within the available set (i.e., bands 3, 4 and 5). Temporal images were acquired in different seasons of the year and were considerably misregistered. Even so, the procedure performed well and was insensitive to these

problems. The methodology developed in an earlier work (Carvalho et al., 2001) and incorporated in the present procedure enabled the automation of change detection with remotely sensed data by taking advantage of singularity detection and denoising capabilities of wavelet transforms. These capabilities have already proven to be useful in the field of remote sensing to automate other tasks like GCPs definition for geometric registration (Djamdji et al., 1993) and extraction of linear features (Ji, 1996). Furthermore, the wavelet approach eases change detection in images with different pixel sizes in a straightforward manner because of its multiresolution nature (Carvalho et al., 2001). Remotely sensed images are relatively noisy signals, which provide lots of information at different spatial scales. In this sense, the procedure presented in this paper provides considerable improvements over post classification comparison and direct multidate classification (figure 7), even considering that the latter provided a slightly better classification accuracy (compare tables 1 and 2).

In spite of considering only one spectral band for analysis, the algorithm proposed here can be easily extended to the multispectral case by adding data integration steps during search and segmentation. Because information provided by various spectral bands is different, detected maxima in the search module would also differ from band to band. Segmentation in multidimensional space would have to evaluate the feature vector of each pixel being considered for inclusion in the region in the very same way as multispectral classification. These are two future directions to improve the procedure.

The possibility of using different decision rules in the segmentation and labelling modules is an important characteristic of the procedure to meet specific requirements in different situations. For instance, when classes under investigation are accurately modelled by unimodal probability distributions, a maximum

likelihood decision rule would be well suited. Unfortunately, this is not always the case and the possibility of using other non-parametric rules is acknowledged. Finally, the procedure is especially attractive for monitoring large areas, where detailed inspection of difference images is prohibitive.

4 CONCLUSIONS

In this paper, a framework for digital change detection and automatic GIS updating has been developed, demonstrated, and compared with other commonly used methods. The approach is relatively simple and provides advantages over traditional methods like post classification comparisons and direct multidate classifications. Firstly, the method is less sensitive to geometric and radiometric misregistrations because of the multiresolution approach to feature extraction included in the search module. Secondly, different from post classification comparisons, it requires ground-truth data only for the present land cover pattern. In comparison to direct multidate classification, change-classes do not need to be defined or training samples to be collected at changed sites. Finally, an object-oriented approach might be used, avoiding speckled misclassifications, which could improve classification accuracy. Further refinements of the procedure include the automatic threshold definition and the possibility of working with multivariate difference images.

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