DOI 10.1590/s1982-21702021000300018

ORIGINAL ARTICLE

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

Backdating de pixels invariantes para detecção de mudanças de uso e cobertura da terra na Mata Atlântica subtropical no Brasil: uma comparação de algoritmos

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Received in 20th August 2020

Accepted in 15th June 2021

Abstract:

A challenge for the use of medium spatial resolution imagery for land use change detection consists of the reduced availability of ground reference data for previous dates. This study aims to obtain invariant training points using the backdating process for supervised classification of images that have no field data available. The study area comprises 1,353 km² in Santa Catarina, southern Brazil. We compared the accuracy performance of invariant area sets (binary change maps) generated by using three methods (IR-MAD - Iteratively Reweighted Multivariate Alteration Detection, CVA - Change Vector Analysis and SGD - 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 abovementioned methods. The accuracies for seven land-use classes were computed. The overall accuracy 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.

Keywords: Invariant pixel; Backdating; IR-MAD; SGD; CVA; LUCC.

How to cite this article: SILVA, M.S.; VIBRANS, A.C.; NICOLETTI, A.L. Backdating of invariant pixels: comparison of algorithms for land use and land cover change (LUCC) detection in the subtropical brazilian atlantic forest. *Bulletin of Geodetic Sciences*. 27(3): e2021018, 2021.

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 (Banskota et al. 2014). 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 (Phiri and Morgenroth 2017).

Atmospheric correction and radiometric normalization, as topographic correction, are essential pre-processing steps for many of these techniques. These corrections attenuate disturbance cause by the atmosphere and also by the geometry of illumination (BRDF effects - bidirectional reflectance distribution function). Furthermore, in order to classify images and determine the classification accuracy, one needs reliable and representative “ground truth” samples (Congalton, 1991). The in-situ collection of these samples is costly and time-consuming. For past dates, the in-situ collection becomes unrealistic being replaced by remotely sensed data with higher spatial or spectral resolution than the original time series of images (Olofsson et al. 2014; Muller-Warrant et al. 2015).

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 (Congalton and Green 2009; Olofsson et al. 2014; Zhu et al. 2017).

Backdating techniques require reference data from raw and classified images of two different dates to enable inferences about pixels of a third image, captured before the examined ones. If invariant areas with known ground truth present stable spectral responses on two observed occasions, the observation of the same pattern in images from previous dates should allow us to infer about LULC classes on these dates. It enables classification results with a high percentage of accuracy, assuming that all images have been submitted to atmospheric correction (Yu et. al 2016).

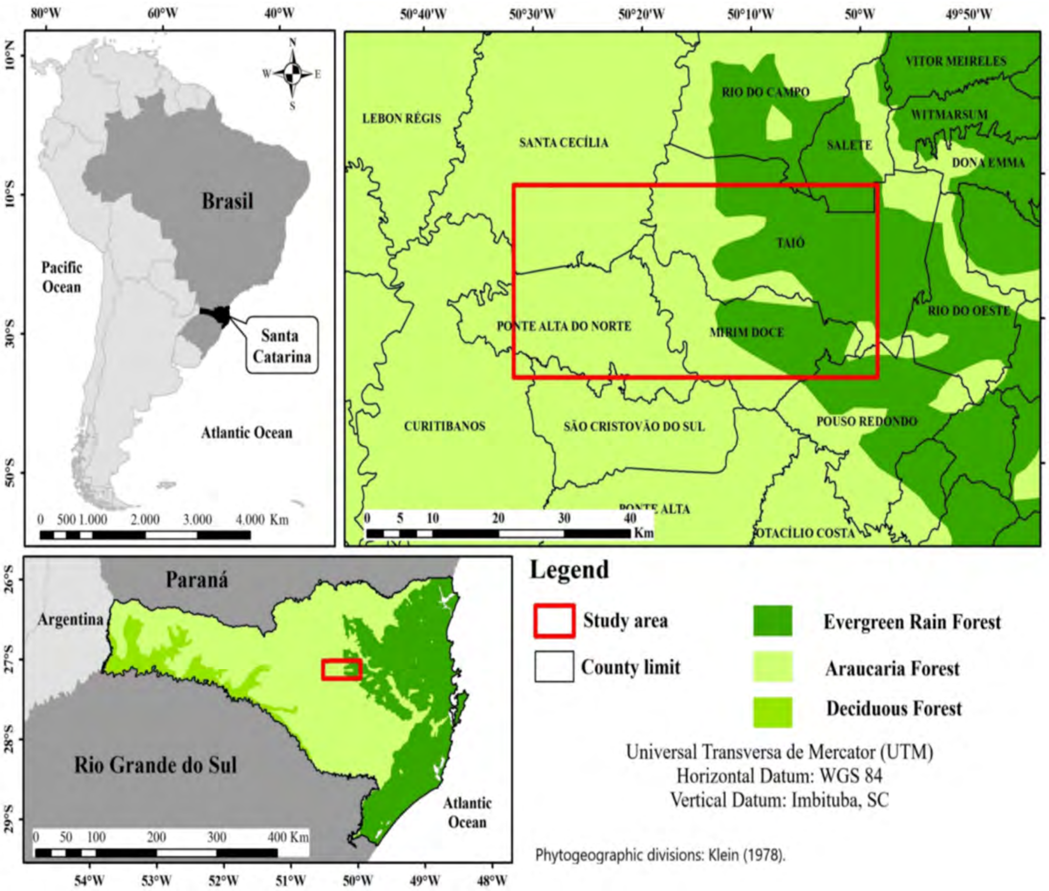
Considering the aforementioned, this study first compares, for an area in southern Brazil, the performance of three different methods to detect invariant pixels in Landsat-5 TM (Thematic Mapper) and Landsat-8 OLI (Operational Land Imager) images from 2006, 2011 and 2017. Secondly, this performance quality 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) (Canty, Nielsen and Schmidt 2004), CVA (Change Vector Analysis) (Yu et al. 2016) and SGD (Spectral Gradient Difference) (Chen et al. 2013). 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 spatial resolution sensors as Landsat, Sentinel-2, and Spot images.

2. Materials and methods

2.1 Study area

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). The area comprises two regions, the “Planalto Serrano”, with the occurrence of Araucaria Forest (AF) and the “Alto Vale do Itajaí” with occurrence of Evergreen Rain Forest (ERF), according to Oliveira-Filho et al. (2014).

The main dynamics at the “Planalto Serrano” are land use changes caused by the clear cutting and afforestation of forest plantations, that are main economic activity in the region. The altitude of 936 m.a.s.l. keeps the average temperature about 15,5° C and total annual precipitation about 1600 to 1700 mm. In the “Alto Vale do Itajaí” region, the rugged relief and steep slopes hindered mechanization, thus small-scale agriculture and forestry have been consolidated over decades. The region has an altitude range between 360 and 900 m.a.s.l. The average temperature is about 18,5°C with total annual precipitation of about 1700 to 1800 mm (Wrege et al. 2012).



Source: The authors.

Figure 1: Location of the study area.

2.2 Materials

For this study, we used one scene for each year (2006, 2001, 2017). We selected scenes acquired during the months of September, October and November because the spring season provides more favorite atmospheric conditions. The scenes belong to path-row 221/79; we used two Landsat-5 TM scenes (date 09/12/2006; id: ‘LANDSAT/LT5_SR/LT52210792006255’ and date 10/28/2011; id: ‘LANDSAT/LT5_SR/LT52210792011301’), as well as of one Landsat-8 OLI scene (date 11/13/2017; id: ‘LANDSAT/LC08/C01/T1_SR/LC08_221079_20171113’). These images were gathered from the United States Geological Survey (USGS, 2018) with geometric and atmospheric corrections (product processing level 1 - L1T), following the “Landsat Ecosystem Disturbance Adaptive Processing System - LEDAPS” algorithm (Masek et al. 2006).

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) (SDS, 2012), RapidEye (REIS - RapidEye Earth Imaging System) (5m resolution) (Planet, 2016) and Spot-4 HVRiR (High-Resolution Visible and Infrared sensor) (20m resolution) (Satimaging, 2003), in addition to images from the Google Earth platform (2011-2017).

2.3 Change detection methods

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 method (Canty, Nielsen and Schmidt 2004), the CVA (Yu et al. 2016) and the SGD (Chen et al. 2013). 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 consists of the detection of pixels with high probability of being invariant or non-invariant by analyzing canonical correlation of the reflectance values of a timeseries of multispectral imagery profiles, and the subsequent binary change maps.

For the application of the CVA method, it is necessary to classify the most recent image (year 2017), in our case using the Random Forest algorithm; in a second moment, for each land use class the mean sd (standard deviation) of its spectral responses were computed; then we created change maps using the mean sd as a threshold to distinguish change and no change areas of every land use class in the most recent and a previous image.

The SGD method is calculated by the ratio of: i) the difference of reflectance values between t1(time one) and t2(time two); and ii) the difference between the central wavelength values between subsequent bands. This transformation delivered the spectral gradient which, by subtracting one gradient from another, allowed to obtain the Spectral Gradient Difference. Thus, this method comprises three steps: (i) computation of the spectral gradient for a set of pixels of each land-use class present in the two images; (ii) generation of an image containing the magnitude of this gradient (change); (iii) generation of a binary change map by applying a conditioning equation.

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 v. 10.1) (ESRI, 2011). Accuracy assessment routines were performed in the R environment (R Core Team, 2018), packages: raster, dplyr, gdal and xlsx (https://cran.r-project.org/web/packages/), based on the method described by Olofsson et al. (2014).

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). In each binary map, 314 change and invariant test points were allocated randomly (Table 1).

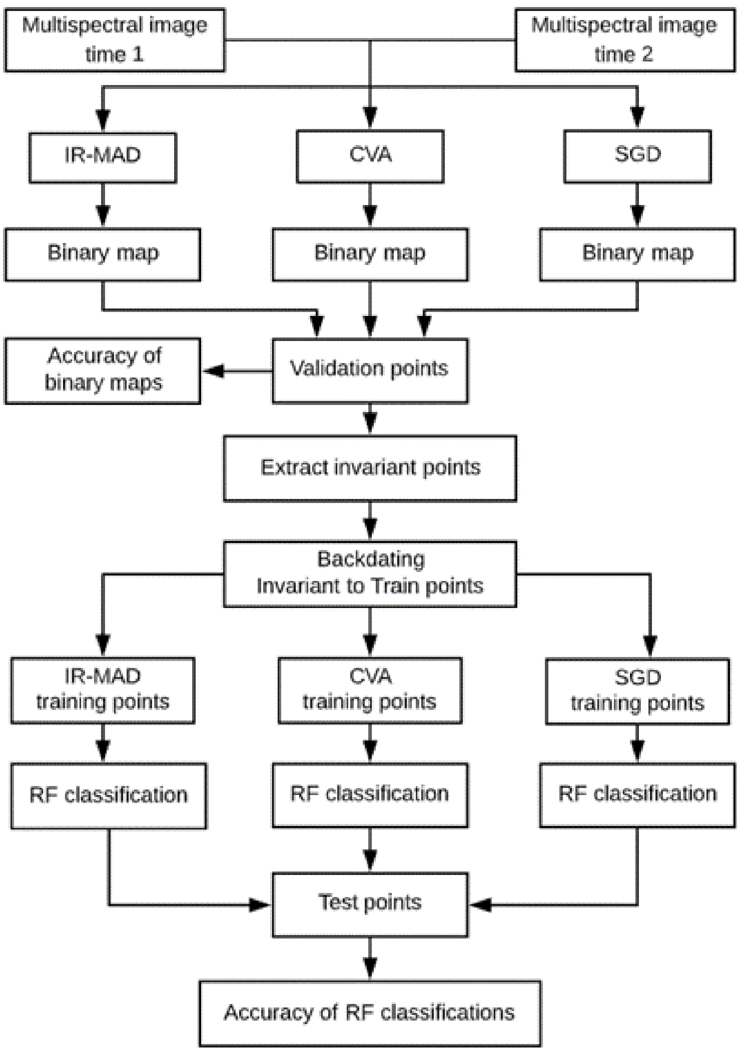
Table 1: Number of change and invariant test points for each method in the two analyzed periods.

Period	Class	IR-MAD	CVA	SGD
2017-2011	change	34	34	36
	invariant	280	280	278
Total		314	314	314
2011-2006	change	33	35	32
	invariant	281	279	282
Total		314	314	314

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). The general data processing workflow is displayed in Figure 2.

Table 2: Number of training points extracted by each method for the classification of the 2006 Landsat-5 TM image.

Class	IR-MAD	CVA	SGD
Agriculture	45	378	252
Bare soil	117	117	117
Florest	702	675	684
Pasture	378	468	243
Forest plantation	324	468	387
Urban	144	171	144
Water	135	225	180
Total	1845	2502	2007



Source: The authors.

Figure 2: General data processing workflow.

3. Results

3.1 Accuracy of binary change maps

Here we focus on the invariant pixel accuracy because of their importance for the backdating of training areas. The overall producer's and user's accuracies for the three methods and for the two periods (2011-2017 and 2006-2011) are shown in Table 3.

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.

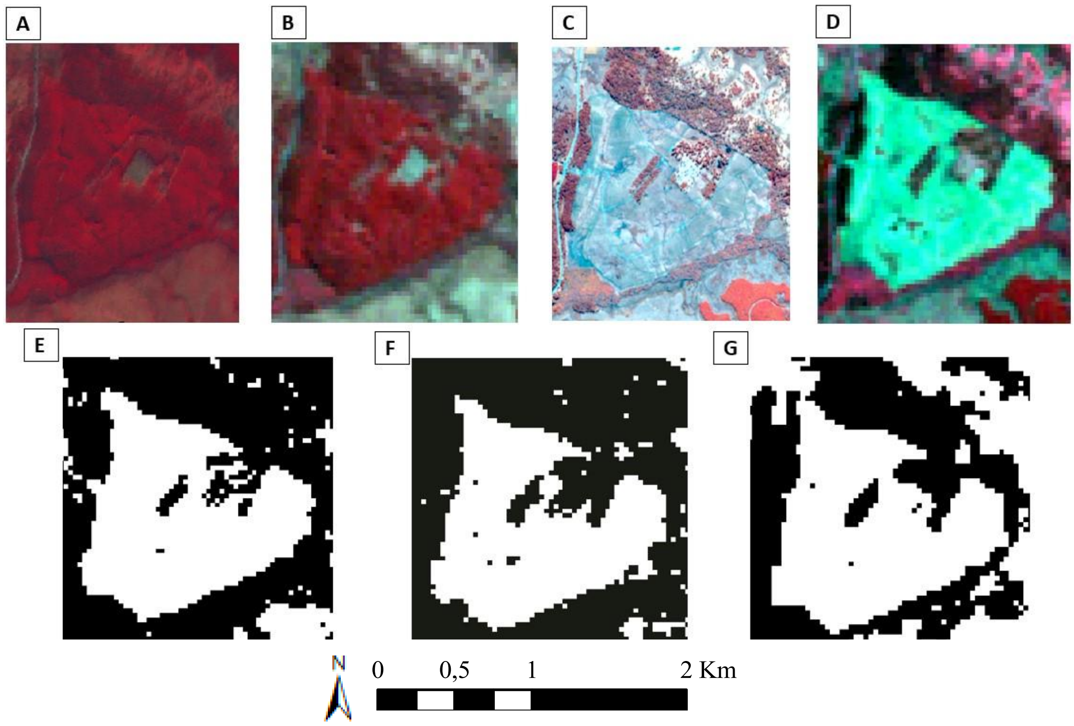
Regarding the user's accuracies of invariant pixels, we may assert that the IR-MAD method was superior with 100%. Nonetheless, the producer's accuracy was much smaller for this algorithm for both periods. This was due to false positives for "change pixels" culminating in commission errors. Due to this fact, several known invariant points were mistakenly classified as change pixels as example in reforested areas with several permanent preservation areas and small agricultural and urban areas. Bearing this in mind, it is possible to verify a similarity between the user's and producer's invariant pixels accuracies for the CVA and SGD methods. For the period from 2011 to 2017, the user's accuracy for the CVA and SGD was 92% and 95%, respectively, and 94% and 95%, respectively for the period from 2006 to 2011.

The overall accuracy for the CVA method was greater for the 2006-2011 period when the images came from the same sensor (Landsat-5 TM). However, the overall accuracy for the SGD method was considerably higher for the period 2017-2011, considering that for this period images of different sensors were utilized (Landsat-8 OLI and Landsat-5 TM).

Table 3: 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).

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%

The use of the three methods produced coincident results in the case of clear cut plantations forests (Figure 3). 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.

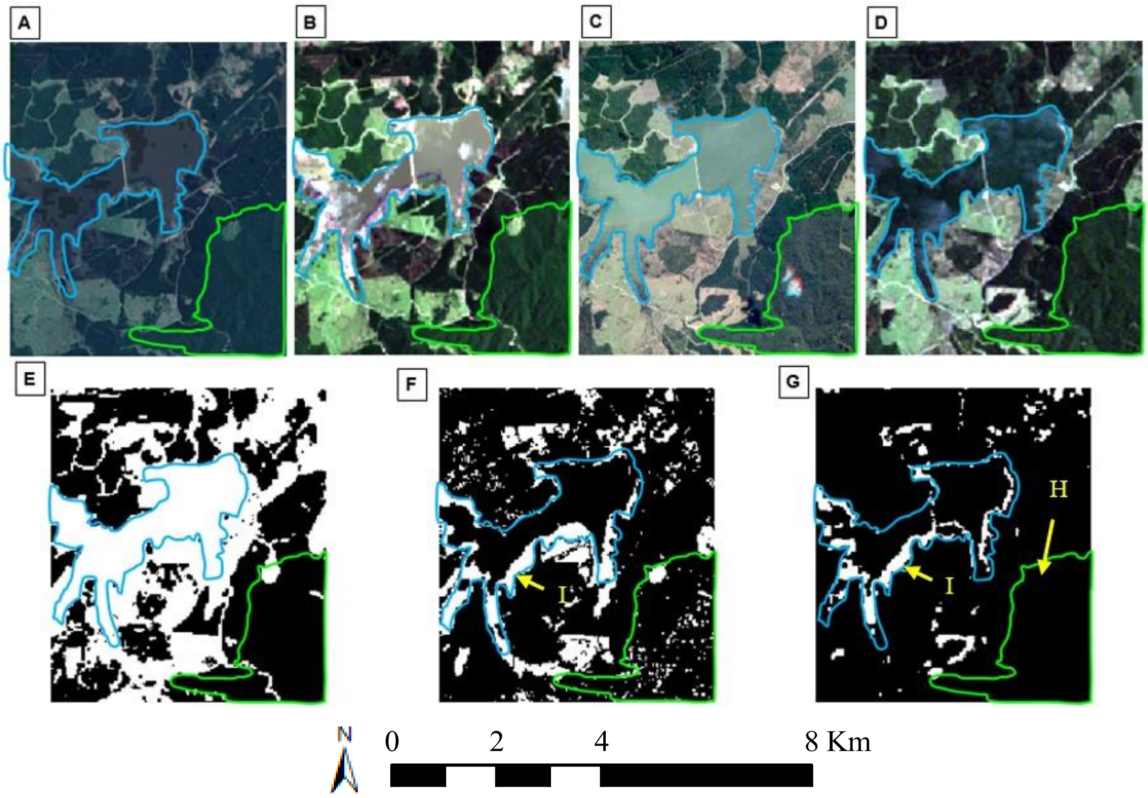


Source: The authors.

Figure 3: 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).

Regarding the monitoring of forest areas (identified in green), in Figure 4 we found that they were correctly identified by all three methods as invariant areas. However, the CVA method resulted in some non-invariant scattered pixels ("salt and pepper" effect). And SGD did not detect a small deforested area at Figure 4G (yellow arrow H).

For lakes, identified in blue, were correctly classified with a lower water level in 2011 (Figure 4C and D) than in 2017 (Figure 4A and B). The resulting change maps by CVA (Figure 4F) and SGD (Figure 4G) methods detected accurately this dynamic of the reservoir levels (as for example at a yellow arrow I). The IR-MAD method, however, misclassified the entire area of the lake as a changing area.



Source: The authors.

Figure 4: Water and Natural forest areas classified in Landsat-5 TM (2011, D) and Landsat-8 OLI (2017, B) images and depicted also in high resolution imagery (RapidEye image for 2011, C) and Google Earth (2017, A); binary change maps resulting from IR-MAD (E), CVA (F), SGD (G) methods. Blank areas (change); black (invariant). Blue polygon: lake; Green polygon: natural forest stands. Yellow arrows: "letter I" highlight dry reservoir borders and "letter H" the small deforested area.

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% ± 3%) than that of the IR-MAD method (76% ± 3,2%). Regarding accuracies by thematic class, the highest value (> 85%) was observed within the three methods for the forest class (Table 4).

For forest plantation class the producer's accuracy was 71% for CVA and SGD data sets and 61% for the IR-MAD method. The user's accuracies obtained for this class were higher than 80% for the three methods.

It is possible to assert that the classification derived from data of the method that uses band mathematics with canonical correlation (IR-MAD) obtained higher accuracies for the classes forest, pasture, and urban areas. For the classification with invariant pixels from the CVA method, satisfactory results were obtained for the classes forest, pasture and agriculture. Thus, the SGD method map produced the highest producer's (90.7%) and user's (91.7%) accuracies for the forest class.

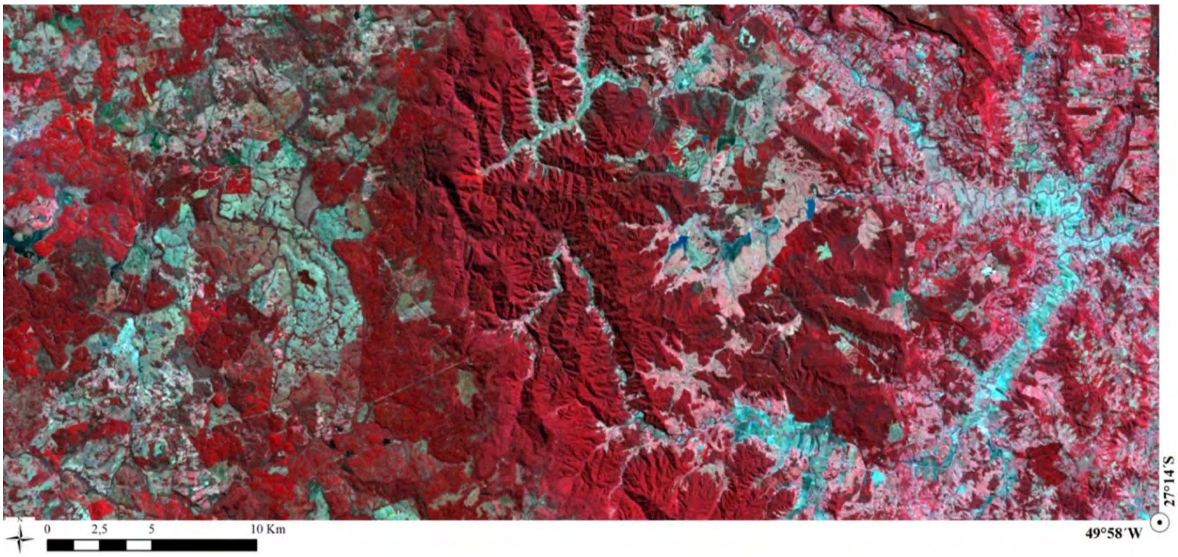
Table 4: Confusion matrix for the Random Forest classification of Landsat-5 TM image of 2006, derived from three sets of invariant pixels determined by the binary maps of the methods SGD, CVA, IR-MAD, computed according to Olofsson et al. (2014), including confidence intervals. (For. plant. - Forest plantation; OA - Overall Accuracy).

RF	IR-MAD		CVA		SGD	
Class	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)
Agriculture	5.94±2.7	83.3±32.7	81.1±10.1	63.2±10.9	73.4±9.9	56.6±11.2
Bare Soil	57.2±14.7	83.3±8.7	31.5±10.6	90.9±7.7	62.7±11.4	77.5±9.8
Forest	89.2±3.2	85.4±4.5	86.5±3.4	92.8±3.5	90.7±2.9	91.7±3.7
Pasture	92.9±5.1	56.3±7.6	86.7±5.2	64.3±8.4	74.1±7.4	60.2±8.9
For. plant.	61.0±6.8	90.9±6.0	71.9±7.1	80.9±7.2	71±6.9	83.2±7.1
Urban	88.3±20.5	45.2±11.5	52.9±28.3	64.6±13.7	90.1±17.7	61.1±13.1
Water	44.6±18.4	53.7±15.5	57.6±20.7	49.1±13.6	40.3±16.0	61.1±16.2
OA	76.1%±3.2%		80.6%±3%		80.2%±2.9%	

On the eastern part of the image at Figure 5 it is possible to observe clearer and brighter areas corresponding to irrigated rice fields; at the center (mountain ridge) native forests are predominant and at the western part forest plantations and recently clear cut plantation stands are prevailing.

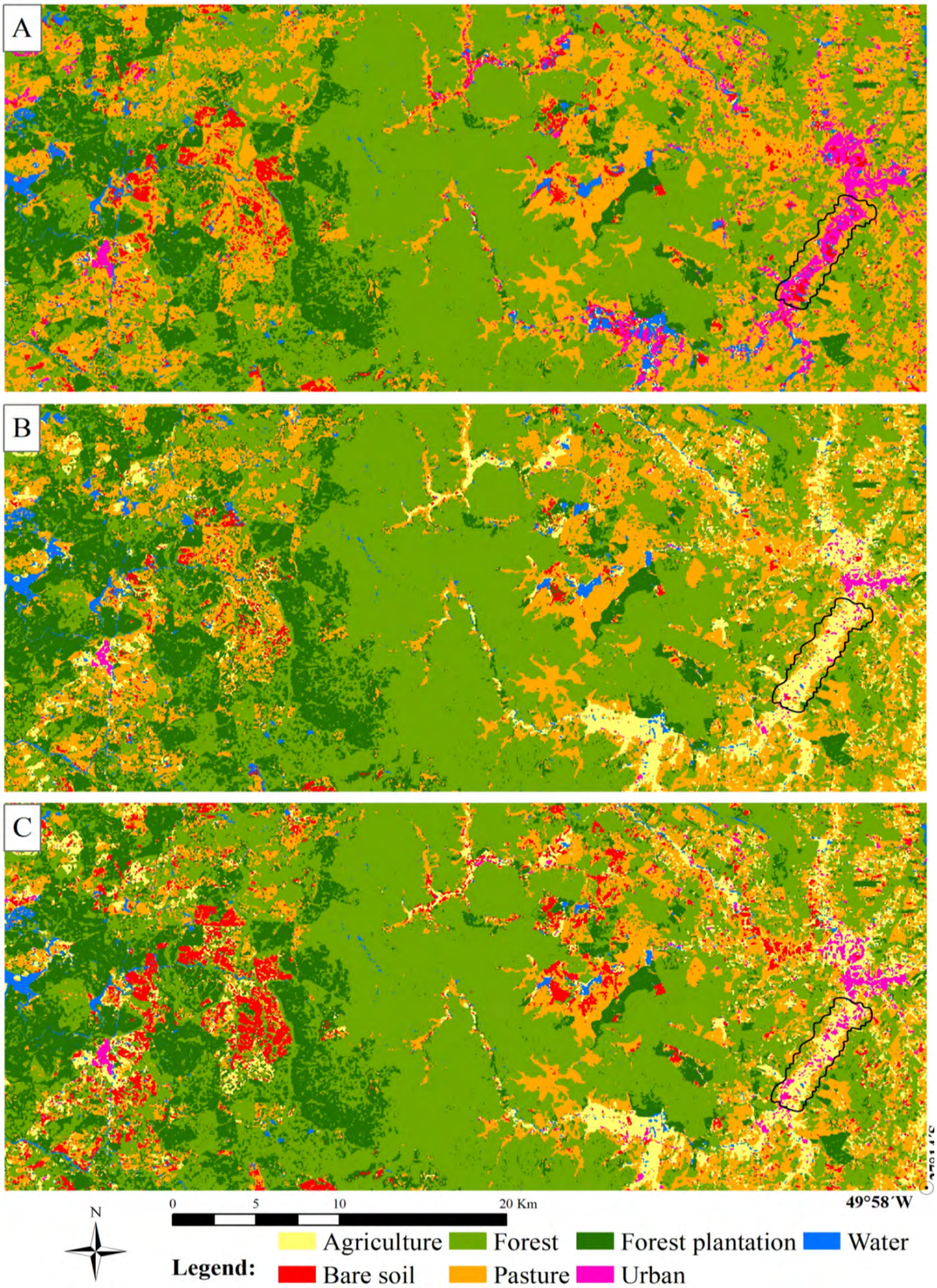
It is noteworthy that the areas identified in pink on the eastern part of Figure 6A, were agriculture fields mistakenly classified as urban areas. Part of this commission error can also be observed, but to a lesser extent, in the classification derived from the SGD method (Figure 6C). For the CVA (Figure 6B) these errors rarely occurred (black circle).

It is also important to highlight the red area at the western part of Figure 6C, which corresponds to an area of bare soil (recently harvested forest stands). One may verify that for the other classifications (Figure 6A and B) there were more errors of omission, being bare soil oftenly mislabelled as pasture or agriculture.



Source: United States Geological Survey (USGS)

Figure 5: Landsat-5 TM satellite image of 2006 of the study area in false color composition (R-4, G-3, B-2).



Source: The authors.

Figure 6: Thematic maps resulting from the Random Forest classification of the study area using the set of training pixels from the method: (A) IR-MAD; (B) CVA and (C) SGD.

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. Some authors recommend caution when comparing the results of TM or ETM+ data with Landsat-8-OLI data (Lu et al. 2004; Vogelmann et al. 2016) or the feasibility of fusing diverse data (You, Cao and Zhou 2020).

With the advancement of technology, the calibrations of the sensors have been improved; consequently, the detection of the targets reflectance on the Earth's surface has been optimized (Vogelmann et al. 2016; Ban and Yousif 2016). As a result, the radiometric differences between the images of the Landsat sensors have become more evident over the years (Banskota et al. 2014; Maldonado, Santos and Graça 2007). 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 (Caldeira et al. 2018; Riaño et al. 2003), 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 (Schowengerdt, 2007). 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 (Jarchow et al. 2018; Zhu et al. 2015).

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 Morissete and Khorram (2000).

When analyzing the invariant pixels separately, producer's accuracies of 94% and 95% for the two evaluated periods were also observed by Yu et al. (2016) 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 Yu et al. (2016) 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 false positives in the number of invariant pixels selected by the method was observed, overestimating the change pixels in the binary map (Marpu, Gamba and Canty 2011). There is evidence that the method may perform poorly when multitemporal scenes have a high noise level due to atmospheric conditions (Choi et al. 2015).

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 Santra et al. (2017) and Byun, Youkyung and Taebyeong (2015). Nielsen and Canty (2005) pointed out that the IR-MAD method provides better detection of invariant pixels and therefore better separation between change and no-change areas.

Chen et al. (2013) 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 2000 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. Conclusion

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.

Further investigations must be conducted to find the reasons for the differences seen between the two analyzed periods, and graphically verify the differences between Landsat-8 OLI and Landsat-5 TM sensors. Therefore, to analyze reflectance metrics like standard deviation, canonical correlation (MAD variables) and spectral gradient could be improved in order to identify profiles of invariant patterns representing each land-use class. Thus, it would be possible to establish an automated process to determine if a given pixel is invariant or not and to which class it belongs, favoring the check over process by the operator.

The three methods we applied present different approaches to obtaining binary maps and therefore, there is no specific model or algorithm for applications with multiple sensors. Success will depend on the purpose, means, and tools available for the study.

ACKNOWLEDGMENT

M.S.S is grateful for grant received from "Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001", A.C.V. acknowledges the research grant of CNPq [309764/2019-0]. The authors are grateful for multiple support received by the scientific team of Project "MonitoraSC". MonitoraSC is funded by FEPEMA under grant [number 2015TR1941]. The authors declare that they have no conflicts of interest.

AUTHOR´S CONTRIBUTION

M.S.S and A.C.V. conceived and executed the work. M.S.S. wrote the basic version. A.L.N. developed data processing codes. All authors read and approved the final version of this manuscript.

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