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Assessment of land use and cover in the Sucuru Watershed using Google Earth Engine

Avaliação do uso e cobertura do solo na Bacia de Sucuru usando o Google Earth Engine

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A B S T R A C T
Human activities modify the natural characteristics of numerous watersheds worldwide. Google Earth Engine provides tools for the analysis of land use and natural resources. In this work, we classify current land use and cover in the Sucuru watershed, Paraíba, Brazil. We compared the accuracy of five supervised classification algorithms of Google Earth Engine. Classifiers based on Decision Trees, such as the Classification and Regression Trees (CART) and Random Forest (RF), showed the best accuracy and visual inspection values. The Google Earth Engine is a powerful tool for analysis of large-scale environmental data, monitoring land use changes, and providing information for sustainable management.

Palavras-chave:
Geotecnologias
Sensoriamento remoto
Classificação supervisionada

R E S U M O
Através das ações antrópicas inadequadas ao longo dos anos na bacia hidrográfica do Alto Curso do Rio Paraíba, onde vem passando por mudanças no ecossistema. Geotecnologias têm contribuido nas pesquisas propiciando a incorporação de informações dos sistemas naturais. O objetivo deste trabalho foi classificar o uso e cobertura da terra atual. Foi utilizado cincos classificadores de classificação supervisionada disponíveis no Google Earth Engine. Os resultados demonstraram que dois classificadores baseados em Árvore de Decisão Classification and Regression Trees (CART) e Random Forest (RF) desempenharam excelentes resultados, entretanto o classificador (CART) se destacou tanto pelo os melhores índices quanto na inspeção visual. O GEE demonstrou ser uma plataforma muito eficaz para a realização do mapeamento do uso e cobertura da terra na área.

INTRODUCTION

Geotechnologies applied to the characterization of watersheds perform the spatialization of the studied environment. These technologies simplify the process of generating information, increase the productivity and versatility of data analysis, and provide low costs real-time updates. Geoprocessing allows complex analyses by integrating data from different sources into georeferenced databases (data with latitude, longitude, and altitude coordinates) that are essential for monitoring the use of natural resources (SANTOS et al., 2020).

New information technologies and Geographic Information Systems offer promising tools for the analysis of Remote Sensing data (LU et al., 2019). Recently, the Google Earth Engine (GEE) platform launched a new method of acquiring remote sensing data (GORELICK et al., 2017). The GEE comprises a global database on a single platform with a catalog of numerous remote sensing data, such as the entire LANDSAT satellite collection. The GEE works through cloud computing, dismissing the need to download large amounts of data, which reduces data manipulation time and increases the processing capacity of images in time series (BUARQUE, 2015; FAGUNDES et al., 2017; JENSEN, 2009).

Through the GEE, several scientific studies in different areas have been developed around the world, such as temperature estimates (PARASTATIDIS et al., 2017), ecosystem assessments (GOLDBLATT et al., 2017), agricultural land mapping (HTITIOU et al., 2021), and monitoring of wetlands (FEKRI et al., 2021).

Studies in the Cariri region of Paraíba, Brazil, exemplify remote sensing and geotechnologies as powerful tools for environmental studies, understanding of hydrological processes, and management of natural resources in watersheds, as they provide varied information and generate maps of vegetation cover that are useful in decision-making

(BARBOSA et al., 2021). Moreover, studies on land cover and use allow the spatialization of environmental degradation, whether due to agricultural practices or deforestation, which may affect hydrological regimes (ALEXANDRE et al., 2016).

This study aims to map current land use and land cover in the Sucuru River Basin, Cariri, Paraíba, Brazil, using the Google Earth Engine (GEE) platform and supervised classification algorithms.

MATERIAL AND METHODS

The Sucuru River basin comprises a vast portion of the Upper Rio Paraíba basin in the Borborema Mesoregion and Homogeneous Microregion of Cariri Occidental. The area of this watershed covers 1,652.5 km², totally or partially comprising the municipalities of Amparo, Monteiro, Ouro Velho, Prata, Sumé, Serra Branca, and Coxixola (Figure 1). It is located between the geographic coordinates of 7°28'00" and 7°50'00" South and 37º14'00" and 36º49'00" West (SANTOS, 2020). The Sucuru River basin is situated in the semiarid region of Brazil, in the Caatinga ecosystem with numerous landscape variations (SILVA, 2017).

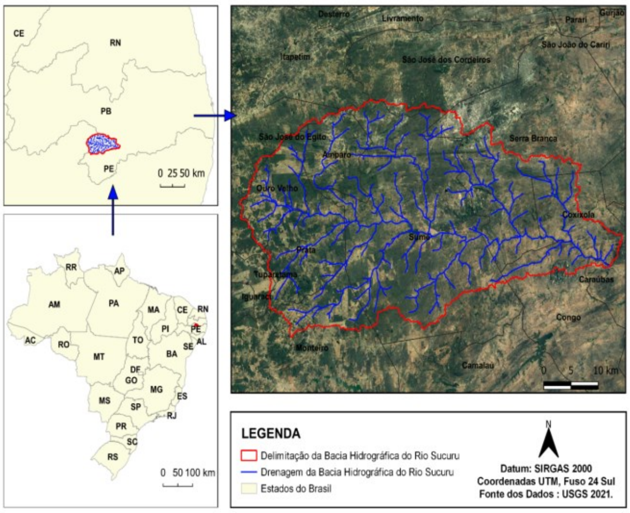

Figure 1. Location map of the Sucuru River Basin, Paraíba, Brazil, 2021.
Source: Adapted from Google Earth Engine (2021); USGS (2021); IBGE (2009).

The Sucuru River is intermittent and its spring is located in the Cariris Velhos mountain chains, with an altitude of about 591 meters, on the border between the states of Paraíba and Pernambuco, draining water from eight municipalities: Amparo, Congo, Coxixola, Monteiro, Ouro Velho, Prata, Serra Branca, and Sumé. These municipalities contribute water flow to the public reservoirs of Sumé and Epitácio Pessoa (GALVÍNCIO et al., 2006; CUNHA, 2011; ALMEIDA et al., 2012; FRANCISCO, 2013).

According to the Köppen-Geiger classification, the prevailing climate in the region is Bsh (hot semi-arid), with low average annual rainfall (around 400 mm). The dry season may last up to 11 months. The Thornthwaite aridity index for the Sucuru basin is 0.22, classifying the climate as semi-arid (ALENCAR, 2008).

The geology comprises the gneissic-migmatite complex and granitoid rocks, from the undivided Precambrian and Quaternary period, by alluvial sediments (SILVA, 1994). The study area locates in the Borborema Plateau, corresponding to the morphological unit Surface of the Plateau Surface or Cariris Surface, comprised of smooth undulating and undulating relief, with altitudes ranging from 380 to 500 m (BRASIL, 1972).

The hyper xerophile caatinga with low trees or shrubby size predominates in the study region. Main vegetal species are pereiro (*Aspidosperma pyrofolium* Mart - Apocynaceae), quixabeira (*Bumelia sertorum* Mart - Sapotaceae), xique-xique (*Pilocereus gounellei* Weber - Cactaceae), aroeira (*Astronium urundeuva* Engl. – Anacardiaceae), baraúna (*Schinopsis brasliensis* Engl – Anacardiaceae), mandacaru (*Cerus Jamacaru* DC – Cactaceae), and marmeleiro (*Croton* sp. – Euphorbiaceae). The region has a high concentration of cactus, bromeliads, algarobeira (*Prosopis juliflora* – SW. DC), and leucena (*Leucena leucocephala* - Lam. de Wit) (BRASIL, 1972).

The soils of the study region are Eutrophic Red-Yellow Argisol; Typical Orthic Chromic Luvisol associated with Eutrophic Litholic Neosol, Vertic Orthic Chromic Luvisol; Eutrophic Litholic Neosol associated with Rock Outcrops, Eutrophic Regolithic Neosol; and in smaller proportions of Eutrophic Fluvic Neosol (SILVA-NETO, 2004).

In the Sucuru River basin, agriculture is based mainly on familiar production, with the crops of beans, corn, sweet potatoes, fava beans, herbaceous cotton, castor beans, cassava, tomato, banana, coconut, guava, mango, and sisal. Livestock includes the extensive rearing of the following herds, in order of importance: goat, cattle, sheep, pigs, horses, donkeys, and mules. Avian production has grown in the last decade (RIBEIRO, 2014).

The United States Geological Survey (USGS, 2021) was used to determine the limits and drainage area of the study. The classification of land use and cover utilized data from the Sentinel 2 satellite from the year 2021, RGB 4-3-2 composition, a spatial resolution of 10 meters, which are available in the GEE database. The images were filtered according to the Sentinel project articulation grid, "24MYS" orbit, and less than 1% of cloud coverage. In the composition of the final image, a median filter was applied to the set of Sentinel images from 01/01/2021 and 12/31/2021, using the command "ee.ImageCollection().median()", which resulted in a single and representative image of the basin.

The land use and cover were classified considering the predominant occupation according to Alencar (2008) as follows: Dense Vegetation, Semi-Dense Vegetation, Sparse Vegetation and Exposed Soil, Exposed Soil, and Waterbody.

A convolution spatial filter with a 3x3 kernel mask was applied to the classification image. Convolution spatial filtering is the simplest method and meets the needs of most users (PARANHOS-FILHO et al., 2008).

The supervised classification used five algorithms available in GEE: Classification and Regression Trees (CART); Minimum Distance - Euclidean (MMD); Random Forest (RF); Naive Bayes (Bayes); and LibSVM (SVM). The training samples were spatially homogeneous and represented distinguishable features of the ground cover so that the system was able to identify patterns in the image (PARANHOS-FILHO et al., 2008).

The land cover patterns were identified in five sampling groups, representing the five pre-defined land cover classes. This procedure was necessary due to the different forms of distribution of natural and anthropic elements on the earth's surface (CARVALHO et al., 2021).

Only one demonstration set was determined collecting samples of the water mirror of the main reservoir in the basin, the dam of the city of Sumé, and other small watercourses, referring to the satellite image sampling.

We collected 1050 sample pixels evenly distributed in the area. The pixels were dispersed among the five sampling groups as follows: Dense Vegetation (175 points), Semi-Dense Vegetation (179), Sparse Vegetation and Exposed Soil (229), Exposed Soil (254), and Waterbody (213).

The quality of classification of the maps was assessed using the Kappa Index, General Accuracy, Producer Accuracy, and User Accuracy, obtained through the Confusion Matrix.

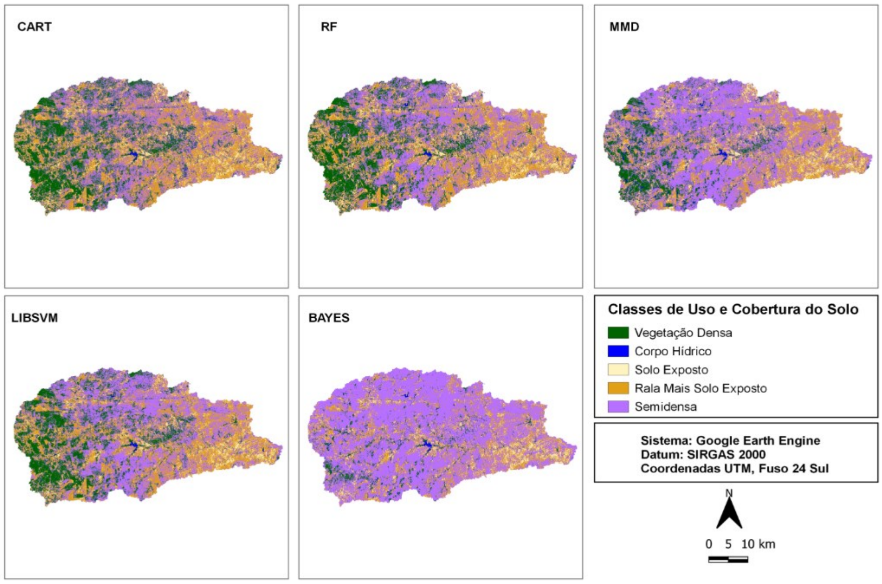

Figure 2. Land use and land cover maps generated by five classification algorithms in the Sucuru River Basin, Paraíba, Brazil, 2021.

RESULTS AND DISCUSSION

The supervised classification algorithms of Classification and Regression Trees (CART) and Random Forest (RF) generated the best land use and land cover maps, demonstrated by the lowest spectral confusion in land cover recognition (Figure 2 and Table 1). This result corroborates the classification evaluation indices of General Accuracy and Kappa Index automatically calculated by the GEE for the five classification methods (CARVALHO et al., 2021). The total studied area comprised 168,029.79 ha but the watershed area is 165,250.00 ha. The process of cutting the satellite image causes this difference by assuming the pixel as an indivisible unity (CARVALHO et al., 2021). Thus, pixels on the boundaries of the watershed will not be split, but retained during the clipping procedure, increasing the total value of final area.

The best supervised classification algorithm was CART, showing General Accuracy and Kappa Index values of 99.80 and 99.76%, respectively. The RF method showed excellent values of General Accuracy of 98.76% and Kappa Index of 98.44%, which must be above 85% according to Tomlinson et al. (1999).

The other classifiers presented values below 85% in the visual inspection. The MMD classifier provided General Accuracy values of 67.14% and Kappa Index of 58.79%; the Naive Bayes method had General Accuracy of 77.33% and Kappa Index of 71.54%; and the LibSVM had General Accuracy and Kappa Index of 83.33 and 79.07%, respectively. The three methods portray omission errors among all classes, showing classes irregularly mapped by the algorithm.

However, according to Stehman and Foody (2019), the 85% threshold for the assessment of land use and land cover characteristics has no universal status. Despite being used in several studies its application is not mandatory. Scaling the accuracy of mappings is a complex domain to measure. As performed in this research, the error matrix, user and producer precisions, and general accuracy are the central elements in classification accuracy assessment.

Table 1. Results of the supervised classification of land use and land cover maps generated by five classification algorithms in the Sucuru River Basin, Paraíba, Brazil, 2021.

Class	Classifier									
	CART		RF		LibSVM		BAYES		MMD	
Class	Area (ha)	(%)	Area (ha)	(%)	Area (ha)	(%)	Area (ha)	(%)	Area (ha)	(%)
Dense Vegetation	40,594.77	24.16	37,319.06	22.21	34,196.89	20.35	8,430.70	5.02	22,761.89	13.55
Semi-Dense Vegetation	59,103.10	35.17	66,357.12	39.49	73,959.70	44.02	118,030.1	70.24	92,240.25	54.90
Sparse Vegetation and Exposed Soil	55,985.68	33.32	51,934.13	30.91	49,459.03	29.43	31,763.79	18.90	40,272.59	23.97
Exposed Soil	10,785.65	6.42	11,859.29	7.06	9,807.90	5.84	9,108.68	5.42	11,238.94	6.69
Waterbody	1,560.59	0.93	560.19	0.33	606.27	0.36	696.48	0.41	1,516.10	0.90
Total	168,029.7	100.0	168,029.7	100.0	168,029.7	100.0	168,029.7	100.0	168,029.7	100.0
AG (%)	*	99.80	*	98.76	*	83.33	*	77.33	*	67.14
IK (%)	*	99.76	*	98.44	*	79.07	*	71.54	*	58.79

(GA): General Accuracy; (KI): Kappa Index.

The RF algorithm showed successful results in other areas of study. For example, Oliveira (2021), using RF in land use and land cover mapping in Luís Eduardo Magalhães, Bahia, Brazil, obtained a Kappa Index of 0.99. She reports that the RF classifier is faster than the others in the training phase and minimizes the model adjustment effect only for the training data. However, it has the disadvantages of possible holes in data and the need for a large amount of data for its training. A large number of decision trees increases the accuracy of the results but slows down the execution of the algorithm.

In another example, Shelestov et al. (2017), mapping crops and land cover in Ukraine, demonstrated that the CART classifier was superior to the RF, but both performed General Accuracy values of 76.9 and 69.9%, respectively. The authors emphasize that supervised classification algorithms based on decision trees, such as CART and RF, had excellent results but require succinct adjustments.

The GEE provides the automatic calculation of Producer Accuracy (PA) through the command ".producersAccuracy()" and User Accuracy (UA) through the command ".consumersAccuracy()" (CARVALHO et al., 2021). Producer Accuracy refers to the probability that a reference pixel has been correctly classified and the User Accuracy indicates the probability that a classified pixel represents that category in the field (CATTANI et al., 2013). Table 2 presents the results of Producer Accuracy and User Accuracy for the five classifiers used.

Table 2. Results of User Accuracy (UA) and Producer Accuracy (PA) of the Land use and land cover classes generated by five classification algorithms in the Sucuru River Basin, Paraíba, Brazil, 2021

Class	Classifier									
	CART		RF		LibSVM		BAYES		MMD	
	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA
Dense Vegetation	100	100	100	96.00	88.16	85.14	88.03	58.85	61.66	42.28
Semi-Dense Vegetation	99.44	100	98.35	100	80.29	91.06	75.84	100	59.85	93.29
Sparse Vegetation and Exposed Soil	100	99.12	99.11	98.25	74.75	65.93	68.78	61.57	65.76	31.87
Exposed Soil	99.60	100	98.82	99.21	82.50	85.43	80.50	74.80	78.35	89.76
Waterbodies	100	100	97.70	100	91.54	91.54	77.73	93.42	65.46	76.52

The CART method showed the best values for Producer Accuracy (99.12 to 100%) and User Accuracy (99.44 to 99.60%). These results suggest that the classification algorithm correctly associated the pixels to the training samples in all classes and that the user made a representative sampling. Other studies comparing classification algorithms also highlighted that the CART and RF methods produce satisfactory values. For example, Carvalho et al. (2021), testing CART and RF algorithms obtained values between 99.67 to 98.71% of PA and between 99.48 to 97.56% of UA. On the other hand, the BAYES classifier had poor results both in PA (44.69 to 48.67%) and UA (52.91 to 55.72%). Only 44.69% of pixels met the BAYES requirements in the Semi-Dense Vegetation class.

Other studies demonstrate the efficiency of RF algorithm. For example, Silva (2019), investigating changes in land use and land cover in the semi-arid region of northeast Brazil between 2000 and 2015, obtained percentages of PA from 82.36 to 99.86% and UA from 81.91 to 99.80% for the Waterbodies class. In this same study, the accuracies for other land covers had satisfactory performances, which confirms the RF algorithm for use in semi-arid regions.

The CART classification algorithm had the best performance in both classification accuracy and visual inspection (Figure 3). According to this classifier, the Semi-Dense Vegetation class occupies approximately 35.17% of the total basin, followed by Sparse Vegetation and Exposed Soil (33.32%), Dense Vegetation (24.16%), Exposed Soil (6.42 %), and Waterbodies (0.93%) (Table 1). The Semi-Dense Vegetation class has an area of 59,103.10 ha, followed by Sparse Vegetation and Exposed Soil (55,985.68 ha), Dense Vegetation (40,594.77 ha), Exposed Soil (10,785.65 ha), and Waterbodies (1,560 ha).

Previous studies carried out in the Sucuru River Basin reported lower values of Dense Vegetation. For example, Santos (2015) reports that 2.32% of the area was covered by dense vegetation in 1990, while in 2013, this vegetation

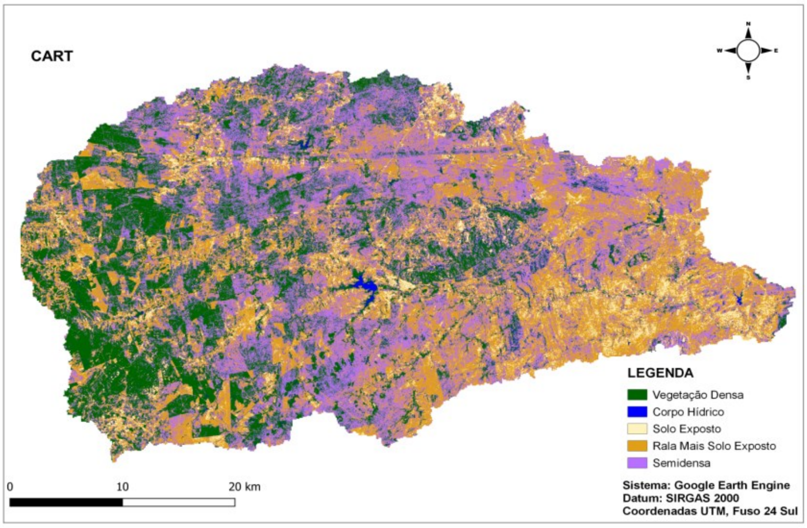

Figure 3. Map with classes of land use and land cover generated by the CART algorithm in the Sucuru River Basin, Paraíba, Brazil, 2021.

occupied 10.57%. Abandoned pastures in ecological regeneration processes may be increasing the dense vegetation areas over time (SANTOS 2015). In addition, part of this vegetation is found in mountainous areas which hampers farming and livestock activities.

The degradation of Caatinga vegetation in the Sucuru watershed occurred mainly due to human activities, such as agricultural exploitation and wood extraction (MOREIRA & TARGINO, 1997; ALVES et al., 2017). Between 1987 and 2005, the Semi-Dense Vegetation increased 7.4% as a result of the increase in these activities and the incorporation of new areas for livestock (ALENCAR 2008). In 2013, the area of Semi-Dense Vegetation was 33.56%. Santos (2015) attributes this increase to the extraction of firewood, especially for charcoal production, while Souza et al. (2009) recognize livestock as the dominant activity in the region, especially cattle, sheep and goats.

There is a deficit in the Sparse Vegetation and Exposed Soil class (Table 1) in the studied period. This class includes areas with crops and soils prepared for cultivation or fallow (ALENCAR, 2008). Cultivation areas are affected by the irregular rainfall in the region (SANTOS, 2015). Our data are comparable to those shown by Alencar (2008) and Santos (2015) with results of 36.51 and 45.59% of Sparse Vegetation and Exposed Soil, confirming the importance of this activity in the region.

Areas previously occupied by native vegetation are converted to livestock fields (SILVA-NETO, 1993). The Caatinga is among the most threatened biomes in the world, with a high replacement of native vegetation by agricultural areas (MENEZES et al., 2012). Deforestation, agriculture, and husbandry cause most of the degradation of natural resources in Caatinga. These activities are developed by populations with low environmental knowledge and impact the watershed they depend on (FERREIRA JÚNIOR & DANTAS, 2018).

The percentage of water surface in the Sucuru watershed decreased from 4.1% to 0.85% between 1987 and 2005 (ALENCAR, 2008). Several factors may reduce the surface storage capacity of watersheds, such as low annual rainfall, irregular rainfall patterns, high evaporation, and the removal of riparian vegetation that leads to silting of waterbodies (SANTOS 2015; RÊGO, 2018).

The Waterbodies class portrays mainly the reservoirs present in the study area (Table 1). The waters present in these reservoirs have multiple uses, such as human and animal consumption and irrigation (SILVA, 2017). The Sumé reservoir basin, within our study area, suffered severe environmental degradation (ROCHA et al., 2016). Even so, variations in precipitation remain the factor with the strongest influence on changes in the hydrological behavior of watersheds in semi-arid regions (SIQUEIRA et al., 2017).

Andrade (2021) recognized 4.96% of Exposed Soil in the Sucuru River basin, while, in this research, the exposed soil occupied 6.42% of the area. Differences in procedures, periods, and software may have generated this discrepancy. In addition, the Exposed Soil class has spectral confusion with urbanized areas, which is a common problem in remote sensing research as the spectral signatures of urban areas and exposed soil are very similar (SILVA, 2017). A variety of coverage types in urban areas, such as the material used in roofs, sidewalks, streets, and soil, may confuse the algorithms.

The mapping carried out by the CART classifier in several surveys shows an increase in areas of Dense Vegetation (native), Semi-Dense Vegetation (forestry/livestock), Waterbodies, and Exposed Soil; and a decrease in the Sparse Vegetation and Exposed Soil class (extensive livestock or crops). However, one should consider that these researches encompass different methodologies, periods, and software.

Our results emphasize the increase in dense vegetation areas, suggesting the strong capacity for regeneration of the caatinga and the growth of forestry and livestock activities. However, there was a small reduction in extensive livestock and agriculture activities.

The use of Google Earth Engine software provides large-scale computational processing, supporting a variety of socio-environmental data. However, the use of this tool in mapping the Caatinga biome needs further studies, especially to solve the spectral confusion between urban areas and exposed soils. We suggest the application of vegetation indices for better accuracy in classifying land use and land cover.

CONCLUSION

The mapping performed by the CART algorithm performed excellently, with a Kappa Index of 99.76%, General Accuracy of 99.80%, Producer Accuracy from 99.12 to 100%, and User Accuracy from 99.44 to 99 .60%.

The RF classifier also showed good performance, with Kappa Index of 98.44%, Overall Accuracy of 98.76%, Producer Accuracy from 96.00 to 98.35%, and User Accuracy from 97.70 to 98.35%.

The LibSVM, BAYES and MMD classifiers resulted in maps with low accuracy of land use and cover classification according to the values obtained by the applied indices.

Comparing our results from the CART classifier with previous studies, we identified an increase of 24.16% in Dense Vegetation, 35.17% of Semi-Dense Vegetation, 0.93% of Waterbodies, and 6.42% of Exposed Soil; and 1.41% decline in the Sparse Vegetation and Exposed Soil.

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