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# INTEGRATION OF DEM DATA WITH SATELLITE IMAGERY FOR FOREST CHANGE DETECTION

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## ABSTRACT

In a standard supervised classification, increases in land cover map classification accuracy have been obtained by including topographic attributes as inputs to the classification algorithm. In this study we investigate the potential of such data as a means to increase the accuracy of supervised forest change detection using Landsat 5 imagery in a target area located in El Bierzo (León). *Pinus radiata* plantations are the most important forest stands in this area, concerning stocks and the economic interest of the owners and timber purchasers. Variations in agricultural policies and the ageing of the rural population have caused continuous and dynamic land use changes, mainly from the farming uses to radiata pine plantations. The aim of this paper it is not only improving the quantitative detection of changes, but also the qualitative approach, a key factor for the management and monitoring of these stands. Once the quantitative change was identified using difference in Landsat TM Wetness Index, the nature of the change was settled by image classification. An accurate land use classification was needed for each image, so that three classification trials were completed: (*a*) using a standard approach without the addition of topographic attributes, (*b*) using elevation data as an additional input to (*a*), (*c*) using elevation and slope data as an additional input to (*a*). The second classification trial (*b*) provided the highest overall accuracy at 90.21%, improving the standard methodology (a) result, which produced in an overall accuracy of 83.92%.

**Keywords:** remote sensing, qualitative change detection, DEM, *Pinus radiata.*

## 1 INTRODUCTION

More frequent updates of information on changes in land use are required as part of land management policies, mainly those referred to changes from farming to forest uses, due to their environmental and socioeconomic repercussions in rural areas. The comparison of two or more remotely sensed images of the same geographic area permits the study of temporal change. Good change detection research should provide the area change and change rate, spatial distribution of changed types, change trajectories of land cover types, and accuracy assessment of change detection results (Lu *et al.,* 2004). The hybrid change detection method combines the advantages of the threshold and classification methods. The threshold method (e.g. image differencing) is used to detect the changed areas, then classification methods are used to classify and analyze detected change areas. These methods are based on the classified images, in which the quality and quantity of training sample data are crucial to produce good quality classification results. The major advantage of these methods is the capability of providing a matrix of change information and reducing external impact from atmospheric and environmental differences between the multi-temporal images (Rogan & Chen, 2004). However, selecting high-quality and sufficiently numerous training sample sets for image classification is often difficult. Petit *et al.* (2001) used the combination of image differencing and postclassification to detect detailed ‘from–to’ land cover change in south-eastern Zambia and such a hybrid change detection method was regarded as better than post classification comparison techniques. Foody (2001) found that post-classification comparison underestimated the areas of land cover change, but where the change was detected, it typically overestimated its magnitude.

Changes in the Tasselled Cup Transformation (TCT) (Kauth & Thomas, 1976) indices may be used to identify changes in land use, especially regarding forest characteristics. Franklin et *al.* (2000a) reported that the accuracy of partial harvest change detection using Landsat imagery approached 71% over a full range of forest change conditions in southeastern New Brunswick (Canada) using the TM Tasseled Cap transformation (Crist & Cicone, 1984) and classifying the brightness/greenness/wetness difference images. Franklin *et al.* (2002) enhanced the difference between wetness indices for several near-anniversary TM dates over a 15-year period and established a threshold for changes associated with clear-cut, partial harvesting, and silviculture in highly variable forest stands. The image data were first atmospherically corrected, transformed into the TCT wetness component, differenced, and then enhanced for computer display and thresholding. Three classes (light, moderate, severe change) were mapped using standard supervised classification with 100% producer's accuracy. Differences in TCT indices have been also used in forest environments for modeling fire hazards (Patterson & Yool, 1998), estimating forest stand density (Horler & Ahern, 1986), structure (Hansen *et al*., 2001), age (Cohen *et al*., 1995) and tree mortality (Collins & Woodcock, 1996; Skakun *et al.,* 2003).

In order to provide quantitative change information accurate classifications of imagery are required. Additional ancillary data can be used to increase supervised land cover classification accuracy. In many environments, digital elevation models (DEM) are used in classification of land cover, as discrimination of cover types whose distributions are influenced by variation in elevation is improved with the inclusion of the DEM in the classification (Franklin *et al.,* 2000b). One approach is to use the DEM data, or derivatives such as aspect and slope, as supplemental logical channels in the classification input data (Strahler, 1981); another is to stratify the image data using the DEM (Skidmore, 1989); another is to modify classifier prior probabilities (Strahler, 1981); another is to employ rule-based or expert systems logic; and still another is using classification trees (Rogan *et al.,* 2003). Improved classification accuracies have been reported with the direct incorporation of a DEM into an unsupervised classification approach. Elumnoh and Shrestha (2000) used an ISODATA algorithm with 13 land cover classes in forested highlands and agricultural lowlands in Thailand. Classification accuracy improved from 65.3% (without the DEM) to 72.4% (with the DEM). The largest improvement was found in discriminating lowland agriculture fields from highland forest. Wulder *et al.* (2004) found that the prestratification of an image into areas of shadow and nonshadow prior to clustering in conjunction with the use of elevation data as an input to the clustering process increased classification accuracy in areas of high relief where topographic shadow is problematic.

The purpose of this research is to examine the increase in classification accuracy that can be obtained by including a DEM or its derivatives in a supervised classification as a part of a hybrid method for change detection in radiata pine stands in a very fragmented area in El Bierzo (León, Spain). In addition, another objective of this study is to test the suitability of the TM Tasseled Cap transformation Wetness index differencing to detect changes, mainly in areas where radiata pine plantations are concerned.

## 2 STUDY AREA

The study area comprises 700 km$^2$ in western León, Castilla y León, Spain, approximately 100 km west of León. The elevation varies from 450 to 1,752 m. Natural vegetation depends on bioclimatic conditions, so that in the peripheral mountains dominant tree species are beech (*Fagus sylvatica*), birch *(Betula* sp.), chestnuts trees *(Castanea sativa*) and oaks (*Quercus pyrenaica*, *Querqus ilex*), following a pattern of decreasing precipitation. Shrubs are also common as secondary succession series and as a result of forests degradation. The area is in a Mediterranean continental climatic environment, characterized by moist, mild winters with warm, dry summers. Mean annual precipitation is 720 mm and mean annual solar radiation ranges reaches 2,100 sun hours, which are very suitable conditions for radiata pine growth.

## 3 IMAGERY AND ANCILLARY DATA

A Landsat 5 TM image (path 203, row 22) acquired on 25 June 2000 was geometrically registered to the UTM Zone 30 WGS84 projection with 92 ground control points at key road intersections dispersed throughout the scene with less than 0.85 pixel root mean square error (RMSE). A second Landsat 5 TM scene (path 204, row 31) acquired on 13 July 2004, was registered to the UTM Zone 30 WGS84 projection with less than 0.64 pixel RMSE using 85 ground control points at key road intersections dispersed throughout the scene. A nearest neighbour algorithm was used to resample both images with an output 30 m grid. Atmospheric corrections were not necessary because simple image subtraction was use to detect changes and the qualitative assessment of changes was achieved by post-classification comparison.

Orthophotographs scale 1:10,000, 0.7 x 0.7 m pixel size, acquired in 2001 were used in the training areas location and for the accuracy assessment, required for the supervised classification. These data were checked by field work in July-August 2004.The digital elevation model (DEM) for the area of interest was generated by spatial interpolation of contour lines from 1:10,000 scale topographic vector maps. The output grid spacing was 30 m. Slope (in degrees) was derived from this DEM using standard methods included in the software ArcGIS$^{TM}$.

## 4 METHODS

The Wetness component of the Tasseled Cap transformation was calculated for each Landsat 5 image using the coefficients proposed by Crist and Cicone (1984). Wetness has been applied because of the strong relationship between reflectance in bands 5 and 7 and moisture content of vegetation and soils, helping in land use change identification (Lu *et al.*, 2003). The final image processing step was to convert the wetness index from each of the two dates (2000 and 2004) to a difference image for that index. Simple image subtraction was used because the high degree of confidence in the geometric correction of the imagery enabled a suitable overlay of the image data and the minimum area of change of interest was several pixels in size.

Supervised classification was performed using Landsat TM images. Therefore as first step a legend with the land use covers to be identified was defined. The following land covers were defined for the study area: agricultural lands (grasslands, vineyards, farming areas) (A), water (W), broadleaved forests (B), shrubs (S), other conifer forests (*Pinus pinaster, Pinus sylvestris*) (C), areas with low canopy cover or without canopy cover (newly afforested areas, unproductive areas, urban areas, roads, mining areas) (LCC), and *Pinus radiata* stands (PR). The second step consisted of selecting training samples which were representative and typical each land cover class, in order to generate the class signatures. For radiata pine 555 pixels were selected in the image from year 2000 and 1,509 in the image registered in 2004. The following step was performing the classification of the Landsat image from 2004 using the maximum likelihood algorithm. This image was selected instead of the 2000 one because field data was gathered in 2004. The strategy for testing the improvement in classification accuracy obtained by including a DEM or its derivatives in the supervised classification resulted in the completion of three classification trials. The initial classification trial (*a*) was the control and had 7 Landsat TM optical channels. The second trial (*b*) used identical methods to those in the first trial, however elevation data were added as input to the classification process as a channel. For the third classification trial (*c*) elevation and slope data were added to the optical channels to be considered in the classification. Accuracy of the classified image was assessed through analysis of a confusion matrix which was generated using the validation areas and through the calculation of the kappa statistic for each class. The best method (*a, b* or *c)* was used to classify the image from 2000; the results were validated with ground truth points identified on the orthophotographs. Both classified images were exported to vector files and intersected using a Geographic Information System (ArcGIS$^{TM}$), so that the obtained polygons had information of land cover in 2000 and 2004. Thus, polygons without/with changes were identified, and detailed 'from–to' land cover changes were detected. Changes detected by overlaying and the 2000 and 2004 classifications were compared to the changes detected by Wetness differences between the images. The resulting post-classification changes were considered as actual changes. Therefore, it was checked the agreement between actual changes and changes predicted from radiata pine land cover to other land covers and vice versa using differences in Wetness and three different thresholds (I, II, and III).

## 5 RESULTS AND DISCUSSION

Using the standard methodology in the first classification trial (*a*) for the 2004 image resulted in an overall accuracy of 83.92% and an overall kappa statistic of 0.80 for the 7 target classes. The second classification trial (*b*) which added elevation data as an input, resulted in a 90.21% overall accuracy and 0.88 overall kappa statistic, while the third one (*c*) resulted in a 89.16% overall accuracy and a 0.87 overall kappa statistic. Table 1 shows the producer's and user's accuracy for each land cover class for each classification trial, as far as the conditional Kappa for each category. For all the categories the best results were obtained from the second trial, adding elevation data to the spectral data. Producer's accuracy for radiata pine increased from 88.64% to 95.45% when including topographic attributes in the classification, regardless it was elevation or slope. Broadleaved forests and agricultural lands classifications were reasonably improved in trials *b* and *c*. Comparing trials *b* and *c*, better accuracies and kappa statistics were achieved by including only elevation data in the classification, therefore the Landsat 5 Tm image from year 2000 was classified using the trial *b* methodology. This result agrees with the results obtained by Wulder *et al.*(2004), whose land cover classification using elevation data as an additional input and prestratifying the image into shadow and nonshadow areas prior to clustering using trials provided the highest level of overall attribute accuracy at 80.1%, improving the approach using only the spectral information (68.7%).

**Table 1.** Producer's and user's accuracy for each land cover class for each classification trial for Landsat 5 TM image (2004), as far as the conditional Kappa for each category. Classification trial (*a*): optical channels as input data; trial (*b*): optical channels and elevation as input data; trial (*c*): optical channels, elevation and slope as input data. Land cover classes: agricultural lands (A), water (W), areas with low canopy cover or without canopy cover (LCC), broadleaved forests (B), shrubs (S), other conifer forests (C), and *Pinus radiata* stands (PR).

| Land cover class | Trial *a* | | | Trial *b* | | | Trial *c* | | |
|---|---|---|---|---|---|---|---|---|---|
| | Accuracy (%) | | Kappa | Accuracy (%) | | Kappa | Accuracy (%) | | Kappa |
| | Producers | Users | | Producers | Users | | Producers | Users | |
| A | 84.34 | 97.22 | 0.9609 | 91.57 | 97.44 | 0.9639 | 90.36 | 97.40 | 0.9634 |
| W | 100.00 | 100.00 | 1.0000 | 100.00 | 100.00 | 1.0000 | 80.00 | 100.00 | 1.0000 |
| LCC | 88.37 | 66.67 | 0.6077 | 90.70 | 70.91 | 0.6576 | 90.70 | 70.91 | 0.6576 |
| B | 75.86 | 93.62 | 0.9199 | 86.21 | 96.15 | 0.9518 | 86.21 | 94.34 | 0.9290 |
| S | 80.00 | 55.56 | 0.5130 | 84.00 | 75.00 | 0.7261 | 84.00 | 70.00 | 0.6713 |
| C | 88.89 | 82.76 | 0.8096 | 92.59 | 96.15 | 0.9575 | 88.89 | 96.00 | 0.9558 |
| PR | 88.64 | 97.50 | 0.9705 | 95.45 | 100.00 | 1.0000 | 95.45 | 100.00 | 1.0000 |

The high accuracies achieved in the classifications resulted consequently in accurate land cover maps for 2000 and 2004: thus forest change detection was improved. The areas concerning radiata pine stands (changes due to new plantations, harvesting, no changes) were mapped in a GIS and the differences in Wetness overlaid. Therefore, the proposed method is very useful to monitor changes in radiata pine stands. The results of the analysis of means showed that there are significant differences among the differences in Wetness index depending on the class of land cover change concerning radiata pine stands. The percentages of agreement comparing actual changes to the predicted using three different thresholds (I, II, and III) are showed in Table 2.

The most interesting changes (regarding their occurrence) are those from agricultural uses and low canopy cover to radiata pine land use. If these changes are correctly detected, an increase (gain) in biomass should be registered. Using the threshold III (which classifies as decrease in radiata pine land use (lost) a difference in wetness lower than -8, and as an increase in radiata pine plantations (gain) a difference in wetness higher than 8), 88% of the pixels which changed from agricultural to radiata pine use were properly detected. Low canopy cover areas reforested between 2000 and 2004 are detected in 69 out of 100 cases using same threshold; 30% of the reforestations are not detected because the change in canopy cover (change in wetness) is not high enough. Changes from radiata pine land use to low canopy cover imply harvested or disturbed (e.g. forest fire) areas; 61% of these areas where detected using the difference in Wetness and the threshold III. Some shrub areas where radiata pine was the previous land cover, are due to forest fires, which explains the fact that increases in land cover were detected by the wetness difference, because small pine plantations were affected by forest fires and in two or three years a dense shrub canopy covered the affected area. Areas where radiata pine is maintained as the main use are mainly classified as non-change areas using the three thresholds, with accuracies of 86.9% to 92.8%. Using the threshold III several areas were identified as areas where biomass had increased, therefore forest growth can be detected when the upper value of the threshold decreases. Even when a simple threshold was selected, changes such as clearcutting and forest growth were successfully detected in radiata pine stands. Threshold III is recommended if interested in detecting this kind of changes. However, more research is needed to define accurately the thresholds for each kind of change.

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**Table 2.** Percent of agreement between land cover changes regarding radiata pine stand using post-classification results and changes detected by differences in Wetness index using thresholds I, II and III. Land cover classes: see Table 1.

| Land Cover (Year) | | Agreement between post-classification land cover change and changes predicted by differences in Wetness (2004 - 2000) (%) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | (I) Loss <-13; Gain>10 | | | (II) Loss <-8; Gain>10 | | | (III) Loss <-8; Gain>8 | | |
| 2000 | 2004 | Loss | Equal | Gain | Loss | Equal | Gain | Loss | Equal | Gain |
| A | PR | 0.00 | 15.71 | 84.29 | 0.00 | 15.71 | 84.29 | 0.00 | 11.97 | 88.03 |
| LCC | PR | 0.19 | 36.36 | 63.44 | 1.06 | 35.49 | 63.44 | 1.06 | 29.69 | 69.25 |
| S | PR | 0.00 | 63.72 | 36.28 | 0.00 | 63.72 | 36.28 | 0.00 | 46.98 | 53.02 |
| PR | A | 73.78 | 24.22 | 2.00 | 78.00 | 20.00 | 2.00 | 78.00 | 19.11 | 2.89 |
| PR | LCC | 48.48 | 47.38 | 4.14 | 61.45 | 34.40 | 4.14 | 61.45 | 32.13 | 6.41 |
| PR | S | 22.79 | 75.66 | 1.55 | 41.59 | 56.86 | 1.55 | 41.59 | 55.53 | 2.88 |
| PR | PR | 0.40 | 92.84 | 6.76 | 1.24 | 92.00 | 6.76 | 1.24 | 86.99 | 11.76 |