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Scientific Article
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Occurrence and spatial distribution of native acai groves in high-production areas of the Amazon region[1]

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ABSTRACT - The floodplain forests of the Amazon estuary have undergone constant change over recent years, where management techniques, especially intensive management, have had an impact on the dynamics of the vegetation and land use. These changes can be monitored using satellite data. With this in mind, the aim of this study was to evaluate the dynamics of ground vegetation on the islands of Jarimbu, Mamangal, Itaboca, Mutirão and Buçu in the district of Igarapé-Miri, Pará, using images from the RapidEye and Planet satellites. The unsupervised ISODATA classification method was used, generating distinct classes of vegetation between each island. To evaluate the efficiency of the classification, an average of 200 random points were used, with another 30 points relating to the type of usage for each class. The Kappa index and overall precision were also analysed, in addition to calculating errors of omission and commission. Monitoring on a seven-year time scale using high-resolution satellites, a more than 50% increase in the Exposed Soil class was seen for the islands of Jarimbu, Mutirão and Itaboca, the latter responsible for an increase of more than 50% in the Urban Area class. On each of the five islands, the Alluvial class, representing the areas of açaí groves, has emerged over the last seven years, increasing in area at the expense of a reduction in the Arboreal class. In this respect, the confusion matrix showed a mean accuracy for the islands of ‘very good’, with a mean overall precision of 77.74%, and a mean Kappa index of 0.73, indicating strong agreement with the reference data and the classification.

Key words: Açaí. Amazon floodplain. Remote sensing. Land use.

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INTRODUCTION

The region of the Amazon estuary is formed by a tangle of islands and adjacent areas, where floodplain forests occur, and which are influenced by the ocean, with two daily flood and ebb-tide cycles (PAROLIN *et al*., 2004).

The Amazon Forest includes the greatest biodiversity of fauna and flora on the planet (MOTA *et al*., 2020). *Euterpe oleracea* Mart. (the açaí palm) is spread over a large part of the Amazon basin, where consumption of the fruit has required the areas of açaí groves to be expanded. According to Tagore, Canto and Vasconcelos Sobrinho (2018), changes in the natural environment of the floodplains have motivated people who live by the river to manage the açai groves, with the aim of increasing production and productivity.

Recent technological advances in agriculture, as well as the need for conservation and the efficient use of natural resources, mean that the scale of ground maps and information on land use and land cover need to be refined so that these surveys can be interpreted and used for different purposes (COSTA *et al*., 2016). This scenario highlights the ability of technology to contribute with accurate information in monitoring large areas, and as the study by Dutra, Elmiro and Garcia (2020) demonstrate, there are many classification techniques currently available for use in remote sensing.

In this context, identifying, mapping and planning are necessary to mitigate the impact of these areas, using geoprocessing together with conservation policies. For Souza *et al*. (2019), the advancement in classification techniques, and improvements in the spatial resolution of sensors have been fundamental for monitoring land use and land cover in the Amazon, corroborating Santos *et al*. (2017), who included the use of Geographic Information Systems (GIS) in geoprocessing techniques.

From a study by Ponzoni *et al*. (2015) on the application of remote sensing, it is possible, through the use of mapping, to explore different ways of monitoring vegetation, even of estimating production. The use of classification techniques makes it possible to represent a real-world object, obtaining a thematic map as a result (FLORENZANO, 2011). For this reason, it is important to map and identify classes of land use and land cover through the analysis of spatial databases (ROSA; SOUZA; SÁNCHEZ, 2020).

The aim of this article was to evaluate the dynamics of ground vegetation in five islands of the district of Igarapé-Miri, Pará (PA), using a spatial-analytical approach employing remote sensing techniques; to quantify the changes that occurred, by classifying the landscape of the region during 2013 and 2019, using high-resolution data from the Planet and RapidEye satellites; and to apply validation techniques to the unsupervised ISODATA classifier for the purposes of environmental activities and planning, aiming for the well-being of the community.

MATERIAL AND METHODS

Characterisation of the study area

The study area is located in the Lower Tocantins region, in the district of Igarapé-Miri, part of the mesoregion of north-eastern Pará. It is 78 km from the capital of the state of Pará and has an area of 199,679 ha (IBGE, 2019). The study was carried out on five islands of the PAE (Agroextractivist Settlement Project) which have the greatest occurrence of açaí (Figure 1).

The soils in the area are considered fertile, with a silty clay loam and silty loam texture, high base saturation (greater than 50%), containing high levels of organic matter and significant amounts of potassium and phosphorus (SOARES *et al*., 2021).

The climate in the region is humid-tropical, corresponding to the Ami megathermal type of the Köppen classification, with an annual rainfall greater than 2,000 mm (ALVARES *et al*., 2013). The temperature range is small, with the mean annual temperature varying around 27 ºC. Rainfall is abundant from January to June (Figure 2), with more water available during the first three months of the year and a water deficit during September and October (FUNDAÇÃO AMAZÔNIA DE AMPARO A ESTUDOS E PESQUISAS, 2016).

The spatial characteristics of the five islands in the study area are shown in Table 1.

Obtaining and pre-processing the digital image

The Planet and RapidEye high-resolution sensors were used in the present study, which included four RapidEye orbital images and eight from the Planet sensor. The RapidEye images were dated 12 August 2013, and were selected from the geo-catalogue of the Brazilian Ministry of the Environment (MMA), reserved for the Federal Rural University of the Amazon (UFRA) for use in research. The images correspond to location code 2237925 and have a spatial resolution of five metres comprising the following spectral bands: Band 1 (440-510 nm), Band 2 (520-590 nm), Band 3 (630-685 nm), Band 4 (690-730 nm) and Band 5 (760-850 nm). The Planet sensor images were obtained from the State Secretariat for the Environment and Sustainability of Pará (SEMAS) offered to UFRA for use in research, and dated 9 and 10 August 2019.

Figure 1 - Location of the study area, Island region of the Tocantins River – Igarapé-Miri, PA

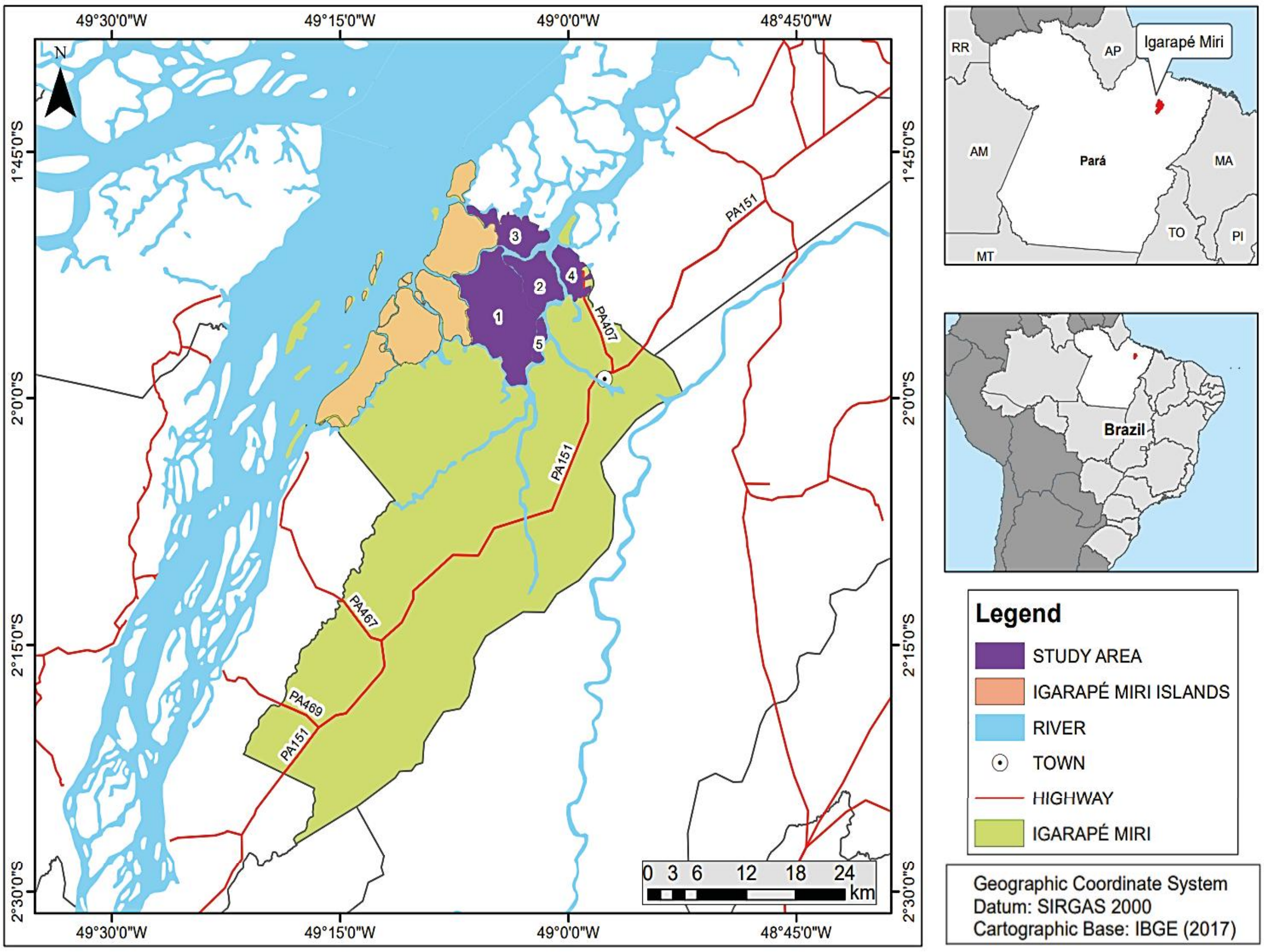
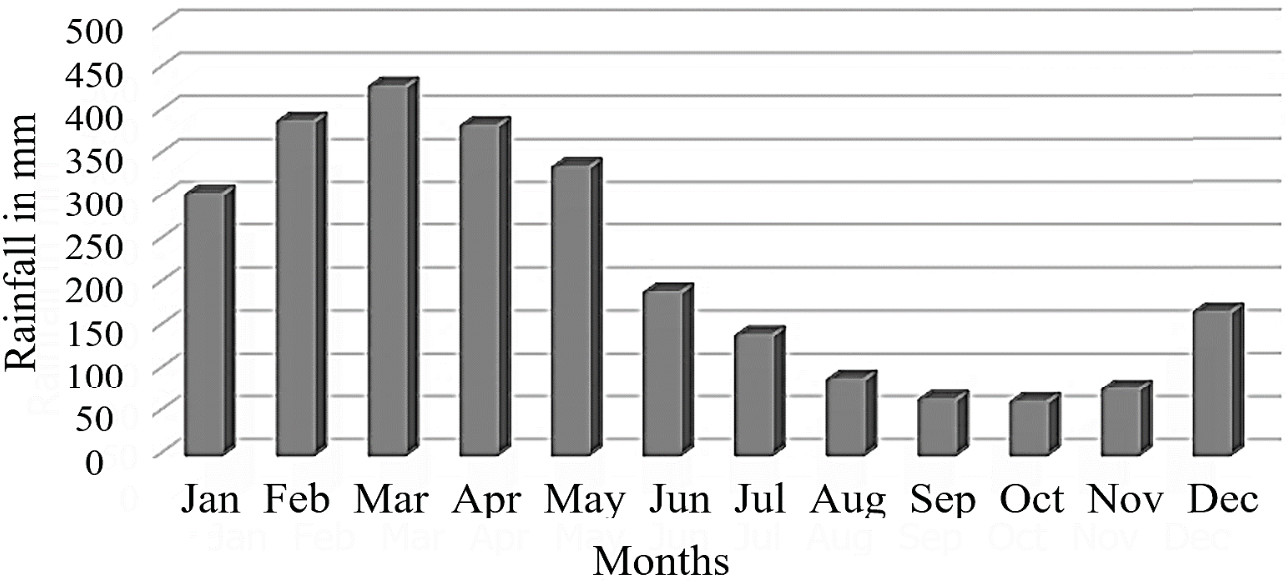


Figure 2 - Rainfall pattern in the Lower Tocantins region, Igarapé-Miri, PA



Source: INMET (2022)

Table 1 - Characteristics of the islands of the Lower Tocantins River in the district of Igarape-Miri

Island	Coordinates		Altitude (m)	Area (ha)
	Latitude	Longitude		
Jarimbu	1°54'27.18"S	49°4'17.25"W	6	8,673.71
Mamangal	1°53'13.67"S	49°1'30.95"W	8	2,590.76
Itaboca	1°50'14.17"S	49°2'54.44"W	16	2,806.13
Mutirão	1°52'21.30"S	49°0'8.44"W	12	1,708.52
Buçu	1°56'3.01"S	49°1'48.35"W	7	506.57

The images have a spatial resolution of three metres comprising the following spectral bands: Band 1 (455–515 nm), Band 2 (500–590 nm), Band 3 (590–670 nm), Band 4 (590–670 nm).

Each of the images was georeferenced and underwent atmospheric correction. The shapefiles of the islands were downloaded directly from the land collection of INCRA (National Institute of Colonisation and Agrarian Reform). The RapidEye and Planet images were then co-registered, followed by the acquisition of control points, spatial transformation into an adjusted image, and subsequent classification using the ENVI software. Using this process, each scene was represented on a standard geographic coordinate system, allowing their spatial correlation (TULLIO, 2018).

All pre-processing of the satellite images was carried out using the QGis v 3.4.11 and ENVI v 5.3 software, generating cropped images showing the boundaries of each island, followed by the mosaic.

Unsupervised classification

The unsupervised classification was prepared with the ENVI 5.3 software using the ISODATA algorithm (Iterative Self-Organising Data Analysis Technique) developed by Geoffrey and Hall (1965). The ISODATA algorithm requires the operator to have no prior knowledge of the area under study (MORARIU *et al*., 2018). The minimum spectral distance formula was used for cluster formation and grouping based on the Euclidean distance (SWAIN; DAVIS, 1978) Equation (1):

$$SD_{xyc} = \sqrt{\sum\nolimits_{i}^{n}=1\left(\mu_{ci} - X_{xyi}\right)^{2}} \tag{1}$$

where: η - number of bands; *i* - band number; *c* - particular class; X_{xyi} data-file value of pixel *X*, y in band i; μ_{ci} Mean of the data-file values (digital numbers); in *i* for the sample of class *c*; SD_{xyc} Spectral distance of pixels *X*, y, the mean value of class *c*.

For this classification, a minimum of five and a maximum of 30 classes was adopted, with a maximum of 15 interactions, at the end of which one combination was generated. This procedure includes recognition of the area by the algorithm, which associates pixels to different classes (BLASCHKE, 1954).

Post-processing the digital images

Visual interpretation was used to analyse the images during post-processing within each result. This procedure consists of interpreting the image directly on the computer screen, making use of such basic elements as colour, texture, shape, tonality, size, shadow, pattern, surroundings and geographic location (BARCELLOS *et al*., 2005; GOMES, 2001; LOCH, 1993; MOREIRA, 2003; TEMBA, 2000).

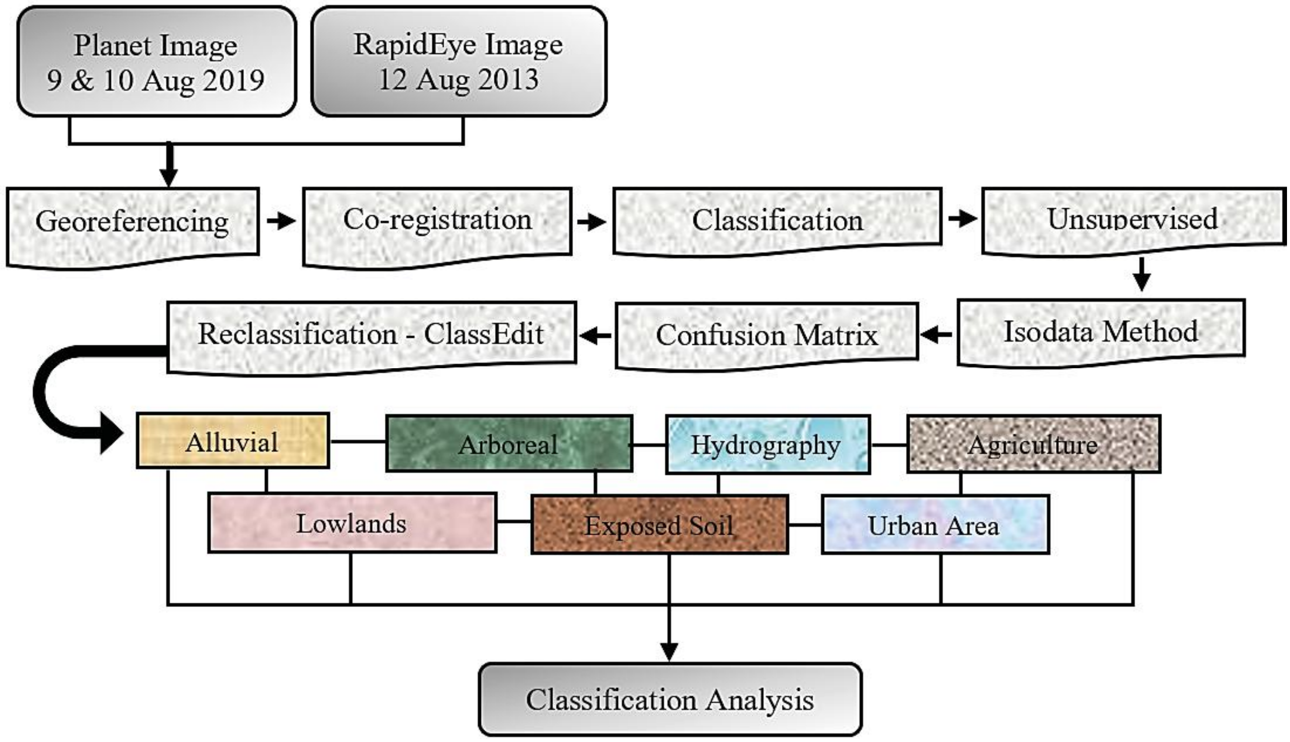
The image reclassification process was carried out manually, pixel by pixel, using the ClassEdit add-on of the ENVI software. The Flowchart (Figure 3) shows the procedures involved, starting with the acquired images through to the unsupervised classification and data validation.

Eight classes were defined for classification: Alluvial - comprising areas with a strong presence of açai groves and the constant presence of water; Arboreal - areas where large and small trees are present; Hydrography - including rivers, holes, lakes and streams; Agriculture - areas consisting of single crops and agroforestry systems; Lowlands - area represented by the presence of açaí groves without the constant presence of water; Exposed Soil - including areas such as sandbanks, bare soil and roads; Urban Areas - consisting of houses, villages and built-up areas, as described by Soares *et al*. (2021); and Cloud - comprising areas of the image that were unidentified due to cloud cover.

Assessing the accuracy of the classification

A confusion matrix was generated to verify the accuracy of the classified land-use and land-cover data from the Planet sensor. For this purpose, an average of 200 points were randomly collected, with another 30 points resulting from collections in each class for the five islands. Furthermore, parameters of global accuracy and the

Figure 3 - Methodological flowchart of the main stages of classification



Kappa index were used, including errors of omission and commission, as per the methodology used by Congalton (1991). Whereas for the error of omission the number of samples is not classified based on the reference classes, the error of commission refers to the number of samples that are included in a class to which they do not actually belong (FRANCISCO; ALMEIDA, 2012).

Starting with the Kappa analysis as a discrete multivariate technique used in the evaluation of thematic precision, all the elements of the confusion matrix are used, as per Equation 2, proposed by Cohen (1960).

$$K = \frac{N\sum_{i=1}^{r} X_{ij} - \sum_{i=1}^{r} X_{i+}X_{+i}}{N^2 - \sum_{i=1}^{r} X_{i+}X_{+1}} \qquad (2)$$

Table 2 - Classification criteria based on the bands of the Kappa index

Kappa value	Quality of the classification
< 0	Very bad
0.0 - 0.2	Bad
0.2 - 0.4	Reasonable
0.4 - 0.6	Good
0.6 - 0.8	Very good
0.8 - 1.0	Excellent

Source: Landis e Koch (1977)

where: r = number of classes; Xij = number of correctly classified elements; Xi+ = total elements classified for category i; X+i = total reference elements sampled for category i; N = total number of samples.

To evaluate the Kappa index, the Landis and Koch criteria (1997) were used, as detailed in Table 2.

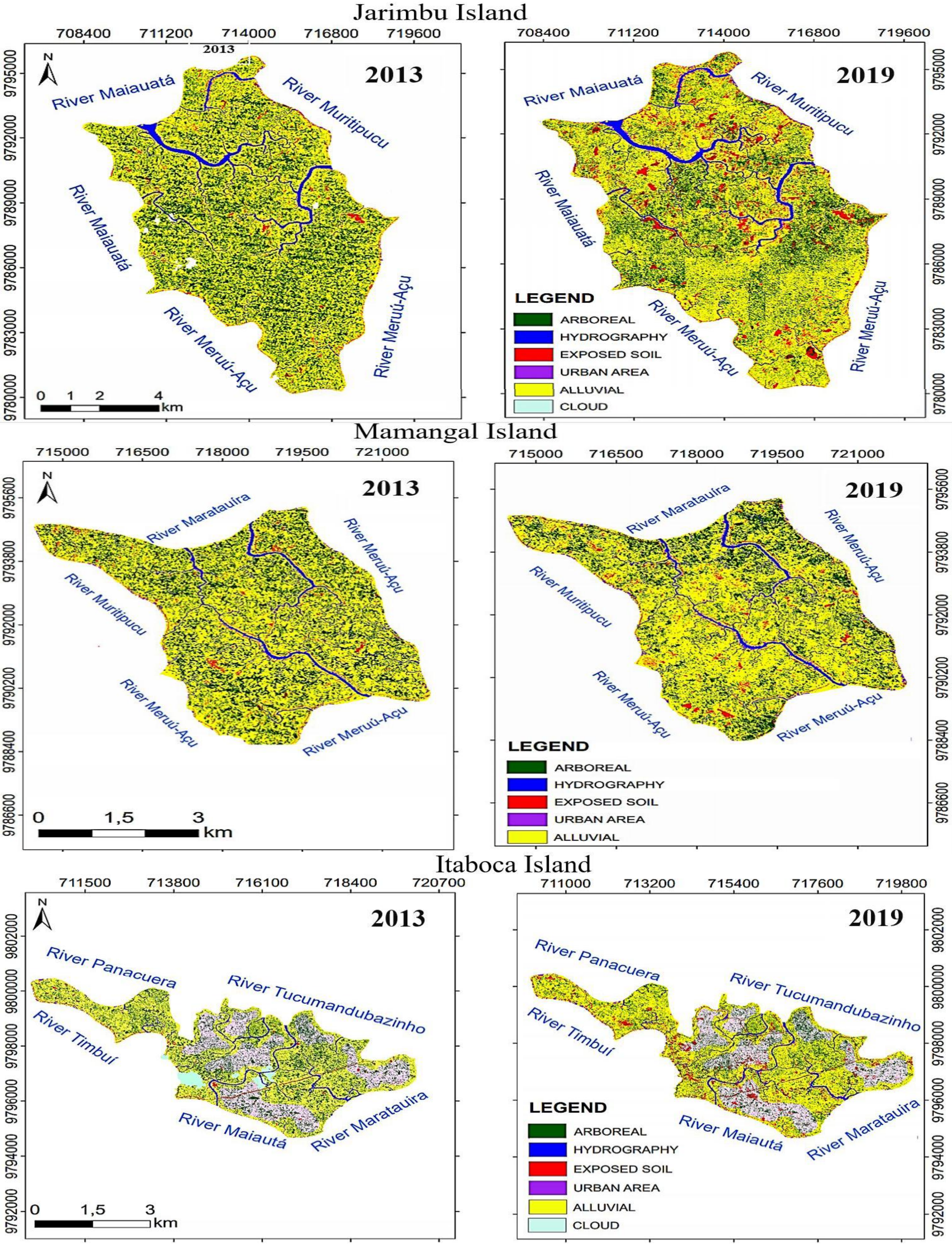
RESULTS AND DISCUSSION

Analysing the land use and land cover maps

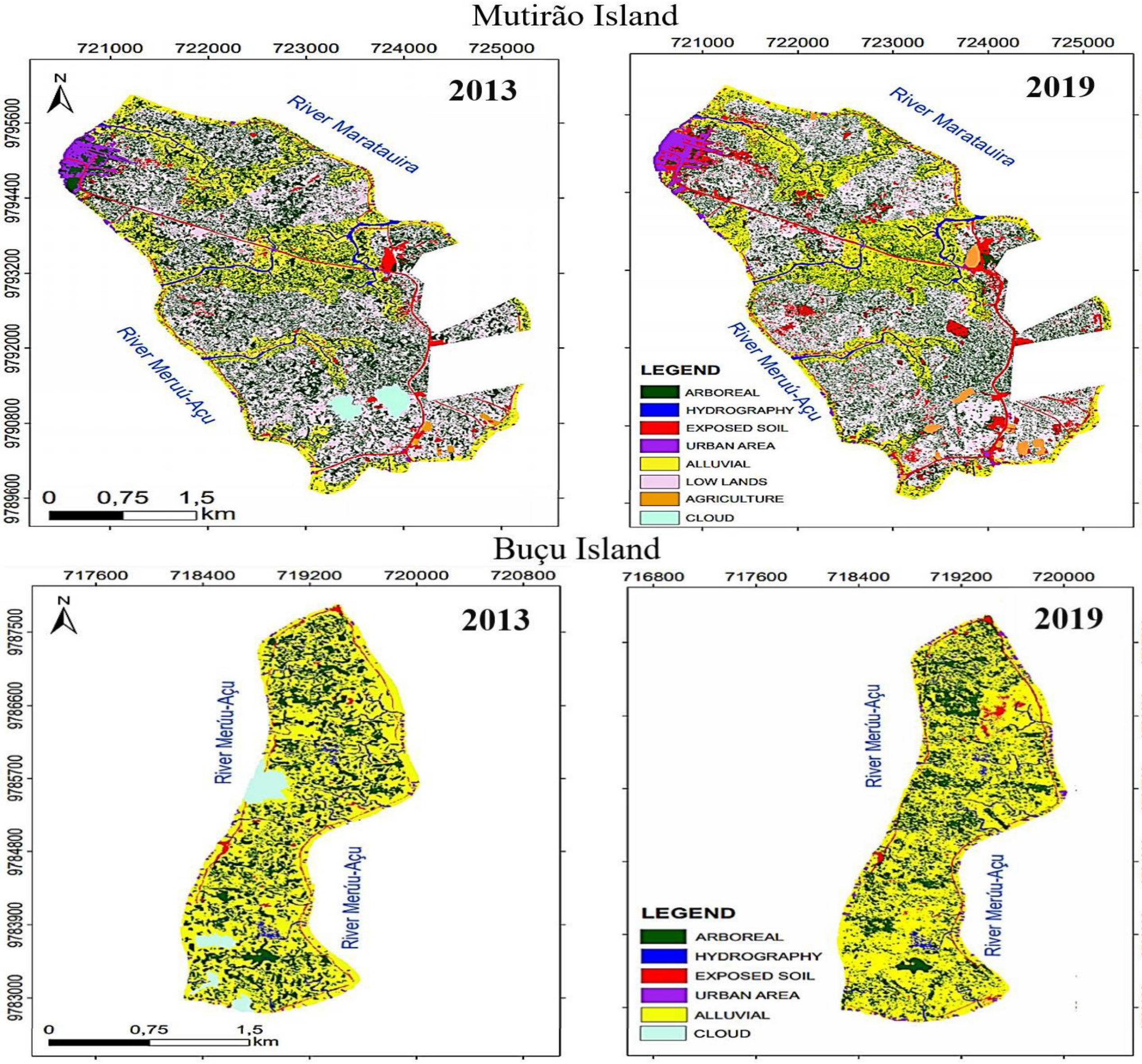
The classification results for the temporal physical characteristics of 2013 and 2019 for the five islands of Igarapé-Miri (Jarimbu, Mamangal, Itaboca, Mutirão and Buçu), including the classes selected for this study (Hydrography, Exposed Soil, Urban Area, Alluvial, Lowlands, Arboreal and Agriculture) are shown in (Figure 4).

A gradual spatial reduction in the Arboreal class could be seen, due to the increasing dynamics of the Alluvial class and Lowlands, in which the açai grove is becoming predominant in the islands (Figures 4 and 5). The identification of clumps of açai groves, as well as the seven generated classes, is a result of the high resolution of the Planet and RapidEye images. This is corroborated by the work of Asner, Martin and Mascaro (2017), studying

Figure 4 - Land-use classification for 2013 and 2019, for the islands of Jarimbu, Mamangal, Itaboca, Mutirão and Buçu in the district of Igarapé-Miri, PA



Continuation figura 4



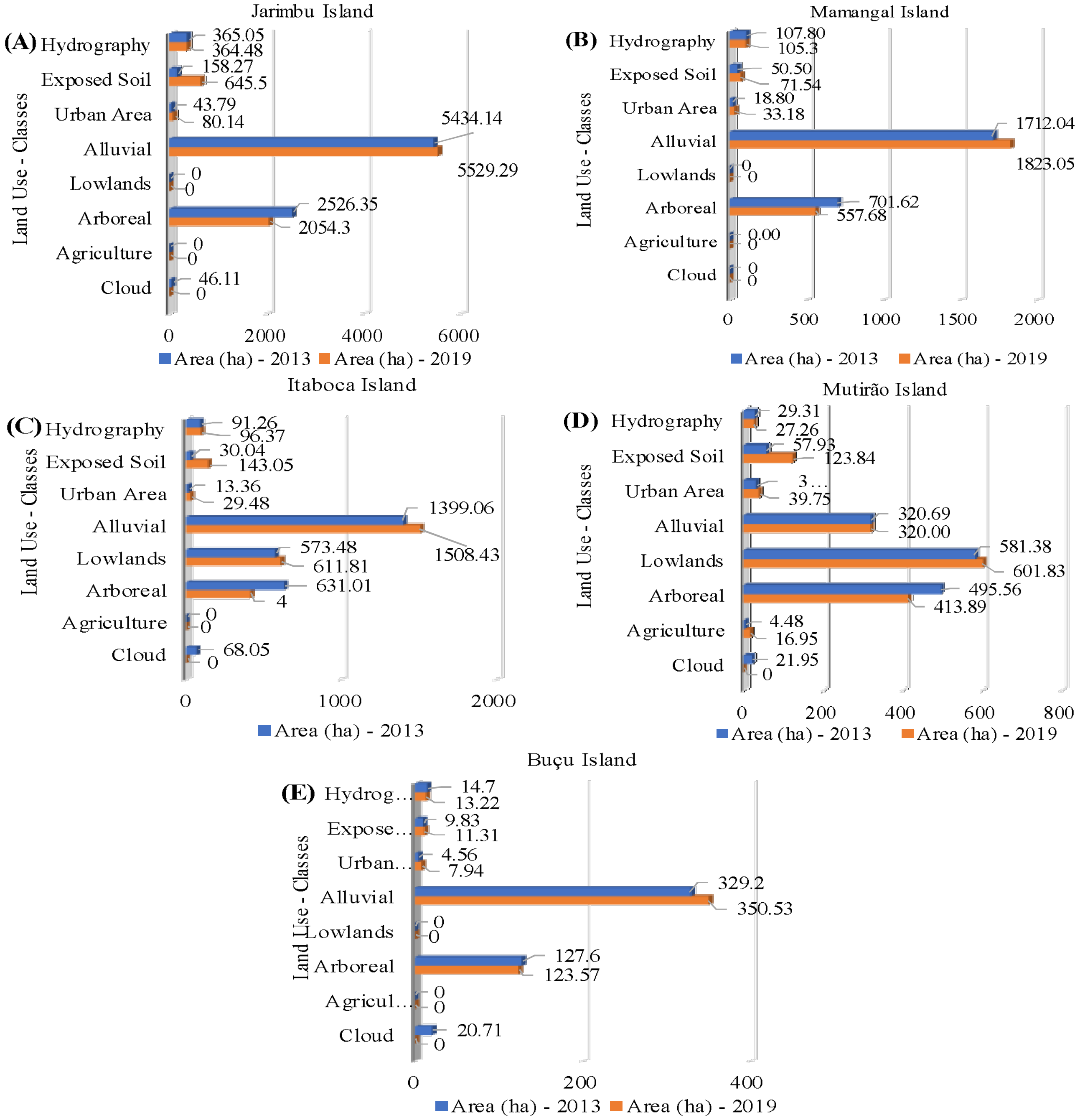
the precision of the Planet data used for unsupervised classification when detecting the extent of shallow coral reefs, and which gave a mean accuracy of 92%.

The Alluvial and Lowland classes for 2013 add up to 64.49% in areas solely of açai groves. However, in the study by Soares *et al*. (2021), this total increased to 67.72%, which confirms the formation of homogeneous clumps and management of the açai groves, as described by Homma (2014).

The dynamics of land use and occupation throughout 2013 and 2019 in the area under study is more significant in some classes, such as the expansion of areas of exposed soil, and urban, alluvial and lowland areas (Figure 5). For Parida and Kumar (2020), multitemporal satellite analysis together with digital image processing are generally employed to monitor changes in vegetation dynamics.

On the islands of Jarimbu and Itaboca (Figure 5A and 5C), the Exposed Soil class more than quadrupled from 2013 to 2019, jumping from 1.82% to 7.44%, and from 1.07% to 5.10% on the islands of Jarimbu and Itaboca, respectively. On Mutirão Island, the area corresponding to this class doubled in size (Figure 5D). This can be attributed to the implementation of new crops and the construction of houses by the community, who cleared the areas for this purpose.

Figure 5 - Classes of land use with their respective areas (ha) for 2013 and 2019, for the islands under study in Igarapé-Miri, Pa



When analysing the Urban Area class, it was found that on the islands of Jarimbu, Mamangal and Itaboca, this class doubled in area (Figure 5A, 5B and 5C), showing how much the population is growing and requires the construction of new homes. Different results were seen on the islands of Mutirão and Buçu, which underwent little change during 2013 and 2019 (Figure 5D and 5E): Mutirão Island, as it is the export route for all production on the islands, and Buçu, which is small, with its entire area inhabited by the local population.

The areas classified as Alluvial on the five islands, and Lowlands on Itaboca and Mutirão (Figure 5), expanded during 2013 and 2019. This shows that açaí was cultivated on these islands. On the other hand, there is also a reduction of the areas classified as Arboreal in four of the five islands under evaluation, namely, Jarimbu, Mamangal, Itaboca and Mutirão, with a reduction in area of 6.6%, 5.5%, 7, 6% and 5.3%, respectively. With the reduction in the Arboreal class, the Exposed Soil, Urban Area, Alluvial and Lowland classes expanded.

Analysing the precision of the classification

Mapping precision was assessed by analysing the confusion matrix for the images from 2019, and is shown in Tables 3 to 7.

The results of this study can be considered very good (Table 2), since the average value of the five islands for overall precision was 77.74% and the mean value for the Kappa index was 0.73. Such results indicate a strong match between the reference and classified data. Oliveira *et al*. (2020) found that the RapidEye sensor, with a resolution of five metres, provided a more accurate classification with rich detailing, in addition to affording greater target differentiation due to the lower spectral mixing of nearby pixels, as seen in the study by Naesset *et al*. (2016) on mapping and estimating forest areas using RapidEye images, which significantly helped to improve the estimates of forest areas due to their high spatial resolution, resulting in better accuracy. In this study, which validated the classification, the Planet sensor with a resolution of three metres was used; this determines far better accuracy in the results for land use and cover.

Table 3 - Confusion matrix for 2019 for Jarimbu Island, district of Igarapé-Miri PA

Class %	Hydrography	Soil	Urban Area	Alluvial	Arboreal	Total
Hydrography	97.56	0	0	1.33	0	20.30
Soil	0	81.39	10.47	9.78	1.69	20.13
Urban Area	0	0	86.43	0	0	18.63
Alluvial	2.44	11.26	3.10	85.78	16.88	22.81
Arboreal	0	7.36	0	3.11	81.43	18.13
Total	100	100	100	100	100	100
Kappa Index - 0.83				Overall Precision - 86.63 %		

Table 4 - Confusion matrix for 2019 for Mamangal Island, district of Igarapé-Miri PA

Class %	Hydrography	Soil	Urban Area	Alluvial	Arboreal	Total
Hydrography	73.18	0.91	0.35	2.69	0	13.85
Soil	0.91	71.82	27.97	1.01	2.28	19.97
Urban Area	4.55	9.09	47.20	6.06	0	14.73
Alluvial	21.36	15.91	23.43	78.79	8.68	32.37
Arboreal	0	2.27	1.05	11.45	89.04	19.08
Total	100.00	100	100	100	100	100
Kappa Index - 0.64				Overall Precision - 71.10%		

Table 5 - Confusion matrix for 2019 for Itaboca Island, district of Igarapé-Miri PA

Class %	Hydrography	Soil	Urban Area	Alluvial	Lowlands	Arboreal	Total
Hydrography	77.46	2.88	0	0	0	0	14.49
Soil	17.25	84.17	10.38	0.55	0	2.67	20.78
Urban Area	1.41	3.96	71.58	0	0	0	17.60
Alluvial	1.76	8.99	15.57	90.71	4.71	15.51	18.74
Lowlands	0	0	0	0	70.29	4.81	12.90
Arboreal	2.11	0	0.55	8.74	25.00	77.01	15.06
Total	100	100	100	100	100	100	100
Kappa Index – 0.73					Overall Precision – 77.51%		

Table 6 - Confusion matrix for 2019 for Mutirão Island, district of Igarapé-Miri PA

Class %	Hydrography	Soil	Urban Area	Alluvial	Arboreal	Lowlands	Agriculture	Total
Hydrography	72.57	0	0	2.03	0	0	0	8.81
Soil	0	81.40	18.58	2.44	8.17	0.82	4.51	14.38
Urban Area	0	9.88	65.93	0	0	0	0	10.95
Alluvial	26.29	1.16	0	71.14	12.98	20.00	2.87	20.18
Arboreal	1.14	1.74	3.98	17.89	70.19	8.16	0.41	14.84
Lowlands	0,00	5.81	0	4.88	8.65	71.02	12.30	16.09
Agriculture	0	0	11.50	0	0	0	79.92	14.58
Total	100	100	100	100	100	100	100	100
Kappa Index – 0.68					Overall Precision – 72.95 %			

Table 7 - Confusion matrix for 2019 for Buçu Island, district of Igarapé-Miri PA

Class %	Hydrography	Soil	Urban Area	Alluvial	Arboreal	Total
Hydrography	55.56	0	0	0	3.27	11.89
Soil	15.97	77.61	5.97	2	0	19.30
Urban Area	2.78	8.96	84.33	8	3.92	20.56
Alluvial	24.31	12.69	9.70	74.67	18.95	28.81
Arboreal	1.39	0.75	0	15.33	73.86	19.44
Total	100	100	100	100	100	100
Kappa Index – 0.66				Overall Precision – 73.01%		

According to the confusion matrix, the Hydrography class had the most hits in the five islands (Tables 3 to 7), particularly Jarimbu Island, which determined good general Kappa indices of 0.83, and an overall precision of 86.63%, i.e. the pixel distribution of the Hydrography class was generally not confused with the other classes in the image. In the study by Caten, Safanelli and Ruiz (2015), the Hydrography class showed low reflectance in relation to the other classes, making any changes both constant and of little significance.

In general, for the Exposed Soil class, an average of 79.27% of hits was obtained for the five islands under evaluation. There was confusion between the Exposed Soil and Urban Area classes, which can be attributed to the similarity of the areas and to their size, since the areas are very small and exposed, making it difficult for them to be separated by the algorithm. On Itaboca Island, an accuracy of 84.17% was found for the Exposed Soil class, in addition to excellent results for the other classes, resulting in the second-best classification, with a Kappa Index of 0.73 and overall precision of 77.51% (Table 5).

The Alluvial class had the highest mean accuracy among the classes, with 80.22%. This class represents all the areas of açai groves, especially as they are areas subject to floods. It was, however, the class with the least pixels mistakenly distributed in other similar classes, such as the Arboreal, or even Exposed Soil or Urban Areas, which are in direct contact with the Alluvial class in question and where the tonality of the targets is very close.

The mean accuracy of the areas classified as Arboreal was good, reaching 78.31%, but there was confusion with the Alluvial class on all five islands. As these classes include vegetation, such interaction between similar targets is common, and causes uncertainty when mapping. However, the Arboreal reference class was more successfully sampled than the areas characterised as wrongly classified, demonstrating the differences between classes. The islands of Itaboca and Mutirão (Tables 5 and 6) have one class in common: Lowlands. This class represents areas of açaí groves without the constant presence of water in their interior; its mean accuracy is the lowest, at 70.65%, being confused with the characteristics of the Arboreal class.

Comparing the classification results for the five islands makes it possible to analyse the accuracy, error of commission and error of omission (Table 8). Jarimbu Island had the best average performance in terms of accuracy (86.2%), with the Hydrography and Urban Area

Table 8 - Accuracy (AC) and errors of commission (C) and omission (O) related to the five classified islands

Class %	Island														
	Jarimbu			Mamangal			Itaboca			Mutirão			Buçu		
	AC	C	O	AC	C	O	AC	C	O	AC	C	O	AC	C	O
Hydrography	97	1	3	73	6	27	77	3	23	73	4	27	56	6	44
Soil	81	22	19	72	36	28	84	28	16	81	36	19	78	25	22
Urbana Area	86	0	14	47	26	53	72	5	28	66	10	34	84	23	16
Alluvial	86	29	14	79	42	21	91	43	9	71	43	29	75	46	25
Arboreal	81	11	19	89	18	11	77	39	23	70	35	30	74	19	26
Lowlands	-	-	-	-	-	-	70	4	30	71	29	29	-	-	-
Agriculture	-	-	-	-	-	-	-	-	-	80	12	20	-	-	-

Adapted from Souza *et al*. (2019)

classes presenting an error of commission of 1% and 0%, respectively. The error of omission in the Hydrography class was 3%, and in the Urban Area class, 14%, which confirms the high level of identification of the areas belonging to this class. However, Buçu Island had the lowest value for accuracy (56%) compared to the other four islands. This can be explained by the error of omission of 44% and of commission of 6%, which implies user error in collecting the data when sampling this class, resulting in pixels left out of their correct class and assigned to another.

Itaboca Island (Table 8) had the second-best mean accuracy (78.5%). Analysing the Alluvial class with 91% accuracy, the error of commission was high at 43%, indicating the incorrect inclusion of several standard samples in other classes. On the other hand, for the same class, the error of omission was lower (9%), showing that few samples were omitted from this class. The same was seen on Mamangal Island for the Arboreal class, where the error of omission was 11% and of commission, 18%, resulting in a good accuracy level of 89%. Olofsson *et al*. (2014) discuss assessing accuracy as being fundamental to the quality of mapping in both a quantitative and significant way.

Validating the data for Mutirão Island (Table 8), the Exposed Soil and Agriculture classes had an accuracy value of 81% and 80%, respectively; however both the error of commission and the error of omission were greater for the Urban Area class. In the study by Souza *et al*. (2019), agglomerations, such as smaller patches, also show similarities, which in turn are confused with other targets, e.g. sand, roads and exposed soil.

In the study by Duarte and Silva (2019) on land-use classification by algorithm, these tools can be used to extract complementary information, helping to optimise the processes and reduce errors.

CONCLUSIONS

1. Space-time analysis by the classification of orbital images from 2013 to 2019 demonstrated a great variation in the pattern of land use and cover on the five islands under study;

2. The overall precision of the method applied in this study was equal to or greater than 71%, and together with the quality of the classification (Kappa index greater than 0.64), demonstrated that the unsupervised ISODATA method can be important for defining the landscape, enabling both speed and accuracy when mapping. In this study, it was evident that the results maintained strong agreement between the classified data and its reference in the field, the only exception being Mamangal Island, where the accuracy of the Urban Area class was low (47%), with errors of commission and omission of 26% and 53%, respectively;

3. In seven years, the Exposed Soil class doubled in size on the islands of Jarimbu, Itaboca and Mutirão. Similarly, the urban areas became more widely distributed on each of the islands, which is a cause for concern. On the other hand, the advance and increase in the Alluvial and Lowland classes is an indication that the local communities began managing the areas of açai groves. With the increase in these areas, there was a reduction in the Arboreal class on the five islands, confirming more intense management of the açai groves to the detriment of the native tree cover.

REFERENCES

ALVARES, C. A. *et al*. Köppen's climate classification map for Brazil. **Meteorologische Zeitschrift**, v. 22, p. 711-728, 2013. DOI: https://doi.org/10.1127/0941-2948/2013/0507.

ASNER, G.; MARTIN, R. E.; MASCARO, J. Coral Reef Atoll Assessment in the South China Sea using Planet Dove satelites. **Remote Sensing in Ecology and Conservatio**n, v. 3, n. 2, p. 57-65, 2017. DOI: https://doi.org/10.1002/rse2.42.

BARCELLOS, C. *et al*. Identificação de locais com potencial de transmissão de dengue em Porto Alegre através de técnicas de geoprocessamento. **Revista da Sociedade Brasileira de Medicina Tropical**, v. 38, n. 3, p. 246-250, 2005. DOI: https://doi.org/10.1590/S0037-86822005000300008.

BLASCHKE, T.; KUX, H. Sensoriamento Remoto e SIG Avançados. 2. ed. São Paulo: **Oficina de Textos**, 1954. 190 p.

CATEN, A. T.; SAFANELLI, J. L.; RUIZ, L. F. Mapeamento multitemporal da cobertura de terra, por meio de árvore de decisão, na bacia hidrográfica do rio Marombas-SC. **Engenharia Agrícola**, v. 35, n. 6, p. 1198-1209, 2015. DOI: https://doi.org/10.1590/1809-4430-Eng.Agric.v35n6p1198-1209/2015.

COHEN, J. A coefficient of agreement for nominal scales. **Educational and Psychological Measurement**, v. 20, n. 1, p. 37-46, 1960. DOI: https://doi.org/10.1177/001316446002000104.

CONGALTON, R. G. A review of assessing the accuracy of classifications of remotely sensed data. **Remote Sensing of Environment**, v. 37, n. 1, p. 35-46, 1991. DOI: https://doi.org/10.1016/0034-4257(91)90048-B.

COSTA, E. M. *et al*. Processamento de imagens RapidEye no mapeamento de uso do solo em ambiente de Mar de Morros. **Pesquisa Agropecuária Brasileira**, v. 51, n. 9, p. 1417-1427, 2016. DOI: https://doi.org/10.1590/s0100-204x2016000900040.

DUARTE, M. L.; SILVA, T. A. da. Avaliação do desempenho de três algoritmos na classificação de uso do solo a partir de geotecnologias gratuitas. **Revista de Estudos Ambientais**, v. 21, n. 1, 2019. DOI: https://doi.org/10.7867/1983-1501.2019v21n1p6-16.

DUTRA, D. J.; ELMIRO, M. A. T.; GARCIA, R. A. Análise comparativa de métodos aplicados na delimitação da cobertura vegetal por meio de imagens Landsat 8. **Sociedade & Natureza**, v. 32, p. 699-710, 2020. DOI: https://doi.org/10.14393/SN-v32-2020-56139.

FLORENZANO, T. G. **Iniciação em sensoriamento remoto**. 3. ed. ampl. e atual. São Paulo: Oficina de Textos, 2011. 123 p.

FRANCISCO, C. N.; ALMEIDA, C. M. Avaliação de desempenho de atributos estatísticos e texturais em uma classificação de cobertura da terra baseada em objeto. **Boletim de Ciências Geodésicas**, v. 18, p. 302-326, 2012. DOI: https://doi.org/10.1590/S1982-21702012000200008.

FUNDAÇÃO AMAZÔNIA DE AMPARO A ESTUDOS E PESQUISAS. **Estatísticas municipais paraenses**: Igarapé-Miri. Belém: Diretoria de Estatística e de Tecnologia e Gestão da Informação, 2016.

GEOFFREY, H. B.; HALL, D. J. **ISODATA, a novel method of data analysis and patern classification**. Menlo Park, California: Stanford Research Institute, 1965.

GOMES, J. C. **Fotointerpretação I**. Guaratinguetá: Centro de Instrução e Adaptação da Aeronáutica, 2001.

HOMMA, A. K. O. **Extrativismo vegetal na Amazônia**: história, ecologia, economia e domesticação. Brasília, DF: Embrapa Amazônia Oriental, 2014. 472 p.

IBGE. **Censo do município de Igarapé-miri-PA**. 2019. Disponível em: https://cidades.ibge.gov.br/brasil/pa/igarape-miri/panorama. Acesso em: 12 abr. 2021.

INMET. Instituto Nacional de Meteorologia. 2022. Disponível em: https://portal.inmet.gov.br/ Acesso em: 2022.

LANDIS, J. R.; KOCH, G. G. Uma aplicação de estatísticas do tipo Kappa hierárquico na avaliação da concordância majoritária entre múltiplos observadores. **Biometrics**, v. 33, n. 2, p. 363-374, 1977.

LOCH, C. **Noções básicas para interpretação de imagens aéreas, bem como algumas de suas aplicações nos campos profissionais**. 3. ed. rev. e ampl. Florianópolis: UFSC, 1993. 120 p.

MORARIU, O. *et al*. Agricultural land cover classification using Rapideye satellite imagery. **Journal of Young Scientist**, 2018.

MOREIRA, M. A. **Fundamentos do sensoriamento remoto e metodologias de aplicação**. 2. ed. Viçosa, MG: UFV, 2003.

MOTA, E. R. *et al*. Diversidade, distribuição espacial e espécies arbóreas estruturantes em Floresta Ombrófila Densa na Amazônia Oriental. **Brazilian Journal of Development**, v. 6, n. 9, p. 71192-71208, 2020. DOI: https://doi.org/10.34117/bjdv6n9-531.

NAESSET, E. *et al*. Mapping and estimating forest area and aboveground biomass in miombo woodlands in Tanzania using data from airborne laser scanning, TanDEM-X, RapidEye, and global forest maps: a comparison of estimated precision. **Remote Sensing of Environment**, v. 175, p. 282-300, 2016. DOI: https://doi.org/10.1016/j.rse.2016.01.006.

OLIVEIRA, H. S. *et al*. Avaliação de algoritmos para classificação de uso e cobertura da terra na porção central do Rio Grande do Sul a partir de imagens de alta e média resolução espacial. **Geo UERJ**, n. 37, 2020. DOI: https://doi.org/10.12957/geouerj.2020.43259.

OLOFSSON, P. *et al*. Good practices for estimating area and assessing accuracy of land change. **Remote Sensing of Environment**, v. 148, p. 42-57, 2014. DOI: https://doi.org/10.1016/j.rse.2014.02.015.

PARIDA, B. R.; KUMAR, P. Mapeamento e análise dinâmica da floresta de mangue durante 2009–2019 usando dados de satélite landsat – 5 e sentinela – 2 ao longo da Costa de Odisha. **Tropical Ecology**, p. 538-549, 2020. DOI: https://doi.org/10.1007/s42965-020-00112-7.

PAROLIN, P. *et al*. Central Amazon floodplain forests: tree survival in a pulsing system. **The Botanical Review**, v. 70, p. 357-380, 2004. DOI: https://doi.org/10.1663/0006-8101(2004)070[0357:CAFFTA]2.0.CO;2.

PONZONI, F. J. *et al*. **Sensoriamento remoto da vegetação**. [*S. l.*]: Oficina de Textos, 2015. Reimpressão.

ROSA, J. C. S.; SOUZA, B. A.; SÁNCHEZ, L. E. Identificação de serviços ecossistêmicos em áreas de floresta mediante sensoriamento remoto. **Desenvolvimento e Meio Ambiente**, v. 53, 2020. DOI: https://doi.org/10.5380/dma.v53i0.62669.

SANTOS, L. A. C. *et al.* Análise multitemporal do uso e cobertura da terra em nove municípios do Sul do Tocantins, utilizando imagens Landsat. **Revista Agro@mbiente On-line**, v. 11, n. 2, p. 111-118, 2017. DOI: https://doi.org/10.18227/1982-8470ragro.v11i2.3915.

SOARES, D. C. de B. L. *et al*. Mapping and environmental diagnosis in Native Acai Areas in the Amazon. **Journal of Agricultural Science**, v. 13, n. 5, 2021. DOI: https://doi.org/10.5539/jas.v13n5p179.

SOUZA, A. R. de *et al.* Cartografia do Invisível: Revelando a agricultura de pequena escala com imagens Rapideye na Região do Baixo Tocantins, Pa. **Revista do Departamento de Geografia**, v. 38, p. 137-153, 2019. DOI: https://doi.org/10.11606/rdg.v38i1.151603.

SWAIN, P. H.; DAVIS, S. M. **Remote sensing**: the quantitative approach. New York: McGraw Hill Book Company, 1978. 375 p.

TAGORE, M. de P. B.; CANTO, O. do; VASCONCELOS SOBRINHO, M. Políticas públicas e riscos ambientais em áreas de várzea na Amazônia: o caso do PRONAF para produção do açaí. **Desenvolvimento e Meio Ambiente**, v. 45, 2018. DOI: https://doi.org/10.5380/dma.v45i0.51585.

TEMBA, P. **Fundamentos da fotogrametria**. Belo Horizonte: Universidade Federal de Minas Gerais. Departamento de Cartografia, 2000.

TULLIO, L. **Aplicações e princípios do sensoriamento remoto**. Ponta Grossa, PR: Atena, 2018. Recurso eletrônico.