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Evolution of MapBiomas Collections' Accuracy for the Highly Fragmented São Paulo landscape

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Resumo: A avaliação da acurácia de mapeamentos da cobertura da terra é essencial para os usos científico, prático e político dos mapas. No Brasil, o projeto MapBiomas vem mapeando anualmente a cobertura da terra em todo o território via classificação automática de imagens Landsat de média resolução espacial (30 m) desde 1985. Cada nova versão do algoritmo de classificação gera uma nova coleção de mapas que são sujeitos a uma avaliação da acurácia em nível nacional. Entretanto, é cada vez mais frequente o uso do MapBiomas para estudos regionais, municipais ou locais para os quais a avaliação da acurácia em nível nacional não é adequada. Aqui avaliamos a acurácia e a evolução da acurácia das principais categorias de cobertura do MapBiomas para o estado de São Paulo (SP), o mais urbanizado do país e objeto de muitos estudos e políticas públicas relacionadas à cobertura da terra. Analisamos as coleções 3.1, 4.1, 5.0, 6.0 e 7.0 para o ano de 2017, o mais recente com coincidência de classes em todas as coleções, considerando as classes: Formação Florestal, Floresta Plantada, Pastagem, Cana de Açúcar, Infraestrutura Urbana e Rio, Lago e Oceano. A acurácia global (AG) foi menor na coleção 4.1 (91%) e maior na 7.0 (96%). As acurácias do produtor (AP) e do usuário (AU) melhoraram da coleção 3.0 para a 7.0, com exceção das AP para Floresta Plantada que praticamente permaneceu inalterada, e de Infraestrutura Urbana que vem piorando gradativamente até atingir o menor valor na 7.0 (0,87). Mesmo assim, o fato da AG, e particularmente da AP e AU da coleção 7.0 estarem acima de 0,84 indica que em São Paulo o MapBiomas é acurado o suficiente para, por exemplo, muitas análises comuns na escala da paisagem, em ecologia (ex. modelagem da distribuição de espécie de mamífero ou ave), agricultura (ex. estimativa de safra) ou engenharia (ex. escolha de sítio aeroportuário).
Palavras-chave: Avaliação da acurácia; Mapeamento da cobertura da terra; QGIS; GRASS.

Abstract: The assessing the accuracy of land cover mappings is essential for the scientific, practical and policy uses of maps. In Brazil, the MapBiomas project has been annually mapping the land cover across the entire territory via automatic classification of Landsat images of medium spatial resolution (30 m) since 1985. Each new version of the classification algorithm generates a new collection of maps that are subject to an accuracy assessment at the national level. However, MapBiomas is increasingly used for regional, municipal or local studies for which the assessment of accuracy at the national level is not adequate. Here we evaluate the accuracy and evolution of accuracy of the main categories of MapBiomas coverage for the state of São Paulo (SP), the most urbanized in the country and the objetic of many studies and public policies related to land cover. We analyzed collections 3.1, 4.1, 5.0, 6.0 and 7.0 for the year 2017, the most recent with coincidence of classes in all collections, considering the classes: Forest Formation, Planted Forest, Pasture, Sugar Cane, Urban Infrastructure and River , lake and ocean. The global accuracy (GA) had its lowest value in collection 4.1 (91%) and highest in 7.0 (96%). Producer (PA) and user accuracies (UA) improved from collection 3.0 to 7.0, with the exception of PA for Planted Forest, which remained virtually unchanged, and for Urban Infrastructure, which has been showing a tendency to worsen over the course of the collections, reaching its lowest value at 7.0 (0,87). Even so, the fact that the GA, and particularly the PA and UA of collection 7.0 are above 0.84 indicates that in São Paulo MapBiomas is accurate enough for, for example, many common analyzes at the landscape scale, in ecology (e.g. distribution modeling of species of mammal or bird), agriculture (e.g. harvest estimation), or engineering (e.g. choice of airport site).
Keywords: Accuracy assessment; Land-cover mapping; QGIS; GRASS.

1. INTRODUCTION

Land use and land cover are related to climate and biodiversity, water availability and agriculture, engineering, economics, and other factors crucial to human life. For example, an assessment of the relationship between deforestation in the Amazon and carbon emissions showed that by 2017, the gain in total carbon stock from forest growth offset around 10% of the emissions from the loss of old-growth forests (SMITH et al., 2020). Meanwhile, in England, the replacement of grasslands with forestry to reduce flooding and build carbon-storing wooden houses is reducing the availability of crucial resources for the common buzzard Buteo buteo, which in the coming decades is expected to induce the third significant decline in this population (ARRAUT et al., 2021; KENWARD et al., 2018). As part of the process of selecting a new regional airport site in a Brazilian municipality, land cover mapping has been essential, for example, to position the new site with simultaneously lower costs via a reduction in the volume of earthworks and lower environmental and social impacts, such as deforestation or draining watercourses, avoiding Indigenous lands, quilombolas, and settlements, and reducing the number of rural properties to be expropriated (ALVES et al., 2020).

With the evolution of remote sensing and the increase in the quantity and diversity of land cover mappings, along with the increased use of this information in analyses involving other geographical data, it has become essential to assess the accuracy of these mappings (CONGALTON, 1991). An assessment of mapping accuracy, reported essentially in a confusion matrix (or error matrix), quantifies the coincidence between the map in general and by category and reality. When this accuracy is done following a well-executed probabilistic sampling design, both the accuracy estimates and the associated standard errors or confidence intervals are valid, ensuring the crucial quantification of the uncertainty related to mapping (STEHMAN, FOODY, 2019 and CONGALTON, 1991).

The MapBiomas project, born in 2015 through collaboration between universities, NGOs, and technology startups, maps land cover and land use throughout Brazil annually and makes its maps available for free. This mapping is done by classifying a history of multispectral images with a spatial resolution of 30m from 1985 to the present, based on the sensors of the Landsat mission satellites (MAPBIOMAS, 2022). As the classification algorithm has been improved, each new version generates a new map for each year of the series. MapBiomas' accuracy assessment is based on a sample of ~75,000 pixels created through visual interpretation of Landsat images, called the reference database. The size and distribution of this reference sample are stipulated considering the entire Brazilian territory.

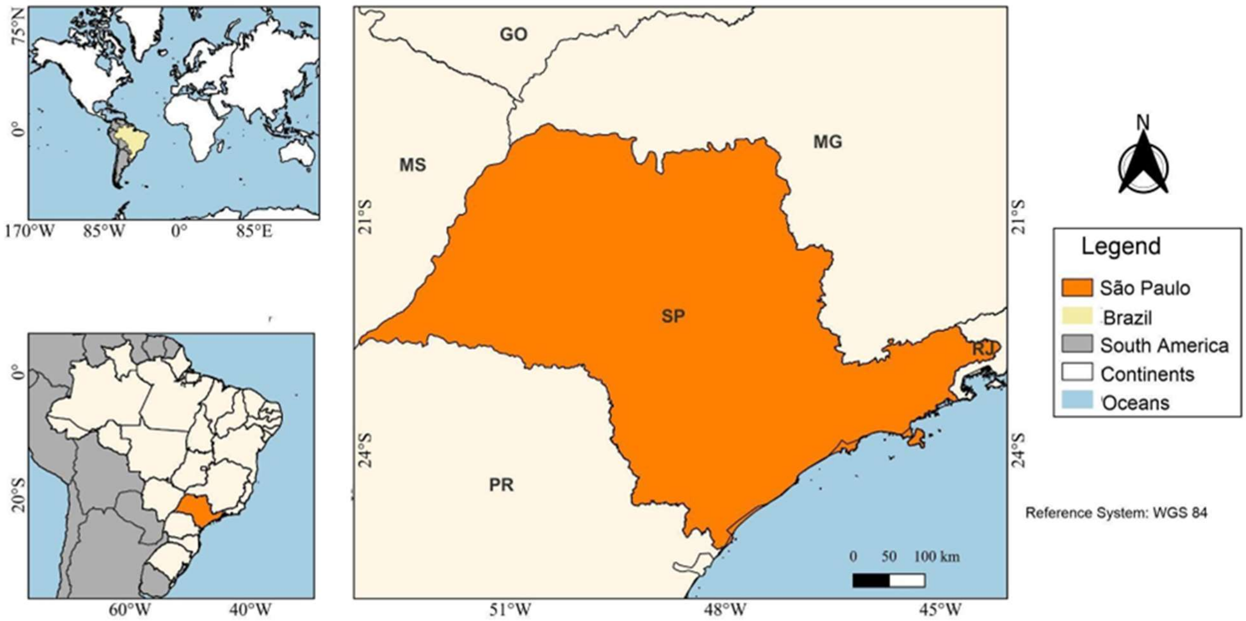
However, it is becoming increasingly common to use MapBiomas for studies in much smaller sub-areas of the country, including states, municipalities, or even specific localities for which an accuracy assessment on a national scale may need to be revised. This is because, despite the robust accuracy assessment methodology used by MapBiomas, and in particular, the minor overall and biome standard errors obtained (SOUZA Jr et al., 2020), in a confusion matrix, there is no information on the spatial patterns of mapping errors, meaning that any changes in error rates derived from variability in a particular class across the country are not detectable (WICKHAM et al., 2017). It is therefore not possible to know how much the results on land use change for the Microregion of Pirapora, northern Minas Gerais, which represents <0.003% of the Brazilian territory, or for the municipality of Bragança-PA, which represents <0.0003 of the national area (SENA-SOUZA et al., 2022; RIBEIRO, 2022), derive from fundamental changes in the landscape or from localized mapping error induced by specificities of local landscapes (e.g. variation in vegetation, soil, relief). Furthermore, given the significant investment made by the MapBiomas team in improving the classification algorithm, it is also important to quantify the change in accuracy between the collections. This article evaluates the accuracy and evolution of the mapping accuracy of MapBiomas collections 3.1 to 7.0 for the entire state of São Paulo, the most populous in the country, and the subject of several studies. For example, in São Paulo, MapBiomas has been used to assess landscape dynamics in the small (compared to the size of the state) buffer zones of conservation units (CUs), Permanent Preservation Areas (PPAs) or peri-urban wetlands, or to support management plans for the state's CUs (CARMO et al, 2023; SANTOS JUNIOR, 2023; CASTOJO, JESUS, 2022; COSTA, 2022). It is hoped that this study will help improve the quality of MapBiomas mapping and provide a baseline of mapping uncertainty for investigations in the state of São Paulo.

2. MATERIALS E METHODS

2.1 Study Area

The study area focuses on the state of São Paulo, with a territorial extension of 248,219.485 km² (IBGE, 2022) within the Cerrado and Atlantic Forest biomes, an estimated population of 46.3 million inhabitants (the most populous state in the country, with 21.9% of the total population) (IBGE, 2020), and a highly heterogeneous and fragmented landscape. According to the 2020 ranking by the Brazilian Institute of Geography and Statistics (IBGE), the state of São Paulo is home to three of the 17 cities with more than 1 million inhabitants in the country, with the city of São Paulo being the most populous, followed by Guarulhos and Campinas, in 13th and 14th place respectively. The São Paulo metropolitan region is the most populous in Brazil, with a population of 21.9 million (IBGE, 2020).

Figure 1 - Location map of the state of São Paulo.



Source: Authors (2022).

2.2 Methodology

For this analysis, which involved collections 3.1, 4.1, 5.0, 6.0, and 7.0, 2017 was chosen because it was the most recent year in all the collections in question (Figs. 2 and 3). To allow comparison between the collections, only the classes standard to all the MapBiomas collections evaluated were considered in the accuracy analysis. Thus, for example, the Coffee, Citrus, and Wooded Restinga classes found only in Collections 6 and 7, the Perennial Crop class found only in Collection 5, as well as the Temporary Crop class exclusive to Collections 3.1 and 4.1 were not included in the analysis. The final courses considered were Forest Formation, Planted Forest, Pasture, Sugar Cane, Urban Infrastructure, and River, Lake, and Ocean. Class 34, the "errors" class, was used when the visual interpretation of the very high spatial resolution base map indicated that MapBiomas had wrongly classified a particular class. For example, if MapBiomas hasclassified an area as "Pasture," but the visual interpretation suggests that it is "Urban Infrastructure," the "errors" class is assigned.

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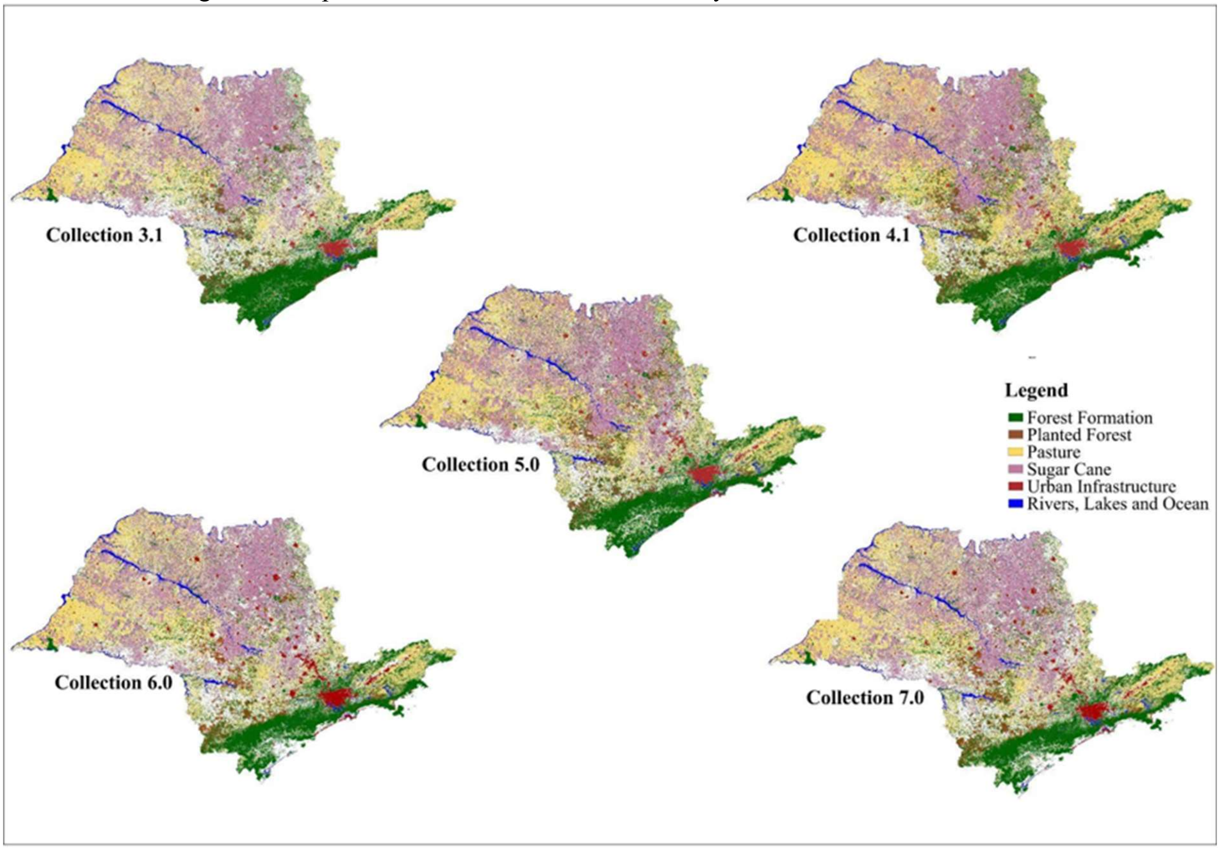
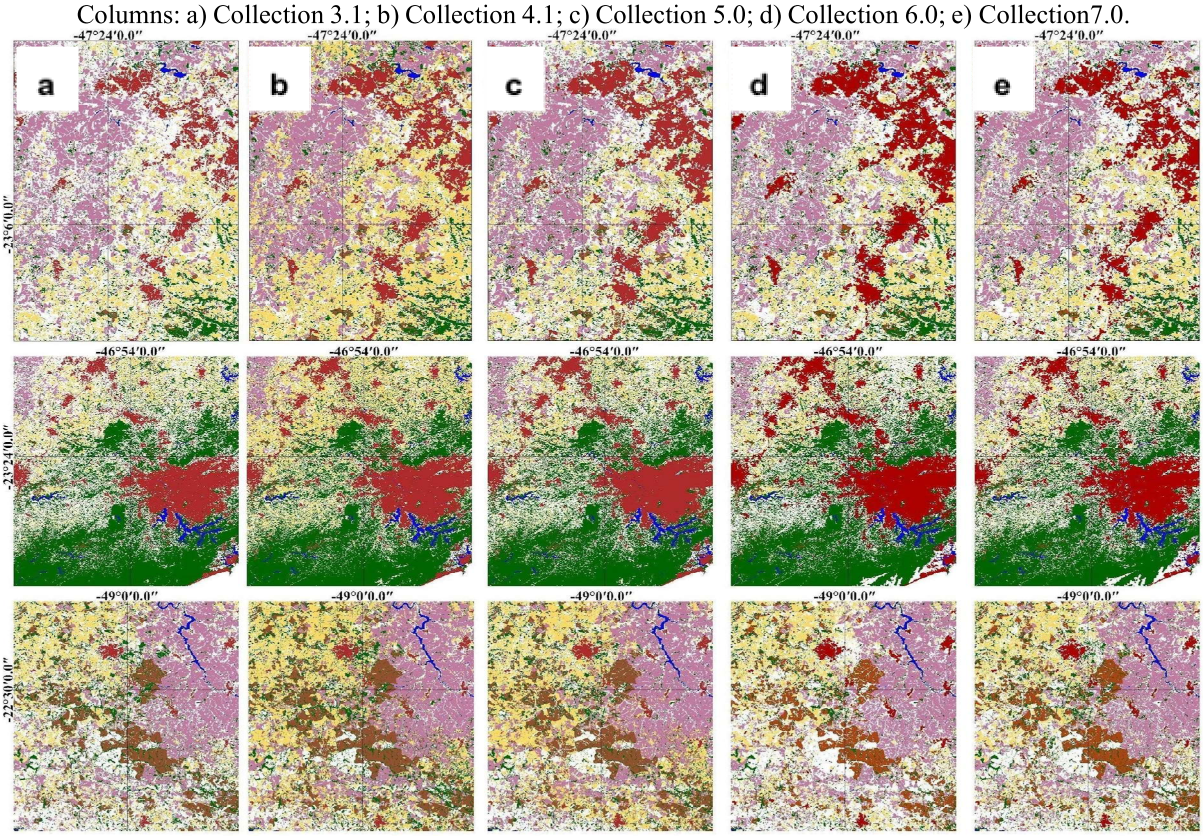
Figure 2 - MapBiomas collections and classes analyzed for the state of São Paulo.



Source: Authors (2022).

Figure 3 - Details of the MapBiomas collections and classes analyzed for three sub-regions of the state of São Paulo with different characteristics in terms of land cover: row 1 = Campinas region and surrounding area, with highly distributed urban cover, large areas of sugarcane and pasture and little native forest, row 2 = metropolitan region of the city of São Paulo and surrounding area, with dense and extensive urban cover surrounded mainly by pasture and native forest, and row 3 = Bauru region and surrounding area, with small urban cover, and plenty of pasture and sugarcane. Columns: a) Collection 3.1; b) Collection 4.1; c) Collection 5.0; d) Collection 6.0; e) Collection7.0.



Source: Authors (2023).

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To carry out the analyses, QGIS 3.22 software with GRASS 7.2.2 was used to calculate the area of the classes, and the AcATama plugin was used to generate the random points and produce the confusion matrix. To estimate the area of the classes, the images were reprojected to UTM coordinates, and then the "r.report" function was used to obtain the area of each class according to the chosen unit of measurement (Table 1).

Table 1 - Proportion of classes per collection. Area in km² of collection 7 for reference: Formation F. (46,837.20), Forest P. (8,752.95), Pasture (46,652.05), Sugarcane (56,299.28), Infrastructure U.(7,310.91) and River, Lake and Ocean (6,144.56).

Classes	Name	Area (%) 3.1	Area (%) 4.1	Area (%²) 5.0	Area (%) 6.0	Area (%) 7.0
3	Forest Formation	20,15	20,14	20,38	19,09	18,87
9	Planted Forest	3,34	4,34	4,06	3,40	3,53
15	Pasture	18,54	26,90	21,49	18,45	18,79
20	Sugar Cane	22,64	24,80	24,84	23,00	22,68
24	Urban Infrastructure	2,42	2,76	3,01	3,33	2,95
33	Rivers, Lakes and Oceans	2,29	2,28	2,35	2,39	2,48

Source: Prepared by the authors (2023).

To ensure a proportional distribution of the sample points according to the size of each class, using the AcATama plugin, 3166 points were distributed following stratified sampling (STEHMAN and FOODY, 2019). The sample size per class was determined using the following formula (STEHMAN and FOODY, 2019) and considering a 90% confidence interval and a 5% margin of error:

$$N = (Z^2 p(1-p))/d^2 \tag{1}$$

where N is the number of samples, Z is the confidence interval, p is the percentage of the class area, and d is the margin of error. Table 1 shows the number of samples needed for each class considered in the analysis per collection.

Table 2 - Number of samples per collection.

Classe	Nome	3.1	4.1	5.0	6.0	7.0
3	Formação Florestal	173	173	174	166	164
9	Floresta Plantada	35	45	42	35	36
15	Pastagem	162	211	181	162	164
20	Cana de Açúcar	188	200	201	190	188
24	Infraestrutura Urbana	25	29	31	35	31
33	Rio, Lago e Oceano	24	24	25	25	26
		608	**682**	**654**	**613**	**609**
			Total: 3166			

Source: Prepared by the authors (2022).

The response design, which is the protocol used to associate the reference class with each sampling unit, consisted of considering as the reference sample class the one that predominated in the buffer with a radius of 10 meters around each point (Fig. 4). The size of this buffer was chosen to fit into the minimum classified unit (one pixel) and at the same time reduce any errors in the visual determination of the class resulting from differences in registration between the map and the reference sample. The determination of the reference class per point was based on the visual interpretation of up to four different images or maps, including Google Satellite, Yandex, ESRI, and the Canasat project (CANASAT, 2013).

When comparing the base maps with the Google Earth Pro (GEP) time-lapse function, it was observed that they were from different dates: the Yandex with older dates, mostly in 2016, and the more up-to-date Google Satellite, mainly from 2023. To improve the distinction of the perennial sugarcane crop, which in these images can be confused with other categories such as pasture (after the sugarcane harvest) or planted vegetation (when it is in its high and dense growth stage), the 2013 map for the state of São Paulo from the Canasat Project was used. The global, producer (AP, or 100% - Error of omission) and user (AU, or

100% - Error of commission) accuracies were calculated for each class in each collection.

Figure 4 - Examples of samples for validation by class and by collection. Background image from Google Satellite. a) Forest Formation (3.1); b) Planted Forest (4.1); c) Pasture (5.0); d) Sugar Cane (6.0); e) Urban Infrastructure (7.0); f)Rivers, Lakes and Oceans (7.0).

Source: Prepared by the authors (2023).

3. RESULTS AND DISCUSSION

The global accuracy of a map represents the proportion of correctness of that map relative to a reference sample of lower uncertainty (Stehman, Foody 2019). Considering the seven MapBiomas categories evaluated here, which together make up 69.29% of the São Paulo area mapped in collection 7.0, there was a decline in global accuracy from collections 3.1 (92%) to 4.1 (91%), followed by a gradual rise to collection 7.0 (96%) (Tables 3-7). This indicates that the average quality of MapBiomas for the state of São Paulo has

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improved over the collections.

Table 3 - Confusion matrix - collection 3.1. FF = Forest Formation; FP = Planted Forest; PA = Pasture; CA = Sugar Cane; IU = Urban Infrastructure; RLO = Rivers, Lakes, and Oceans; 34 = error Class; AU = User Accuracy and AP= Producer Accuracy.

		MapBiomas 3.1								
		FF	**FP**	**PA**	**CA**	**IU**	**RLO**	**34**	**Total**	**UA**
Base Map	**FF**	154	1	2	0	0	0	0	157	0,98
	FP	8	32	0	0	0	0	0	40	0,80
	PA	8	1	147	7	0	0	0	163	0,90
	CA	0	0	10	177	0	0	0	187	0,95
	IU	0	0	1	0	25	0	0	26	0,96
	RL0	3	0	0	0	0	24	0	27	0,89
	34	0	1	2	4	0	0	0	7	
	Total	173	35	162	188	25	24	0		
	PA	0,89	0,91	0,91	0,94	1	1			**92%**

Source: Prepared by the authors (2022).

Table 4 - Confusion matrix - collection 4.1. FF = Forest Formation; FP = Planted Forest; PA = Pasture; CA = Sugar Cane; IU = Urban Infrastructure; RLO = Rivers, Lakes, and Oceans; 34 = error Class; AU = User Accuracy and AP= Producer Accuracy.

		MapBiomas 5.0								
		FF	**FP**	**PA**	**CA**	**IU**	**RLO**	**34**	**Total**	**UA**
Base Map	**FF**	157	3	8	2	0	0	0	170	0,92
	FP	13	38	6	0	0	0	0	57	0,67
	PA	2	2	182	8	1	0	0	195	0,93
	CA	0	1	10	189	0	0	0	200	0,95
	IU	0	0	1	0	28	0	0	29	0,97
	RLO	1	1	4	1	0	24	0	31	0,77
	34	0	0	0	0	0	0	0	0	
	Total	173	45	211	200	29	24	0		
	PA	0,91	0,84	0,86	0,97	0,97	1	0		**91%**

Source: Prepared by the authors (2022).

Table 5 - Confusion matrix - collection 5.0. FF = Forest Formation; FP = Planted Forest; PA = Pasture; CA = Sugar Cane; IU = Urban Infrastructure; RLO = Rivers, Lakes, and Oceans; 34 = error Class; AU = User Accuracy and AP= Producer Accuracy.

		MapBiomas 5.0								
		FF	**FP**	**PA**	**CA**	**IU**	**RLO**	**34**	**Total**	**UA**
Mapa Base	**FF**	161	1	5	1	2	1	0	171	0,94
	FP	9	37	1	0	0	0	0	47	0,79
	PA	1	3	156	6	1	0	0	167	0,93
	CA	1	1	12	193	0	0	0	207	0,93
	IU	0	0	1	0	28	0	0	29	0,97
	RLO	1	0	1	0	0	24	0	26	0,92
	34	1	0	5	1	0	0	0	7	
	Total	174	42	181	201	31	25	0		
	PA	0,93	0,88	0,86	0,96	0,90	0,96	0		**92%**

Source: Prepared by the authors (2022).

Table 6 - Confusion matrix - collection 6.0. FF = Forest Formation; FP = Planted Forest; PA = Pasture; CA = Sugar Cane; IU = Urban Infrastructure; RLO = Rivers, Lakes, and Oceans; 34 = error Class; AU = User Accuracy and AP= Producer Accuracy.

		MapBiomas 6.0								
		FF	**FP**	**PA**	**CA**	**IU**	**RLO**	**34**	**Total**	**UA**
	FF	155	2	2	1	1	0	0	161	0,96
	FP	6	33	0	1	0	0	0	40	0,83
	PA	5	0	149	4	0	0	0	158	0,94
Base Map	**CA**	0	0	9	184	0	0	0	193	0,95
	IU	0	0	0	0	34	0	0	34	1
	RLO	0	0	0	0	0	25	0	25	1
	34	0	0	2	0	0	0	0	2	
	Total	166	35	162	190	35	25	0		
	PA	0,93	0,94	0,92	0,97	0,97	1,00	0		**95%**

Source: Prepared by the authors (2022).

Table 7 - Confusion matrix - collection 7.0. FF = Forest Formation; FP = Planted Forest; PA = Pasture; CA = Sugar Cane; IU = Urban Infrastructure; RLO = Rivers, Lakes, and Oceans; 34 = error Class; AU = User Accuracy and AP= Producer Accuracy.

		MapBiomas 7.0								
		FF	**FP**	**PA**	**CA**	**IU**	**RLO**	**34**	**Total**	**UA**
	FF	157	3	1	0	2	0	0	163	0,96
	FP	6	32	0	0	0	0	0	38	0,84
	PA	0	0	155	2	1	0	0	158	0,98
Base Map	**CA**	0	0	5	185	0	0	0	190	0,97
	IU	0	0	1	0	27	0	0	28	0,96
	RLO	0	0	0	0	1	26	0	27	0,96
	34	1	1	2	1	0	0	0	5	
	Total	164	36	164	188	31	26	0		
	PA	0,96	0,89	0,95	0,98	0,87	1,00	0		**96%**

Source: Prepared by the authors (2022).

However, when a map is used in practice, it is expected to be interested in specific categories, whose accuracy also needs to be known. Producer accuracy (PA), which tells you the fraction of reference pixels in a given category that have been correctly mapped, increased progressively up to collection 7. The exceptions were the Grassland (15) class, with the lowest accuracy in collection 4.1 and the highest accuracy in collection 6.0, and Forestry, which peaked in collection 6. Each collection improved the Forest Formation (30) and Sugar Cane (20) classes. On the other hand, Urban Infrastructure (24) worsened consistently from collection 3.1 to 7.0.

The primary sources of confusion were between Forest Formation, Planted Forest, and Pasture and Sugar Cane. In the first case, the confusion derived from the predominance of tree vegetation in both classes, differentiated predominantly by the more excellent shading of the Forest Formation derived from the more significant irregularity of the canopy. The confusion between pasture and sugar cane was mainly due to the fact that both are dominated by shrubby vegetation and are quite similar when the cane is still young, as well as the fact that sugar cane is a perennial crop which, after harvest, is spectrally similar to pasture.

User accuracy, which indicates the probability that a pixel classified within a certain class belongs to that class in the field, for Forest Formation (3) was highest in collection 3.1 (98%), lowest in collection 4.1 (92%), and gradually improved until collection 7.0 (0.96). The Pasture class (15) showed an increase in accuracy over the collections, while Planted Forest (9) had a considerable drop in collection 4.1 (67%) and reached its maximum value (87%) in collection 7. Sugarcane had the worst result in collection 5 (93%), while Urban Infrastructure (24) and Rivers, Lakes and Oceans (33) obtained maximum accuracy (100%) in collection 6.0.

In short, analyzing the five collections' global, producer, and user accuracies indicated improved mapping quality for most of the classes analyzed. The only exception was Urban Infrastructure, which reached the lowest AP and AU values in the 7.0 collection (0.87 and 0.96, respectively). This slight worsening in the accuracy of the Urban Infrastructure classification is related to at least two factors: i) the greater diversity of materials present in urban areas (e.g., concrete, clay tiles, tree vegetation, and undergrowth), some of which are present in the other mapped categories and are therefore likely to be confused by the classifier (e.g. exposed soil and clay roofing), and ii) the faster rate of change in target compositions over time, such as the paving of streets that were previously dirt. This variability of targets in the urban area often leads to mapping confusion with non-urban classes, such as agricultural fields (GUINDON et al., 2004).

When MapBiomas was compared to the other main land cover mapping of São Paulo, carried out by the São Paulo State Department of Infrastructure and Environment (SIMA-SP) using Landsat 5 images from 2010, four classes coincided. The accuracy of the SIMA-SP map was estimated using a reference sample of 100 points per class (a total of seven classes and 700 points), with an overall accuracy of 97.14% and several hits per class of over 90% (SÃO PAULO, 2013). These results are comparable to those obtained for the latest MapBiomas collection regarding overall accuracy and by class considered here. No other mapping subjected to a systematic accuracy assessment was found to compare the results.

4. FINAL CONSIDERATIONS

This study presents the first systematic assessment of accuracy and its evolution over the MapBiomas collections at the state level. The results showed that collections 4.1 to 7.0 had global accuracy values of over 90%, demonstrating good mapping quality for the state of São Paulo since the start of the project. Notably, collection 7.0 obtained the best performance compared to the values calculated for Brazil, suggesting a gradual improvement of the MapBiomas classification algorithm for the São Paulo landscape. However, when we look specifically at urban infrastructure, for example, to estimate the expansion of these areas, the results indicate that MapBiomas' accuracy is gradually worsening. When considering the coverages present in rural areas, the fact that the PA and AU of the 7.0 collection are all above 0.84 indicates that MapBiomas is accurate enough for, for example, many standard landscape-scale analyses in ecology (e.g., modeling the distribution of mammal or bird species), agriculture (e.g., crop estimation) or engineering (e.g., airport site selection). We hope that the quantification of accuracy presented here will contribute to the evolution of this important mapping project and provide a baseline of accuracy for MapBiomas-based research in the state of São Paulo.

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Authors' Contribution

Nadinne Fernandes de Oliveira: Formal analysis; Acquisition of funding; Investigation; Methodology; Project management; Resources; Software; Validation; Visualization and Drafting -initial draft. Eduardo Moraes Arraut: Conceptualization; Supervision and Writing -revision and editing.

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Conflicts of Interest

The authors declare that there is no conflict of interest.

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