BACKDATING OF INVARIANT PIXELS: COMPARISON OF ALGORITHMS FOR LAND USE AND LAND COVER CHANGE (LUCC) DETECTION IN THE SUBTROPICAL BRAZILIAN ATLANTIC FOREST

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ABSTRACT

A challenge for the use of medium spatial resolution imagery for change detection consists of the reduced availability of ground reference data for previous dates. We compared the accuracy of invariant area sets, generated by three methods (Iteratively Reweighted Multivariate Alteration Detection, Change Vector Analysis and Spectral Gradient Difference) for two periods (2017-2011 and 2011-2006). The classification of the Landsat-5 TM image of 2006 was performed using as training data the sets of points indicated as invariant in the binary maps resulted from the three methods. Overall accuracy for seven land-use classes was greater (80,5% and 80,2%) when using training areas achieved by CVA and SGD, respectively than IR-MAD (76%). Were obtained accuracies greater than 80% for the forest class. The results stress that the combination of the IR-MAD and SGD is preferable since the CVA is more time consuming due to the subjective application of thresholds.

Palavras-chave — Backdating; IR-MAD; SGD; CVA.

1. INTRODUCTION

Land Use and Land Cover Change (LUCC) detection is an important tool for several applications, such as land use surveys (especially deforestation), as also monitoring of wildfires, reforestation, forest regeneration, agricultural and forest growth, crop forecasting and landscape dynamics features [1]. The detection relies on the availability of multi-temporal series of satellite images, ideally from the same sensors or spectral bands. Commonly employed analysis techniques are the generation of two-date difference images, based on surface reflectance data, vegetation indices, or independent (LUCC) classification of multi-temporal time series of satellite images. Based on this information it is possible to model the land use dynamic with change detection algorithms [2].

Among change detection algorithms, the ones are known as “backdating” have been developed in order to suppress the lack of ground truth data referring to past dates by means of detection of “invariant” pixels. In this context, the so-called “invariant pixels” are those classified under the same LULC class throughout a given time series of images. Therefore, they may be used to train and validate supervised classifiers, allowing the determination of hits and errors of a classification result [3]

Considering the aforementioned, this study first compares, for an area in southern Brazil, the performance of three different methods to detect invariant pixels in Landsat-5 TM (Thematic Mapper) and Landsat-8 OLI (Operational Land Imager) images from 2006, 2011 and 2017. Secondly, this performance quality was assessed by determining the accuracy of supervised classifications of the 2006 Landsat image resulting from the use of invariant pixels as training points. These pixels have been generated by three different methods: IR-MAD (Iteratively Reweighted Multivariate Alteration Detection) [4], CVA (Change Vector Analysis) [5] and SGD (Spectral Gradient Difference) [6]. Therefore, the study is expected to deliver important methodological advances for efforts regarding long term, especially backward monitoring of land use changes through multispectral data from medium resolution sensors such as Landsat, Sentinel-2, and Spot images.

2. MATERIAL AND METHODS

The study area is located in the central region of the Brazilian state of Santa Catarina, at latitude 27° 07’ S and longitude 50°15’ W, approximately, with an area of 1,353.68 km², of which 35% is forest land (Figure 1)

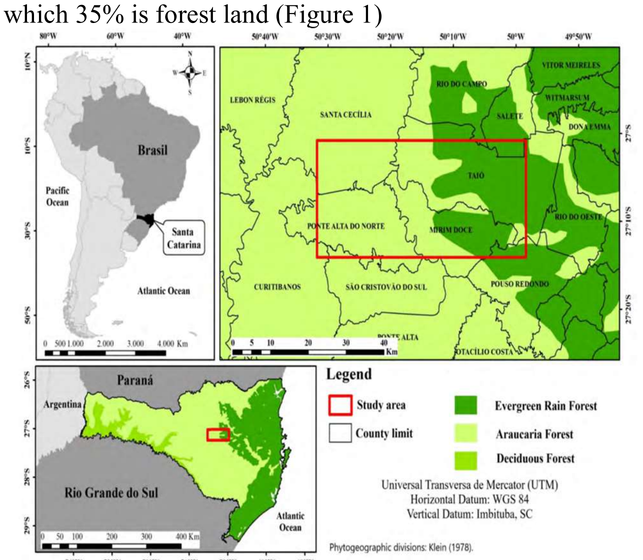

Figura 1. Location of the study area.

For this study, we used one scene for each year (2006, 2011, 2017). We selected scenes acquired during the months of September, October and November. The scenes belong to path-row 221/79; we used two Landsat-5 TM scenes (date 09/12/2006 and date 10/28/2011); and one Landsat-8 OLI scene (date 11/13/2017), all scenes product processing level 1 - L1T.

Ground truth data were derived from high spatial resolution imagery: Aerial photography from sensor SAAPI - Airborne Digital Imaging Acquisition and Postprocessing System (0.36m resolution), RapidEye and Spot-4, in addition to images from the Google Earth platform (2011-2017).

Three methods for change detection in land use and invariant pixel detection were compared for two different periods (2006-2011 and 2011-2017): the IR-MAD, the CVA and the SGD. To assess the performance of the three methods, we first computed the accuracies of binary change maps resulting from each method of invariant pixel detection for the period between 2011 and 2017. For this period, we also consulted high spatial resolution images for ground truth checking. Next, we evaluated the accuracy for the period between 2006 and 2011. Finally, we assessed the performance of Random Forest classification of the 2006 Landsat-5 TM image. These classifications were performed using as training points the invariant pixels selected by each of the three above mentioned change detection methods.

The IR-MAD, CVA, and SGD methods were performed at Google Earth Engine (GEE) (https://code.earthengine.google.com/) platform; the ground truth checks were carried out in geoprocessing software ArcGIS. Accuracy assessment routines were performed in the R environment, packages: raster, dplyr, gdal and xlsx (https://cran.r-project.org/web/packages/), based on the method described by [7].

In the stage of obtaining the binary maps, we generated one map for each method and period (three binary maps for the 2011-2017 period and three binary maps for the 2006-2011 period).

For purpose of classification, the invariant points, with a 3 x 3 pixel window (9 pixels) were used as training points (Table 2) to perform the RF classification of the 2006 image. Finally, we constructed the accuracy matrix of this classification based on 680 randomly selected validation points with at least 30 points per class, in seven land-use classes (Agriculture-76 points, Bare soil-73, Forest-233, Pasture-103, Forest plantation-128, Urban-34 and Water-33).

3. RESULTS

3.1. Accuracy of binary change maps

Regarding the performance of the methods for generating the binary change maps, it was observed that for the period of 2011-2017, the CVA and SGD methods showed similar performances, with overall accuracies of 88 and 90%, respectively. On the other hand, the IR-MAD presented overall accuracy below 57%. However, for the period between 2006 and 2011, the performance of the CVA method was superior to the others (Table 1).

Period		**2011-2017**			**2006 -2011**		
Sensor			**OLI – TM**			**TM - TM**	
Method		**IR-MAD**	**CVA**	**SGD**	**IR-MAD**	**CVA**	**SGD**
Producer's Accuracy	Change	100%	32%	59%	94%	54%	63%
	Invariant	52%	94%	94%	62%	95%	74%
User's Accuracy	Change	20%	41%	56%	23%	59%	22%
	Invariant	100%	92%	95%	99%	94%	95%
Overall Accuracy		57%	88%	90%	66%	91%	73%

Table 1. Overall producer's and user's accuracy percentage of binary change maps obtained by each method in the two evaluated periods (2011-2017 and 2006-2011).

The use of the three methods produced coincident results in the case of clear cut plantations forests (Figure 2). This may have caused the big reflectance changes in these cases. In both periods, all methods classified areas with *Pinus* sp. plantations as invariant, despite the significant change in forest cover due to the plantation's growth. In the binary map of the CVA method, we found several white pixels indicating changes in that forest stands, that have not been confirmed by ground truth data. In contrast, SGD and IR-MAD classified the entire region correctly, as having no changes.

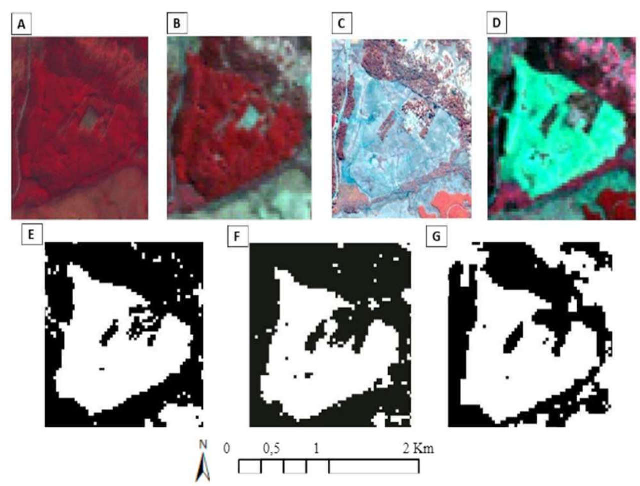

Figure 2. Forest plantation area in Landsat-5 TM (B, 2006) and (D, 2011) false color images and depicted also in high resolution imagery (Spot-4, A, 2006) and (RapidEye, C, 2011); binary change maps resulting from the methods IR-MAD (E), CVA (F), SGD (G). Blank areas (change); black (invariant).

3.2. Accuracy of the thematic map (2006)

The overall accuracy of the 2006 image classifications, generated with training points from CVA and SGD methods was higher (80%) than that of the IR-MAD method (76%). Regarding accuracies by thematic class, the highest value (> 85%) was observed within the three methods for the forest class (Table 2).

RF	IR-MAD		CVA		SGD	
Class	P. A. (%)	U. A. (%)	P. A. (%)	U. A. (%)	P. A. (%)	U. A. (%)
Agriculture	5.9	83.3	81.1	63.2	73.4	56.6
Bare Soil	57.2	83.3	31.5	90.9	62.7	77.5
Forest	89.2	85.4	86.5	92.8	90.7	91.7
Pasture	92.9	56.3	86.7	64.3	74.1	60.2
For. plant.	61	90.9	71.9	80.9	71	83.2
Urban	88.3	45.2	52.9	64.6	90.1	61.1
Water	44.6	53.7	57.6	49.1	40.3	61.1
OA	76.10%		80.60%		80.20%	

Table 2. Confusion matrix for the Random Forest classification of Landsat-5 TM image of 2006, derived from three sets of invariant pixels determined by the binary maps of the methods SGD, CVA, IR-MAD, computed according to [7]. (For. plant. - Forest plantation; OA - Overall Accuracy, P. A. - Producer`s Accuracy, U.A. - User`s Accuracy).

4. DISCUSSION

Among the binary maps accuracies, the CVA and IR-MAD methods resulted in similar accuracies for the two analyzed periods; this was not observed for the SGD method. The latter showed differences in accuracies obtained on both periods (90% between 2017 and 2011; 73% between 2011 and 2006). The SGD binary maps for the period 2011-2017 performed poorly. This may be partly due to the fact that different sensors were used for 2017-2011 (Landsat-8-OLI and Landsat-5-TM) whose bands have slightly different widths for the Near-Infrared region. In this case, SGD is less sensitive for these differences.

Radiometric differences between the images of the Landsat sensors have become more evident over the years [1], [8]. One of the causes related to radiometric differences are variations in solar angulation (bidirectional reflectance distribution function-BRDF effects) that can modify the solar illumination condition in the entire study area [9], mainly in the region of “Planalto Serrano” and “Alto Vale do Itajaí” where the relief is rugged.

Furthermore, studies demonstrated differences between images from the TM, ETM + and OLI sensors in the face of differences in wavelength, in reflectance values and class mixing within the GIFOV-ground instantaneous field of view [10]. It was possible to prove a lower RMSE (Root Mean Square Error) between the surface reflectance values of Landsat-5-TM in relation to Landsat-8-OLI in the comparison between beginning, middle and end of the period of greatest vegetative growth [11], [12].

When analyzing the invariant pixels separately, producer’s accuracies of 94% and 95% for the two evaluated periods were also observed by [2] for the CVA method; however, the user’s accuracy of invariant pixels (79.9%) obtained by these authors was lower than the ones (92% and 94%) obtained in our study. This difference can be explained by the fact that [2] did not perform any post-classification edition of the maps used for threshold application. This highlights the dependence of the CVA method on a step of manual editing for the correction of mislabeled pixels. Thus, this method requires a higher training level of the analyst that will produce the classification.

The IR-MAD method has been developed originally for radiometric normalization of remote sensing data, using pixels most likely to be invariant. To create the change map, it is necessary to drop the confidence interval considering an alpha of 0 (zero), that is, without a reliability criterion, thus within the set of selected pixels can occur false invariant pixels. Therefore, pixels with a small probability of being invariant are considered non-invariant (change). In this sense, the use of the method can overestimate the change areas. Applying the IR-MAD method in Landsat-7-ETM+ images, the occurrence of false positives in the number of invariant pixels selected by the method was observed, overestimating the change pixels in the binary map [13]. There is evidence that the method may perform poorly when multitemporal scenes have a high noise level due to atmospheric conditions [14].

With a different approach, the CVA method uses a threshold to characterize the reflectance of each land-use class, as a multiple of the standard deviation of the mean class values. Here, we used the threshold as 1.5 times the standard deviation and obtained an overall accuracy of 88% for 2017-2011 and 90% for 2011-2006, similar to the results (90%) found by [15].

In our study, the classes with highest commission errors using the IR-MAD method, are agriculture, urban and pasture, between both 2006-2011 and 2011-2017 periods. On the other hand, this method proved to be efficient in identifying invariant pixels in scenes with high rates of change without overestimating them, which corroborates with the results of [16]. [17] pointed out that the IR-MAD method provides better detection of invariant pixels and therefore better separation between change and no-change areas.

[3] compared several change detection methods (SGD, CVA, SAD-Spectral Angle Difference, Image Difference, and Image Correlation) in a study area in Shaanxi Province, China. Landsat-TM images from to 2009 were used, where

the SGD method proposed by the authors obtained an overall accuracy of 96.5%, hence higher than that achieved in our study. For the invariant class, the producer's accuracy reached 99% and the user's accuracy 98.1%.

5. CONCLUSIONS

The conclusions may be summarized as follows: 1) the three evaluated methods allowed the identification of invariant areas as well as areas with land use land cover changes with satisfactory accuracy in multispectral images from 2011 and 2017; 2) following that, it was possible to identify invariant training areas for several land use classes in a 2006 image, a date for which there are no ground truth data available; 3) the classification that used the training areas generated by the CVA method showed the highest overall, user's and producer's accuracies for the forest, agriculture, pasture, and urban classes; 4) Thus, it is possible to use invariant observations for creating "backdated" training and validation points for supervised digital image classification as Random Forest algorithm in images from previous dates for which there is no longer any possibility of obtaining direct field observations; 5) However, the need of a pre-classification for threshold application and post-classification editing to eliminate coarse errors, makes the application of the CVA algorithm time consuming, which is a downside to its application, along with being able to cause errors in the aforementioned steps.

Among the results obtained by the IR-MAD and SGD methods, we found that a fusion of these two could be implemented for applying the backdating and obtaining thematic maps. The statistical application of the IR- MAD algorithm without dropping statistical reliability added to a qualitative variable, transforming reflectance information into a spectral gradient (SGD) may be a relevant focus.

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