Cocoa agroforest systems classification with high resolution images

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Abstract. The objective of this work is to verify the viability of cocoa agroforestry classification with High Resolution imagery to include, in the cropland area, the mapping of cocoa planted under forest, as well as open cocoa plantation. In order to avoid overestimating the cocoa area, we introduce the concept of counter-examples (CE). Counter-examples are areas of known classes, not directly involved in classification focus, but identified to avoid the classes of focus being misleadingly classified. Two set of CE was used. The first one is the merging of 7 non-cocoa classes in one training set. The other uses each of these 7 CE classes separately in the training set. Among the several classifiers tested, the best one was SVM with RBF kernel. Results showed that using one CE set produces a more uniform classification map than using 7 CE separately and captures 20% more cocoa cultivated area in a test field, than mapping open cocoa only, with similar user accuracy.

Keywords: remote sensing, image processing.

1. Introduction

Cocoa cultivation is naturally an agroforestry system (SILVA NETO et al. 2001; CALVI et al. 2010). Cocoa can be planted in open air or under the forest. Several studies indicate that native trees and culture integration practices play important roles in the maintenance and conservation of forests and at the same time constitute an important means of livelihood of local families (ASARE & ASARE, 2008). Using regular resolution (15m-30m) optical imagery and usual classification techniques, it is found that cocoa cultivation in agroforestry systems has spectral characteristics similar to those of dense forest areas, thereby causing difficulties in separation and classification (VALADARES, 2014). The objective of this work is to verify the viability of cocoa agroforestry classification with High Resolution imagery and with the concept of counter-examples. Counter-examples are defined as classes not directly involved in classification focus , but identified to avoid the classes of focus being misleadingly classified in non-adequate areas.

2. Materials and methods

In this work, a high spatial resolution image was classified in cocoa classes and some other land cover classes, identified as counter-examples, following the steps illustrated in Figure 1. Different features combination, supervised classifiers and number of counter-examples were tested, in order to seek an optimum classification of cocoa classes. These are explained as follows.

ISBN: 978-85-17-00088-1

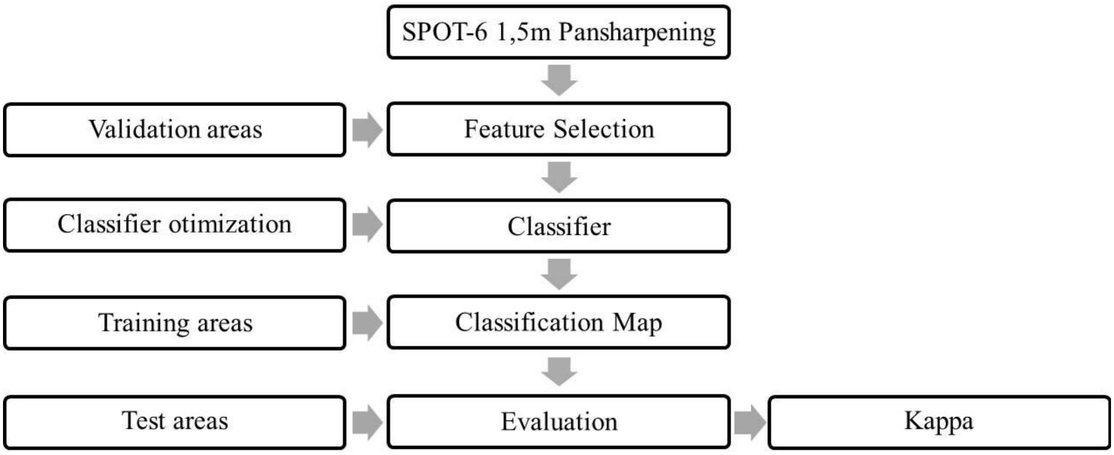

Figure 1. Flowchart of the overall methodology.

2.1 Studied area

The study area comprises mainly parts of Brasil Novo and Medicilândia municipalities and located in the micro region of Altamira, in the western site of Pará state, about 900 km from the capital Belém (Figure 2). It is a relatively recent occupation of the region, derived from the National Integration Program of the military government in the early 1970s (CALVI, 2009). The model of colonization was based on standard orthogonal settlements, such as "herringbone" (BATISTELLA et al., 2003). Field data collection was performed in August 2015 and complemented several times by researchers living locally.

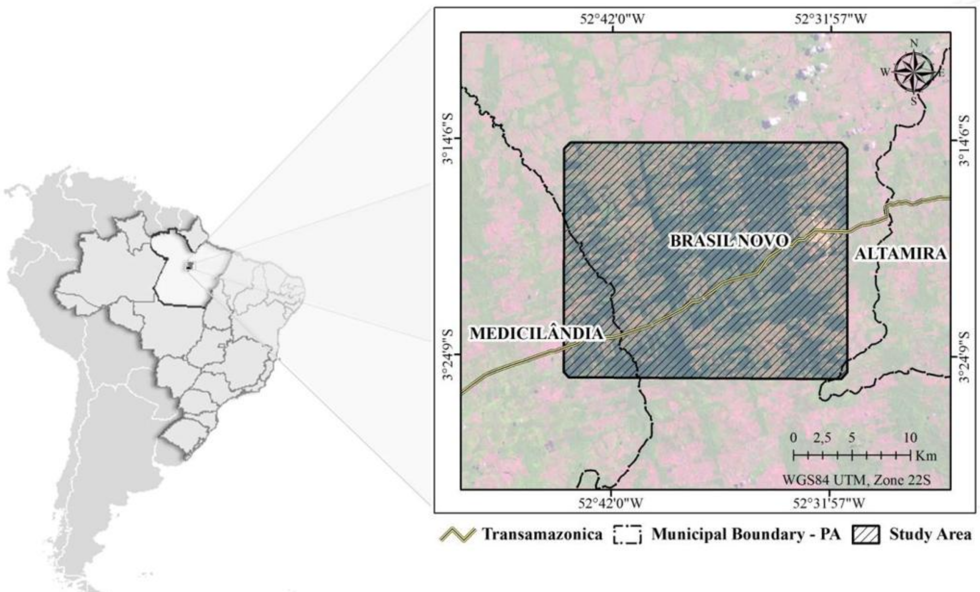

Figure 2. Location study area

2.2 Imagery

The sensor onboard the SPOT (*French Satellite Pour l'Observation de la Terre*) satellite provides imagery with a spatial resolution of 1.5 meters in panchromatic band and 6 meters in the four multispectral bands, containing bands on the near infrared and red wavelengths. An orthorectified and fused SPOT-6 image, from August 19 2015 was used in this work.

ISBN: 978-85-17-00088-1

2.3 Legend determination

We identified two cocoa classes of interest in the studied area, namely Cocoa Monoculture (CM, open air), and Cocoa Agroforestry (CAF, under the forest). Other seven types of land cover classes were also identified and used as counter-examples in the classification process. These classes are Mature Forest (MA), Secondary Vegetation (SV), Pasture (P), Recent Deforested Area (RD), Bare Agricultural Soil (BS), Impervious Surface (IS) and Water (WA). These classes are described in Table 1.

Table 1. Description legend determination

Acronym	Name	Description
CM	Cocoa Monoculture	Cocoa planted without forest cover
CAF	Cocoa Agroforestry	Cocoa planted under a forest cover
MA	Mature Forest	Well-structured forests
SV	Secondary Vegetation	Not planted vegetation grown after the complete razing of natural vegetation
P	Pasture	Areas used for grazing
RD	Recent Deforested Area	Areas recently deforested, with unknown future use
BS	Bare Agricultural Soil	Agricultural areas in which the cover in the sensing time was bare soil
IS	Impervious Surface	Constructed areas such as roofs and highways
WA	Water	Water bodies, as rivers and lakes

Samples of these classes were collected over the SPOT6 image and divided in three sets: validation, training and test, as presented in Figure 3. The validation set was used to perform feature selection, and classifier tuning, the training set was used to train the classifiers and the test set was used to evaluate the results. These classes were also organized in two legends: 2 cocoa classes and 1 CE and 2 cocoa classes and 7 CE, as illustrated in Figure 4. Only for comparison purposes, an additional legend was composed, in which we use either 1 or 7 CE, but only Cocoa Monoculture class.

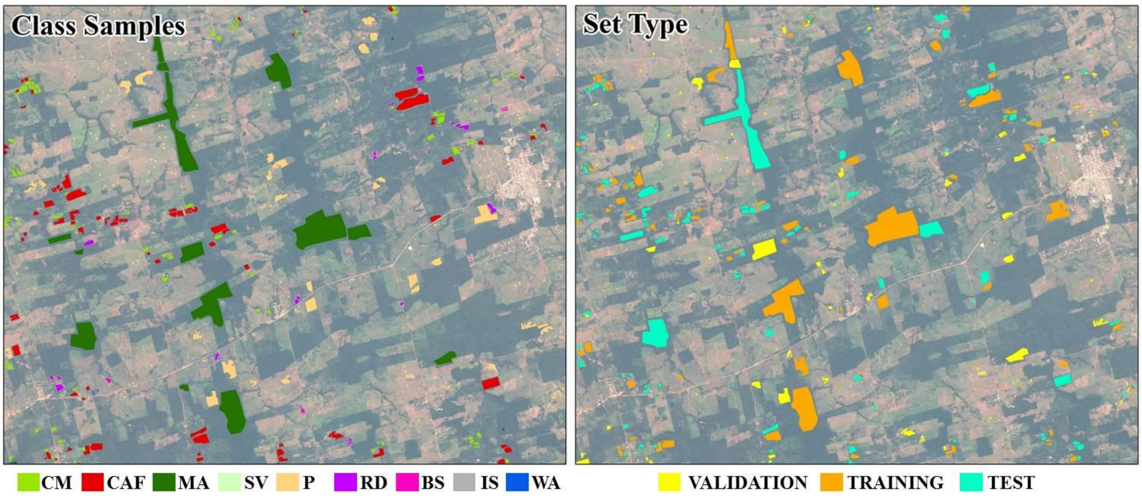

Figure 3. Validation, training and test samples per class.

2.4 Feature Selection

Three sets of bands from the SPOT6 image were selected: the set of two and three bands that is indicated by the highest minimum Jeffries-Matusita (JM) distance between any pair of classes and the four original bands of the image. (SCHOWENGERDT, 2006; THEODORIDIS; KOUTROUMBAS, 2006)

This analysis was made considering 1000 randomly selected samples of each class from the validation set, with the counter-examples held separately or merged in a super class named Counter- Examples (CE). In the second case, samples were selected so that the number of samples from which original class was similar (1000 samples for each cocoa class and 142 or 143 samples for each counter-example class).

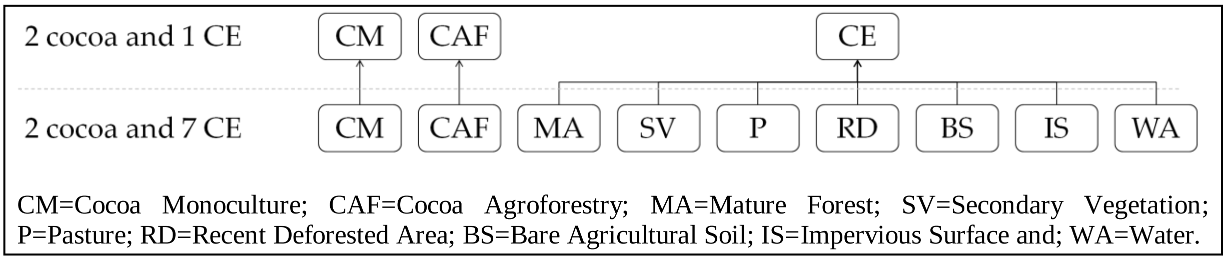

Figure 4. Legend sets organization

2.5 Image classification

We randomly selected 1000 pixels for each class to train the classifiers. For the legend with 2 cocoa classes and 1 CE, this selection was made so a balanced amount of pixels from each CE class was selected. The three data sets (with 2, 3 or 4 bands) were classified using the two proposed legends (2 cocoa classes and 1 CE and 2 cocoa classes and 7 CE) and different classifiers in varied configurations. We tested the Support Vector Machine (SVM) classifier in a one-against-one approach, using linear and radial kernel, and Maximum Likelihood (ML), in a by pixel and with a contextual approach, based on *Interated Conditional Modes* (ICM)(BESAG,1986). For SVM classifications we tested the Cost values 0.01, 0.1, 1, 10, 100, 1000 and 10000 both for linear and radial kernels. The gamma parameter needed for SVM using radial kernel was kept to the default value (1/data dimension).

Since the objective of this work is to evaluate the cocoa classification, an additional merging step was done, after any classification with 7 counter-examples in which the labels of the 7 counter examples (for 2 cocoa and 7 CE legend based classifications) were merged in the map forming what we called pCE (post-processed Single Counter-Example class) This process is illustrated in Figure 5.

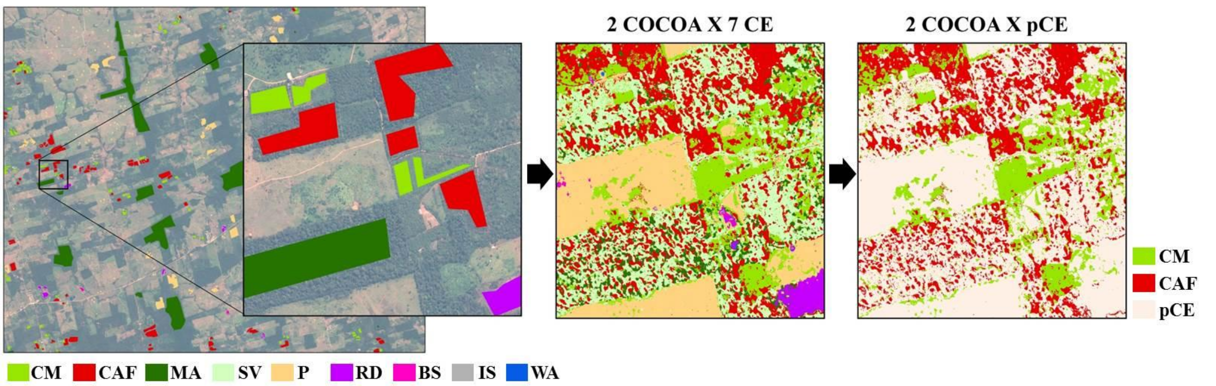

Figure 5. After a classification with 9 classes (2 cocoa classes and 7 counter-examples), counter-examples labels assume just one color in the final map.

2.6 Evaluation

We randomly selected 1000 samples for each class from the test set and used these samples to calculate the confusion matrix for each classified image. The Overall Accuracy

(OA), the Kappa index and the theoretical variance of Kappa index were obtained from these matrixes, as well as the Producer Accuracy (PA) and the User Accuracy (UA) for each class. Kappa index values were then compared using a hypothesis z-test with 5% of significance level. For each classification case (a set of a classifier and the channel set) the case of the highest Kappa value is pointed out. If there is another classification case with a Kappa value not statistically different for each legend and classifier, but with a smaller set of channels, this set is kept for analysis.

3. Results and discussion

The set of two bands that obtained the highest minimum JM distance between pair of classes, for both legends, was composed by band 1 and 2. For three bands and both legends, it was composed by bands 1, 2 and 3. These sets were classified and the Kappa index for each classification was calculated and compared using the z-test with 5% of significance. The best configuration for each legend and classifier is specified in Table 2. Note that when Kappa values for classifications of a given classifier and legend with different number of features was statistically equal, the classification of the smallest set was selected. The Kappa value for the classified image generated by these classifiers is presented in Table 3. Note that the values presented for legends with 7 CE consider these separately. The statistically higher Kappa value for each legend set is highlighted in bold font. For comparison purposes, the Kappa value of the classified image obtained using the best classifier and configuration, but with a legend considering either 1 or 7 counter examples and with only Cocoa Monoculture is also presented in the Table 3 and an example of these classifications is illustrated in Figure 6.

Table 2 - Best configuration for classifiers, as defined by validation samples usage, and number of bands for each classifier and legend.

Classifier	2 cocoa classes and 1 CE		2 cocoa classes and 7 CE	
	# of bands	Configuration	# of bands	Configuration
SVM-Linear	4 (all bands)	Cost=0.01	4 (all bands)	Cost=100
SVM-Radial	4 (all bands)	Cost=0.01	4 (all bands)	Cost=10000
ML	3 (bands 1, 2 and 3)	-	4 (all bands)	-
ML-ICM	2 (bands 1and 2)	-	3 (bands 1, 2 and 3)	-

Table 3 – Kappa value for the best classifier and legend.

	2 cocoa classes				Only CM
	SVM-Linear	SVM-Radial	ML	ML-ICM	Best classifier[1]
1 C.E.	0.381	**0.399**	0.298	0.315	0.628
7 C.E.	0.513	**0.545**	0.509	0.510	0.850

[1] For the legend with 1 C.E the used classifier was SVM-Radial with Cost=0.01, for 7 C.E. it was also SVM-Radial, but with Cost=10000.

ISBN: 978-85-17-00088-1

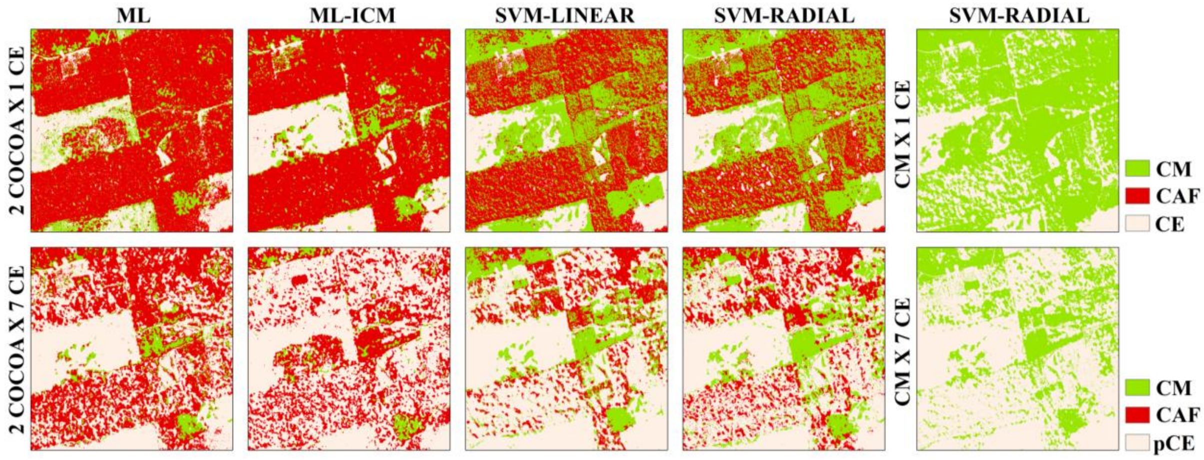

Figure 6. Best classification per classifier.

As can be seen in Table 2, the best classified image with both legends was obtained by SVM with radial kernel, with varied Cost values, both considering all bands of SPOT6 image. We can also observe that for 2 cocoa classes and 1 CE the used classifier greatly impacted the classification result (gain of 33.0% of the Kappa value for the best ML based classified image to the Kappa value of the SVM-Radial based one), while for 2 cocoa and 7 CE, this appears to be less expressive (gain of 7.1% of Kappa value of the best ML classified image to the one with the highest Kappa value). In addition, leaving the cocoa under forest out of the legend results in classified images with improved Kappa value, for both legends.

The confusion matrix of the best classified image of the legend with 2 cocoa classes and 1 CE is illustrated in Table 4, and for 2 cocoa classes and 7 CE in Table 5. In these tables, Kappa value, Overall Accuracy (OA) and the User and Producer Accuracy (UA and PA, respectively) for class is also registered. As can be seen in these tables, the two cocoa classes presented high confusion between themselves, and also between classes such as Forest, Secondary Vegetation and Pasture. The confusion between cocoa classes is somewhat smaller when using only 1 CE than when using 7 CE regarding the selected SVM classified images. The higher Kappa value of the classified image with 7 CE is due the better classification of some of the CE classes, such as Impervious Surface and Water.

Table 4 – Confusion matrix, in percentage, of the classified image obtained using SVM with radial kernel with Cost=0.01 and the legend with 2 cocoa classes and 1 CE.

Reference

Classification	CM	CAF	CE	UA
CM	74.2	51.9	15.9	0.522
CAF	18.6	40.1	18.6	0.519
CE	7.2	8.0	65.5	0.812
PA	0.742	0.401	0.655	
OA	0.599			
Kappa	0.399			

ISBN: 978-85-17-00088-1

As in both cases great confusion is noted between the two types of cocoa, another assessment can be made merging the mapping of 2 cocoas in 1 cocoa type. Table 6 shows the user accuracy values for either cases, with 1 CE and 7 CE. It is noticed that the user accuracy of the joint mapping of the 2 cocoa types is quite acceptable in spite of regular Kappa values for both cases. In this procedure, one is not primarily interested in a great overall Kappa, but to enhance the cocoa mapping itself. In Table 6 it is also shown that classifying just open cocoa the user accuracy would be more or less the same, but the under-forest cocoa, in this case, would be underrepresented. It is also noticeable that, in spite of similar user accuracy considering the joint mapping of (CM+CAF) with classifying CM alone, both mappings cover much less area when using 7 CE, a fact that can also be observed in Figure 5. Visual inspection of Figure 5 suggests that the usage of only one set of CE leads to less noisy classification mapping.

Table 5 – Confusion matrix, in percentage, of the classified image obtained using SVM with radial kernel with Cost=10000 and the legend with 2 cocoa classes and 7 CE.

Reference

Classification

	CM	**CAF**	**SV**	**MA**	**P**	**RD**	**BS**	**SI**	**WA**	**UA**
CM	32.8	27.2	10.9	9.9	3.6	0.0	0.0	0.5	0.0	0.386
CAF	35.6	17.4	29.0	20.1	0.0	0.0	0.0	0.0	0.0	0.170
SV	9.4	18.9	56.9	36.1	1.1	0.0	0.0	0.0	0.0	0.465
MA	8.5	17.5	2.6	32.8	11.4	1.5	0.0	0.0	0.0	0.441
P	13.3	18.9	0.5	1.0	76.9	0.4	26.9	0.0	0.0	0.558
RD	0.4	0.1	0.0	0.1	5.2	85.7	30.2	0.8	0.0	0.700
BS	0.0	0.0	0.0	0.0	1.4	1.3	42.7	7.7	0.0	0.804
SI	0.0	0.0	0.0	0.0	0.4	0.1	0.0	90.8	0.0	0.995
WA	0.0	0.0	0.0	0.0	0.0	11.0	0.0	0.2	100.0	0.899
PA	0.328	0.174	0.570	0.328	0.769	0.857	0.428	0.908	1.000	
OA	0.596									
Kappa	0.545									

Table 6 – User accuracy of cocoa plantation of the classified image obtained using SVM with radial kernel with Cost=0.01 and the legend with 2 cocoa classes and 7 post-classification merged CE (pCE). This table also shows comparison with the case of CM classification only.

	CM	**CAF**	**CM + CAF**	**Area (%)**	**Only CM**	**Area (%)**
CE	0.522	0.519	0.728	82.48	0.75	68,35
pCE	0.386	0.170	0.842	38.24	0.95	27.67

4. Final considerations

For both considered legends, the best classification result was obtained from SVM using radial kernel and all bands from the SPOT 6 images. Classification of cocoa classes was better using the 7 counter examples merged in the training samples level, which leaded to UA of 52.2% for CM and 51.9 for CAF. The Kappa in this case is 0.399. Classifying cocoa with seven CE leads to a higher Kappa, but poorer UA for CM and CAF. The important conclusion in this point is that not always a higher overall Kappa means the best classification for every purpose. The proposed methodology in this work permitted the inclusion of the under-forest cocoa in the final mapping with similar accuracy of the open cocoa mapping itself, this way improving the total cocoa mapping. It was also observed that the usage of a higher number of counter-examples leads to a smaller area mapped as cocoa, with a noisier mapping.

Cocoa classes were misclassified mainly as Mature Forest, Secondary Vegetation and Pasture. It is believed that the use of texture attributes and other images, such as Synthetic Aperture Radar ones, may improve the cocoa classification results.

Acknowledgements

The authors thank CNPq for the grants # 314610/2014-6; 313077/2015-0#312753/2015-2, #401528/2012-0, # 409936/2013-8 and #309135/2015-0.

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