Potential of Using Sentinel-1 Data to Distinguish Targets in Remote Sensing Images

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Abstract. Copernicus is the World's largest single Earth Observation (EO) programme, whose satellite constellations are planned to be launched between 2014 and 2025. Among the constellations, Sentinel-1 (S-1) is a C-band SAR able to support land cover mapping. Although optical data are commonly used for land cover monitoring, the low availability of cloud-free scenes along the year hinders the mapping process. In such a way, S-1 presents an important source of data, able of providing all-weather and day-and-night imagery of EO. In this study, we investigate the potential of using S-1 data to distinguish targets in Remote Sensing images in three different Brazilian biomes, Amazon, Cerrado, and Atlantic Forest. Based on that, we proposed a methodology to classify SAR images, which was validated considering a different area from the ones used for sampling purposes. The results showed that through S-1 data, it is possible to detect mainly water and urban area targets, with overall accuracy of 0.90, evidencing that our approach is reproducible in other regions.

Keywords: Radar · Sentinel · Land cover mapping · Satellite imagery · Pattern analysis

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1 Introduction

A set of satellite constellations, called Sentinels, is being developed in order to fulfill Global Monitoring for Environmental Security (GMES) service needs [3,24]. Such constellations are planned to be launched between 2014 and 2025 [3], ensuring a significant data continuity, which is fundamental for Earth Observation (EO) studies [4]. Among them, Sentinel-1 (S-1) is a polar-orbiting satellite constellation, whose first spacecraft was launched in 2014 and the second in 2016. Designed to carry a C-band Synthetic Aperture Radar (C-SAR), S-1 presents the possibility to monitor land cover [3,4,24].

Optical data sources are commonly used for land cover monitoring, such as the Landsat Series [5,14,35,36], however, accurate mapping of extensive areas based on this kind of data is an arduous task, due to the low availability of cloud-free scenes along the year [34]. For this reason, S-1 is an alternative data source, considering its potential of providing day-and-night and all-weather imagery [24]. Therefore, S-1 presents an important source of data, although it is not as used as optical data. Aiming to explore SAR Remote Sensing (RS) signal pattern and support other studies in the thematic, in this paper, we investigate the potential of using S-1 data to distinguish a variety of land cover classes, called here as targets, in RS images in different Brazilian biomes, namely: *Natural Vegetation* (NVA) and *Water* from Amazon biome; *Eucalyptus Plantations* (EP), *Pasture*, *Soil*, *Turfgrass* and *Natural Vegetation* (NVC) from Cerrado biome; and *Urban Areas* from Atlantic Forest biome.

After an exploratory data analysis, we analyzed the signal behaviour and categorized the dataset in three classes: *Water*, *Urban Areas* and *Others*. Based on that, we proposed a methodology to classify SAR images, which was validated considering a different area from the ones used for sampling purposes, Colônia Crater, in the extreme southern of the São Paulo metropolitan region. The results may provide a better comprehension about RS signal pattern, enabling the assessment and monitoring of land cover changes in future studies, as well as temporal data fusion of both radar and optical data.

2 Material and Methods

2.1 Study Area

Brazilian Biomes. Although there are different concepts, a biome is considered an uniform environment [9,44], which can take into account a range of factors. Brazil presents six main biomes, Amazon, Cerrado, Atlantic Forest, Caatinga, Pantanal, and Pampa. Among them, Amazon, Cerrado and Atlantic Forest are considered the three main Brazilian biomes for Carbon sequestration [27] (Fig. 1).

Amazon is the worlds largest rainforest. Two-thirds of its basin is localized in Brazil, which represents about 5 million km^2 [12]. Although it congregates a great biodiversity, it faces a range of threats, such as deforestation [13] and fire processes [2].

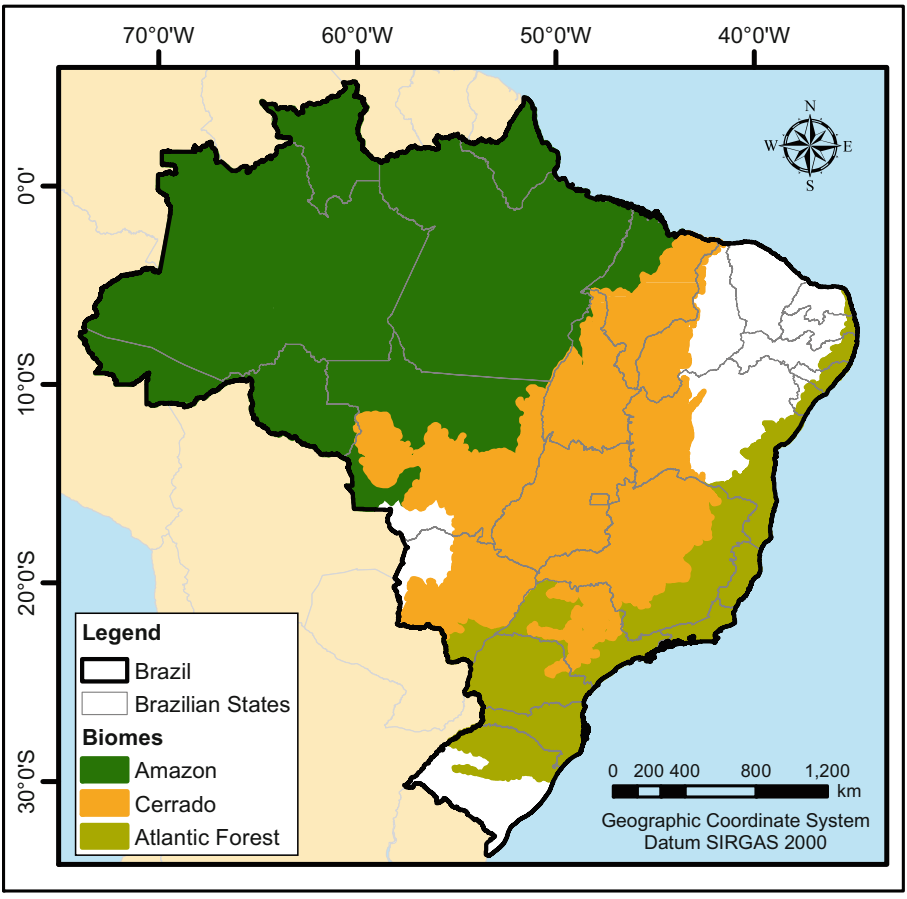

Fig. 1. Brazilian Amazon, Cerrado and Atlantic Forest Biomes.

Comprehending more than 20 million km^2 [16], the Cerrado biome is the second largest biome in South America and it presents the richest biodiversity among the tropical savannas [35]. Even though, only 6% of Brazilian savannas are located in areas of integral protection [14]. If compared with efforts performed in order to monitor and manage Land Use and Land Cover (LULC) changes in the Amazon, Cerrado biome has been overlooked [5,38]. Moreover, this biome has become one of the top grain and beef-producing regions in the world [29]. In such a way, both points of view unravels the importance of preserving this rich biome not only due to its biodiversity but also for its role in global food production. In this context, the lack of conservation approaches associated with the high level of land conversion to agriculture performs the major environmental problem faced by Cerrado [37].

The original area of the Atlantic Forest ranged from 1 to 1.5 million km^2 along 15 Brazilian States, housing three of the most populated urban centers on

the continent and almost 70% of Brazilian population. The Atlantic Forest is also considered one of the richest biomes in the world. Nonetheless, only about 7–8% of its original forest cover still remains. In this context, due to its critical areas and high biodiversity and endemism, the Atlantic Forest was recognized as a biodiversity hotspot. Although there are several initiatives to preserve this environment, the loss processes are highly complex and more efforts are required for monitoring and controlling LULC in the area [21,39].

Due to the importance of these biomes, some initiatives aim at LULC monitoring, such as Terra Class Cerrado [26], which includes manual edition aiming to minimize possible errors, and MapBiomas Project [25], with high degree of process automation and overall accuracy around 80%.

Colônia Crater. Inserted in the Brazilian Atlantic Forest biome and located in the extreme southern of the São Paulo metropolitan region, Colônia Crater is a prominent geomorphological feature generated by an extraterrestrial body impact [41]. Colônia Crater presents, in its northern area, an irregular allotment called Vargem Grande, and in the northeast region, the Colônia neighborhood, besides others communities in the surrounds. Furthermore, it covers water catchments from the Billings reservoir [42] (Fig. 2).

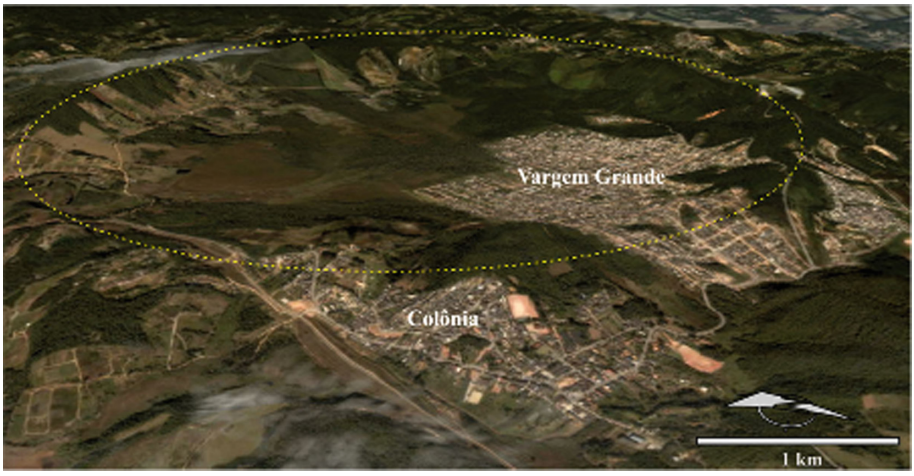

Fig. 2. Colônia Crater from an oblique view. Extracted from [40].

2.2 Exploratory S-1 Data Analysis and Processing

For this exploratory analysis, eight targets were selected along the Amazon, Cerrado and Atlantic Forest biomes (Table 1). The sampling data of *Natural Vegetation* (NVA) and *Water* of a river were manually extracted from a portion of Itamaraty municipality in the Amazon biome. The region is characterized by

constant high temperature, which coldest month is of 18 °C or higher [19]. Data of *Eucalyptus Plantations* (EP), *Pasture*, *Soil*, *Turfgrass* and *Natural Vegetation* (NVC) from the Cerrado biome were based on [33] field campaign conducted in Campo Verde – MT, Brazil (May 9–13, 2016). The area is characterized by an average temperature of 22.3 °C, and rainfall of 1726 mm [33]. According to the authors, *Soil* refers to uncultivated areas, such as bare soil, soil with weeds, or with crop residues from the previous harvest. Finally, *Urban Areas* target sampling was extracted from the Bela Vista district limits in the central region of the São Paulo municipality.

Table 1. Analyzed targets.

Target	Data source (biome)
Eucalyptus Plantations (EP)	Cerrado
Natural Vegetation (NVA)	Amazon
Natural Vegetation (NVC)	Cerrado
Pasture	Cerrado
Soil	Cerrado
Turfgrass	Cerrado
Water	Cerrado
Urban Areas	Atlantic Forest

Scenes from Sentinel-1, Level-1 Single Look Complex (SLC) were selected according to its temporal proximity to the field campaign conducted by [33]. Operating in C-band (central frequency of 5.404 GHz), Sentinel-1 products are distributed by ESA (European Space Agency) and can be accessed freely (scihub.copernicus.eu/). Among the four exclusive modes that Sentinel-1 Synthetic Aperture Radar (SAR) instrument can acquire, we used the Interferometric Wide Swath (IW). With a swath width of 250 km on the ground at 5 m by 20 m spatial resolution, the provided imagery are dual-polarisation (vertical transmit and vertical receive - VV, and vertical transmit and horizontal receive - VH) [11].

The processing of SLC product was performed on the Sentinel Application Platform, SNAP (Fig. 3). After splitting the images into subswaths, the process was divided in two. In order to obtain the backscatter coefficient (Sigma0), the data were radiometric calibrated. Then, we removed eventual gaps, multilooked the data (look = 4), corrected the orbit and the terrain, removed thermal noise, and applied Speckle Filter (Refined Lee, 5×5). After that, the data were decomposed using eigenvalue decomposition, proposed by [7], engendering the polarimetric parameters VV and VH. Meanwhile, a similar process based on polarimetric tools was applied to obtain the complex data of entropy (measure of the randomness of the scaterring mechanism) and alpha angle (dominant

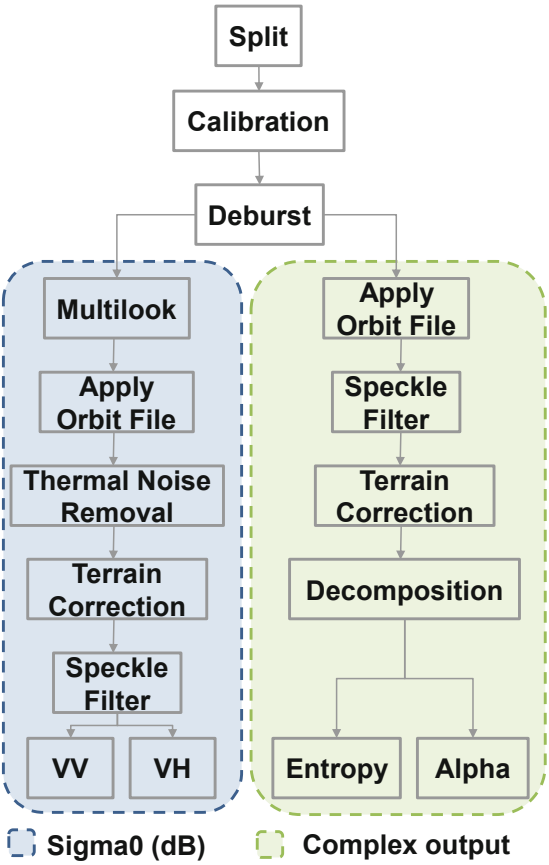

Fig. 3. Methodology flowchart.

scaterring mechanism). Different variables were used, once it is an important step in image classification [1].

After that, SAR signal pattern was analyzed through boxplots in order to statistically characterize the behaviour of targets in images. According to the boxplots analysis, targets with similar behaviour were grouped in the class named *Others*.

2.3 Development of the Methodology to Classify SAR Images

For each class resulted from the previous stage, 1,000 randomly samples were selected in order to develop a methodology to classify SAR images. For that, we used the workbench for machine learning WEKA (Waikato Environment for Knowledge Analysis) [15].

Firstly, the data were classified using the data mining algorithm J48, an implementation of the C4.5 algorithm [30]. This algorithm is widely used, and

it has been commonly applied in order to analyze novel approaches [32], once it enables fast comparisons. Furthermore, C4.5 is considered to have one of the best relations of error rate and speed [22]. The results were evaluated based on a stratified k-fold cross validation [18], which splits the training data into $k = 10$ equal-sized partitions. After that, based on the classification model generated by C4.5 algorithm, the methodology to classify SAR images was applied.

2.4 Accuracy Assessment

An image of the Colônia Crater region was classified by means of the developed methodology in order to assess its accuracy. After that, the classified data results were analyzed based on a reference datased from the MapBiomas Project [25].

Areas smaller than 0.2 ha were filtered in both, classified and reference data, due to the difference in spatial resolution and noise interference. Moreover, in order to harmonize the data, the legend from the reference data was adapted according to the targets used to compose the methodology (listed in Table 1). The final accuracy assessment was performed through a Cohen's Kappa coefficient [8]; the Producer's Accuracy, which is a complement of the omission error; and, the User's Accuracy, which corresponds to the commission error. The detailment of the classification result based on the proposed methodology and the reference dataset from MapBiomas Project is then presented in a confusion matrix.

3 Result and Discussion

3.1 SAR Remote Sensing Signal Pattern

For VV polarimetric parameter (Fig. 4A), it is possible to notice that NVA presented higher values than EP, NVC and *Pasture*. Furthermore, the two last aforementioned targets were similar. *Turfgrass* and *Water* presented also similar distributions. Finally, *Urban Areas* presented high variability if compared to the other targets, as can be observed by the wide range [0.00; 2.00 dB], and interquartile range intervals [0.25; 1.00 dB].

According to the VH polarimetric parameter (Fig. 4B), NVA presented higher values than EP, NVC was similar to *Pasture*, and *Turfgrass* and *Water* presented similar distribution. *Soil* values distribution is asymmetrical and surprisingly wide. As identified in VV, the range of values in *Urban Areas* is also ample in VH parameter. Entropy values distribution (Fig. 4C) shows that *Turfgrass*, *Urban Areas* and *Water* could be better distinguished from other targets, and again the range of distribution for *Urban Areas* is wider. For the polarimetric parameter of Alpha (Fig. 4D), *Urban Areas* and *Water* could be better identified, with ample values distribution and low values, respectively.

Although it is not consolidated yet, [6] identified in an agricultural perspective that the polarimetric parameter VV is not well correlated with canopy height. Besides that, according to [43], VV may be sensitive to surface and volume scaterring, nonetheless, theorical modelling indicated also double bounce

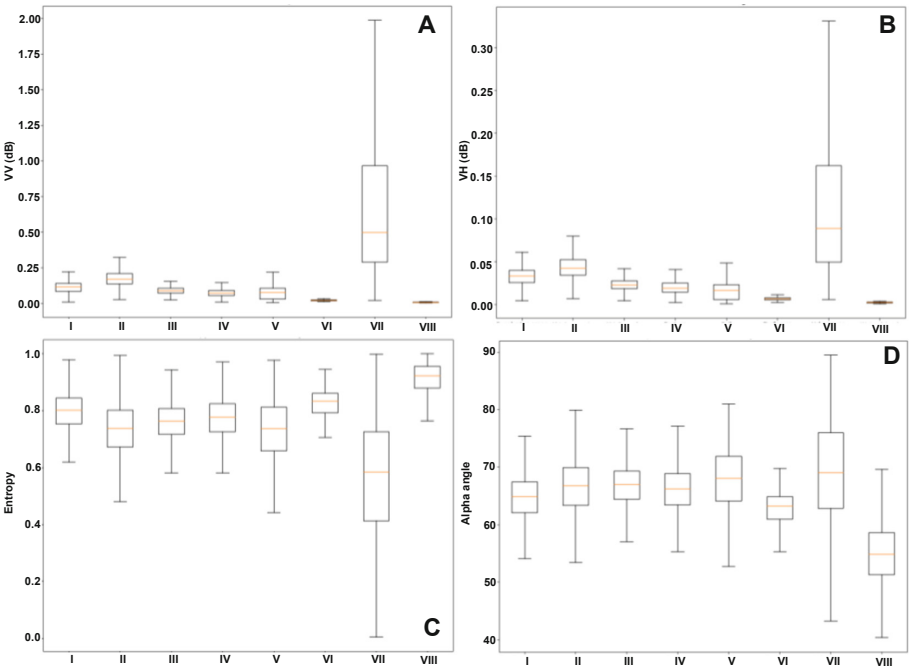

Fig. 4. Results according to polarimetric parameters. A. VV (dB); B. VH (dB); C. Entropy; D. Alpha angle. I. *Eucalyptus Plantations* (EP); II. *Natural Vegetation from Amazon* (NVA); III. *Natural Vegetation from Cerrado* (NVC); IV. *Pasture*; V. *Soil*; VI. *Turfgrass*; VII. *Urban Areas*; VIII. *Water*.

term. In the present work, it was not possible to correlate the parameter VV with canopy height. However, we identified that NVA presented higher values, as well as *Urban Areas*, probably due to volume and double bounce scaterring, respectively. Moreover, the polarimetric parameter VH could distinguish targets in a similar way as VV.

According to [6,17], cross polarizations (i.e. VH) are sensitive to crop growth. As such, this parameter may be able to better distinguish and monitor for instance crops through multitemporal and auxiliary data [31]. Another approach also based on a multitemporal perspective is regarding the potential of Sentinel-1, polarizations VV and VH, for burned area mapping [20]. The process was performed based on change detection, statistical analysis, and unsupervised classification. According to the authors, due to the fire occurrence, there is an increasing of the backscattering, making the burned areas present lighter pixels than the rest of the image. Polarimetric parameters also could be integrated to optical data in order to improve classification accuracy. For instance, HH and HV amplitudes from PALSAR-2 combined with spectral bands from Landsat-OLI improved the classification process in 6% in northern Brazilian Amazon, indicating the potential of hybrid models to classify LULC [28].

Entropy and Alpha angle are effective to distinguish certain land covers, such as low vegetated and agricultural areas [45]. However, in the present study, such polarimetric parameters were found to be effective mainly for *Water* target. Soil values distribution along the analyzed parameters was asymmetrical and surprisingly wide, probably due to its land cover heterogeneity, according to the reference data used in this research.

In this manner, according to SAR remote sensing signal patterns, *Urban Areas* and *Water* were the most distinguished targets by S-1 in the analyzed regions. The remaining six targets presented similar behaviour, and consequently were grouped in the class *Others*.

3.2 Methodology Assessment

A total of 3,000 samples from *Urban Areas*, *Water* and *Others* targets were classified using the C4.5 algorithm. The C4.5 tree presented 24 leaves and the size was 47 (Fig. 5). The classification model represented by the decision tree is relatively simple, once more complex classification tasks can grow massively, with more than 100 nodes. Considering that it is hard to comprehend large decision trees, the developed methodology's extension is an advantage. If required, it is also possible to use more generic rules through the simplification of the tree. For that, it is necessary to respect the condition that every outcome must be able to be tracked along the path of the root of the tree [30].

For the first order numbers (0, 1, 2), the main parameters selected by the methodology were VV and VH (Fig. 5). Entropy is included just in order number 3, and Alpha in number 4. Entropy and Alpha also are the only parameters presented in the last order, 8, which indicates that both are used in refined classifications in the developed approach. Furthermore, the target *Water* was classified in the order number 0, and from 1 to 8, the targets *Urban Area* and *Others* are classified, evidencing the difficulty of its segregation, probably due to its land cover characteristics.

As a result of the cross validation process, more than 91% of the data were correctly classified with Kappa statistic of 0.87. Moreover, the Precision ranged from 0.837 to 0.991, Recall from 0.822 and 0.998, and F-measure from 0.867 and 0.995 (Table 2).

Table 2. Detailed accuracy from the cross validation step.

Class	Precision	Recall	F-Measure
Urban Areas	0.917	0.822	0.867
Water	0.991	0.998	0.995
Others	0.837	0.918	0.876
Average	0.915	0.913	0.912

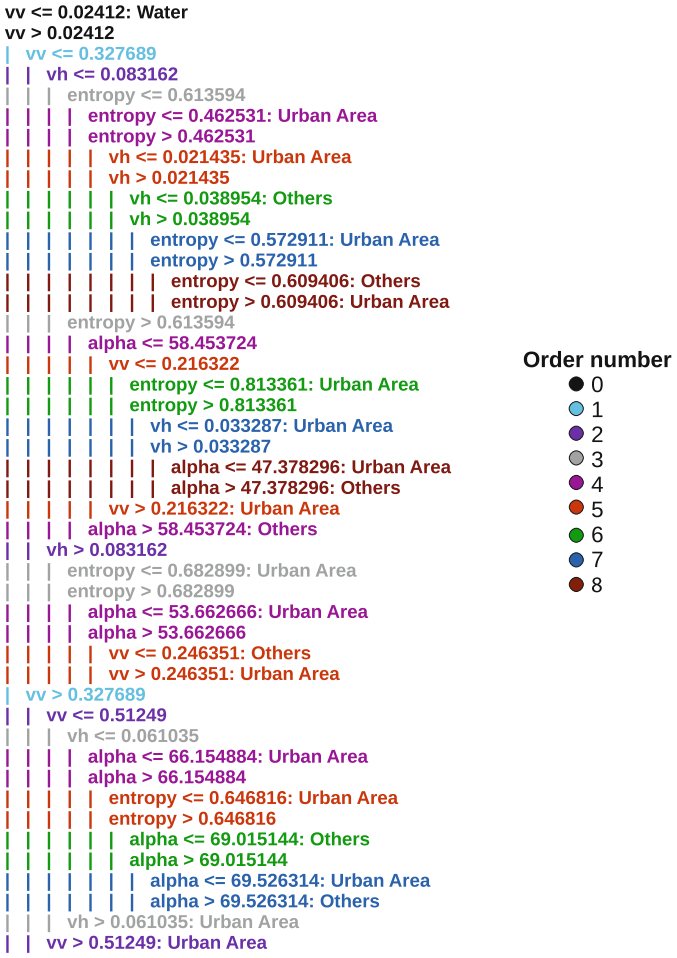

Fig. 5. Developed methodology tree.

Aiming to assess the developed methodology, it was applied to classify an image of the Colônia Crater region, a totally different area from those used to acquire training data. The overall accuracy was of 0.90. The misclassified data are spread along the area, but mainly in the *Urban Areas* of the southern region (Fig. 6).

The confusion matrix indicates that the most accurate classes are *Others*, *Water*, and *Urban Areas*, respectively (Table 3). The target *Water* was not representative in the area, with less than 18.00 ha. Although this target did not suffered a severe omission error ($PA = 92\%$), the commission error was the second highest among the results, which was confused with *Others* by the classifier ($UA = 68\%$).

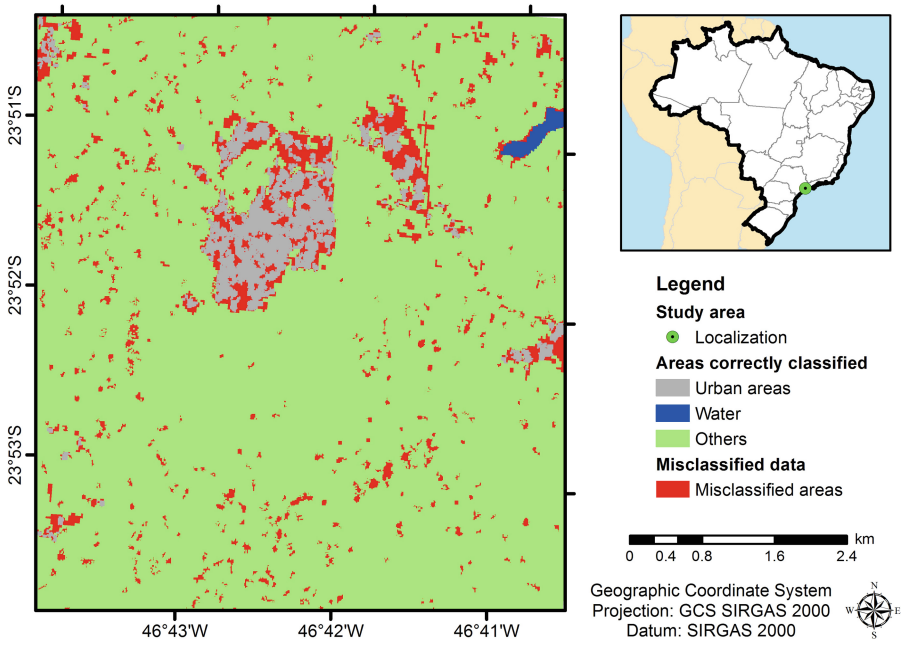

Fig. 6. Developed methodology accuracy.

Table 3. Confusion matrix. Classification result based on the proposed methodology (Sentinel-1 data), and the reference dataset (MapBiomas Project). Producer's accuracy - PA; User's accuracy - UA.

		MapBiomas (ha)			Row total (ha)	UA
		Water	*Urban Areas*	*Others*		
Sentinel-1 (ha)	*Water*	16.259	0.000	7.518	23.777	68%
	Urban areas	0.000	145.655	239.404	385.059	38%
	Others	1.470	192.174	3843.292	1036.936	95%
Column total (ha)		17.729	337.829	4090.214	**4445.772**	
PA		92%	43%	94%		

Expressively more *Urban Areas* targets were misclassified with *Others* than correctly classified, presenting thus the lowest UA (38%), and PA of 43%. As already found by [10,23], low building areas can be misclassified with targets such as vegetation/forest and bare land. *Others* was misclassified mainly by *Urban Areas*, followed by *Water*, but presented the highest accuracy among the targets, once it is the most extensive area and is generic enough to incorporate different targets. Furthermore, there was no confusion between *Urban Areas* and

Water, due to its fundamental differences, such as water content and dielectric constant.

4 Conclusions

We analysed SAR signal patterns for different targets in RS images. Results show that the behaviour of *Eucalyptus Plantations*, *Natural Vegetation* in Amazon, *Natural Vegetation* in Cerrado, *Pasture*, *Soil*, and *Turfgrass* were similar according to boxplot analysis.

In this study, S-1 data could distinguish more precisely *Urban Areas* and *Water* targets. Furthermore, the findings also indicate the reproducibility of the developed methodology. It was generic enough to be extrapolated to a completely different region, with overall accuracy of 0.90 for Colônia Crater, located at the southern region of the São Paulo municipality.

As future research, we suggest to explore the developed methodology, for instance, in others biomes with the support of other variables, such as difference imagery (VV-VH).

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