

Article

Analysis of a Landscape Intensely Modified by Agriculture in the Tietê–Jacaré Watershed, Brazil

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Citation: Peruchi Trevisan, D.; Bispo, P.C.; Gou, Y.; Souza, B.F.; Liesenberg, V.; Harris, A.; Balzter, H.; Moschini, L.E. Analysis of a Landscape Intensely Modified by Agriculture in the Tietê–Jacaré Watershed, Brazil. *Sustainability* **2021**, *13*, 9304. <https://doi.org/10.3390/su13169304>

Academic Editor: Ivo Machar

Received: 8 July 2021

Accepted: 4 August 2021

Published: 19 August 2021

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Abstract: Anthropogenic actions influence landscapes, and the resulting mosaic is a mix of natural and anthropogenic elements that vary in size, shape, and pattern. Considering this, our study aimed to analyse the land use and land cover changes in the Tietê–Jacaré watershed (São Paulo state, Brazil), using the random forest (RF) algorithm and Sentinel-2 satellite data from 2016 to 2018 to detect landscape changes. By overlapping the environmental data and the proposed model evaluation, it was possible to observe the landscape structure, produce information about the state of this region, and assess the environmental responses to anthropic impacts. The land use and land cover analysis identified eight classes: exposed soil, citriculture, pasture, silviculture, sugar cane, urban area, vegetation, and water. The RF classification for the three years reached high accuracy with a kappa index of 0.87 in 2016, 0.85 in 2017, and 0.85 in 2018. The model developed was essential for the temporal analysis since it allowed us to comprehend the driving forces that act in this landscape and contribute to the discussions about their impacts over time. The results showed a predominance of agricultural activities over the three years, with approximately 900.000 ha (76% of the area), mainly covered by sugarcane cultivation.

Keywords: watershed management; landscape analysis; environmental planning; land use; land cover

1. Introduction

The changes and disturbances in the landscapes of Brazil have increased in the last two decades due to economic progress and modifications in environmental laws, such as the Brazilian Forest Code [1]. Such changes reduced the restrictions on environmental preservation and legalized the areas that were already deforested and destined for agricultural production. Additionally, new urban settlements, pasture, and agricultural regions brought some additional pressure to forest remnants. Consequently, deforestation and degradation have been observed, resulting in a substantial loss of biodiversity and impacts on climate change [2].

After the Amazon biome, the Brazilian Savanna (*Cerrado*) and the Atlantic Forest are the regions that endure the most anthropic impacts in Brazil. The *Cerrado* is the second largest biome in South America, covering about 22% of the national territory (2,036,448 km²). On the other hand, only 12.4% of the original Atlantic Forest remains, cover 15% of the

national territory. Interestingly, it contains 72% of the Brazilian population and 70% of the national gross domestic product (GDP) [1,2].

The landscapes are usually studied as spatial units whose heterogeneity is mainly modified by the interaction between nature and society. Thus, it is characterized by the connection or fragmentation among its different elements. Nevertheless, anthropic actions can affect and modify most landscapes, causing impacts such as deforestation, fragmentation, and loss of biodiversity. The resulting mosaic is a blend of natural and anthropogenic features that differ in size, shape, and structure [3–6].

Planning and decision-making involve choosing a course of action among several alternatives. They are based on the quantification of environmental conditions, such as land use and land cover, conservation status, and resilience of the landscape [7,8]. More recently, landscape indicators have been used to provide insights into conservation practices. The demand for results on small timescales has led scientists to search for measures calculated based on accessible indicators in order to serve as a basis for decision-making, meanwhile trying to encompass some of the most important ecosystems on Earth [7,8].

Authors such as Turner [9], O'Neill et al. [10], Gustafsson and Parker [11], McGarigal and Marks [12], Schumaker [13], Moretti [14], and Trevisan et al. [15] studied and developed a variety of indices and descriptive measures to analyse spatial landscape patterns. Thus, modelling is considered to be an established method for obtaining information and generating hypotheses in landscape ecology and population issues [9–15].

From this perspective, geographical information systems (GIS) and remote sensing have facilitated the characterization process of diagnostic analyses and activities. Additionally, they help simulate geographic space and natural processes, besides integrating spatial information [16]. The efficiency of satellite imagery for monitoring land use and land cover changes and the consequent impact of anthropic activities on the environment contribute to governmental planning and action regarding the conservation of natural ecosystems [17].

An example is the work developed by Menezes and Salgado [18], whose objective was to identify the land use and the landscape configuration of the Ceroula Environmental Protection Area in the Angico Sub-basin, MS, Brazil. In such study, remote sensing imagery and field measurements were integrated into a GIS. The ground measurements, digital image processing, and geoprocessing techniques used revealed that the area is predominantly used for agriculture. However, the authors also reported that several areas are degraded and deforested.

Aiming to monitor land use and land cover, as well as other environmental applications, the European Space Agency (ESA) created in 2012 the Copernicus Program, an European system coordinated and managed by the European Commission for monitoring the Earth. In this context, the ESA has been currently developing a new family of missions called Sentinels, designed specifically to meet the Copernicus program's operational needs. Each Sentinel mission is based on two satellite constellations to fulfil the coverage requirements, providing robust datasets for Copernicus Services [19].

The Sentinel-2 mission captures optical images at a high spatial resolution (from 10 m to 60 m) over both land and coastal waters. Twin satellites, the Sentinel-2A and the Sentinel-2B, support a range of applications and services, such as Earth monitoring and observation applications [19].

In this setting, the watershed analysis approach is of fundamental importance for being the central unit of the landscape. Additionally, water management is more efficient when a watershed is considered. In this sense, policy initiatives and the monitoring of environmental resources are also feasible for managers and decision-makers, assuring biodiversity maintenance. Forest coverage is usually restricted to small and fragmented forest remnants where several species are still found. However, these endemic species are facing a high degree of environmental degradation. Myers identified this issue in 1988 as biodiversity hotspots, whose regions have a more urgent need of conservation actions and the constant monitoring of anthropic impacts [8,20].

Particularly in Brazil, river basin committees were established to manage regional planning in several watersheds. They contribute to the environmental and socio-economic management plan of the watersheds and define sustainable water usage and policy rules. Interestingly, planning is predominantly done locally, that is, despite following both the state and federal legislation each municipality or county acts locally. Nonetheless, this organization is insufficient to solve and cover all the regional administrative obstacles in many cases, especially when the focus of the management is on the conservation and preservation of natural resources [21].

In the Tietê–Jacaré Watershed, an intense modification and an increase in agricultural activities have been identified over the past 30 years, which occur without environmental planning. Therefore, further studies are still necessary to understand the impacts of anthropic activities on a watershed scale and how they modify the landscape structure [22–24]. This concept is also important when facing pressure from society and the financial sector that aims at sustainability over economic growth.

In this context, it is highly essential to conduct studies on the most efficient methods to accelerate analyses that evidence the loss of natural areas and environmental quality in the Brazilian and international contexts. To handle the large amount of data from optical imagery, machine learning such as the random forest (RF) approach is suggested for environmental studies at the watershed scale [25,26], as it is able to deal with many datasets [24–26]. This study aimed to analyse the land use and land cover changes in the Tietê–Jacaré Watershed (São Paulo state, Brazil) using the RF algorithm and Sentinel-2 satellite data from 2016 to 2018 to detect landscape changes.

2. Materials and Methods

2.1. Study Area

The water resources management in São Paulo state is carried out through the Water Resources Management Units (WRMU), instituted by State Laws No. 7.663 of 30/12/1991 and No. 9.934 of 27/12/1994 [27,28]. The state currently has twenty-two WRMUs delimited by river basins, which encompass the water resources that converge into the mainstream, justifying the need for a link between research and management [29]. Figure 1 represents the Tietê–Jacaré Watershed, located in São Paulo state, Brazil, between 49°14' and 47°70' West and 21°62' and 22°79' South.

The region is divided into 37 municipalities, with 1,500,000 inhabitants and a total area of 1,181,090 hectares. The Tietê–Jacaré Watershed has a drainage area of 8669.09 km and contains three main rivers: the Tietê River, the Jacaré–Guaçu River, and the Jacaré–Pepira River. According to Köppen–Geiger classification, the climate of this region is between humid tropical (Aw—from October to March) and dry winter (Cfa—from April to September) [30,31].

The Tietê–Jacaré Watershed region is located in both the Atlantic Forest (23%) and Brazilian Savanna (*Cerrado*) (77%) biomes, considered biodiversity hotspots. These regions remain important fragments that preserve an endemic fauna and flora surrounded by an agricultural matrix, where the leading economy is related to agroindustry (sugar, alcohol, citrus, and cellulose) [30,31].

The watershed territory and boundaries have had an industrial and agricultural outline since the 18th century. During this period, coffee and sugar production and cattle were the three main economic activities in São Paulo state. However, in the 19th century, coffee production increased and became the primary income source for the state and the country [32,33]. In addition, the region experienced a development process in this period due to the construction and opening of railroads, which were the main factor of the urban network, attracting the growth of cities near the stations [33,34].

The first three decades of the 20th century experienced overproduction crises, primarily attributed to the decrease in external demand because of the economic crisis of 1929. In response to the coffee market crisis, there was an intensification in the production of food crops, livestock, cotton, and sugar cane in Brazil. Between 1931 and 1945, sugarcane

production increased by 570%, consolidating São Paulo state as the largest producer in Brazil [32,33]. This remains the case into modern times, further potentialized by ethanol production from sugarcane since 1970.

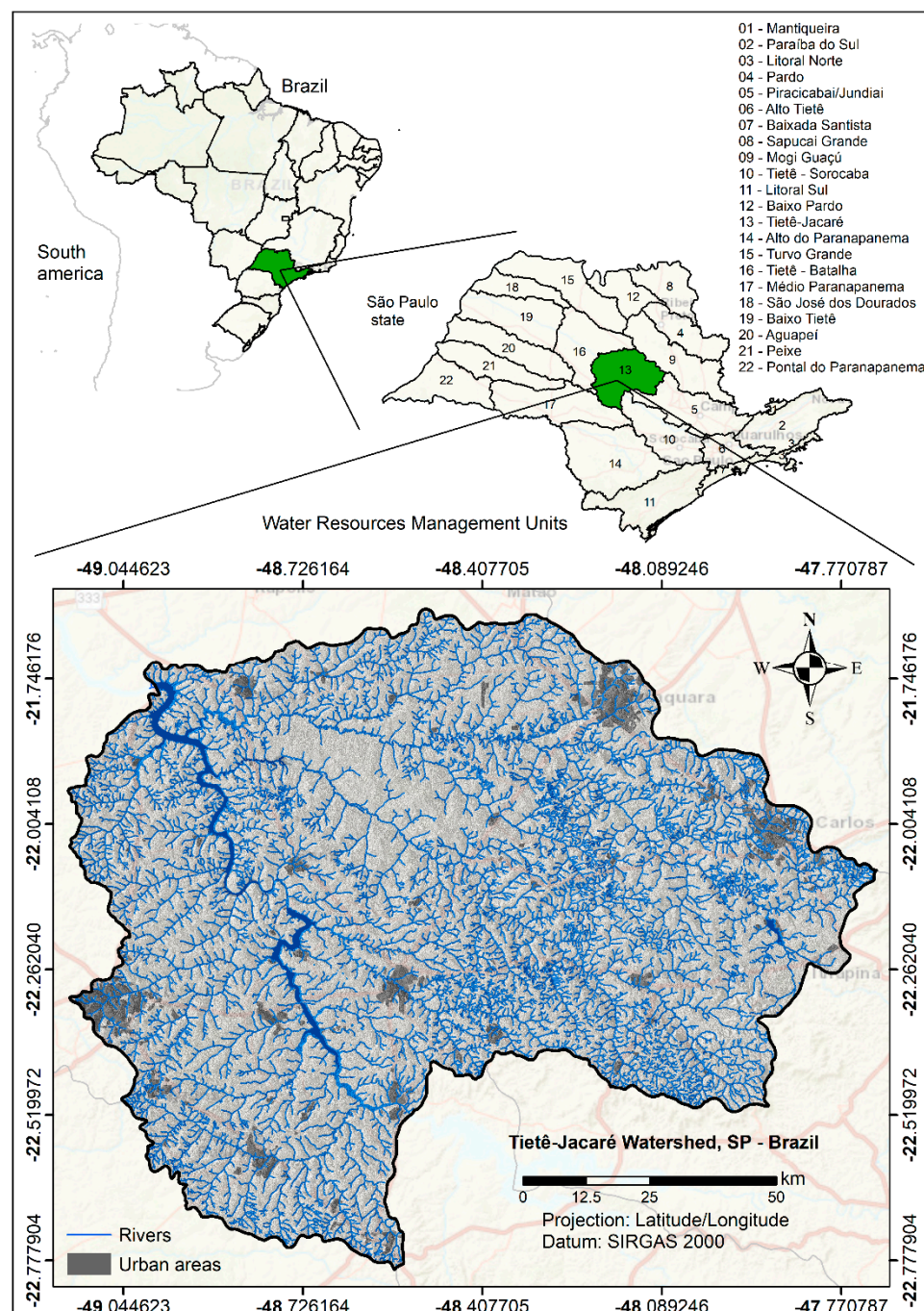


Figure 1. Tietê-Jacaré Watershed-SP study site.

Between the 1960s and 1970s, a reasonable number of health and education infrastructures, including hospitals and higher education schools, were developed. Other agro-industrial segments expanded in this period, such as vegetable oils, soy, meat, milk products, and citrus juice [32,33]. The modernization of agricultural activities and the regional road and water network influenced the growth of agro-industrial facilities and industries producing chemical inputs, farming implements, and equipment for plants and distilleries,

which contributed to the expansion process of this region, mainly between the 1980s and the 1990s [30,33].

The drainage network was, and continues to be, vital for the occupation, management, and development of the region. Through the Tietê–Paraná Waterway, various products, such as construction materials, limestone, bran, soybeans, sugar cane, grains, wood, and fertilizers, are transported over an expanse of 1000 km. Currently, the Tietê–Jacaré Watershed region presents a diversified economy, with sectors focused on drinks, paper, mechanical metal, and tourism, while also emphasizing the alcohol and sugar complex and the planting and processing of citrus fruits [34,35].

The Tietê–Jacaré watershed has consolidated development characteristics and encompasses municipalities with high urbanization, industrial, and agricultural potential inserted into a sensitive natural ecosystem transition region (the Atlantic Forest and the *Cerrado*). For this reason, it is very important to monitor and analyse the impact of changes in the land use and land cover in this region, as well as the interrelationships between anthropic development and natural ecosystems. This type of analysis allows us to understand how these relationships can influence the strategies adopted for the conservation of the natural landscape.

2.2. Methodology

The methodological approaches involved the use of the region's environmental database [36], land use and land cover from Sentinel 2 satellite images, and the application of the change detection analysis with random forest techniques. First, the Tietê–Jacaré Watershed data were obtained from the Brazilian Institute of Geography and Statistics (IBGE) digital grid, version 2015 [36]. Then, the information was analysed in the geographic information systems ArcGIS® 10.5 and Datum SIRGAS2000 (for the geographic projection latitude/longitude). Finally, the Sentinel-2 remote sensing dataset was processed in SNAP v 6.0 (Sentinel Application Platform) [37] in four stages (Figure 2).

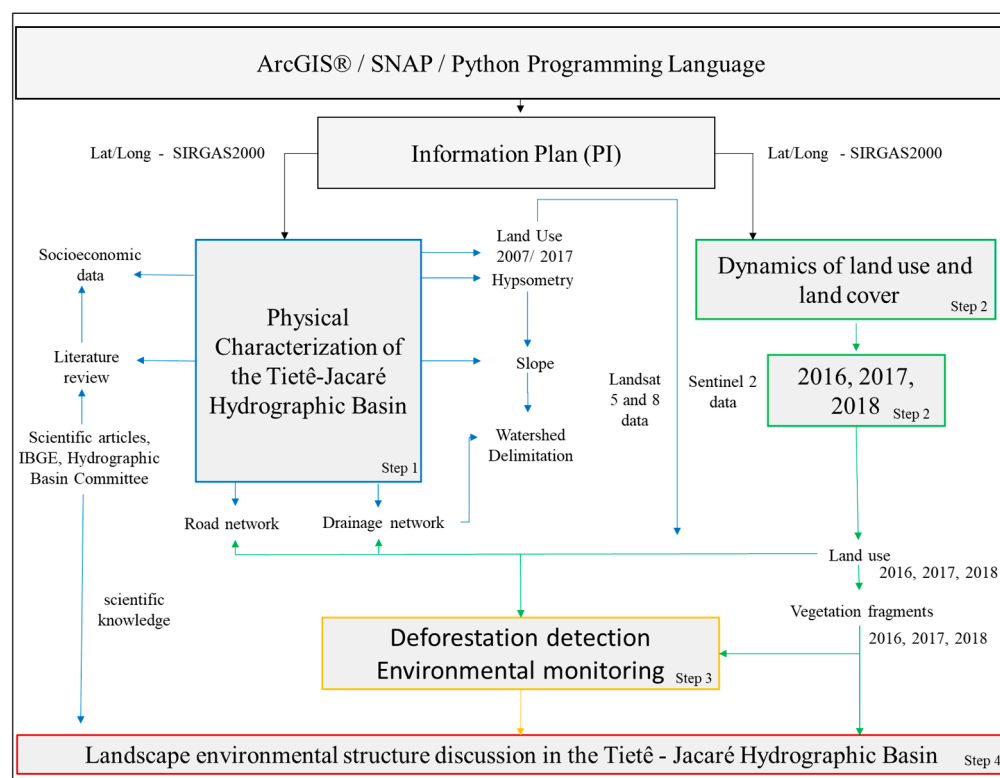


Figure 2. Flowchart of the methodology.

We digitized the land use and land cover using the on-screen visual technique, and the classification was based on the multi-level classification system proposed by the Technical Manual of Land Use from the Brazilian Institute of Geography and Statistics [38], which considers four classes indicating the main land use category, followed by the type of land uses that were included and the explanation of the land uses themselves (Table 1).

Table 1. Description of land use and land cover classes and categories.

| Class (I) | Type (II) | Description (III) |
|--------------------------------|--------------------------|--|
| Anthropic and non-agricultural | Urban and suburban areas | Urban areas and areas with rural developments (industrial and household) |
| | Sugar cane | Cultivation of <i>Saccharum officinarum</i> L. |
| Anthropic-agricultural | Citriculture | Cultivation of <i>Citrus sinensis</i> |
| | Pastures | Predominance of herbaceous vegetation (native or exotic), used for extensive livestock farming |
| | Silviculture | Cultivation of <i>Eucalyptus</i> spp. or <i>Pinus</i> spp. |
| | Exposed soil | Soil fallow area for cultivation of <i>Saccharum officinarum</i> L. |
| Forest cover | Vegetation | Predominance of shrub or tree vegetation (semi-deciduous forest and <i>Cerrado</i>) |
| Water resources | Water | Rivers, lakes, ponds, and reservoirs |

2.2.1. Random Forest Approach Applied in Sentinel-2 Images

A random forest (RF) machine learning algorithm was used to generate land use and land cover maps of the study site from imagery acquired between 2016 and 2018. RF is an ensemble method and a non-parametric, supervised classifier that has been used in the last two decades in the field of remote sensing due to its high performance when dealing with a large amount of data from different sources (active or passive sensors). It is also a strong technique applicable to regression and classification problems that can be used when the response variable is quantitative or qualitative [39,40].

In the RF method, no assumptions of normality are needed, since the algorithm can deal with highly correlated variables and is relatively insensitive to overfitting [39,40]. Due to these attributes, this technique has become heavily used for Earth observation analyses in as much as the datasets are rarely customarily distributed and unimodal.

According to Persson [41], the RF classifier is built by training an ensemble of decision trees with samples drawn with replacement from the original dataset (bagging, for example). He states that individual decision trees in the ensemble are formed by the stratification of the feature space into regions by applying splitting questions on each node's samples. This means that the model creates an entire forest of random, uncorrelated decision trees to find the best possible answer [41,42].

Figure 3 shows the architecture of the random forest model [43,44] and the scheme to determine the class of land use and land cover in our study, where the RF method is employed to combine the results of several decision trees by utilizing a voting mechanism. At the end of the process, each tree gives a rating or a vote for a class. Herein, the final classification of each class received the highest number of options among all trees in the forest [40,42].

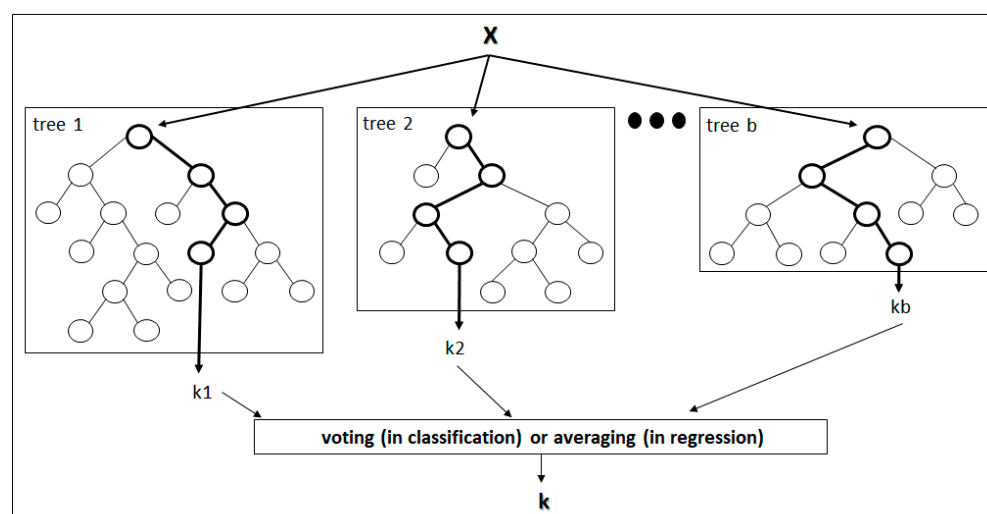


Figure 3. Architecture of the random forest model.

In our study, we used Sentinel-2 L1C images. They were atmospherically corrected to L2A in SNAP 6.0 software using the Sen2Cor (Optical Tools for Sentinel 2), and then pre-processed. The classification of land use and land cover used a machine learning RF algorithm for the years 2016, 2017, and 2018. The following Python libraries were used: NumPy; OSGeo; joblib; Gdal; pandas; sklearn.ensemble; difflib; ogr; and difflib [43].

A total of 1600 training areas containing an average size of 1.36 ha were randomly selected in ArcGIS. The areas were labelled as exposed soil, citriculture, pasture, silviculture, sugar cane, urban area, vegetation, and water. A total of 200 samples were adopted per class. Afterwards, the RF algorithm was applied using the Sentinel-2 processed images as input.

2.2.2. Change Detection—Land Use Monitoring of the Tietê–Jacaré Watershed

The land use and land cover monitoring, including the *Cerrado* and Atlantic Forest areas in the Tietê–Jacaré Watershed, were carried out using the random forest technique for the Sentinel-2 (S2) processing chains (Figure 4), which worked in parallel with the ArcGIS® and SNAP software and the Python programming language, version 3.6.

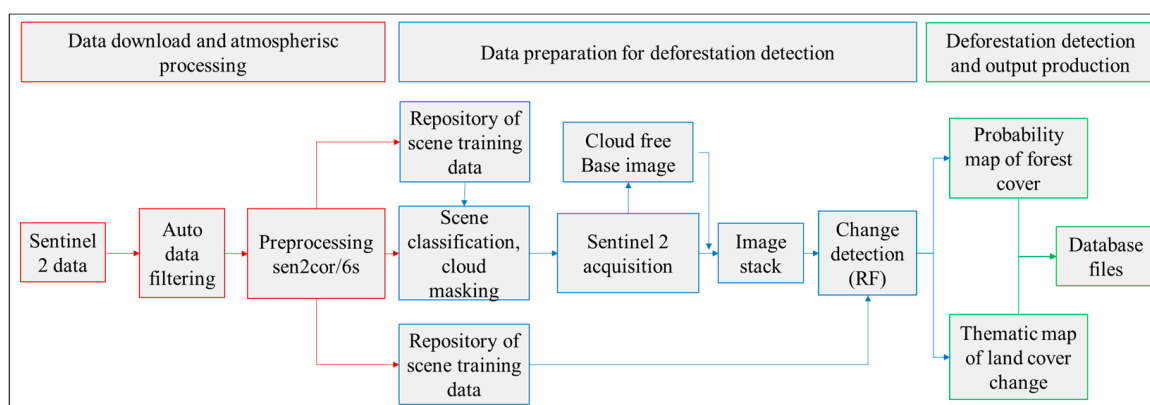


Figure 4. Sentinel-2 detection processing chains.

The Sentinel-2 MSI sensor, bands 8/4/3/2 and points/orbits T22KGB, T22KFA, T22KGA, T22KHA and T22KGV (Table 2) were used to analyse the temporal dynamics of land use and land cover for 2016, 2017 and 2018 in the Tietê–Jacaré Watershed. The Sentinel-2 images were acquired from September 2016, July 2017, and August 2018 [37].

Table 2. Sentinel-2 images information.

| Acquisition Date (Month/Year) | Points Orbits | Cloudy Pixels % | Granule ID | Spatial Resolution |
|----------------------------------|---------------|-----------------|---------------------|--------------------|
| 09/2018 | T22KGB | 0% | S2A_MSIL2A_20180917 | 10 m |
| 08/2018 | T22KFA | 0% | S2A_MSIL2A_20180828 | 10 m |
| 09/2018 | T22KGA | 0% | S2A_MSIL2A_20180917 | 10 m |
| 09/2018 | T22KHA | 0% | S2A_MSIL2A_20180917 | 10 m |
| 08/2018 | T22KGV | 0% | S2A_MSIL2A_20180828 | 10 m |
| 07/2017 | T22KGB | 0% | S2B_MSIL2A_20170729 | 10 m |
| 07/2017 | T22KFA | 0% | S2B_MSIL2A_20170729 | 10 m |
| 07/2017 | T22KGA | 0% | S2B_MSIL2A_20170729 | 10 m |
| 07/2017 | T22KHA | 0% | S2B_MSIL2A_20170729 | 10 m |
| 07/2017 | T22KGV | 0% | S2B_MSIL2A_20170729 | 10 m |
| 09/2016 | T22KGB | 0% | S2A_MSIL2A_20160917 | 10 m |
| 08/2016 | T22KFA | 0% | S2A_MSIL2A_20160828 | 10 m |
| 09/2016 | T22KGA | 0% | S2A_MSIL2A_20160917 | 10 m |
| 09/2016 | T22KHA | 0% | S2A_MSIL2A_20160917 | 10 m |
| 08/2016 | T22KGV | 0% | S2A_MSIL2A_20160828 | 10 m |

The use of different satellite scenes (S2A and S2B) occurred due to the limited availability of cloud-free images from a single satellite during the referred period. The three Sentinel-2 images datasets for this study had a spatial resolution of 10 m. The dates were selected according to the work schedule. The periods of July to September were chosen because of the seasonality of the region's agricultural practices. The difference of one year between the images allowed the study of the landscape's temporal patterns, essential for regional planning, which considered the present growth and development aspects.

For the random forest method already mentioned, we randomly created 1600 training areas (average size of 1.36 ha) in ArcGIS related to the exposed soil, citriculture, pasture, silviculture, sugar cane, urban area, vegetation, and water classes (200 samples per class).

2.2.3. Accuracy Assessment

The accuracy assessment was based on ≥ 1 year of change data to ensure a representative number of possible samples. The validation was done using 800 samples collected independently for each year analysed in this study (100 for each class), based on previous field visits [30–32] and the researcher's expertise. To evaluate how well the classifications were performed, we used a cross-validation method. The confusion matrix included overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), and the Kappa coefficient [44–47]. The confusion matrix [46,48–50] compares the relationship between reference data (ground truth) and the corresponding results of a class-by-class classification [47,50,51].

Finally, to improve the discussion on the classification, the results were compared to the land use and land cover data reported by Trevisan et al. [21], who used Landsat-8 images from 2017 to analyse the environmental landscape quality of the Tietê–Jacaré Watershed using ecological indices. The authors obtained a deep knowledge of the study site by doing fieldwork and visiting these sites constantly. It is essential to highlight here that the comparison between the classification by Trevisan et al. and our results was only visual, as the resolution of the images and the methodology used them were different from ours. The analyses conducted here were used only to reinforce and complement the discussion proposed in this study. Additionally, to make this comparison we overlapped our data with those obtained by Trevisan et al. in ArcGIS.

3. Results

The one-year interval showed a predominance of agricultural activities, with 900,000 ha (76%) in 2018 being classified as exposed soil, citriculture, pasture, silviculture, sugar cane, urban area, vegetation, and water (Figure 5 and Appendix A). In 2016, 900,885 ha was

occupied with agricultural activities (as opposed to 907,529 ha in 2017, and 894,719 ha in 2018), especially sugar cane (20%) activities, followed by exposed soil (22.62%), pasture (13.53), citriculture (13.58), and silviculture (5.83%) (Figure 6 and Table 3). The regions did not have significant changes during the analysed period; however, the small change observed could explain the consolidation state of the activities, as the regions in which agricultural activities occur are already predefined and delimited.

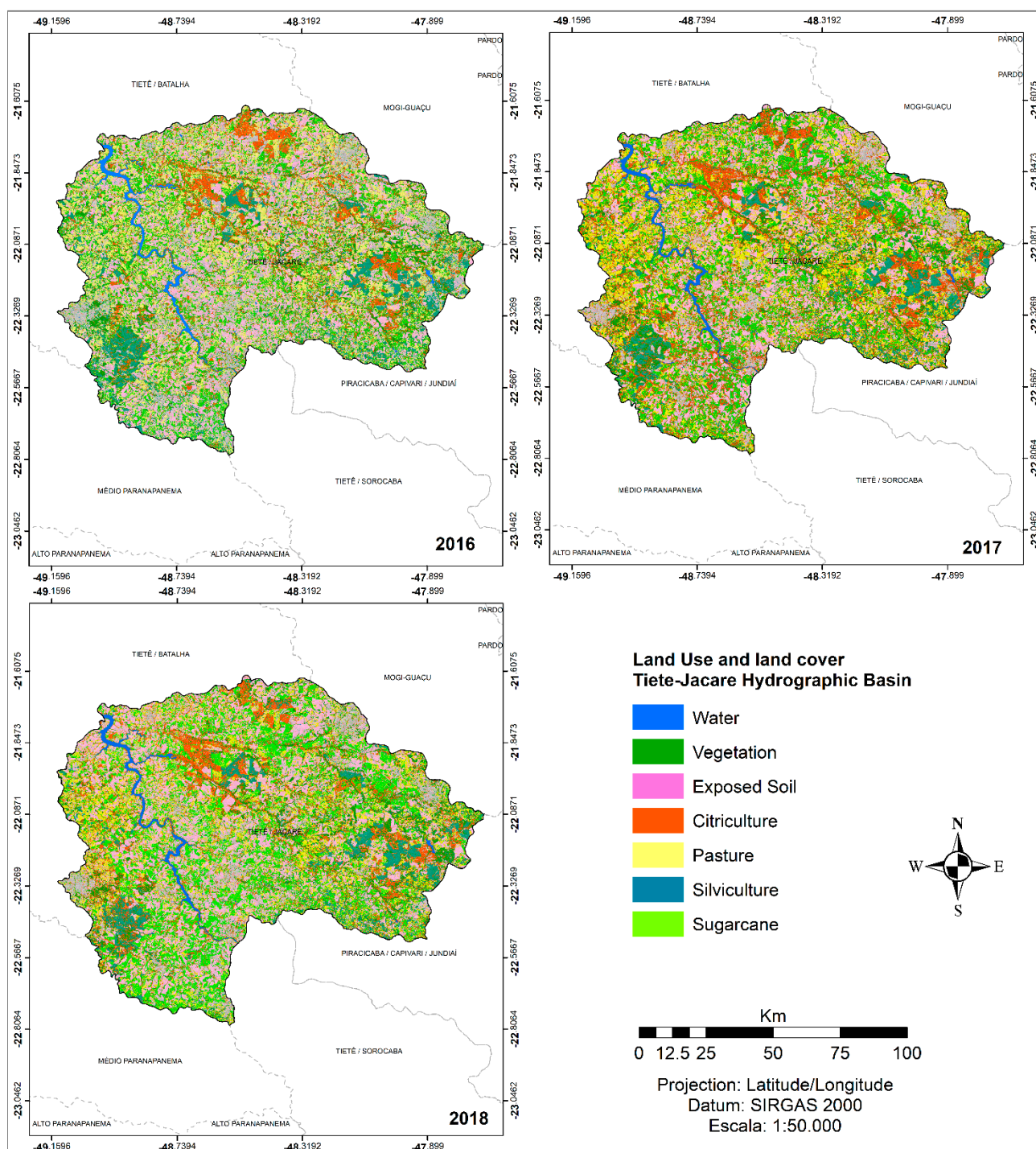


Figure 5. Land use and land cover of the Tietê–Jacaré Watershed between 2016 and 2018.

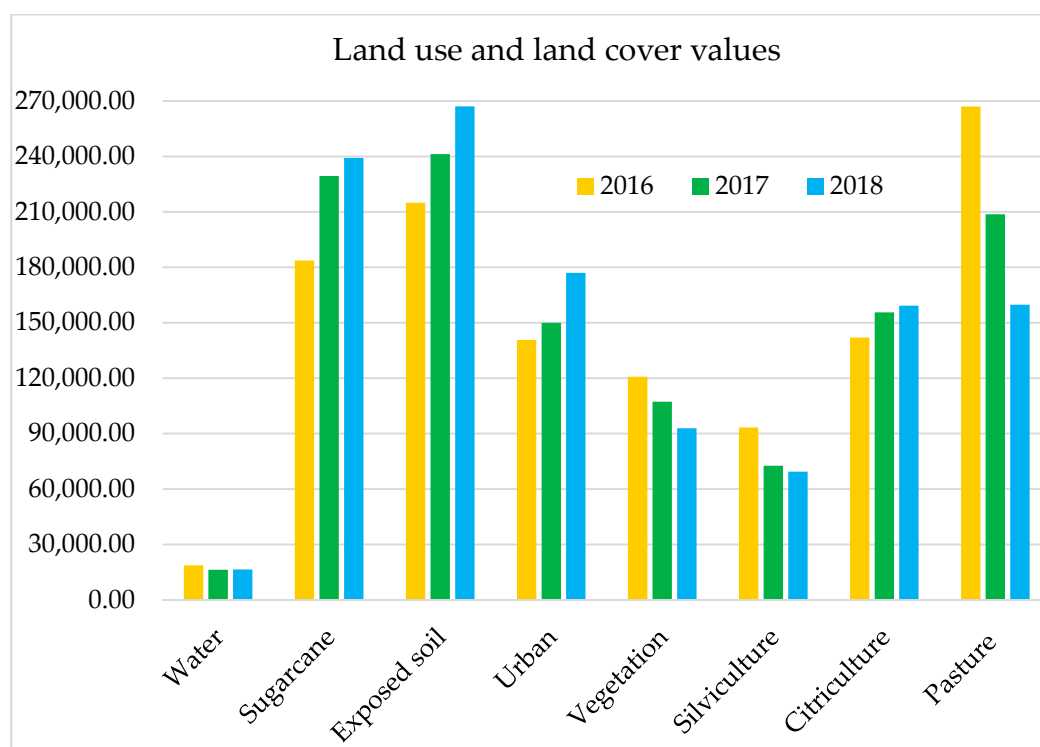


Figure 6. Land use and land cover of the Tietê-Jacaré Watershed between 2016 and 2018 (in hectares).

Table 3. Distribution of land use and land cover classes in the Tietê-Jacaré Watershed between 2016 and 2018.

| Class | Land Use in 2016 | | Land Use in 2017 | | Land Use in 2018 | |
|--------------|------------------|--------|------------------|--------|------------------|--------|
| | Area (ha) | % | Area (ha) | % | Area (ha) | % |
| Water | 18,756.00 | 1.59 | 16,325.19 | 1.38 | 16,443.45 | 1.39 |
| Sugar cane | 183,655.50 | 15.55 | 229,364.60 | 19.42 | 239,164.90 | 20.25 |
| Exposed soil | 214,901.40 | 18.0 | 241,243.10 | 20.43 | 267,116.60 | 22.62 |
| Urban area | 140,654.00 | 11.91 | 149,998.10 | 12.70 | 177,015.20 | 14.99 |
| Vegetation | 120,794.97 | 10.23 | 107,237.45 | 9.08 | 92,911.95 | 7.87 |
| Silviculture | 93,350.43 | 7.90 | 72,652.86 | 6.15 | 69,413.40 | 5.88 |
| Citriculture | 142,019.00 | 12.02 | 155,569.60 | 13.17 | 159,254.40 | 13.48 |
| Pasture | 266,958.70 | 22.60 | 208,699.10 | 17.67 | 159,770.10 | 13.53 |
| Total | 1,181,090.00 | 100.00 | 1,181,090.00 | 100.00 | 1,181,090.00 | 100.00 |

Because of the agricultural characteristics, in Brazil exposed soil areas are mainly associated with crops, as they refer to the fallow period and soil preparation for the next harvest. In the Tietê-Jacaré Watershed they follow the same traits, being these regions associated with sugar cane production. As the cattle economy decreased in the region over the past decades, pasture areas appear only in small territorial portions, becoming a subsistence or small-scale production activity.

The sugar cane areas are predominant in practically all municipalities of the watershed. However, in some regions other kinds of crops are prevalent, for example, citriculture and silviculture cultivations. The urban areas occupied 140,654 ha in 2016, 149,998.10 ha in 2017, and 177,015.20 ha in 2018, and this growth was more noticeable in medium to large municipalities, such as Bauru, Jaú, Araraquara, and São Carlos. Small municipalities such as Bocaina, Ibaté, and Itirapina retained their structures focused on activities related to the first and second sectors, with technical support from the larger municipalities.

The increase in the urban area reflects the urbanization process in the region, the state, and the country, which started in the 20th century as a result of the industrialization

process and was considered one of the main factors for the population's displacement from the rural to urban areas. This process also caused a change from an agrarian-exporting to urban-industrial model. Currently, more than 80% of the Brazilian population lives in urban areas, which is equivalent to the urbanization levels of developed countries. The vegetation areas occupied 120,795 ha in 2016, 107,237 ha in 2017, and 92,912 ha in 2018. These fragments are immersed in the agricultural matrix and are primarily associated with water bodies. This fact correlates with the reduction in the central water resources in the region, with a loss of 2431 ha. These natural fragments are located near the main rivers around the watershed: the Tietê–Jacaré River, in the Bariri, Itajú, Ibitinga, and Bocaina municipalities; the Jacaré–Guaçu River, in the São Carlos, Ribeirão Bonito, Ibaté, and Itirapina municipalities; the Jacaré–Pepira River, in the Dourado and Brotas municipalities; and the Jaú River, in the Jaú and Mineiros do Tietê municipalities.

Figure 7 shows the land use and land cover transitions of the watershed region, where it is possible to observe some changes in all regions, mainly related to the growth of agricultural activities. Only urban and water areas remained without modifications. Sugar cane was the most significant vector of change.

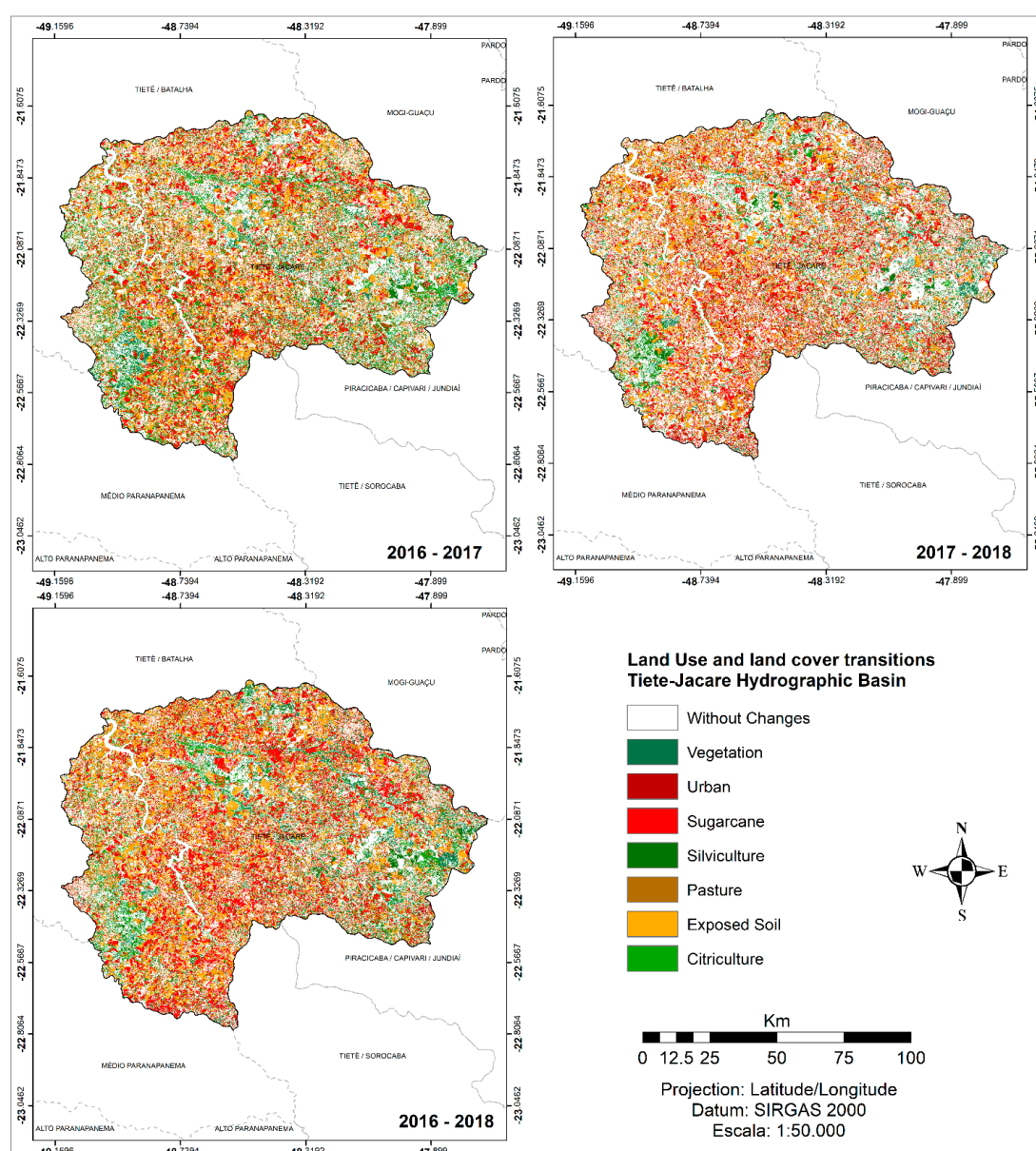


Figure 7. Land use and land cover transition areas in the Tietê–Jacaré Watershed between 2016 and 2018.

Figures 8 and 9 show the southeast of the watershed region. It is possible to note significant transitions that happen seasonally, e.g., the transition between exposed soil to sugar cane, as well as permanent changes, e.g., the transition between vegetation to other crops. In these scenarios, the crop area increase evident in all regions was found to replace some forest areas, even near the water streams. Such behaviour occurs in different locations within the selected watershed.

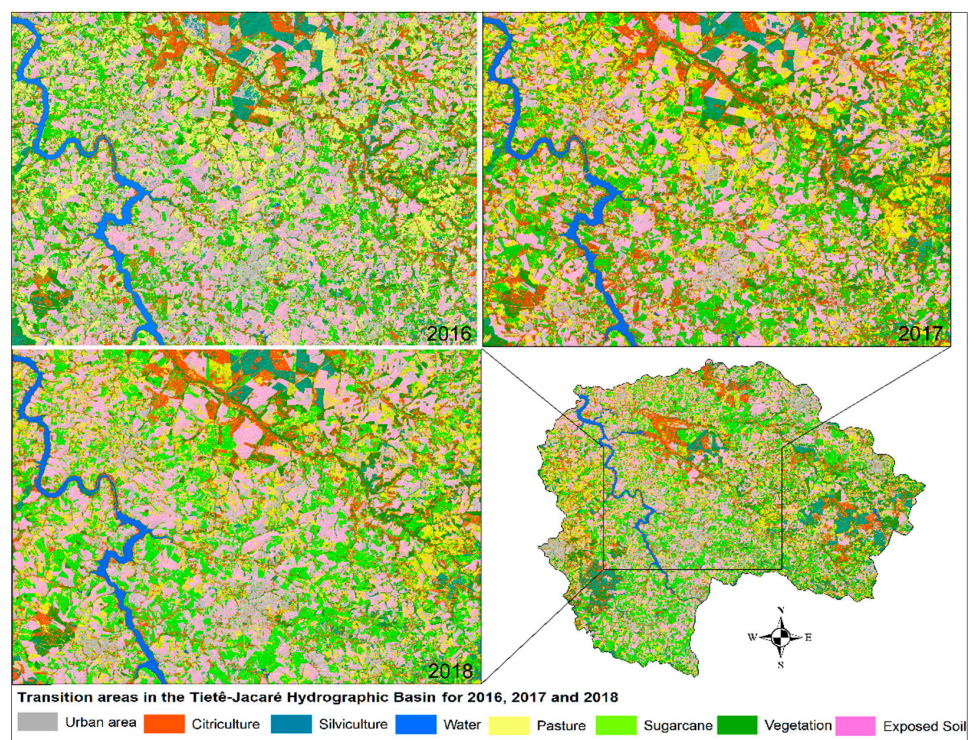


Figure 8. Transition areas in the Tietê–Jacaré Watershed between 2016 and 2018.

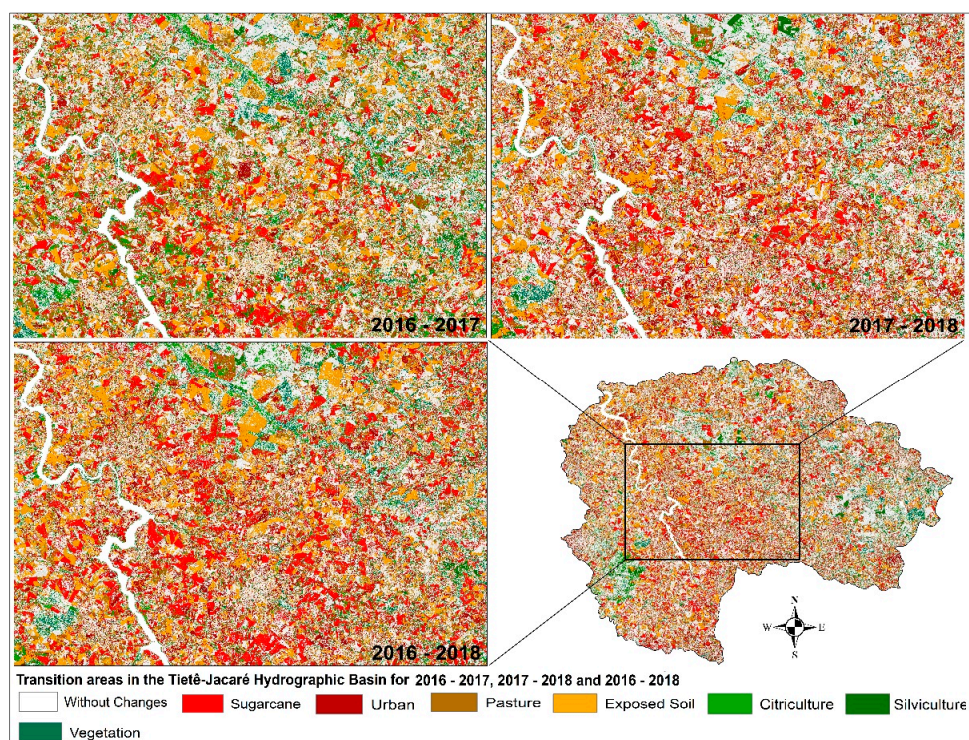


Figure 9. Transition areas in the Tietê–Jacaré Watershed between 2016 and 2018.

The validation was analysed and classified using the number of pixels found for each land use and land cover class in 2016, 2017, and 2018 (Tables 4–6 and Figure 10). The kappa index was classified between substantial agreement and almost perfect agreement, with a value of 0.876 in 2016, 0.854 in 2017, and 0.851 in 2018. The overall index reached a value of 0.90, 0.88 and 0.87 in 2016, 2017 and 2018, respectively. The producers' error index was 9.77 in 2016, 12.23 in 2017, and 12.51 in 2018.

Table 4. Number of pixels found for each class in 2016.

| Class (2016) | Water | Sugarcane | E. soil | Urban | Vegetation | Silviculture | Citriculture | Pasture | Total |
|--------------|--------|-----------|---------|-------|------------|--------------|--------------|---------|--------|
| Water | 37,110 | 8 | 0 | 3 | 0 | 2 | 15 | 2 | 37,140 |
| Sugar cane | 0 | 6548 | 0 | 42 | 0 | 3 | 450 | 287 | 7330 |
| E. soil | 0 | 0 | 5798 | 396 | 0 | 144 | 0 | 77 | 6415 |
| Urban | 3 | 325 | 766 | 7010 | 30 | 215 | 318 | 546 | 9213 |
| Vegetation | 2 | 2 | 0 | 0 | 8882 | 915 | 436 | 0 | 10,237 |
| Silviculture | 0 | 3 | 309 | 249 | 416 | 9625 | 87 | 132 | 10,821 |
| Citriculture | 0 | 378 | 0 | 69 | 622 | 215 | 4049 | 51 | 5384 |
| Pasture | 0 | 395 | 547 | 328 | 1 | 18 | 20 | 3388 | 4697 |
| Total | 37,115 | 7659 | 7420 | 8097 | 9951 | 11,137 | 5375 | 4483 | 91,237 |

Table 5. Number of pixels found for each class in 2017.

| Class (2017) | Water | Sugarcane | E. soil | Urban | Vegetation | Silviculture | Citriculture | Pasture | Total |
|--------------|--------|-----------|---------|-------|------------|--------------|--------------|---------|---------|
| Water | 28,723 | 0 | 0 | 0 | 33 | 1 | 10 | 0 | 28,767 |
| Sugarcane | 0 | 8614 | 0 | 0 | 0 | 0 | 11 | 359 | 8984 |
| E. soil | 0 | 0 | 12,059 | 354 | 0 | 101 | 91 | 150 | 12,755 |
| Urban | 3 | 38 | 2075 | 7340 | 14 | 49 | 541 | 490 | 10,550 |
| Vegetation | 0 | 13 | 0 | 2 | 6584 | 558 | 480 | 10 | 7647 |
| Silviculture | 0 | 38 | 1307 | 202 | 880 | 8340 | 949 | 321 | 12,037 |
| Citriculture | 0 | 183 | 2 | 54 | 1349 | 144 | 9922 | 218 | 11,872 |
| Pasture | 0 | 420 | 821 | 241 | 0 | 2 | 107 | 8192 | 9783 |
| Total | 28,726 | 9306 | 16,264 | 8193 | 8860 | 9195 | 12,111 | 9740 | 102,395 |

Table 6. Number of pixels found for each class in 2018.

| Class (2017) | Water | Sugarcane | E. soil | Urban | Vegetation | Silviculture | Citriculture | Pasture | Total |
|--------------|--------|-----------|---------|-------|------------|--------------|--------------|---------|---------|
| Water | 29,891 | 1 | 0 | 0 | 19 | 2 | 14 | 0 | 29,927 |
| Sugarcane | 0 | 8259 | 0 | 1 | 0 | 0 | 220 | 85 | 8565 |
| E. soil | 0 | 0 | 8865 | 333 | 0 | 0 | 0 | 562 | 9760 |
| Urban | 5 | 203 | 1520 | 7812 | 29 | 14 | 287 | 503 | 10,373 |
| Vegetation | 6 | 7 | 9 | 11 | 6330 | 1003 | 1005 | 0 | 8371 |
| Silviculture | 0 | 0 | 0 | 0 | 877 | 10,884 | 276 | 0 | 12,037 |
| Citriculture | 0 | 181 | 26 | 41 | 1213 | 871 | 9693 | 33 | 12,058 |
| Pasture | 0 | 94 | 2493 | 689 | 0 | 0 | 28 | 6808 | 10,112 |
| Total | 29,902 | 8745 | 12,913 | 8887 | 8468 | 12,774 | 11,523 | 7991 | 101,203 |

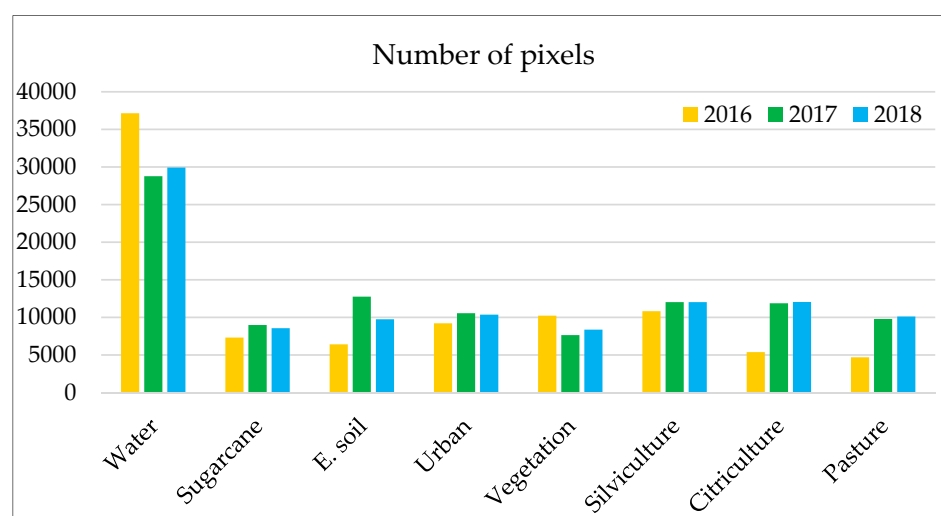


Figure 10. Number of pixels found for the years 2016, 2017, and 2018.

The classification demonstrated low uncertainty when considering the validation process. In 2016, for instance, urban areas were classified as other land uses (766 pixels and 8.31%), exposed soil as pasture (77 pixels and 1.20%), and vegetation as silviculture (915 pixels and 8.93%) and citriculture (436 pixels and 4.02%). In 2017, 2075 pixels of urban areas were classified as exposed soil (19.66%), while 1349 pixels (11.26%) of citriculture belonged to the vegetation class. Finally, in 2018, 2493 pixels (29.10%) of pasture were included in the exposed soil class, whereas 1003 (11.98%) and 1005 pixels (11.981%) of vegetation were classified as silviculture and citriculture, respectively.

4. Discussion

The increase and predominance of agricultural activities driven by sugar cane coincide with the history of São Paulo, which is considered to be the largest sugar cane and alcohol producer in Brazil. As is also the case in the Tietê–Jacaré Watershed, this is due to the favourable conditions for sugar cane cultivation, with a high number of areas with fertile soils and water resources, which causes the increase in average productivity in some regions to be higher than in other regions of the country [52,53].

These characteristics, such as natural vegetation conversion in other land use and land cover and forest loss in general, were also found in other studies on different regions in the state and the country [54–56]. This vegetation loss value over time was similar to that reported by Moraes [57] and Mello [58], who also evaluated the forest and vegetation covers in the *Cerrado* and the seasonal semideciduous forest regions (vegetation types present in the study area) [57,58]. The authors evidenced the progression of vegetation loss, isolation, and fragmentation in the landscape due to anthropic actions. Other regions in the country with different biomes and contexts also presented similar results, such as those found by Rego et al. [6], who showed the loss of vegetation in the São Luis municipality, Maranhão state which is a highly urbanized region. It is essential to highlight that this study did not focus on the fragmentation processes and their spatial patterns. However, we noticed in our study area an increase in forest loss, and consequently in the fragmentation process, due to land use and land cover changes.

Important initiatives to analyse the land use and land cover changes in Brazil are the Brazilian Annual Land Use and the Land Cover Mapping Project (MapBiomias). The project involves a collaborative network that relies on the Google Earth Engine platform and its cloud processing and automated classifiers' capabilities to generate Brazil's annual time series on a scale of 1: 250.000. The results encompass the years 1985–2019, when a significant loss of vegetation was noticed in all Brazilian biomes due to agricultural activities [59].

A management plan is then necessary to develop actions and policy strategies to minimize the impacts of land use and land cover changes, and to avoid the landscape's fragmentation. This is an ongoing process due to the expansion of anthropogenic activities, not only for the watershed studied herein, but for the state and the country as a whole.

These negative impacts can compromise the environmental structures and ecosystem services, affecting the biodiversity, water resources, climate regulation, and the quality of soils that support forest cover and are significant energy sources for life [60,61]. The unplanned land use and land cover occupation and the inadequate soil management have caused several environmental problems, including soil compaction and desertification. On watersheds, these impacts decrease the infiltration of rainwater and increase runoff – factors that intensify the water erosion process and the loss of soil quantity and quality [62,63].

In the case of water resources management, the issue of water quantity and quality is attributed to the pollution caused by different sources, such as industrial, household, urban, and agricultural effluents, as well as to deforestation (in a landscape perspective). The contamination by effluents involves the improper discharge of materials and industrial products used in many processes, which are a complex concern to the environment, considering the concentration and volume of the waste produced. The resulting scenario is the degradation of water sources, with a consequent increase in plants and algae due to the use of nitrogen and phosphorus by farms and confined animal production [64,65].

Various authors debate about the negative impacts of the transition and simplification from natural or even agricultural fragments to monoculture crops [66–68]. Zimmermann (2009) [69] argues that the oversimplification of natural ecosystems is a result of the process for the development of agriculture in extensive monocultures, which is consequently enormously dangerous for the maintenance and conservation of the ecosystem complexity.

Freen et al. [70] also discuss the importance of political actions for the preservation of forests and natural ecosystems to mitigate climate change. According to these authors, it is essential to increase the knowledge of the magnitude, drivers, and implications of environmental factors on biodiversity, such as forest or natural ecosystem microclimates. This information can, for instance, help to create better management and actions plans, supporting their sustainable use and keeping viable ecosystem services for future generations.

Despite the promising results that we got in terms of accuracy in our study, the methodology used for the change detection in the Sentinel-2 images (10 m of spatial resolution) showed, as expected, different results when compared to the classification of land use and land cover using the 2017 Landsat-7 images done manually by Trevisan et al. (with a 30 m of spatial resolution) [21]. The classes with similar results in both analyses were water, silviculture, and exposed soil. However, the urban, pastures, and citriculture classes showed more areas in the Sentinel-2 images than in the Landsat-7 images. Moreover, sugar cane and vegetation were lower in the Sentinel analysis.

The differences in our results could be assigned to uncertainties related to differences in spatial resolution (Sentinel 2 = 10 m spatial resolution and Landsat 7 = 30 m spatial resolution), spectral resolution (Sentinel 2 = 4 spectral bands and Landsat 7 = 7 spectral bands), and time of acquisition between these images. Brus et al. [71] discuss the depiction of uncertainty in the visually interpreted land use and land cover data. They state that the resolution indicates the values and degree of details in the area of interest distinguished by space, time, and topic. Therefore, lower resolution images present fewer details, thus being less accurate.

Time accuracy has a major impact on the current validity of the dataset and its subsequent use. In the land use and land cover maps derived from visual interpretation, it was possible to distinguish the quality of interpretation from the positional accuracy of the image. Brus et al. [71] also mention that errors can be caused by incorrect category inclusion because of the subjectivity of interpretation, which differs according to individuals, leading to different results. In this study, the visual interpretation and sample classification were performed by the same individual [21]. The change detection presented some differences in the analysis of the classes due to the similarities between the Tiete–Jacaré Watershed pixel

images. When comparing the vegetation in 2017 (Figures 11 and 12) with the Landsat and Sentinel images, it was possible to see that there were some differences in the vegetation (Table 7) during classification, considering that citriculture and silviculture have similar reflectance to some forest areas.

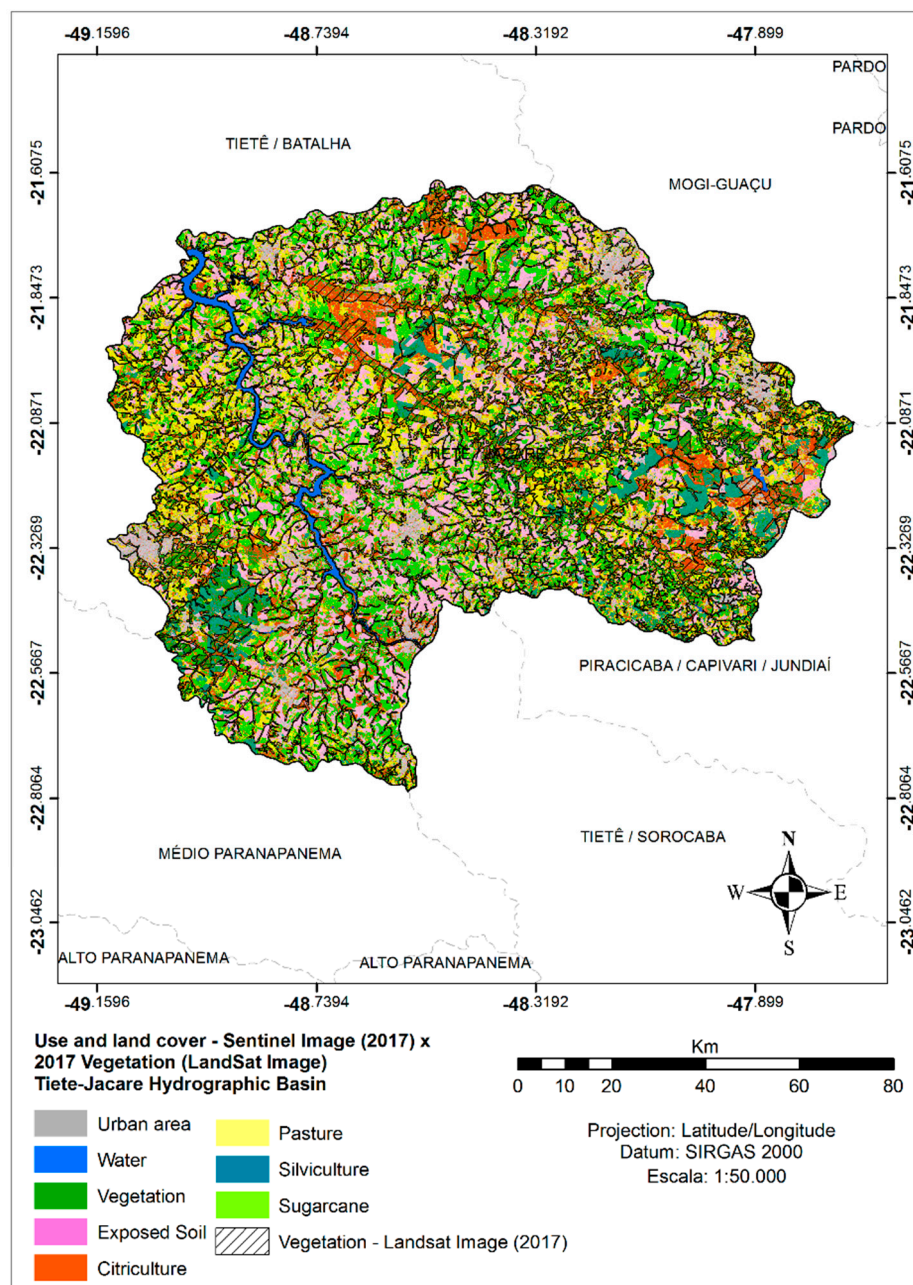


Figure 11. Sentinel images regarding land use and land cover vs. vegetation using 2017 Landsat images from the Tietê–Jacaré Watershed.

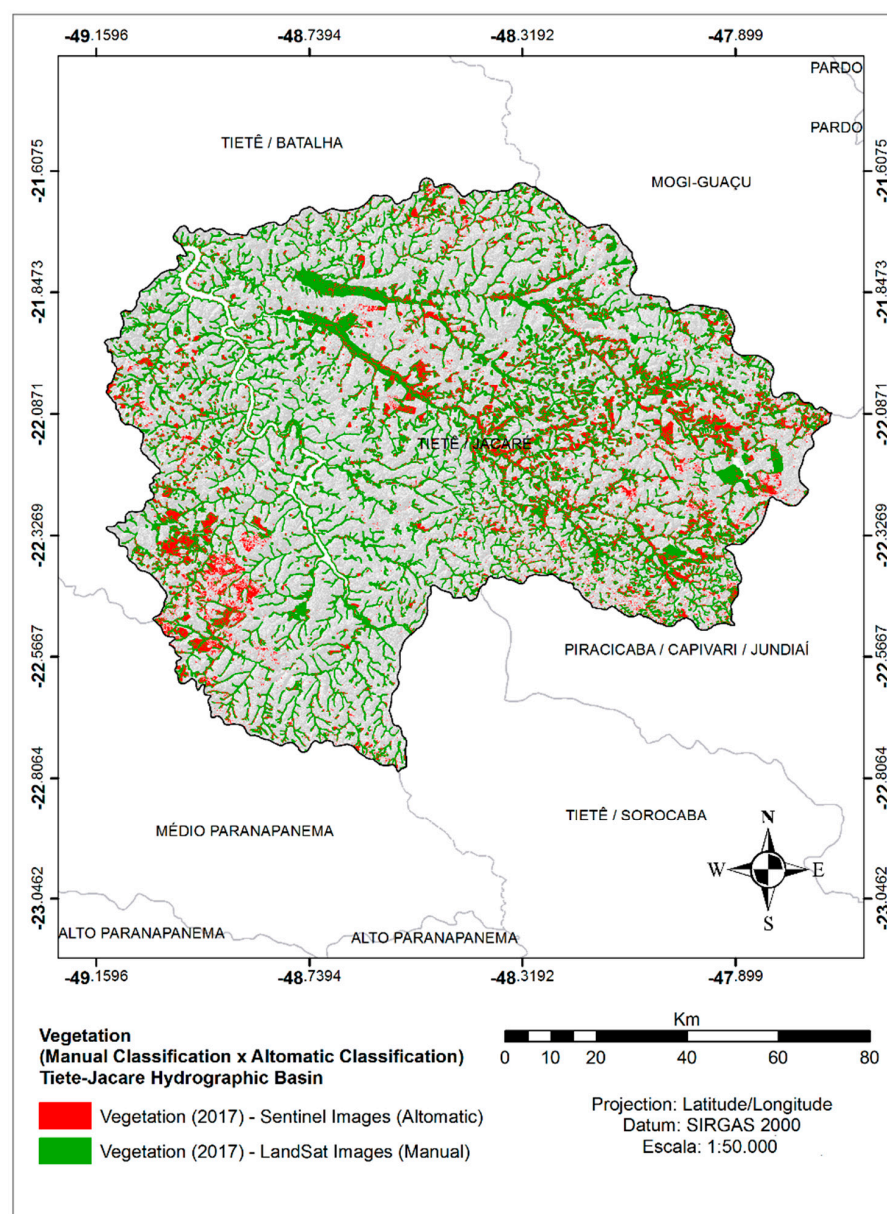


Figure 12. Comparison between vegetation using 2017 Sentinel images vs. 2017 Landsat images from the Tietê-Jacaré Watershed.

Table 7. Land use and land cover using 2017 Sentinel images vs. vegetation using 2017 Landsat images from the Tietê-Jacaré Watershed.

| Vegetation Classified as Other Land Use | Area (ha) | % |
|---|-----------|--------|
| Water | | 0 |
| Sugar cane | 10,404.73 | 15.43 |
| Exposed soil | 7383.10 | 10.95 |
| Urban area | 0.00 | 0.00 |
| Silviculture | 5873.40 | 8.71 |
| Citriculture | 31,580.34 | 46.82 |
| Pasture | 12,209.22 | 18.10 |
| Total | 67,450.78 | 100.00 |

By comparing the manual with the automatic classification, we observed that 67,000 ha of the area covered by vegetation was classified as other land use and land cover types. The highest confusion with the vegetation involved the citriculture (31,000 ha), pasture (12,000 ha), and silviculture (5000 ha) classes. On the other hand, the urban and water classes did not present any problems, mainly because their reflectance was found to be different from that of the vegetation. The integration between machine learning and visual classification techniques is the best way to analyse and obtain information about the environmental and anthropic changes in different landscapes and contexts. For future studies, we plan to increase the training and validation samples and include other classes of land use and land cover, as well as other natural ecosystems. This process will be important because the natural landscape in the study area is being rapidly modified and converted. Through our methodology, we can detect the changes faster in order to provide the necessary information to decision-makers to act in the conservation of the natural ecosystems still present in the area.

Figure 11 shows the comparison between both classifications for 2017 (automatic and manual). It is possible to see that the automatic classification diverges from the manual in small areas, especially related to the riparian vegetation found near streams. Although the comparison was made visually, it is worth highlighting that the maps were based on two different sensors, resulting in images acquired at different spatial and spectral resolutions.

The study conducted by Sakamoto et al. [60] proposes a method to use multi-temporal Landsat Satellite data for determining a water index to constantly monitor the spatial distribution of rice planted in Japan without using complex interactive manual operations [60]. According to the authors, this method has a much more straightforward approach when compared to the semi-automatic or automatic techniques, as it determines the water index based on statistical analyses using manual training data or the difference in histogram distribution information between flooded and non-flooded pixels.

Fisher et al. [72] used 1 m pixel images from the Digital Globe Satellite and 30 m pixel images from the Landsat Satellite to evaluate the impact of the spatial resolution of a satellite image on land use and land cover classification via the ArcGIS Feature Analyst tool and on total suspended solids (TSS) load estimates from the Soil and Water Assessment Tool (SWAT) for the Camboriú watershed in Santa Catarina state, southeastern Brazil. The authors found that the models using 1 m data had better results for predicting both analyses. Moreover, besides higher costs, the high spatial resolution requires additional analysis time.

Other critical aspects for enhancing mapping accuracy are the increase in the number of spectral bands and the increase of the radiometric resolution. Rao et al. [73] worked in a comparative study to evaluate the utility of the simulated 12-bit LISS-III sensor against the original 7-bit LISS-III sensor for land use and land cover classification. An increase of 3% was noticed in the overall accuracy when using high radiometric resolution data.

The development and variation of machine learning (ML) techniques and visual classification could increase the speed and accuracy for classifying land use and land cover changes in natural and anthropic landscapes. Additionally, such approach could support government agencies' efforts to avoid deforestation and to develop action plans so as to mitigate the impacts of these processes on the landscapes, thus increasing sustainability in the different biomes worldwide [74–76]. An example is the work conducted by Ximenes et al. [77], who provided a map of the terrestrial ecoregions of the Purus–Madeira interfluvium in the Brazilian Amazon region using the random forest technique. They developed an ecoregion map from a set of variables, including altitude, slope, drainage density and percentage of tree cover, and a vegetation map related to the environmental diversity of the region that can reproduce valid and accurate results over different areas.

5. Conclusions

The Tietê–Jacaré Watershed has high potential for the development of agricultural activities, as observed by the land use and land cover classification documenting the

predominance of such activities in the region. Furthermore, these datasets corroborate the demographic analyses of 1970, 1980, 1991, and 2015 [22]. They show that the region's growth process is due to the intensification of the urbanization processes (especially the large municipalities, such as São Carlos, Araraquara, Bauru, and Jaú) and the expansion of land use areas due to agricultural activities.

The growth of anthropic activities and the loss of natural areas can compromise the biodiversity still present in the study site. Furthermore, it may represent a loss of environmental services and functions, and consequently of benefits from natural areas that provide resources and support for the maintenance of urban and agricultural activities. Therefore, necessary actions such as the revision of the Forest Code and other environmental laws should be discussed more scientifically, focusing on the conservation of ecosystems. In this way, they should aim at the benefits of the preservation and conservation of natural areas, rather than focusing on the advance of anthropogenic activities or financial interests.

The diversification and rotation of crops is a possibility to control soil fertilization since monocultures interfere with nutrient cycles, causing soil impoverishment and leading to problems such as desertification and salinization. Desertification is a dynamic process that results in the transformation of certain areas into a desert, whereas salinization refers to the degradation of environments under humid climates with the formation of islands of exposed and loose sand.

The use of Sentinel-2 images and the random forest machine learning approach enabled a temporal analysis of the Tietê–Jacaré Watershed region. This methodology allowed us to identify the driving forces that promote the changes in the landscape, contributing to discussions about their consequences over time. Such tools can also accelerate the analysis of evidence of the loss of natural areas and the regional environmental quality, as well as the growth of negative impacts on the watershed landscape, which culminate in the reduction of vegetation areas and water networks. Additionally, the implementation and use of machine learning can increase the efficiency and accuracy of the analysis in studies related to deforestation and the impacts of land use and land cover changes in natural and anthropic landscapes, which is an important factor for the sustainability of the different biomes worldwide.

Author Contributions: Conceptualization, D.P.T., L.E.M. and H.B.; Data curation, D.P.T. and P.C.B.; Formal analysis, D.P.T. and P.C.B.; Funding acquisition, D.P.T. and L.E.M.; Investigation, D.P.T. and P.C.B.; Methodology, D.P.T. and P.C.B.; Project administration, D.P.T., P.C.B., L.E.M. and H.B.; Resources, D.P.T., L.E.M. and H.B.; Software, D.P.T., P.C.B. and Y.G.; Supervision, L.E.M. and H.B.; Validation, D.P.T., P.C.B. and Y.G.; Visualization, D.P.T. and P.C.B.; Writing—Original draft, D.P.T., P.C.B., L.E.M., V.L. and H.B.; Writing—Review and editing, D.P.T., P.C.B., L.E.M., Y.G., V.L., A.H., B.F.S. and H.B. All authors have read and agreed to the published version of the manuscript.

Funding: Trevisan D.P. was supported by the São Paulo Research Support Foundation (FAPESP) (under grant Nos. 2015/19918-3 and 2018/00162-4). Bispo P.C. received the financial support from the European Union's Horizon 2020 (Research and innovation program under the Marie Skłodowska-Curie grant agreement No. 660020). Balzter H. was supported by the UK's Natural Environment Research Council (agreement between the NERC and National Centre for Earth Observation (NCEO) No. PR140015). Liesenberg V. acknowledges the financial support from the National Council for Scientific and Technological Development (CNPQ) (under grant No. 313887/2018-7) and the Foundation for Research and Innovation of the State of Santa Catarina (FAPESC) (under grant No. 2017TR1762).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data are available in the Federal University G-Suit (Google Drive Storage): https://drive.google.com/file/d/10Fqkh_w0LkZ2EU3XgqJgrCY6ZG-qd0Uq/view?usp=sharing (accessed on 3 August 2021).

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Appendix A. Supplementary Results

1. Field photos of land use and land cover found in the Tiete–Jacaré Watershed



Figure A1. Sugar cane and exposed soil ($-21^{\circ}58'45.16''$; $-48^{\circ}0'5.21''$)—09/05/2019.



Figure A2. Spring close to sugar cane ($-21^{\circ}58'44.80''$; $-48^{\circ}0'5.27''$)—09/05/2019.



Figure A3. Citriculture areas ($-22^{\circ}22'47.27''$; $-48^{\circ}07'33.26''$)—10/10/2019.



Figure A4. Transition area between pasture and forestry ($-22^{\circ}25'42.12''$; $-48^{\circ}10'54.29''$)—10/10/2019.



Figure A5. Tietê River dam in the municipality of Barra Bonita ($-22^{\circ}31'10''$; $-48^{\circ}32'04''$). Source: [78].

2. Link for the Script in Python language used in the change detection and the validation <https://drive.google.com/file/d/16BPNLmvYB5ir1qNouSYEIXKPfwL0IR8R/view?usp=sharing> (accessed on 3 August 2021).

References

1. Brasil. The Federative Republic of Brazil. Law n°12.651/2013. 2013. Available online: www.planalto.gov.br/ccivil_03/_Ato2011-2014/2012/Lei/L12651.htm (accessed on 13 May 2020).
2. Duffy, J.E.; Godwin, C.M.; Cardinale, B.J. Biodiversity effects in the wild are standard and as strong as key drivers of productivity. *Nature* **2017**, *549*, 261–264. [CrossRef]
3. Goerl, R.F.; Siefert, C.A.C.; Schultz, G.B.; Santos, C.S. Elaboration and application of fragmentation indexes and landscape connectivity for watershed analysis. *Braz. J. Phys. Geogr.* **2011**, *5*, 1000–1012.
4. Mateiro, B.; Kastenholz, E.; Breda, Z. The sensory dimension of the tourist experience in mountain destinations: The case of serra da estrela natural park. *Rev. Tur. Desenvolv.* **2017**, *27*, 1–12.
5. Intergovernmental Panel on Climate Change. *Climate Change 2007: Synthesis Report*; IPCC: Geneva, Switzerland, 2007; 184p.
6. Rego, J.C.L.; Soares-Gomes, A.; Silva, F.S. Loss of vegetation cover in a tropical island of the Amazon coastal zone (Maranhão Island, Brazil). *Land Use Policy* **2018**, *71*, 593–601. [CrossRef]
7. De Leo, G.A.; Levin, S. The multifaceted aspects of ecosystem integrity. *Conserv. Ecol.* **1997**, *1*, 1–16. [CrossRef]
8. Dong, Y.; hauschild, M.Z. Indicators for environmental sustainability. In Proceedings of the 24th Conference on Life Cycle Engineering, Kamakura, Japan, 8–10 March 2017; pp. 697–702. [CrossRef]
9. Turner, M.G. Spatial simulation of landscape changes in Georgia: A comparison of 3 transition models. *Landscape Ecol.* **1987**, *1*, 29–36. [CrossRef]
10. O'Neil, R.V.; Krummel, J.R.; Gardner, R.H.; Sugihara, G.; Jackson, B.; De Angelis, D.L.; Milne, B.T.; Turner, M.G.; Zygmunt, B.; Christensen, S.W.; et al. Indices of landscape pattern. *Landscape Ecol.* **1988**, *1*, 153–162. [CrossRef]
11. Gustafson, E.J.; Parker, G.R. Relationships between landcover proportion and indices of landscape spatial pattern. *Landscape Ecol.* **1992**, *7*, 101–110. [CrossRef]
12. Mcgarigal, K.; Marks, B. Fragstats Manual. Available online: https://www.umass.edu/landeco/research/fragstats/documents/fragstats_documents.html (accessed on 25 July 2021).
13. Schumaker, N.H. Using landscape indices to predict habitat connectivity. *Ecology* **1996**, *77*, 1210–1225. [CrossRef]

14. Moretti, R.S. Content and procedures for preparing master plans. In *Diretores Municipais—Novos Conceitos do Planejamento Territorial*; ANNABLUME: São Paulo, Brazil, 2007; pp. 265–271.
15. Trevisan, D.P.; Moschini, L.E.; Moraes, M.C.P. Evaluation of natural conditions of landscape in Ibaté county, São Paulo, Brazil. *Geogr. Rio Claro* **2016**, *41*, 467–482.
16. Ribeiro, S.L. Initial considerations on water security in Brazil. *Braz. J. Def. Stud.* **2018**, 61–82. Available online: <https://rbed.abedef.org/rbed/article/view/70306> (accessed on 3 August 2021).
17. Linder, H.L.; Horne, J.K.; Ward, E.J. Modeling baseline conditions of ecological indicators: Marine renewable energy environmental monitoring. *Ecol. Indic.* **2017**, *83*, 178–191. [CrossRef]
18. Menezes, C.R.; Salgado, C.M. Land use and landscape aspects of the Do Angico River Basin, in the Ceroula Environmental Protection area—Campo Grande/Ms. *Rev. Formação* **2018**, *25*, 261–277. [CrossRef]
19. ESA. European Space Agency. Available online: <https://sentinel.esa.int/web/sentinel/missions/sentinel-2/satellite-description> (accessed on 18 April 2019).
20. Oliveira, D.A.; Pietrafesa, J.P.; Barbalho, M.G.S. Biodiversity maintenance and the savannah hotspots. *Geogr. Paths* **2008**, *9*, 101–114.
21. Trevisan, D.P.; Bispo, P.C.; Almeida, D.; Imani, M.; Balzter, H.; Moschini, L.E. Environmental vulnerability index: An evaluation of the water and the vegetation quality in a brazilian savanna and seasonal forest biome. *Ecol. Indic.* **2020**, *112*, 1–15. [CrossRef]
22. Trevisan, D.P. *Análise das Variáveis Ambientais Causadas Pelas Mudanças dos Usos e Cobertura da Terra do Município de São Carlos*. Master's Thesis, Federal University of São Carlos, São Carlos, Brazil, 2015.
23. Baró, F.; Baggethun, E.G.; haase, D. Ecosystem service bundles along the urban-rural gradient: Insights for landscape planning and management. *Ecosyst. Serv.* **2017**, *24*, 147–159. [CrossRef]
24. Hamilton, L.S. *Forest and Watershed Development and Conservation in Asia and the Pacific*, 3rd ed.; Routledge: London, UK, 2018; 300p.
25. Gibson, R.; Danaher, T.; Hehir, W.; Collins, L. A remote sensing approach to mapping fire severity in south-eastern Australia using sentinel 2 and random forest. *Remote Sens. Environ.* **2020**, *240*, 111702. [CrossRef]
26. Phalke, A.R.; Özdoğan, M.; Thenkabail, P.S.; Erickson, T.; Gorelick, N.; Yadav, K.; Congalton, R.G. Mapping croplands of Europe, Middle East, Russia, and Central Asia using Landsat, Random Forest, and Google Earth Engine. *ISPRS J. Photogramm. Remote Sens.* **2020**, *167*, 104–122. [CrossRef]
27. São Paulo. State law n°7.663, de 30/12/1991. Available online: <https://www.al.sp.gov.br/repositorio/legislacao/lei/1991/lei-7663-30.12.1991.html> (accessed on 26 October 2019).
28. São Paulo. State law n°9.034, de 27/12/1994. Available online: <https://www.al.sp.gov.br/repositorio/legislacao/lei/1994/lei-9034-27.12.1994.html> (accessed on 26 October 2019).
29. CBH-SM. Serra da Mantiqueira River Basin Committee. Water Resources Management Unit. Available online: <https://scihub.copernicus.eu> (accessed on 26 October 2019).
30. Tundisi, J.G.; Matsumura-Tundisi, T.; Pareschi, D.C.; Luzia, A.P.; Von haeling, P.H.; Frollini, E.H. The Tietê–Jacaré Watershed: A case study in research and management. *Adv. Stud.* **2008**, *22*, 159–172.
31. CBH-TJ. Tietê–Jacaré Watershed Committee. *Water Resources Status Report of the Tietê–Jacaré Watershed Plan*; Final Report, CD-ROM; São Paulo State Water Resources Foundation: São Paulo, Brazil, 2017.
32. Moschini, L.E. Environmental Zoning of the Middle Mogi-Guaçu Superior Watershed. Ph.D. Thesis, Federal University of São Carlos, São Carlos, Brazil, 2008.
33. DAEE. Department of Water and Energy of the State of São Paulo. Parque Nascentes do Tietê. Available online: <http://www.dae.sp.gov.br/> (accessed on 27 March 2020).
34. Attanasio, C.M.; Paula, L.W.; Sergius, G.; Brito, Z.M.J.; Junior, V.; Toledo, J.C. Method for the identification of the riparian zone: Watershed of ribeirão são joão (mineiros do tietê, SP). *Sci. For.* **2006**, *71*, 131–140.
35. Castro, F. *Organization Almanach-Album de São Carlos, 1916–1917*; EduUFSCar: São Carlos, Brazil, 2007; 250p.
36. IBGE. Brazilian Institute of Geography and Statistics. Planialtimetric Charts. 2019. Available online: ftp://geoftp.ibge.gov.br/cartas_e_mapas/folhas_topograficas/editoradas/escala_50mil/ (accessed on 26 October 2018).
37. Copernicus Open Access Hub. Sentinel Images. 2019. Available online: <https://scihub.copernicus.eu/dhus/#/home> (accessed on 25 April 2020).
38. IBGE. Brazilian Institute of Geography and Statistics. *Technical Manual for Land Use*, 3rd ed. Available online: http://www.ibge.gov.br/home/geociencias/recursosnaturais/usodaterra/manual_usodaterra.shtm (accessed on 26 October 2018).
39. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32. [CrossRef]
40. Speriser, J.L.; Wolf, B.J.; Chung, D.; Karvellas, C.J.; Koch, D.G.; Durkalski, V.L. BiMM forest: A random forest method for modeling clustered and longitudinal binary outcomes. *Chemom. Intell. Lab. Syst.* **2019**, *185*, 122–134. [CrossRef] [PubMed]
41. Persson, M. Tree Species Classification using Multi-Temporal Sentinel-2 Data. Master's Thesis, Swedish University of Agricultural Sciences, Uppsala, Sweden, 2018.
42. Diniz, F.A.; Neto, F.M.M.; Júnior, F.C.L.F.; Laysa, M.O.F. RedFace: A facial recognition system based on principal component analysis techniques and autofaces: Comparison with different classifiers. *Rev. Bras. Comput. Apl.* **2013**, *5*, 42–54. [CrossRef]
43. Python. *The Python Standard Library*. 2020. Available online: <https://docs.python.org/3/library/> (accessed on 26 October 2018).
44. Schaffer, C. Selecting a classification method by cross-validation. *Mach. Learn.* **1993**, *13*, 135–143. [CrossRef]

45. Kohavi, R.A. A study of cross-validation and bootstrap for accuracy estimation and model selection. *Int. Jt. Conf. Artif. Intell.* **1995**, *10*, 1137–1145.
46. Verikas, A.; Vaiciukynas, E.; Gelzinis, A.; Parker, J.M.; Olsson, M.C. Electromyographic Patterns during golf swing: Activation sequence profiling and prediction of shot effectiveness. *Sensors* **2016**, *16*, 592. [\[CrossRef\]](#)
47. Lillesand, T.; Kiefer, R.W.; Chipman, J. *Remote Sensing and Image Interpretation*, 6th ed.; John Wiley & Sons: New York, NY, USA, 2014; 300p.
48. Congalton, R. A comparison of sampling schemes is used to generate error matrices for assessing the accuracy of maps generated from remotely sensed data. *Photogramm. Eng. Remote Sens.* **1988**, *54*, 593–600.
49. Ahmad, A.; Quegan, S. Analysis of maximum likelihood classification on multispectral data. *Appl. Math. Sci.* **2012**, *6*, 6425–6436. [\[CrossRef\]](#)
50. Richards, J.A.; Xiuping, J. *Remote Sensing Digital Image Analysis*; Springer: Berlin/Heidelberg, Germany, 2006; 325p.
51. Landis, J.R.; Koch, G.G. The measurement of observer agreement for categorical data. *Biometrics* **1997**, *1*, 159–174. [\[CrossRef\]](#)
52. Natale Netto, J. *The Alcohol Saga: Facts and Truths about 100 Years of Fuel Alcohol in Our Country*, 1st ed.; Osasco, S.P., Ed.; Novo Século: São Paulo, Brazil, 2007; 343p.
53. Medrano, L.; Recaman, L. Space and society in the 21st century. Study case of São Paulo. *Bitácora Urbano Territ.* **2018**, *28*, 69–81. [\[CrossRef\]](#)
54. Trevisan, D.P.; Ruggiero, M.H.; Bispo, P.d.C.; Almeida, D.; Imani, M.; Balzter, H.; Moschini, L.E. Evaluation of environmental naturalness: A case study in the Tietê-Jacaré Watershed, São Paulo, Brazil. *Sustainability* **2021**, *13*, 3021. [\[CrossRef\]](#)
55. Rudorff, B.F.T.; Aguiar, D.A.; Silva, W.F.; Sugawara, L.M.; Adami, M.; Moreira, M.A. Studies on the rapid expansion of sugarcane for ethanol production in São Paulo State (Brazil) using Landsat Data. *Remote Sens.* **2010**, *2*, 1057–1076. [\[CrossRef\]](#)
56. Moraes, M.C.P.; Toppa, R.H.; Mello, K. Sugarcane Expansion as a pressure factor for protected natural areas. In *Faces of Landscape Polysemy: Ecology, Planning, and Perception*, 1st ed.; Dos Santos, J.E., Zanin, E.M., Eds.; Rima: São Carlos, Brazil, 2013; pp. 163–173.
57. Moraes, M.C.P. Landscape Dynamics of the Porto Ferreira State Park Buffer Zone. Master's Thesis, Federal University of São Carlos, Sorocaba, Brazil, 2013.
58. Mello, K.; Petri, L.; Cardoso-Leite, E.; Toppa, R.H. Environmental scenarios for land planning of permanent preservation areas in Sorocaba, SP. *Tree Mag.* **2014**, *38*, 309–317. [\[CrossRef\]](#)
59. MapBiomes. Brazilian Annual Land Use and Land Cover Mapping Project. Available online: <https://mapbiomas.org/en> (accessed on 26 September 2020).
60. Sakamoto, T.; Sprague, D.S.; Okamoto, K.; Ishitsuka, N. Semi-automatic classification method for mapping the rice-planted areas of Japan using multi-temporal landsat images. *Remote Sens. Appl. Soc. Environ.* **2018**, *10*, 7–17. [\[CrossRef\]](#)
61. Bertoni, J.; Lombardi Neto, F. *Soil Conservation*, 6th ed.; Ícone: São Paulo, Brazil, 2008; 355p.
62. Hernandez, R.R.; Hoffacker, M.K.; Mariscal-Murphy, M.L.; Wu, G.C.; Allen, M.F. Solar energy development impacts on land cover change and protected areas. *Proc. Natl. Acad. Sci. USA* **2015**, *112*, 13579–13584. [\[CrossRef\]](#)
63. Silva, L.E.; Cruz, E.P.; Junior, M.C.; Almeida, R.R.; Moura, A.A. East Atlantic Hydrographic Region: The challenges of water resources management. *Exact Technol. Sci.* **2016**, *3*, 197–206.
64. Xu, S.; Liu, H.; Xu, G. Selection of Recycling Channels and Product Eco-Design with Take-Back Regulation. *Sustainability* **2021**, *13*, 8961. [\[CrossRef\]](#)
65. Merten, G.H.; Minnelli, J.P. Water quality in rural watersheds: A current challenge for future survival. *Agroecol. E Desenvol. Rur. Sustent.* **2002**, *4*, 33–36.
66. Musharafi, S.K.; Mahmoud, I.Y.; Bahry, S.N. Environmental contamination by industrial effluents and sludge relative to heavy metals. *J. Geosci. Environ. Prot.* **2014**, *2*, 14–18. [\[CrossRef\]](#)
67. Azevedo, T.N. Effect of the Expansion of Sugarcane Cultivation on the Composition of the Landscape in the State of São Paulo. Master's Thesis, São Paulo University, São Paulo, Brazil, 2013.
68. Macedo, R.C.; Almeida, C.M.; Santos, J.R.; Rudorff, B.F.T. Spatial dynamic modeling of land cover and land-use changes related to sugarcane expansion. *Bol. Ciênc. Geod.* **2013**, *19*, 313–337. [\[CrossRef\]](#)
69. Zimmermann, C.L. Monoculture and transgenics: Environmental impacts and food insecurity. *Law Paths* **2009**, *6*, 79–100.
70. Frenne, P.; Lenoir, J.; Luoto, M.; Schffers, B.; Zellweger, F.; Aalto, J.; Ascroft, M.; Christiansen, D.; Decocq, G.; Pauw, K.; et al. Forest microclimates and climate change: Importance, drivers and future research agenda. *Glob. Chang. Biol.* **2020**, *1*, 1–19. [\[CrossRef\]](#)
71. Brus, J.; Pechanec, V.; Machar, I. Depiction of uncertainty in the visually interpreted land cover data. *Ecol. Inform.* **2018**, *47*, 10–13. [\[CrossRef\]](#)
72. Fisher, J.R.B.; Acosta, E.A.; Frank-Dennedy, P.J.; Kroeger, T.; Boucher, T.M. Impact of satellite imagery spatial resolution on land use classification accuracy and modeled water quality. *Remote Sens. Ecol. Conserv.* **2018**, *4*, 137–149. [\[CrossRef\]](#)
73. Rao, R.N.; Garg, P.K.; Ghosh, S.K. Evaluation of radiometric resolution on land use/land cover mapping in an agricultural area. *Int. J. Remote Sens.* **2007**, *2008*, 443–450. [\[CrossRef\]](#)
74. Zhang, M.; Muñoz-Mas, R.; Martinez-Capel, F.; Qu, X.; Zhang, H.; Peng, W.; Liu, X. Determining the macroinvertebrate community indicators and relevant environmental predictors of the hun-tai river basin (northeast china): A study based on community patterning. *Sci. Total Environ.* **2018**, *634*, 749–759. [\[CrossRef\]](#) [\[PubMed\]](#)
75. Upadhaya, S.; Dwivedi, P. Conversion of forestlands to blueberries: Assessing implications for habitat quality in Alabaha river watershed in Southeastern Georgia, United States. *Land Use Policy* **2019**, *89*, 104229–104235. [\[CrossRef\]](#)

-
76. Kupfer, J.A.; Franklin, S.B. Linking spatial pattern and ecological responses in human-modified landscapes: The effects of deforestation and forest fragmentation on biodiversity. *Geogr. Compass* **2009**, *3*, 1331–1355. [[CrossRef](#)]
 77. Ximenes, A.C.; Amaral, S.; Monteiro, A.M.V.; Almeida, R.M.; Valeriano, D.M. Mapping the terrestrial ecoregions of the Purus-Madeira interfluvium in the Amazon Forest using machine learning techniques. *For. Ecol. Manag.* **2021**, *488*, 1–13. [[CrossRef](#)]
 78. Barra Bonita. Rio Tietê Dam in Barra Bonita. Available online: http://bes-br.com/?page_id=1507 (accessed on 30 October 2019).