



Enhanced land use/cover classification of heterogeneous tropical landscapes using support vector machines and textural homogeneity

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ABSTRACT

Land use/cover classification is a key research field in remote sensing and land change science as thematic maps derived from remotely sensed data have become the basis for analyzing many socio-ecological issues. However, land use/cover classification remains a difficult task and it is especially challenging in heterogeneous tropical landscapes where nonetheless such maps are of great importance. The present study aims at establishing an efficient classification approach to accurately map all broad land use/cover classes in a large, heterogeneous tropical area, as a basis for further studies (e.g., land use/cover change, deforestation and forest degradation). Specifically, we first compare the performance of parametric (maximum likelihood), non-parametric (k-nearest neighbor and four different support vector machines – SVM), and hybrid (unsupervised–supervised) classifiers, using hard and soft (fuzzy) accuracy assessments. We then assess, using the maximum likelihood algorithm, what textural indices from the gray-level co-occurrence matrix lead to greater classification improvements at the spatial resolution of Landsat imagery (30 m), and rank them accordingly. Finally, we use the textural index that provides the most accurate classification results to evaluate whether its usefulness varies significantly with the classifier used. We classified imagery corresponding to dry and wet seasons and found that SVM classifiers outperformed all the rest. We also found that the use of some textural indices, but particularly homogeneity and entropy, can significantly improve classifications. We focused on the use of the homogeneity index, which has so far been neglected in land use/cover classification efforts, and found that this index along with reflectance bands significantly increased the overall accuracy of all the classifiers, but particularly of SVM. We observed that improvements in producer's and user's accuracies through the inclusion of homogeneity were different depending on land use/cover classes. Early-growth/degraded forests, pastures, grasslands and savanna were the classes most improved, especially with the SVM radial basis function and SVM sigmoid classifiers, though with both classifiers all land use/cover classes were mapped with producer's and user's accuracies of ~90%. Our classification approach seems very well suited to accurately map land use/cover of heterogeneous landscapes, thus having great potential to contribute to climate change mitigation schemes, conservation initiatives, and the design of management plans and rural development policies.

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1. Introduction

Accurate land use/cover (LUC) maps derived from remotely sensed data form the basis for quantifying and monitoring the spatio-temporal patterns of LUC change. In most tropical regions, LUC change is taking place at unprecedented rates (Gibbs et al., 2010) and, therefore, accurate LUC maps are key for assessing its implications for climate change, biodiversity conservation, and peoples' livelihoods. Nevertheless, LUC classification remains a

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challenging task in heterogeneous tropical areas for several reasons. A major problem lies in the difficulty of acquiring cloud-free multispectral imagery, which may be partly overcome through the use of radar imagery (Freitas et al., 2008), but their interpretation is not straightforward in tropical areas (Almeida-Filho et al., 2007). Another major drawback is related to the limitations (in terms of cost, time, and accessibility) for carrying out fieldwork to collect sufficient information on LUC classes, which hampers the training and validation stages of supervised and hybrid LUC classification approaches. Other constraints for accurate LUC mapping in tropical regions are the usual lack of aerial photography, of previous LUC maps, and of ancillary data (e.g., digital elevation models – DEMs, geological maps) that may be used to improve classification results.

To address the problems related to LUC classification in tropical areas, a fundamental issue is the selection of the classifier. The use of machine learning algorithms has gained momentum in recent years and some assessments of their relative performance compared to other classifiers have been conducted in the Amazon region (Lu et al., 2004; Carreiras et al., 2006). Specifically, support vector machines (SVM) have been shown to attain high accuracies in LUC mapping and outperform other algorithms (Huang et al., 2002; Foody and Mathur, 2004a; Pal and Mather, 2005; Kavzoglu and Colkesen, 2009; Mountrakis et al., 2011; Szuster et al., 2011). SVM have two significant advantages for LUC mapping. First, since SVM classifiers seek to separate LUC classes by finding a plane in the multidimensional feature space that maximizes their separation, rather than by characterizing such classes with statistics, they do not need a large training set but just the training samples that are support vectors (Foody and Mathur, 2004b). Thus, for SVM classifiers Foody and Mathur (2006) suggested to use small training sets composed of purposely selected mixed pixels containing the support vectors, as this approach does not compromise classification accuracies and may save considerable time. Second, SVM algorithms are independent of data dimensionality (Dixon and Candade, 2008), which is a key feature when using many spectral bands such in hyperspectral imagery or when ancillary data are included in the classification process; conversely, for classifiers that depend on dimensionality (e.g., artificial neural networks), training sets must exponentially increase in size to maintain classifier performance (Dixon and Candade, 2008).

Another fundamental issue to enhance LUC classification is the adequate selection of input variables, which some authors suggest may have the same impact as the selection of the classifier (Heinl et al., 2009). Nevertheless, we argue that the combination of an allegedly superior classifier such as SVM with appropriate ancillary data should improve results, as observed by Watanachaturaporn et al. (2008) using multisource classification with SVM. Different textural measures are a potential source of ancillary data and their benefits for LUC classification have been highlighted in studies using different techniques and classifiers (e.g., Berberoglu et al., 2000; Chica-Olmo and Abarca-Hernández, 2000). Specifically for forest classification, the inclusion of textural data has proven useful for mapping forest age, forest types, detecting forest cover change, and characterizing canopy structure (e.g., Palubinskas et al., 1995; Franklin et al., 2000; Zhang et al., 2004; Kayitakire et al., 2006; Malhi and Román-Cuesta, 2008), particularly with high spatial resolution imagery (Ota et al., 2011). A significant advantage of using texture to enhance image classification in tropical regions, where other ancillary data sources may not exist, is that textural data can be extracted from the image itself. Thus, for example, the gray-level co-occurrence matrix method can be used to extract textural indices that can be included as data bands in the classification process (Gong et al., 1992).

Given the current limitations for classifying LUC in complex tropical areas, in this paper our main goal is to establish a robust

classification approach to accurately map all the broad LUC classes considered in a heterogeneous tropical area. Specifically, we first test if LUC classification results obtained with SVM classifiers compare favorably with other parametric, non-parametric, and hybrid classifiers; we then assess what textural indices from the gray-level co-occurrence matrix lead to greater classification improvements at the spatial resolution of Landsat imagery (30 m), and rank them accordingly; and finally, we evaluate if the usefulness of a textural index for LUC classification varies significantly in relation to the classifier utilized.

2. Study area, field surveys, and map legend definition

2.1. Study area

The study area is located in the department of Beni, Bolivia (Fig. 1). We selected this large area because its landscapes are highly heterogeneous as a transition across three biogeographic areas: (1) montane tropical forests covering the foothills (over 400 m) of the Andes to the west, (2) lowland tropical forests to the south and center of the study area, and (3) wet savanna areas to the north and east. Lowland forests are located below 400 m and contain some deciduous species owing to a marked seasonality (dry and wet seasons) (Guèze et al., *in press*). In wet savannas vegetation is controlled by small variations in ground elevation and relief, which in turn are shaped by river dynamics and periodic flooding. Savanna areas consist of swamps, marshes and lagoons with aquatic vegetation in the lowest areas; semi-natural grasslands and pastures in areas less prone to be flooded; and scrublands and patches of forests on mounds that do not get seasonally flooded. The vegetation formations of the study area are also shaped by the land use type and intensity of its different inhabitants, who range from Andean indigenous peoples in montane forests, to local peasants, cattle ranchers, and different native and colonist indigenous peoples in lowland forests and savanna areas.

2.2. Field surveys and map legend definition

Two field surveys were undertaken across the study area to collect LUC data. The first focused on forested areas (old-growth, early-growth, and degraded forests), water, bare soil, and infrastructure/urban categories, and was carried out in June–August 2009 (dry season). The second one took place in April–May 2010 (end of the wet season) and focused on the large savanna areas that are present across the study area, which mix with patches of pastures, semi-natural grasslands and scrublands. Planning the acquisition of ground-truth data was done upon preliminary analyses of the most recent Landsat-5 Thematic Mapper (TM) scenes (April 2009). LUC data were acquired with handheld GPS units, with typical mean positioning errors of 2–4 m in open areas and 4–6 m in forested areas. Additionally, to assist in the processes of geometric correction and geometric accuracy assessment, we collected GPS points at road crossings and other human-made features on the ground, and GPS tracks along the major roads and rivers across the study area.

The definition of broad LUC classes was carried out prior to the field surveys and was based on previous knowledge of the area and initial remotely sensed data exploration, which consisted in carrying out several unsupervised ISODATA classifications on the most recent Landsat imagery we had, and checking the classification obtained by Killeen et al. (2007) for our study area. Nevertheless, the definition of LUC classes was modified according to our field observations and thorough examination of the spectral signatures extracted from our field data. Eight broad LUC classes were finally considered (Table 1).

Table 1
Definition of land use/cover classes included in the study.

LUC Class	Definition
Early-growth/degraded forest (EGDF)	Forested areas with varying degrees of disturbance due to human activities (e.g., typically slash and burn agriculture or logging) or natural dynamics (e.g., flooding regimes). Typically composed of regenerating trees, dead trees and logs, crops such as rice, manioc and bananas, sometimes with scattered old big trees. The canopy is rather open, structurally simple, and the average tree height is 3–10 m.
Old-growth forest (OGF)	Forested areas with low levels of disturbance that consist of mature trees forming a dense and structurally complex canopy with few gaps and a typical height range of 10–40 m.
Water (W)	Water bodies such as creeks, rivers, shallow lakes, and deep lakes.
Bare soil/urban (BSU)	Sand banks along rivers, urban areas including towns, unpaved streets and roads.
Pasture (P)	Areas typically used for cattle ranching, both in deforested and savanna areas. In deforested areas, pasture species are frequently sown, while in savanna areas pasture species are usually natural. In both instances it is common to have varying amounts of bare soil.
Savanna (S)	Low relief savanna areas that are seasonally inundated and may form swamps and marshes.
Semi-natural grassland (G)	Grassland patches that occur mostly across the savanna areas, with very little or total absence of woody species.
Scrubland (SC)	Open canopy areas dominated by bushes or short trees, commonly present across the savanna areas, growing on dry ground of low quality; sometimes in the fringe or vicinity of forested areas.

3. Materials and methods

3.1. Satellite data and pre-processing

LUC classifications were carried out on Landsat satellite mosaics composed of two scenes (path 233, rows 70, 71). We used two dates (25/08/2001 and 17/04/2009, corresponding to the dry and the end of the wet seasons, respectively) so as to account for differences in phenology, illumination, and reflectance, and hence strengthen the classification comparison among different algorithms. We chose Landsat data because of the large extent we needed to cover and because Landsat is arguably the world's most commonly used satellite to undertake ecological studies,

including LUC classifications (Cohen and Goward, 2004), which renders our results more comparable to those from other studies. In addition, to carry out topographic and illumination corrections we used the ASTER Global Digital Elevation Model (GDEM) v.1 (Fig. 1). GDEM v.1 has 30 m horizontal and 20 m vertical accuracies at 95% confidence and therefore it is more accurate than the older DEM provided by the Shuttle Radar Topography Mission (SRTM). The two 25/08/2001 Landsat-7 Enhanced Thematic Mapper (ETM+) scenes were acquired through the United States Geological Survey (USGS). Their geometric accuracy was assessed through the ground control points and GPS tracks we had collected in the field and we found misalignments of ~0.5 pixels in both cases. The two 17/04/2009 Landsat-5 TM scenes were acquired from the

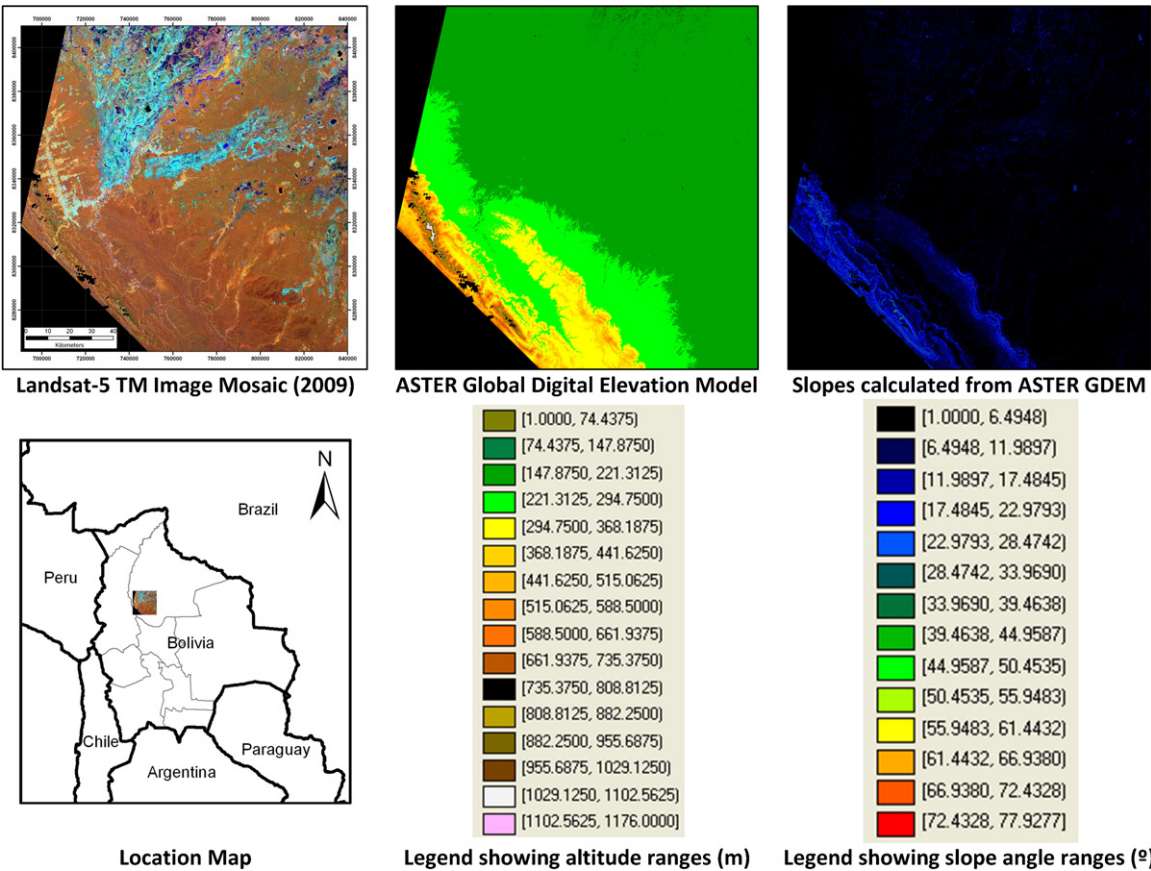


Fig. 1. Study area showing the most recent Landsat image mosaic (RGB:4-5-3) and the range of altitudes and slopes extracted from the DEM used.

Table 2

Size of training samples (# pixels) collected for each classification.

LUC class	2009	2001
Early-growth/degraded forest	10,025	5008
Old-growth forest	10,035	5003
Water	2506	2000
Bare soil/urban	1000	600
Pasture	5000	1000
Savanna	5000	1508
Grassland	2005	1000
Scrubland	1352	1008

Brazilian National Institute for Space Research (INPE) and required geometric and topographic corrections, which were carried out with MiraMon software using the procedure developed by Palà and Pons (1995). The geometric errors obtained for both Landsat-5 TM images after the corrections were consistent with those of the reference Landsat-7 ETM+ scenes (~ 0.5 pixels). Subsequently, each pair of images corresponding to the same date was mosaicked and radiometric corrections were performed using the method implemented in MiraMon (Pons and Solé-Sugrañes, 1994). Finally, the two mosaics were cropped to the extent of the area of interest and, for each image mosaic (image hereafter), a cloud and cloud-shadow mask was manually built through visual interpretation and applied to, being thus each image ready for classification analysis.

3.2. Classification algorithms

We used a parametric classifier (maximum likelihood – ML), non-parametric classifiers (k-nearest neighbor – KNN, and four different support vector machines – SVM: linear, polynomial, radial basis function and sigmoid), and a hybrid classifier (unsupervised–supervised, contained in MiraMon software – MMHC). We do not explain here how the ML, KNN and SVM algorithms work since detailed descriptions abound in remote sensing and pattern recognition textbooks (e.g., Tso and Mather, 2009). MMHC involves the use of an unsupervised ISODATA algorithm to retrieve spectral classes, and a subsequent supervised classification performed on the ISODATA results using training areas to obtain thematic classes (Serra et al., 2003). MMHC has been successfully used to classify Mediterranean environments (Serra et al., 2003) and has also been used in tropical dry areas of Nicaragua to classify vegetation (García-Millán and Moré, 2008). To our knowledge this is the first time MMHC has been used to classify tropical forests and savannas.

3.3. Training data

We carefully examined field data and spectral signatures across the images to select the training sets from the two images. In most cases training data consisted of small polygons, though there were few instances in which single pixels were chosen in narrow areas (e.g., roads, sand banks and rivers). Much care was taken to scatter training areas across each image to ensure they were representative of the entire image, and to retrieve as many training samples for each LUC class (Table 2) as needed to satisfy previously suggested criteria to establish an appropriate minimum sample size (Tso and Mather, 2009). To enhance the comparability of results between the classifications of both dates we tried to use the same training areas as much as possible (i.e., when no change had occurred). The Jeffries–Matusita transformed divergence index was used to assess the separability of training data for both dates. We confirmed that separability was rather high for water, bare soil/urban and old-growth forest, but much lower for the other LUC classes.

3.4. Textural data

We extracted textural measures from the gray-level co-occurrence matrix (GLCM), which is often employed to extract textural information from remote sensing images (Haralick et al., 1973). Specifically, we calculated eight textural indices from six Landsat reflectance bands (1–5, 7) using moving windows of 3×3 and 7×7 pixels. We then used the six textural bands calculated for each index and moving window size, along with the six Landsat spectral bands, to carry out a maximum likelihood classification. We assessed the potential usefulness of each index based on the overall accuracies obtained for each classification and the producer's and user's accuracies attained for the two forested classes. We performed all calculations for both images.

3.5. Classification post-processing, accuracy assessment, and comparison

We applied a 3×3 -pixel majority filter to all the classifications to eliminate the salt and pepper effect prior to their accuracy assessment. Reference data retrieval for accuracy assessment was based on a stratified random sample selection, with sample units taken at a minimum distance of 2 km to avoid the potential effects of spatial autocorrelation (Congalton and Green, 2009). Reference data were ground-truthed by expert-knowledge from the images themselves (we did not use data collected in the field as they had not been randomly selected due to logistic reasons). Sample units lying on the fringe of two or more LUC classes were not discarded so as not to affect the randomness principle of accuracy assessment. We used the rule of thumb proposed by Congalton and Green (2009) regarding the minimum reference dataset size required for accuracy assessment, whereby 75–100 testing sample units per thematic class should suffice for large areas and less than 12 thematic classes.

We carried out both hard and soft (also known as fuzzy) classification accuracy assessments. The soft classification assessment may enable a better evaluation of the behavior of a classifier, particularly regarding points that are challenging because they lie on transition or mixed zones (Woodcock and Gopal, 2000), being thus well suited to compare classifiers. For the soft assessment we assigned by expert-knowledge two possible LUC classes to each reference point: a primary class, which coincided with that used in the hard classification assessment and that was supposed to represent the ground *truth*, and a secondary class, which was specific to the soft assessment and was considered to be right too because it represented a *good* or *acceptable answer* given the location of the reference point. However, whenever a reference point was located in a homogeneous area and its LUC class was deemed clear, we assigned the same LUC class to both primary and secondary classes.

For both types of accuracy assessment and for each classification obtained we generated a confusion matrix (also known as error matrix), which is the most standard method for remote sensing classification accuracy assessment (Congalton and Green, 2009). Through the construction of confusion matrices, for each assessment we retrieved the classification overall accuracy as a global measure of classification accuracy, and the producer's and user's accuracies as specific accuracy measures for each LUC class. We did not retrieve the kappa coefficient as some authors reported this measure of global map accuracy is problematic (Stehman, 1997; Foody, 2004) because it does not have a probabilistic interpretation (unlike overall, producer's, and user's accuracies). Moreover, the kappa coefficient has been shown not to be an appropriate map accuracy measure for comparing the accuracy of thematic maps, particularly when (as in this study) the reference data used have always been the same (Foody, 2004). Finally, to assess the statistical significance of the difference in overall accuracy between each

Table 3
Hard versus soft overall accuracy assessment of classifications obtained for 2009 and 2001 imagery using only reflectance bands. OA, overall accuracy; ML, maximum likelihood; SVM, support vector machine; KNN, k-nearest neighbor; MMHC, hybrid classification.

Accuracy assessments	17/04/2009		25/08/2001	
	Hard OA	Soft OA	Hard OA	Soft OA
ML	71.50	80.50	70.25	70.88
SVM linear	79.25	86.75	73.25	76.63
SVM polynomial (6th grade)	79.25	86.63	74.50	74.88
SVM radial basis function	79.38	87.00	73.88	74.25
SVM sigmoid	80.13	87.75	75.25	75.63
KNN	72.63	80.50	75.75	76.75
MMHC	70.75	79.75	64.13	67.88

pair of classifications, we used the McNemar test because we had used identical reference data to generate the confusion matrices (Foody, 2004).

4. Results

4.1. Improvements in overall land use/cover classification results using SVM

We find that, for both images and types of accuracy assessment, all four SVM classifications attain the highest overall accuracy and only KNN for 2001 imagery is comparable to them (Table 3). On the contrary, MMHC attains the lowest overall accuracy for both dates and assessments, though these are similar to ML and KNN for 2009 imagery. ML results are far less accurate than those of SVM for both dates and assessments, whereas KNN results appear somehow contradictory as they are similar to SVM for 2001, and to MMHC and ML for 2009, irrespective of the type of accuracy assessment. We only evaluated differences in overall accuracy of hard accuracy assessments as the differences in overall accuracy of soft assessments followed the same pattern (Table 3). Results of McNemar

tests are shown in Table 4 and three facts stand out. First, the statistical significance of the differences between any SVM and MMHC is always maximum regardless of the date, whereas that between any SVM and ML ranges from significant to extremely significant for 2001 and is always extremely significant for 2009. Second, KNN shows no statistically significant differences with the least accurate classifiers (ML and MMHC) for 2009 imagery (although its overall accuracy is slightly higher than theirs). However, for 2001 imagery KNN shows no statistically significant differences with the most accurate SVM classifiers, attaining in fact the highest overall accuracy of all the classifiers. Third, the relative performance of the different SVM algorithms is very similar. There are no statistically significant differences among them for 2009 and minor differences for 2001 imagery.

4.2. Usefulness of textural indices for land use/cover classification

We distinguish among three groups of indices ranked in accordance with their potential usefulness (Table 5): (1) homogeneity and entropy, which provide significant improvements, (2) mean, dissimilarity, and second moment, that lead to moderate improvements, and (3) variance, contrast, and correlation, which actually decrease classification accuracies when compared with those without texture. Based on these results we focus hereafter on the use of textural homogeneity (extracted from a 7 × 7-pixel moving window), thus discarding the use of other textural indices. We did not use entropy along with homogeneity so as not to increase data dimensionality, and because we tried different combinations of entropy and homogeneity bands that did not increase the accuracies obtained using just homogeneity (results not shown).

4.3. Improvements in overall land use/cover classification results using textural homogeneity

The use of the homogeneity index (HI or homogeneity hereafter) greatly improves the results obtained by any classifier regardless

Table 4
McNemar tests showing the statistical significance of the differences in overall accuracy from a hard accuracy assessment among classifiers, for both 2009 and 2001 imagery, using only reflectance bands. Codes are as follows: 0 – no significant ($p > 0.05$), 1 – hardly significant ($p \sim 0.5$); 2 – significant ($0.5 < p \leq 0.01$); 3 – very significant ($p \sim 0.001$); 4 – extremely significant ($p \sim 0.0001$). Left values refer to 2009 and right values to 2001 classifications. Positive values indicate better performance of the row classifier whereas negative values indicate better performance of the column classifier.

17/04/2009\25/08/2001	SVM linear	SVM polynomial	SVM RBF	SVM Sigmoid	KNN	MMHC
ML	–4 –2	–4 –3	–4 –2	–4 –3	0 –4	0 3
SVM linear		0 –2	0 0	0 –1	4 –1	4 4
SVM polynomial			0 0	0 0	4 0	4 4
SVM RBF				0 0	4 0	4 4
SVM sigmoid					4 0	4 4
KNN						0 4

Table 5
Comparative assessment of the usefulness of using textural indices (extracted from the gray-level co-occurrence matrix) in combination with spectral bands, carried out using the maximum likelihood classifier. No classification could be obtained using the correlation index extracted from 2001 imagery. Only results from indices extracted with 7 × 7-pixel moving windows are shown as they led to higher accuracies than indices extracted from 3 × 3-pixel windows. OA, overall accuracy; PA, producer's accuracy; UA, user's accuracy; EGDF, early-growth/degraded forest; OGF, old-growth fores.

Accuracy assessments	17/04/2009					25/08/2001				
	OA	PA EGDF	UA EGDF	PA OGF	UA OGF	OA	PA EGDF	UA EGDF	PA OGF	UA OGF
Without texture	81.64	75.56	97.84	98.22	84.35	81.67	85.78	97.23	97.11	88.73
With a textural index										
Mean	84.17	88.89	98.52	98.33	98.22	82.74	94.67	74.35	95.33	83.54
Variance	76.88	73.22	89.30	86.33	87.60	77.21	83.89	74.46	87.11	91.48
Homogeneity	85.54	89.67	97.46	98.11	94.95	86.21	90.11	86.18	95.22	91.76
Contrast	78.90	73.89	89.38	91.89	87.05	81.63	87.78	80.94	91.11	92.24
Dissimilarity	84.03	88.44	94.54	94.78	94.46	82.85	91.22	87.43	93.44	95.68
Entropy	84.92	88.33	96.95	96.78	94.16	85.21	90.33	83.64	93.78	92.75
Second moment	82.20	81.67	97.35	97.78	88.80	84.76	85.56	86.03	95.00	88.14
Correlation	76.55	82.67	86.61	88.78	90.18	–	–	–	–	–

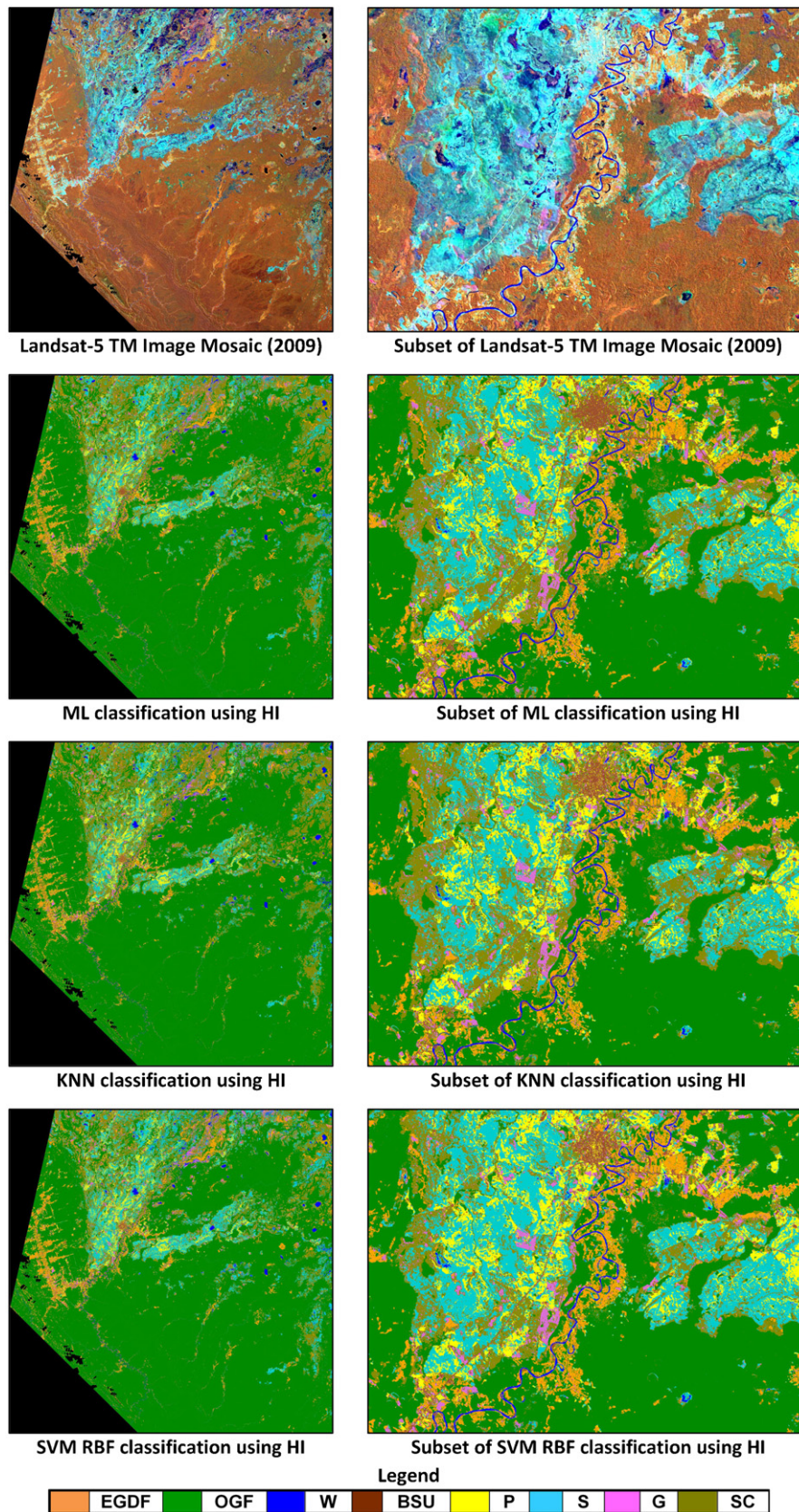


Fig. 2. ML, KNN and SVM RBF classifications using reflectance bands along with homogeneity (HI) bands. Left column shows classifications for the entire image mosaic and right column shows a subset of 1280×944 pixels from the center of the mosaic where the high heterogeneity of the area can be observed. EGDF, early-growth/degraded forest; OGF, old-growth forest; W, water; BSU, bare soil/urban; P, pasture; S, savanna; G, grassland; SC, scrubland.

Table 6
Overall accuracy assessment for 2009 and 2001 imagery using both reflectance and textural homogeneity bands. IOA, improvement in overall accuracy owing to the inclusion of textural homogeneity in the classification.

Accuracy assessments	17/04/2009				25/08/2001			
	Hard OA	Hard IOA	Soft OA	Soft IOA	Hard OA	Hard IOA	Soft OA	Soft IOA
ML	78.88	7.38	85.25	4.75	79.38	9.13	81.50	10.62
SVM linear	90.50	11.25	93.88	7.13	90.38	17.13	90.50	16.87
SVM polynomial (6th grade)	89.13	9.88	92.25	5.62	89.88	15.38	90.13	15.25
SVM RBF	92.63	13.25	95.63	8.63	96.13	22.25	96.25	22.00
SVM sigmoid	92.75	12.62	95.50	7.75	90.63	15.38	92.00	16.37
KNN	79.75	7.12	86.25	5.75	86.75	11.00	88.63	11.88
MMHC	72.00	1.25	81.38	1.63	71.25	7.12	75.38	7.50

of the imagery date and the type of accuracy assessment (Table 6). We find that the differences in overall accuracy are extremely significant for all the classifiers, with the sole exception of the MMHC classification for 2009 imagery. Yet, even in that case, the overall accuracy increases 1.25% with the inclusion of homogeneity. Looking carefully at the magnitude of the improvements achieved in the classifications with the inclusion of homogeneity (Table 6), we find that there is a gradient from small to moderate improvements in MMHC (1.25% and 7.12%), moderate to large improvements in ML (7.38% and 9.13%) and KNN (7.12% and 11.00%), and large to very large improvements in the four SVM classifiers (ranging from around 11% to 13% for 2009 imagery to around 16% and up to 22% for 2001 imagery). Fig. 2 illustrates classification results showing examples of ML, KNN and SVM radial basis function (RBF) with the use of homogeneity.

Results from McNemar tests (Table 7) show that with homogeneity all four SVM algorithms outperform even further all the other algorithms. For instance, it is remarkable that without homogeneity and for 2001 imagery, KNN shows no significant difference with any SVM and actually performs a bit better than SVM linear (Table 4), whereas with homogeneity the statistical significance of the superiority of SVM algorithms over KNN ranges from significant to extremely significant (Table 7). Similarly, the superiority of all SVM over ML classifiers increases for 2001 imagery with the inclusion of homogeneity, as evidenced by the increase in the statistical

significance of their differences (see Tables 4 and 7). Therefore, all four SVM classifiers optimize the use of homogeneity compared to KNN, ML and MMHC. Looking at the differences in performance among the four SVM algorithms we observe that, with homogeneity, SVM sigmoid and particularly SVM RBF obtained the best results for both imagery dates, thus maximizing the usefulness of homogeneity (without homogeneity all SVM performed similarly well).

4.4. Improvements in classification results by land use/cover class using textural homogeneity

To assess what LUC classes benefit more with the inclusion of homogeneity in terms of an increase in their producer's and user's accuracy, we present here the confusion matrices of ML, KNN and SVM RBF classifications. We do not show confusion matrices of SVM linear, SVM polynomial and SVM sigmoid as overall SVM RBF appears to be the best classification of all when homogeneity is included. Neither do we show confusion matrices of MMHC because its improvement with homogeneity for 2009 is not significant, only moderate for 2001, and the overall accuracy attained with this classifier for either date is not satisfactory compared to the rest of classifiers tested here. We focus on hard accuracy assessments and show confusion matrices just for 2009 classifications though the results presented are coherent with those obtained for 2001 imagery and with the fuzzy assessments of both dates.

Table 7
McNemar tests showing the statistical significance of the differences in overall accuracy from a hard assessment among classifiers, using the homogeneity index (HI), for both 2009 and 2001 imagery. Codes as in Table 4.

17/04/2009/25/08/2001	SVM linear + HI	SVM polynomial + HI	SVM RBF + HI	SVM sigmoid + HI	KNN + HI	MMHC + HI
ML + HI	−4 −4	−4 −4	−4 −4	−4 −4	0 −4	4 4
SVM linear + HI		0 0	−4 −4	−3 0	4 3	4 4
SVM polynomial + HI			−4 −4	−4 0	4 2	4 4
SVM RBF + HI				0 4	4 4	4 4
SVM sigmoid + HI					4 3	4 4
KNN + HI						4 4

Table 8
Hard assessment confusion matrices for the maximum likelihood classifications of Landsat data (17/04/2009). Left values refer to the classification without textural homogeneity and right values to the classification with homogeneity. EGDF, early-growth/degraded forest; OGF, old-growth forest; W, water; BSU, bare soil/urban; P, pasture; S, savanna; G, grassland; SC, scrubland.

Classification data	Reference data																			
	EGDF		OGF		W		BSU		P		S		G		SC		Total		User's accuracy	
EGDF	57	77	0	1	0	0	0	0	0	0	0	0	0	0	1	3	58	81	98.3	95.1
OGF	15	3	94	90	1	0	0	0	0	0	0	0	0	0	0	0	110	93	85.4	96.8
W	0	0	0	0	57	66	0	0	0	0	0	0	0	0	0	0	57	66	100.0	100.0
BSU	0	0	0	1	11	14	88	96	6	8	0	1	9	5	0	0	114	125	77.2	76.8
P	0	0	0	0	0	0	5	4	67	84	7	9	0	0	1	1	80	98	83.7	85.7
S	0	0	1	1	30	20	0	0	13	0	65	66	0	1	9	6	118	94	55.1	70.2
G	4	1	1	0	1	0	1	0	1	0	0	2	60	67	5	5	73	75	82.2	89.3
SC	24	19	4	7	0	0	6	0	13	8	28	22	31	27	84	85	190	168	44.2	50.6
Total	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	800	800	78.3	83.1
Producer's accuracy	57.0	77.0	94.0	90.0	57.0	66.0	88.0	96.0	67.0	84.0	65.0	66.0	60.0	67.0	84.0	85.0	71.5	78.9		

Table 9

Hard assessment confusion matrices for k-nearest neighbor classifications of Landsat data (17/04/2009). Left values refer to the classification without textural homogeneity and right values to the classification with homogeneity. EGDF, early-growth/degraded forest; OGF, old-growth forest; W, water; BSU, bare soil/urban; P, pasture; S, savanna; G, grassland; SC, scrubland.

Classification data	Reference data																			
	EGDF		OGF		W		BSU		P		S		G		SC		Total		User's accuracy	
EGDF	45	63	0	0	0	0	0	0	0	0	0	0	0	1	1	1	46	65	97.8	96.9
OGF	27	14	94	93	5	10	0	0	0	0	0	2	0	0	1	1	127	120	74.0	77.5
W	0	0	0	0	78	81	0	0	0	0	0	0	0	0	0	1	78	82	100.0	98.8
BSU	0	0	0	0	0	1	85	87	3	2	0	0	4	1	0	0	92	91	92.4	95.6
P	0	0	0	0	0	1	9	10	68	87	5	6	0	0	0	0	82	104	82.9	83.6
S	0	0	0	0	10	1	0	0	11	3	50	62	0	0	5	4	76	70	65.8	88.6
G	2	1	1	1	5	3	2	1	2	0	0	1	73	78	5	6	90	91	81.1	85.7
SC	26	22	5	6	2	3	4	2	16	8	45	29	23	20	88	87	209	177	42.1	49.1
Total	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	800	800	79.5	84.5
Producer's accuracy	45.0	63.0	94.0	93.0	78.0	81.0	85.0	87.0	68.0	87.0	50.0	62.0	73.0	78.0	88.0	87.0	72.6	79.7		

Table 10

Hard assessment confusion matrices for SVM radial basis function classifications of Landsat data (17/04/2009). Left values refer to the classification without textural homogeneity and right values to the classification with HI. EGDF, early-growth/degraded forest; OGF, old-growth forest; W, water; BSU, bare soil/urban; P, pasture; S, savanna; G, grassland; SC, scrubland.

Classification data	Reference data																		User's accuracy	
	EGDF		OGF		W		BSU		P		S		G		SC		Total			
EGDF	60	91	0	0	0	0	1	0	0	0	0	0	2	0	1	2	64	93	93.7	97.8
OGF	28	6	95	93	2	0	0	0	0	0	0	0	0	0	8	1	133	100	71.4	93.0
W	0	0	0	0	79	98	0	0	0	0	0	1	0	0	0	1	79	100	100.0	98.0
BSU	0	0	0	0	0	0	88	92	2	1	0	0	3	0	0	0	93	93	94.6	98.9
P	0	0	0	0	0	0	7	5	71	91	5	2	0	0	1	0	84	98	84.5	92.9
S	0	0	1	1	15	0	0	0	14	2	84	94	0	0	10	4	124	101	67.7	93.1
G	1	0	1	0	4	1	3	3	2	1	0	0	80	93	2	3	93	101	86.0	92.1
SC	11	3	3	6	0	1	1	0	11	5	11	3	15	7	78	89	130	114	60.0	78.1
Total	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	800	800	82.3	93.0
Producer's accuracy	60.0	91.0	95.0	93.0	79.0	98.0	88.0	92.0	71.0	91.0	84.0	94.0	80.0	93.0	78.0	89.0	79.4	92.6		

Table 8 shows the confusion matrices of ML without and with homogeneity, respectively. Regarding producer's accuracies we observe very large improvements in early-growth/degraded forest (20%) and pasture (17%), and a moderate improvement in grassland (7%) when homogeneity is included. Both savanna and scrubland remain with the same producer's accuracies and old-growth forest slightly decreases (4%) but still has a 90% producer's accuracy. Regarding user's accuracies we see moderate improvements in grassland (7.14%) and scrubland (6.39%), and larger ones in old-growth forest (11.32%) and savanna (15.13%). Both early-growth/degraded forest and pasture remain with the same user's accuracies. Results from the confusion matrices from 2001 imagery are similar. The main differences in relation to producer's accuracies are higher increases in pasture and grassland (48% and 23%, respectively) while savanna and scrubland decrease 8% and 7% respectively, whereas for user's accuracies the main differences relate to greater improvements in savanna and scrubland (28.47% and 19.53%), and a significant decrease in early-growth/degraded forest (14.74%). Table 9 shows the confusion matrices of KNN. Remarkably, they are very similar both in values and trends to those of ML. The main differences are that, for KNN, savanna's producer's accuracy is improved in one date and that early-growth/degraded forest's user's accuracy is not affected in either date.

Table 10 shows the confusion matrices of SVM RBF. With respect to producer's accuracies everything improves except old-growth forest, which decreases to 93%. Producer's accuracies gains are most remarkable for early-growth/degraded forest (31%) and pasture (20%), but notable for savanna (10%), grassland (13%), and scrubland (11%). User's accuracies improvements are very large for old-growth forest (21.57%), savanna (25.33%), and scrubland (18.07%), and moderate for pasture (8.34%), grassland (6.06%), and early-growth/degraded forest (4.10%). Results from the 2001 classification are very similar though even greater improvements in

producer's and user's accuracies are observed. Therefore, SVM RBF seems to maximize the use of homogeneity and it does so for all eight LUC classes (not just for some as ML and KNN do) and up to very high levels of producer's and user's accuracies (typically >90%, unlike ML and KNN that did only achieve similar accuracies for old-growth forest). Lastly, even though the other 3 SVM classifiers did not perform as well as SVM RBF, they show very similar producer's and user's accuracies values (usually >85–90%) and trends of improvement by LUC class with the inclusion of homogeneity.

5. Discussion and conclusion

Three main findings stand out from our study: (1) SVM classifiers outperform parametric (ML), non-parametric (KNN), and hybrid (MMHC) classifiers, (2) homogeneity appears to be the most useful textural index for LUC classification, and (3) SVM classifiers maximize the use of homogeneity, attaining overall, producer's, and user's accuracies of ~90% for all LUC classes. We discuss each finding and finalize with some concluding remarks highlighting the usefulness of our classification approach.

Our first finding is consistent with research that has shown the superiority of other non-parametric machine learning algorithms for LUC mapping in the Amazon basin (Lu et al., 2004; Carreiras et al., 2006) and demonstrates the usefulness of SVM for LUC classifications of heterogeneous tropical landscapes, something seldom explored to date aside from few studies (e.g., Wijaya and Gloaguen, 2009; Liesenberg and Gloaguen, 2013). One substantial advantage of SVM (and other non-parametric classifiers) over non-parametric and hybrid classifiers, is that there is no need to assume any particular data distribution, which is more appropriate (particularly when some LUC classes are highly heterogeneous as in this study) and facilitates the use of ancillary data in the classification process (Lu and Weng, 2007). Indeed, we have verified that some of

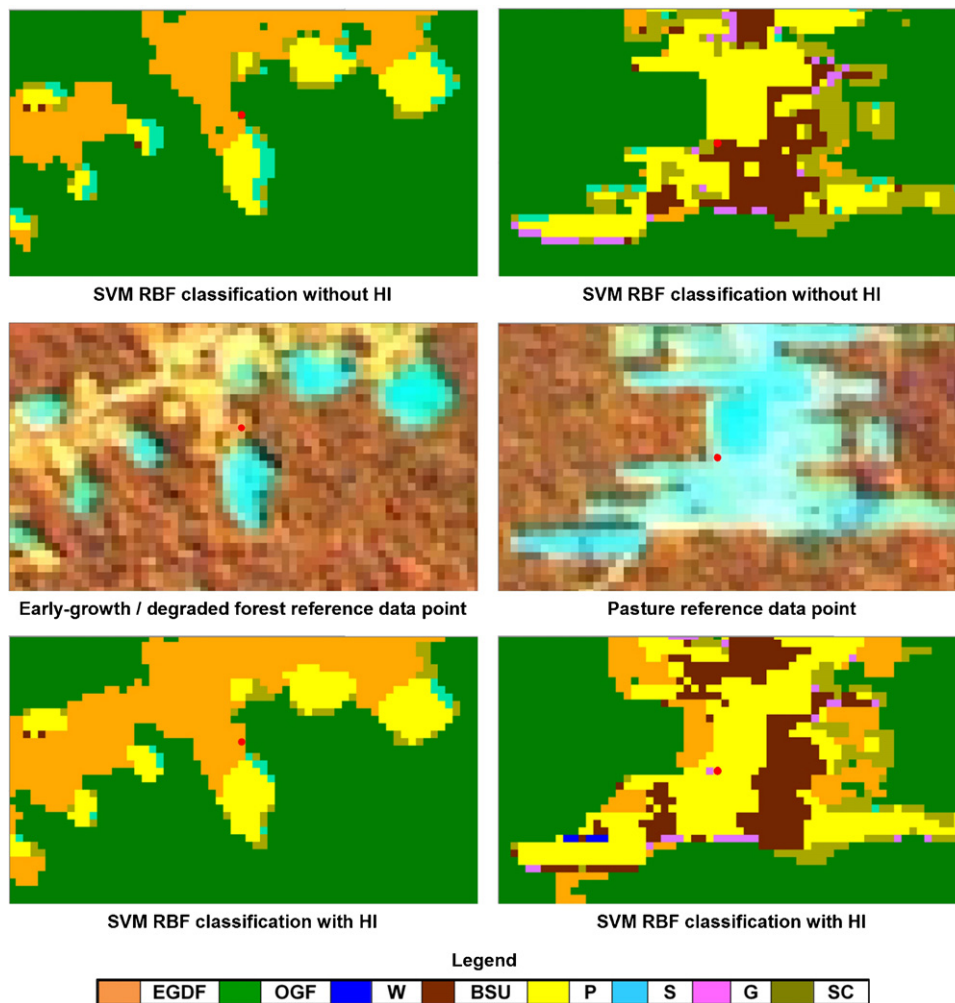


Fig. 3. Both examples show misclassification (top row) and accurate classification (bottom row) of reference data points (in red at the center of subsets) lying on the fringe of different LUC classes. The inclusion of the homogeneity index (HI) significantly improves the classification of these points in the case of SVM classifiers, particularly for EGDF (left column) and P (right column) classes. EGDF, early-growth/degraded forest; OGF, old-growth forest; W, water; BSU, bare soil/urban; P, pasture; S, savanna; G, grassland; SC, scrubland.

our training data do not follow a normal distribution, which may partly explain why SVM have significantly outperformed the rest of classifiers. Yet, possibly the main reason underlying the superiority of SVM may be related to the training sets we have used and the certain occurrence of mixed pixels within them. As Foody and Mathur (2006) demonstrated, SVM use mixed pixels to obtain the support vectors they need for classifying data, whereas the rest of classifiers tested in our study cannot cope well with mixed pixels as they derive LUC class statistics from training samples to characterize such classes, which we believe is the main reason why ML, KNN, and MMHC have attained less accurate results than SVM. In the specific case of MMHC, given its poor performance we claim that it may not be appropriate for classifying tropical areas as they are typically too complex spectrally and, therefore, a very large training set may be needed to derive an accurate supervised classification from the many spectral classes obtained with the ISODATA classification.

Our second finding unveils the usefulness of using textural homogeneity in LUC mapping. Specifically, our results suggest that homogeneity and (to a lesser extent) entropy may be the most appropriate textural indices for LUC classification endeavors, among those that can be extracted from the gray-level co-occurrence matrix. However, while both textural indices have been shown to describe nearly all the textural information contained in sonar imagery (Huvenne et al., 2002; Blondel and Gómez Sichi, 2009), they have seldom been used to classify LUC from

multispectral imagery (especially homogeneity). Though few studies can be found that have examined or used entropy and homogeneity to classify LUC from multispectral imagery (Chan et al., 2003; Chehade et al., 2009), we have not found any study that exploits homogeneity on its own together with spectral bands. In fact, studies comparing the performance of different textural indices for image classification have not regarded homogeneity as one of the most useful ones (Haralick et al., 1973; Gong et al., 1992; Baraldi and Parmiggiani, 1995). Nonetheless, our study suggests that homogeneity is a very powerful textural index for LUC mapping as the improvements in overall accuracy of both hard and soft accuracy assessments for 2001 and 2009 classifications are extremely significant irrespective of the classifier employed (with the sole exception of MMHC for 2009 imagery). We believe the improvements we have obtained may be explained by two main reasons.

First, based on the fact that the combination of entropy and homogeneity has not improved the results attained in preliminary classifications with respect to those attained using just homogeneity, it seems that homogeneity by itself may be able to characterize most textural variability found in the imagery, thus improving classification results. Second, as illustrated in Fig. 3, we have observed that the inclusion of homogeneity has often enabled the classifier to correctly allocate ambiguous reference points, i.e., points located in the transition between different covers (mixed pixels) or corresponding to transition covers not considered specifically in the

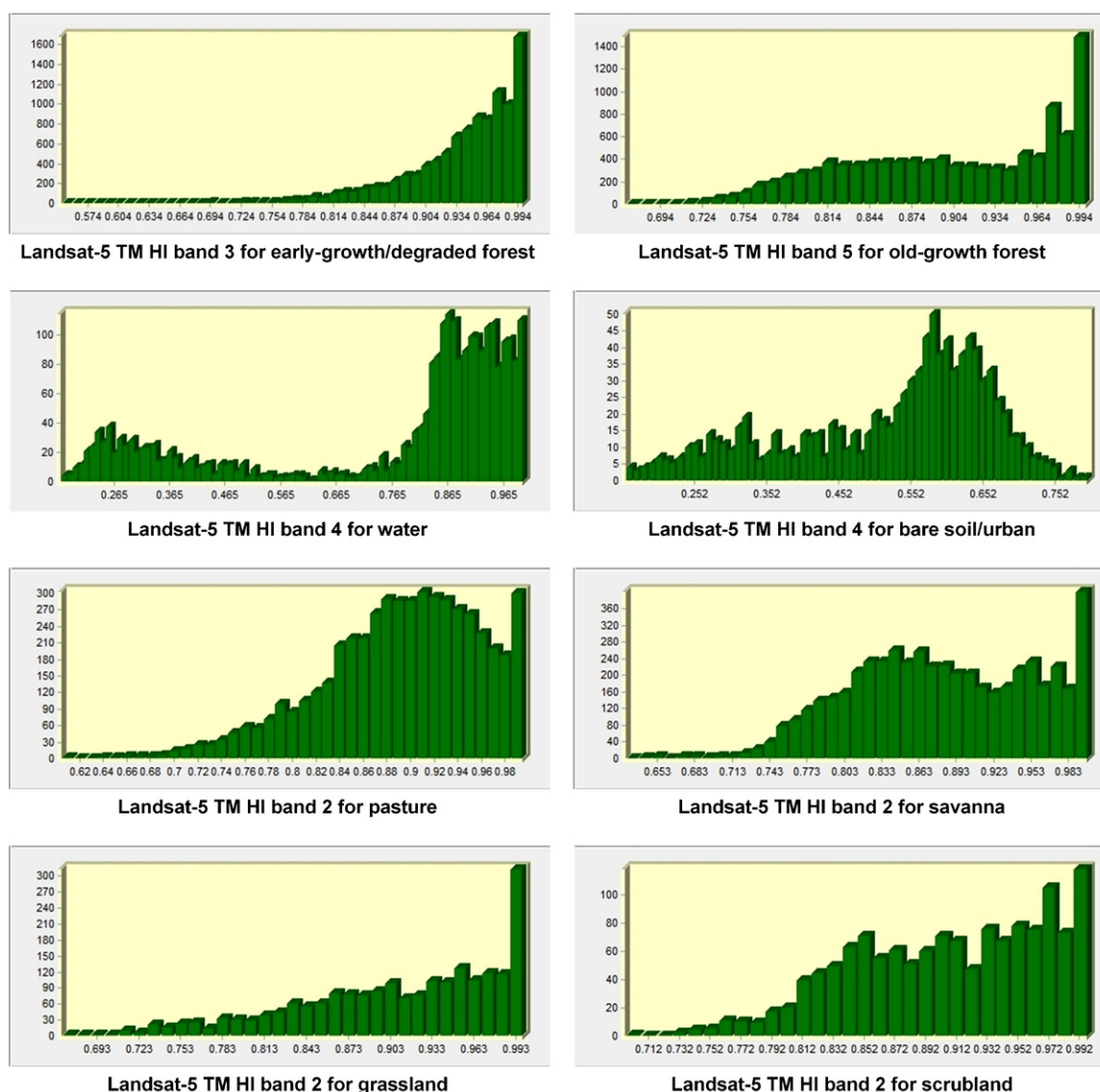


Fig. 4. Examples of non-Gaussian data distributions in training data (histograms refer to the homogeneity index (HI) bands and one example is given per LUC class; frequencies are shown in Y axis and HI values in X axis).

classification scheme. For instance, for 2009 imagery, when homogeneity was used the SVM RBF algorithm correctly classified 31 reference points more for the early-growth/degraded forest class. We verified that 28 out of those 31 points lied in between two or more LUC classes (normally either old-growth forest or scrubland), and only 3 points were located within homogeneous areas. Similarly, 20 reference points more for the pasture class were correctly classified when using homogeneity, from which 17 were ambiguous. This trend is followed by other LUC classes and explains the improvements obtained using soft accuracy assessments. Therefore, the inclusion of homogeneity alleviates the classification problem posed by spectrally mixed pixels.

Additionally, we have found two facts in conflict with previous research. First, contrary to what was suggested by Augusteijn et al. (1995), small window sizes (7×7 -pixel in our study) seem to accurately characterize textural information in relation to LUC classes. We believe this responds to the relatively small size of patches of some LUC classes such as early-growth/degraded forest, pasture and grassland, which therefore may make texture to change over small areas. Second, contrary to the findings of Ota et al. (2011), our classification accuracies improve with the inclusion of textural

information at 30 m spatial resolution, including producer's and user's accuracies of forest types. This is important as demonstrates the potential usefulness of using texture with Landsat imagery and not just with very high spatial resolution images such as IKONOS or QuickBird, which are frequently too expensive for operational use and inappropriate when large areas are to be mapped.

Finally, our third finding reveals that SVM classifiers, and particularly SVM RBF and SVM sigmoid, optimize the use of homogeneity, attaining overall, producer's, and user's accuracies of $\sim 90\%$ for all LUC classes (unlike the other classifiers tested, that could only improve the producer's, and/or user's accuracies of some LUC classes after the inclusion of homogeneity). One possible explanation is that SVM classifiers are independent of data dimensionality (Dixon and Candade, 2008) contrary to the rest of the classifiers compared in this study. Since we did not increase the size of the training sets after including the six homogeneity bands in the classification, the improvements in performance of SVM classifiers may have been more significant than those of the rest, as being dimensionality-dependent classifiers they would have required bigger training datasets to increase their performance. In addition, we have verified that some training data extracted from the six

homogeneity data bands calculated for each Landsat image do not follow a normal distribution (Fig. 4), which may explain why non-parametric algorithms deal with the inclusion of homogeneity in the classification in a better way. This fact may also explain why certain LUC classes show large improvements in producer's, and/or user's accuracies while others are not seemingly affected or may even slightly decrease their accuracies. Further research should address this issue more in-depth and better analyze differences in misclassification errors among LUC classes.

Our findings are promising because accurate mapping of land use/cover is highly challenging over heterogeneous areas, particularly in tropical regions, and yet this task is key to conservation initiatives, climate change mitigation strategies, and the design of management plans and rural development policies. For instance, our classification approach has enabled us to map the two forested classes (early-growth/degraded forest and old-growth forest) with producer's and user's accuracies >90% for both Landsat imagery dates (corresponding to wet and dry seasons). These results suggest that our approach is well-suited to map and monitor tropical forest cover change as needed for ecological assessments and REDD+ schemes. Similarly, the rest of land use/cover classes included in this study were mapped to producer's and user's accuracies of ~90%, thus rendering our approach very interesting too for land change analysis, ecological studies, and natural resource assessments in areas other than forests. Finally, our classification approach presents the advantage of being easy to implement, as both the calculation of the homogeneity index and the presence of SVM classifiers are readily available in remote sensing software, and cost-effective, as SVM classifiers may use smaller training datasets without compromising classification accuracy. Importantly, the very accurate results obtained with this approach suggest its great potential for land use/cover mapping in other tropical areas and, quite possibly, in non-tropical areas too, something we will assess in the near future.

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