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Forestry database updating based on remote sensing change detection

Luis Marcelo Tavares de Carvalho [1]
Jan G. P. W. Clevers [2]
Steven M. de Jong [3]
Andrew K. Skidmore [4]

[1] Universidade Federal de Lavras – UFLA/DCF/LEMAF
Caixa Postal 3037 - 37200-000 - Lavras, Brasil
passarinho@ufla.br

[2] Wageningen University and Research Centre – WUR/GRS
P.O. Box 47 - 6700 AA - Wageningen, The Netherlands
jan.clevers@wur.nl

[3] Utrecht University – UU/Department of Physical Geography
P.O. Box 80115 - 3508 TC - Utrecht, The Netherlands
s.dejong@geog.uu.nl

[4] International Institute for Geoinformation Sciences and Earth Observation – ITC/NRS
P.O. Box 6 - 7500 AA - Enschede, The Netherlands
skidmore@itc.nl

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.

Palavras-chave: wavelets, segmentation, classification, raster, change detection, remote sensing, ondaletas, segmentação, classificação, detecção de mudanças, sensoriamento remoto.

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). Most research efforts for monitoring land cover change with remote sensing have dealt with localised case studies of an 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, 1997).

The aim of this study was to develop an automated, simple and flexible procedure for updating raster-based forestry databases.

2 Materials and methods

The procedure uses as input two remotely sensed images acquired at different points in time, GIS layers representing the land cover types under investigation, and a set of ground-truth data 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.

Feature extraction is performed with the aid of multiresolution wavelet analysis and the so-called multiscale products (Sadler and Swami, 1999; Carvalho et al., 2001), where maxima points are extracted at changed sites. 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). 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.

Segmentation of changed areas is 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.

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.

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.

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.

The post classification 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.

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 and 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 and 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 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 1**), 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 2**). 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.

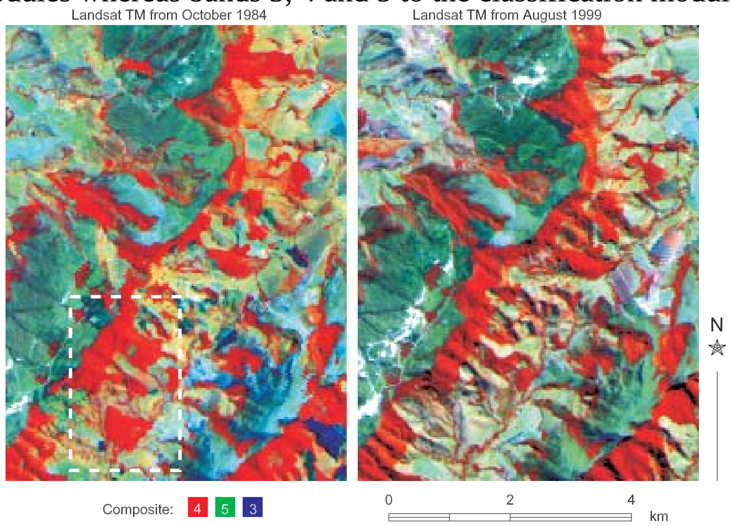

Figure 1. Images used in this study.

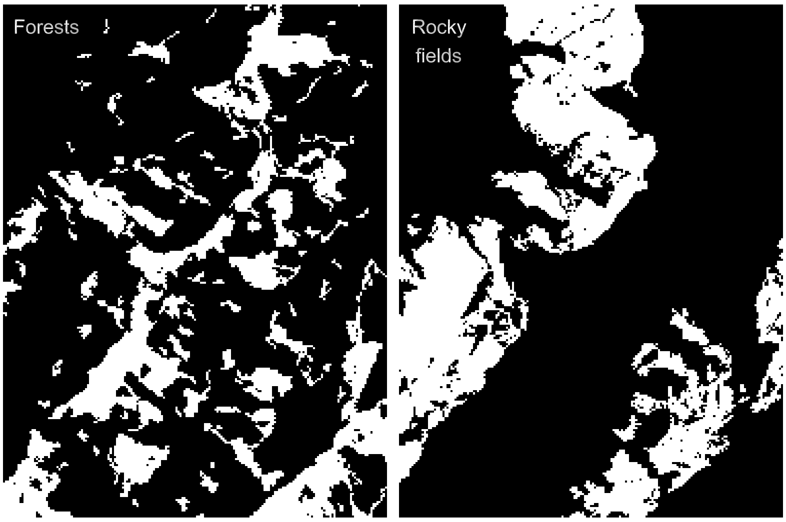

Figure 2. GIS database to be updated.

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 3 (a) and **(b)** illustrate 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 3(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 this case, corresponds to a single band difference image (**Figure 3c**). The regions segmented with the region growing algorithm are illustrated in **Figure 3 (d)**. Pixels surrounding the detected maxima were considered to have changed and included in the region if they exceeded the threshold value. 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 3 (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.

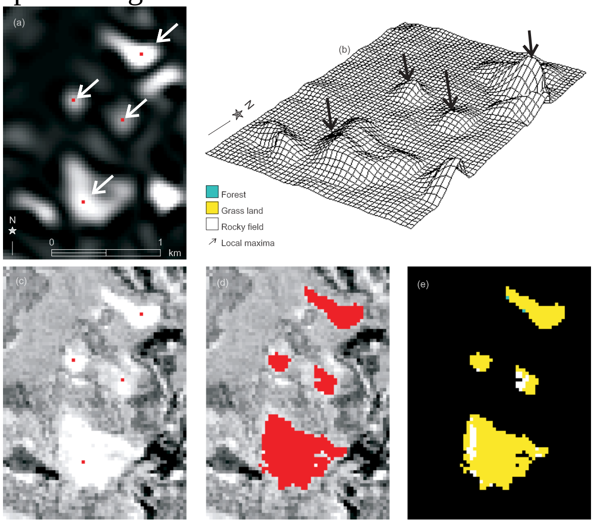

Figure 3. Sequence of the results produced by the first three modules of the procedure proposed in this work. Identification of maxima points (a and b), output from search module (c), output from segmentation module (d), and output from classification module (e).

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.

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

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 results produced by the neural network-based change detection.

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 the results produced by the post classification comparison method.

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 edges of the segmented objects. On the other hand, classification of deforested areas was well described by the confusion matrix, since visual evaluation showed just a few misclassifications.

Figure 4 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 4c**) and the neural network-based change detection

(**Figure 4b**). The method proposed here (**Figure 4a**) was more effective in depicting important changes.

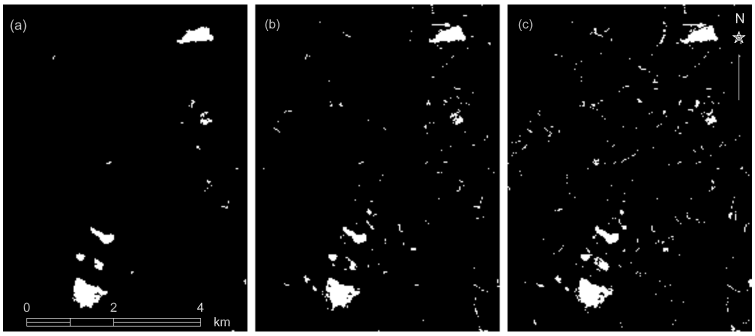

Figure 4. Change maps produced with our compound procedure (a), with artificial neural networks (b), and with post classification comparison (c).

The techniques currently available for detecting changes on remotely sensed data are dependent on accurate radiometric and geometric rectification (Dai and 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 4**), even considering that the latter provided a slightly better classification accuracy (compare **Tables 1** and **2**).

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 groundtruth 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.

References

Carvalho, L.M.T., Fonseca, L.M.G., Murtagh, F., Clevers, J.G.P.W. Change detection at multiple spatial scales with the aid of multiresolution wavelet analysis. **International Journal of Remote Sensing**, v. 22, p. 3871-3876, 2001.

Cohen, J. A coeficient of agreement for nominal scales. **Educational and Psychological Measurement**, v. 20, p. 37-46, 1960.

Dai, X., Khorram, S. The effects of image misregistration on the accuracy of remotely sensed change detection**. IEEE Transactions on Geosciences and Remote Sensing**, v. 36, p. 1566-1577, 1998.

Dai, X., Khorram, S. Remotely sensed change detection based on artificial neural networks. **Photogrammetric Engineering and Remote Sensing**, v. 65, p. 1187-1194, 1999.

Djamdji, J.P., Bijaoui, A., Manière, R. Geometrical registration of images: the multiresolution approach. **Photogrammetric Engineering and Remote Sensing**, v. 59, p. 645-653, 1993.

INPE. **Monitoramento da Floresta Amazônica por Satélite 1998-1999**. Relatório Periódico, Instituto Nacional de Pesquisas Espaciais, São José dos Campos. 2000.

Janssen, L.L.F. 1993. p. 173 **Methodology for Updating Terrain Object Data from Remote Sensing Data: The Application of Landsat TM Data with Respect to Agricultural Fields**. (PhD Thesis: Wageningen Agricultural University, Wageningen), 1993.

Ji, C.Y. Delineating agricultural field boundaries from TM imagery using dyadic wavelet transforms. **ISPRS Journal of Photogrammetry and Remote Sensing**, v. 51, p. 268-283, 1996.

Sadler, B.M., Swami, A. Analysis of multiscale products for step detection and estimation. **IEEE Transactions on Information Theory**, v. 45, p. 1043-1051, 1999.

Schott, J.R., Salvaggio, C. Volchok, W.J. Radiometric scene normalization using pseudoinvariant features. **Remote Sensing of Environment**, v. 26, p. 1-16, 1998.

Townshend, J., DeFries, R., Dubayah, R., Goward, S., Kearney, M., Tucker, C.J. Vermonte, E. 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**, (Nottingham: The Remote Sensing Society). 1997.

Wyatt, B.K. Remote sensing of land cover and land cover change. In **Observing Land from Space: Science, Customers and Technology**, edited by M.M. Verstraete, M. Menenti, and J. Peltoniemi (Dordrecht Kluwer), p.127-136. 2000.