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Multitemporal Analysis of Land Use and Land Cover in the Amazon: The Expansion of Large-Scale Agriculture in the Curuá-Una River Basin

Análise Multitemporal do Uso e Cobertura da Terra na Amazônia: A Expansão da Agricultura de Larga Escala na Bacia do Rio Curuá-Una

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Abstract: Soybean expansion brought important changes to the Brazilian Amazon, due to land concentration processes, landscape homogenization, and expansion over other forms of produce. In Pará, intensive soybean expansion occurred in the municipalities of Santarém, Belterra, and Mojuí dos Campos, which are part of the Curuá-Una river basin. This study aims to analyze the dynamics of land use during the period of 2000 to 2019, in the Curuá-Una River basin, by identifying areas of land conversion to Large-Scale Agriculture (LSA). The current land use and land cover databases in the Amazon exclude the Small-Scale Agriculture (SSA) class. We applied multi-resolution segmentation techniques and object-oriented classification of TM/OLI/Landsat images to include SSA areas in the map. For the analysis of LSA dynamics, we built transition matrices for the following periods: 2000-2010, 2010-2019, and 2000-2019. Our study found a LSA expansion from 23 km² to 1,093 km² during the period of 2000-2019. During the period of 2000-2010, we found the greatest increase in LSA of 25%. In addition, we identified that LSA's expansion has occurred mainly over Pasture (38%), followed by Secondary Vegetation (31%), Forest (27%), and SSA (2%). About 25% of the SSA classified area in the year 2000 was converted to LSA in 2019. This proportion may be higher, since part of the Secondary Vegetation converted to LSA, may be part of the SSA fallow system. Our results reinforce the importance of establishing public policies to regulate and strengthen the local economy.
Keywords: Large-Scale Agriculture. Small-Scale Agriculture. Object-Oriented Classification. Brazilian Amazon.

Resumo: A expansão da soja tem gerado importantes mudanças na Amazônia brasileira devido a processos de concentração de terras, homogeneização da paisagem e ao avanço sobre outras formas de produção. No Pará, esse processo ocorre mais intensamente nos municípios de Santarém, Belterra e Mojuí dos Campos, que integram a bacia do rio Curuá-Una. Esse estudo se propõe a analisar dinâmicas de uso e cobertura da terra para o período de 2000 a 2019 na bacia do Rio Curuá-Una, observando sobre quais classes a Agricultura de Larga Escala (LSA) se expandiu. As atuais bases de dados de uso e cobertura da terra da Amazônia não contemplam a Agricultura de Pequena Escala (SSA). Para incluir essa classe, fez-se uso de imagens TM/OLI/Landsat, técnicas de segmentação multirresolução e classificação orientada à objeto. Para a análise das dinâmicas da LSA utilizou-se matrizes de transição para os períodos de 2000-2010, 2010-2019 e 2000-2019. Como resultado, observou-se um ganho de área da LSA no período de 2000-2019, de 23 km² para 1.093 km². O período de 2000-2010 foi o que apresentou maior ganho (25%). A expansão da LSA se deu primordialmente sobre áreas de Pastagens (38%), Vegetação Secundária (31%), Floresta (27%) e SSA (2%). Cerca de 25% da área de SSA de 2000 foi convertida para LSA em 2019. Essa proporção pode ser ainda maior, pois parte da Vegetação Secundária convertida para LSA, compõe o sistema de pousio da SSA. Esses resultados reforçam a importância de se estabelecer políticas púbicas que valorizem e fortaleçam a economia local.
Palavras-chave: Agricultura de Larga Escala. Agricultura de Pequena Escala. Classificação Orientada a Objeto. Amazônia.

1 INTRODUCTION

The Amazon biome is characterized by its rich biodiversity and vast territorial extension, from the Atlantic

Ocean to the slopes of the Andes, with an average altitude of 600 m and occupying 40% of the South American territory. Of this entire territory, which corresponds to approximately 7,000,000 km^2, 69% belongs to Brazil or about 4,871,000 km² (AB'SABER, 1977; BRASIL, 2020). One of the main features of this biome is its capacity to transport humidity to other regions of the continent, retaining carbon from the atmosphere, regulating water, maintaining biodiversity, and providing food, fiber, timber, and medicinal products (CORREIA et al. 2007; NOBRE, C.A, 2002).

Human occupation of the Brazilian Amazon intensified after the 1970s, resulting in major environmental, economic, and social changes. These changes are a result of the occupation strategies of the Brazilian military government in the 1960s, aiming at integrating the Amazon with other regions of Brazil disregarding possible socio-environmental impacts. One of those strategies was to encourage the migration of small and large rural producers to the Amazon, while expanding basic city infrastructure such as building roads, hydroelectric facilities, and telecommunication networks, increasing Amazon's connection with surrounded city networks (BECKER, 2005; MACHADO, 1998). The rapid transformation of this region combined with governmental financial aid allowed the establishment of agriculture, timber extraction, and mining companies, enabling large farms, and colonization projects to establish (AB'SABER, 1989; BECKER, 2004). All these activities entailed profound environmental impacts, yet the most evident is deforestation in the Amazon.

In the late 1990s the "Avança Brasil" program was launched, as a multi-year government plan (CARDOSO, 2008), envisioning changes in the country for the period of 2000 to 2003. This program aimed to improve and expand basic infrastructure throughout Brazil, making large investments in the construction of pipelines, roadways, improving water systems, and building hydroelectric plants. During this period, soybean cultivation expanded from the cerrado (savannah) to the Amazon's biome, with high concentration in the States of Mato Grosso and Pará. (IBGE, 2020). Part of the funding for improving transportation was designated to facilitate the flow of soybeans to international markets (FEARNSIDE, 2001), which also received private funding from other stakeholders such as the Cargill port in Santarém, and, more recently, the port of Miritituba, a district of the municipality of Itaituba, located in the lower Tapajós region (DAL'ASTA et al., 2017). As a result of this process, with increased land use and structural changes in the Amazon's landscape, there was a shift in land concentration which often hindered family farming and smallholders (BRONDÍZIO; SIQUEIRA, 1997; MONT-MÓR, 2008). These changes impacted cropping practices leading to transformations in the labor force, stimulating commercial agriculture (agribusiness) in the region. With increased investments in infrastructure for the flow of grain's production, and the lack of an effective policy to combat deforestation, in 2004 the second highest deforestation rate in the Amazon since the beginning of monitoring was registered, at 27,772 km² (PRODES, 2021).

In response to the increase in deforestation rates, the Brazilian government created the "Action Plan for the Prevention and Control of Amazon Deforestation" (PPCDAm[1]), which included as part of its actions the creation of an alert system for the Detection of Deforestation in Real Time (DETER), established in 2004 (DINIZ et al., 2015). Based on data from PRODES [2] and DETER, an agreement was made in 2006, called the Soy Moratorium, involving non-governmental organizations, agribusiness, and the government, to stop deforestation resulting from soybean cultivation. In this agreement, which came into effect in July 2008, industries were committed not to purchase soy grown on deforested lands. With additional policies and increased enforcement, deforestation rates declined from 2005 on, reaching 4,571 km^2 in 2012, the lowest deforestation rate recorded since the establishment of PRODES. After 2012, deforestation rates have shown an upward trend, reaching 10,851 km^2 in 2020 (INPE, 2021).

The western region of Pará concentrates most of the soybean cultivation, mainly in the municipalities of Santarém, Mojuí dos Campos and Belterra (Figure 1) (BECKER, 1995; D'ANTONA et al., 2011; DAL'ASTA et. al, 2013), the study area of this work. This region is known for the intense cultivation of soybeans that started in

[1] PPCDAm - The Action Plan for Prevention and Control of Deforestation in the Legal Amazon (PPCDAm), created in 2004, aimed to reduce deforestation and create conditions for the transition to a sustainable development model in the Legal Amazon. With the establishment of the PPCDAM, the fight against deforestation gained important allies besides environmental agencies, and now was also managed by agencies of the Federal Government (MMA, 2021).

[2] PRODES - Project for Monitoring Deforestation in the Legal Amazon by Satellite (PRODES) is a government initiative of the National Institute for Space Research (INPE) that monitors annual rates of clear-cutting in the nine states of the Legal Amazon (INPE, 2021).

the late 1990s, with sophisticated cropping practices using chemical and mechanical inputs, which led small farmers to experience new ways of production. Those sophisticated and technological practices differed from traditional cropping and demand high initial capital and skilled labor. As a result, extensive areas of land were designated to soybean production, modifying the landscape of this region and leaving wider footprints, which changed previous landscape patterns (DAL'ASTA, A. P. et al, 2017; SANTOS, 2020).

Not surprisingly, displacement of the rural population to the city and/or to urbanized centers was observed during this period (late 1990s) mainly in the municipalities of Santarém and Mojuí dos Campos (SANTOS, 2020). This urbanization process was noted by D'Antona et al. (2011); Dal'Asta et al. (2013) and Souza (2017) in the region of Santarém. Souza et al. (2017) performed an integrated analysis of land use intensification and landscape diversity showing that in 2012 Santarem's landscape was not entirely transformed by agribusiness, and there was still several areas of Small-Scale Agriculture in its interstices, with forest remnants and secondary vegetation. However, this process is still ongoing in the region and should be investigated in both dimensions, spatial and temporal, monitoring the effects on landscape structure, cropping practices, and rates of forest cover conversion.

To better understand the dynamics of Large-Scale Agriculture (LSA) expansion in the Amazon biome, it is important to investigate and map the various existing types of agriculture, to evaluate which of those pushes LSA advances. The classes of Small-Scale Agriculture (SSA) are harder to be identified and/or mapped adequately in the current systems that monitor land use and land cover in the Amazon (TerraClass[3], Mapbiomas[4]), due to their size, and the generation of a complex fragmented and heterogenous landscapes. The identification of these classes requires the development of algorithms capable of characterizing small areas and identifying different contexts. Souza et al. (2019) applied an object-oriented approach, through the adapted KNN (k-nearest neighbors' algorithm) algorithm (TRIMBLE, 2021), considering attributes of size and shape of agriculture polygons, in addition to image spectral attributes for the discrimination of small-scale agriculture areas, obtaining an accuracy of 62%. In the current study, these algorithms are used for the mapping of land use and land cover classes and for refining SSA class in pre-existing mappings not contemplated by TerraClass. This procedure is paramount for a complete understanding of LSA expansion dynamics in western Pará, where it has greatly advanced. In summary, this study aims to map and analyze the dynamics of land use and land cover from 2000 to 2019, in the Curuá-Una River basin, located in the western portion of Pará, where LSA has greatly expanded over other classes of land use and land cover. This analysis takes advantage of remote sensing data and digital image processing techniques, including multiresolution segmentation and object-oriented classification, to identify and characterize land use and land cover classes present in the region.

The results obtained are important to support the development of public policies that aim to strengthen the local economy, encouraging and preserving traditional and small-scale agricultural practices. These smallholder production strategies are largely responsible for the food production that supplies the nearby cities (SANTO JUNIOR et al., 2010). Besides responsibly taking advantage of technology to improve production and having deep knowledge of the biome, smallholders' practices are in general sustainable, characterized by low CO_2 emission economies (COSTA, 2009).

1.1 Small-Scale Agriculture Cartography

For a complete evaluation of LSA dynamics, all land use and land cover classes should be contemplated in the map, including fragmented and small agricultural fields, such as SSA, that are rarely identified in the literature for the study area. These studies often analyze secondary data to obtain an approximation of SSA locations. The cartographic representation of extensive areas is generally carried out with remote sensing data, which allows a synoptic view, covering large areas and ensuring a certain frequency/periodicity of images, which enables temporal evaluations. Extensive mapping of land use and land cover areas in the Amazon has been performed by analyzing

[3] TerraClass is developed and executed by the Amazon Regional Center (CRA/INPE) in partnership with the Brazilian Agricultural Research Corporation (Embrapa), which quantifies the deforestation observed in the Brazilian Legal Amazon region and is an important source for a better understanding land use and cover in the region (ALMEIDA et al., 2016).
[4] MapBiomas is an initiative of the Climate Observatory created and developed by a multi-institutional network involving universities, NGOs and technology companies with the purpose of mapping the land cover and use in Brazil and monitoring changes in the territory in an annual basis (SOUZA et al., 2020).

Landsat images, with 30m spatial resolution (WALKER; MORAN, 2000; MARGULIS, 2003; SOUZA, et al., 2017; CRESPIM-BOUNCADA et al., 2020). These maps built by TerraClass (EMBRAPA and INPE, 2019), for example, allow to understand the dynamics of the processes occurring in the Amazon. However, the identification and mapping of small and heterogeneous regions, such as SSA areas, requires the use of classification algorithms, ideally with the input of high-resolution images to better identify land features, with a spatial resolution of 5 to 10 meters, for example.

Coelho et al. (2021) evaluated the dynamics of soybean expansion in Santarém for the periods of 1999-2007 and 2007-2015. The authors combined land use and cover data derived from remote sensing with data on properties occupying public areas (official traditional and sustainable use settlements) and private areas, such as boundaries of protected areas, settlement projects, rural environmental cadaster (CAR), roadways, municipal seat and localities among others. As a result, they noted a significant difference in vegetation loss between private and public areas. They also found that 82% of mechanized agriculture was in areas previously occupied by Family Farmers (42%), Secondary Vegetation (20%), and Pasture (20%). In this work, the SSA class is represented by a class called *family farming,* which is a mixed class composed of Secondary Vegetation and Pasture.

The current work aims to accurately map SSA classes following the methodologies developed by Souza (2016), Souza et al. (2019), and Pacheco et al. (2021). These authors used RapidEye (5 m), Landsat (30m), and Cbers (5 and 10 m) data for mapping SSA in some regions of Pará. Santos (2018) performed segmentation using Linear Spectral Mixture Model (MLME) in TM/Landsat images (30m) to classify land use and land cover, and identify, through refinement of these images, with CBERS images (5/10m), SSA areas and agroforestry in the region of the municipalities of Mocajuba and Cametá, in Para.

In another context, for SSA classification and to monitor land use dynamics in mountainous areas of Madagascar, Crespin-Boucaud et al. (2020) combined high spatial resolution imagery (Spot 6/7), time series with a high revisit rate, (Sentinel 2, Landsat 8) and Spatio-temporal models based on certain defined rules. Their land use map was created by an object-oriented classifier combined with the Random Forest algorithm. As a result, they obtained an error map of the spatial distribution of crop (omission or commission) lately corrected by the joint use of Spatio-temporal rules and reference class association probabilities. The authors emphasize that the combination of remote sensing data and spatial modeling provides a better method to characterize and monitor complex agricultural systems, such as SSA areas.

Among the types of classification techniques to map SSAs, stands out the object-oriented classification, also known as GEOBIA, which considers a set of pixels (regions), instead of a pixel alone, allowing the exploration of region features such as field's shape and texture, improving classification accuracy (BRANCO et al., 2018). Regarding to traditional models of image classification, these object-oriented approaches have proven to be effective, usually matching features automatically extracted from digital images (FRIEDRICH et al., 2009; TAUBENBÖCK et al., 2010; ULISSES & KUX, 2014; PACHECO et al., 2021) to information derived from human reasoning and photointerpretation.

Some authors have already applied object-oriented classification algorithms and visual interpretation to mapping land use and cover in the Amazon. Souza (2016) developed a methodology based on visual interpretation to identify and characterize areas of small-scale agriculture near riparian and upland communities, in the western region of Pará. They used RapidEye data jointly with land use and land cover maps obtained from the TerraClass project in 2012, to identify the different classes. In this mapping project, the author visually classified SSA areas in a radius of 8 km away from communities.

Souza et al. (2019) tested the use of an object-oriented classification algorithm with RapidEye images (5m spatial resolution), for the municipalities of Cametá, Mocajuba, and Baião, located in the Northeast region of Pará. To evaluate the refinement capability of the Occupation Mosaic class, coming from the data produced by TerraClass, the authors tested the *MAXVER*, *Bhattacharya,* and *K-Nearest Neighbor* algorithms. Among the algorithms tested, the K-Nearest Neighbor (KNN) obtained the best result for the identification of the small-scale agriculture classes. This technique allows two neighboring regions to be grouped into a single region according to a given similarity criterion (BAATZ; SCHAPE, 2000). In order to split or group regions, the algorithm uses shape and color attributes and evaluates the degree of similarity between regions. According to Matsuoka and Haertel

(2007), the color attribute separates objects with different shades, since it represents the variations in pixel values within a segment in each spectral band. The shape attribute is composed of two factors: compactness, and smoothness. Compactness is defined mathematically by the ratio of an object's perimeter to the square root of its number of pixels. Smoothness is a metric used to evaluate whether a segment has curves in its geometry and whether it is elongated. This metric is expressed by the ratio between the perimeter of the object and the perimeter of the rectangle that surrounds it. A spectral difference parameter is used to join neighboring objects according to their average values of layer intensity. This parameter works as a filter to clean the segmentation, decreasing the number of groups that have similar spectral characteristics, generated during the segmentation process.

Pacheco et al. (2021) compared the adapted KNN and C5.0 decision tree algorithms using Planet mosaic images with approximately 5m spatial resolution and obtained a better performance (75% accuracy) in mapping the small-scale agriculture class, with C5.0, in the municipality of Mocajuba, Para. However, this algorithm was over performed for other land use and land cover classes.

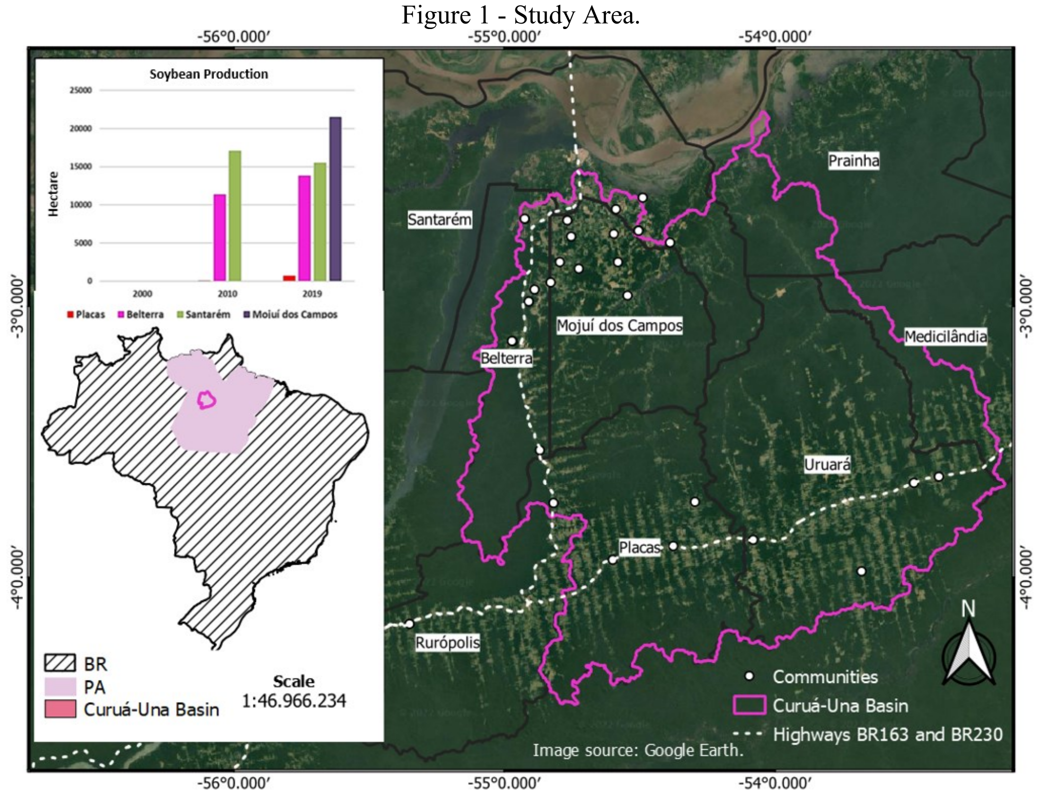
2 MATERIAL AND METHODS

2.1 Study area

The study area is delimited by the hydrographic basin of the Curuá-Una River (Figure 1), a tributary of the Amazon River, which is approximately 31 thousand km², encompassing the municipalities of Uruará, Placas, Mojuí dos Campos, and part of the municipalities of Santarém, Prainha, Medicilândia, and Belterra.

One of the most important historical landmarks of the region is the Curuá-Una Hydroelectric Plant, inaugurated in 1977 and located at Cachoeira do Palhão, at 70 km from Santarém. The plant's installation brought new settlements along the basin. Records from 2003 estimated a population around the dam of 1,900 people, engaged primarily in extractive activities and agriculture (MPEG, 1985; OLIVEIRA, et al., 2003).

Figure 1 - Study Area.



Source: The authors (2022).

This region is characterized by the presence of small to large rural properties, extensive cattle ranching, annual Large-Scale and Family Agriculture, and extractive activities (PRINTES, 2017). This region is well known for the production of açaí, sugarcane, cassava, soybeans, rice, corn, urucum, and black pepper (IBGE, 2017). The soybean production started in the 1990s, and it significantly increased in the 2000s due to the support of public policies for local infrastructure development (BECKER, 2005; MACHADO, 1998) as the paving of important roadways like the highway BR-163 and the construction of the Cargill's port in Santarém in 2003, which stimulated soybean production in the region (AMARAL et al., 2009; SANTOS, 2020).

Among the agricultural products cultivated along the basin, according to IBGE (2017, 2020) in the period from 2000 to 2019 (Figure 1), soybeans expanded the most, from 50 hectares in 2000 to 51,581 hectares in 2019. The municipalities of Santarém and Mojuí dos Campos remained the largest producers within the study area in 2019. Mojuí dos Campos was established in 2013 from the dismemberment of Santarém.

2.2 Data

For mapping of land use and land cover to evaluate LSA expansion, we performed classifications of images from the study area, for all the years analyzed. Data from Landsat and auxiliary data from different sensors were analyzed as shown in Table 1. Landsat images from the TM and OLI sensors were input for the classification model to estimate land use and land cover mapping, while images from Google Earth and the Planet image mosaic, with 5m spatial resolution, were used for the evaluation of the land use and land cover map classifications. All procedures were performed by the software eCognition, version 9 (TRIMBLE, 2021) Geographic Information Processing System, SPRING 5.4 (CÂMARA et al., 1996), and QGIS 3.18.

Table 1- Material used in the methodology. Legend: 1 - Refinement, 2 - Classification, 3 - Mask and 4 - Evaluation.

	Satllite/ Sensor	Orbit/ point	Used bands (RGB)	Espatial resolution	Temporal resolution	Date
1	Landsat 5/TM	226/063,226/062 227/062,227/063	5,4,3, EVI	30 m	16 days	99-2000
	Landsat 5/TM	226/063,226/062 227/062,227/063	5,4,3, EVI	30 m	16 days	2010
2	Landsat 8/OLI	226/063,226/062 227/062,227/063	4,3,2, EVI	30 m	16 days	2019
	Data	**Source**		**Espatial resolution**	**-**	**Date**
3	PRODES	INPE		30 m	Yearly	2019
	Land use and land cover- TerraClass	INPE		30 m	-	2014
4	Google Earth Pro	Google		-	-	-
	Planet Mosaic	Planet/INPE		-	-	-

Source: The authors (2022).

In this study, we analyzed images in bands 5, 4, and 3, plus the EVI (Enhanced Vegetation Index) (HUETE et al. 1997), to improve vegetation mapping and mitigate the interference of image processing in the data, such as lighting and atmospheric attenuation. Although the NDVI (Normalized Difference Vegetation Index) is the index commonly used to correct effects resulting from the imaging process, we chose to apply the EVI, as NVDI may be affected by variation in soil properties, causing pixel saturation (ROUSE, J. W. et al. 1974). According to Huete et al. (1997), the EVI optimizes vegetation signals, minimizing the influence of atmospheric attenuations as shown in Eq. (1).

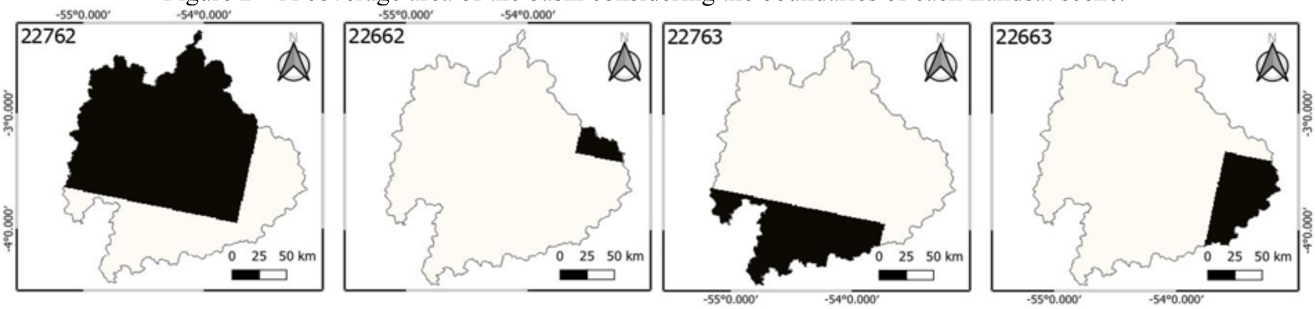
$$EVI = G\frac{\rho_{NIR}-\rho_{RED}}{L+\rho_{NIR}+C_1*\rho_{RED}-C_2*\rho_{BLUE}} \tag{1}$$

Where, L is the adjustment factor for soil; G is the gain factor, C1 and C2 are adjustment coefficients for the effect of aerosols present in the atmosphere; and ρ NIR, ρ RED, and ρ BLUE refer to the near-infrared, red, and blue surface reflectance, respectively. In this case, the EVI was obtained from ESPA-USGS (2020), calculated as shown in Eq. (2).

$$EVI = 2{,}5\frac{(Band\ 5-Band\ 4)}{(\text{Band } 5 + 6 * \text{Band } 4 - 7{,}5 * \text{Band } 2 + 1)} \tag{2}$$

The choice of bands was performed by empirical tests. Several bands were tested in the segmentation stage, using different thresholds. The bands shown below delivered the best results. The EVI was included in the mapping because it significantly improved the segmentation results. The overlays of each Landsat scenes that compose the Curuá-Una basin are shown, in black color in Figure 2.

Figure 2 – A coverage area of the basin considering the boundaries of each Landsat scene.

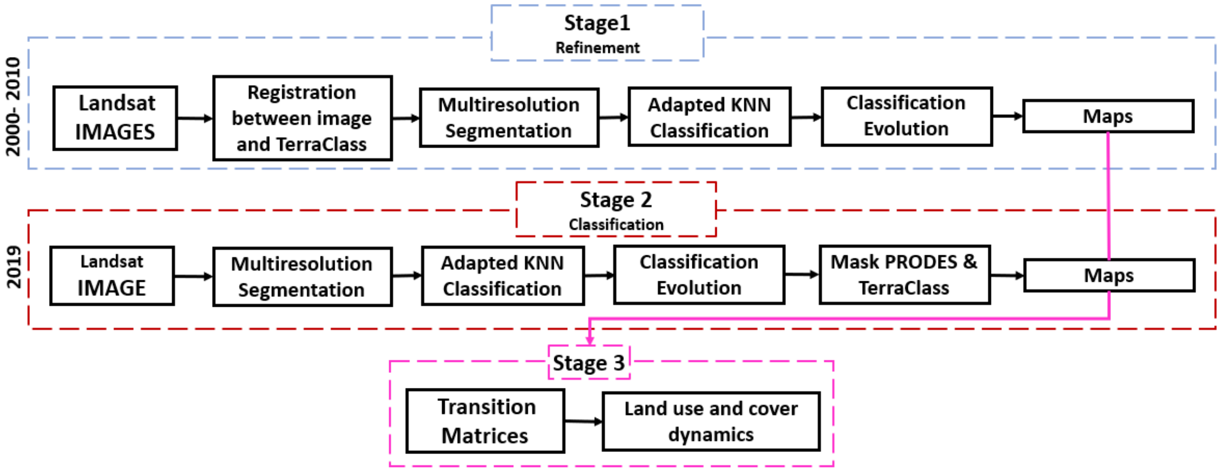


Source: The authors (2022).

2.3 Methods

The methodology applied is presented in three steps as shown in the flow chart below (Figure 3). In the first step we refined the data from TerraClass for 2000 and 2010, performing the mapping of SSA areas. The second step refers to the classification of land use and land cover performed for the year 2019. In the third step, the results are analyzed through maps visualizations, transitions matrices, and Sankey diagrams.

Figure 3 - Methodological flowchart.



Source: The authors (2022).

For the land use and land cover mapping of the years 2000 and 2010 (Stage 1), two procedures were applied. The first one was the reclassification of the land use and land cover maps simplifying TerraClass legend. The criteria adopted for the reclassification and generation of the simplified legend were defined according to the classes of interest. Initially, the original TerraClass *Annual Agriculture* class was renamed to Large-Scale Agriculture (LSA). The remaining classes considered for the reclassification were: R*eforestation* and *Mining* which were aggregated to the class named *Others*. The *Regeneration with Pasture* class was aggregated to the S*econdary Vegetation* class, while the other classes were kept. The second procedure consisted in refining the TerraClass land use and land cover data for the years 2000 and 2010 to include the *Small-Sscale Agriculture* class. For the identification and mapping of *SSA,* a class inexistent in the TerraClass data, we refined the TerraClass *Mosaic of Occupations* class (years 2000 and 2010) based on Landsat 5/TM images and classification procedures developed by Souza et al (2019) and by Santos (2018) for the northeastern region of Pará.

Souza (2016) and Souza et. al. (2019) refined the *Mosaic of Occupations and Secondary Vegetation* classes to identify and to map the SSA class*,* considering that this type of agriculture largely occurs in areas of cassava, pepper and cocoa cultivation compounded with Secondary Vegetation, due to the fallow system (JAKOVAC et al., 2017). Following this methodology, we chose to refine only the *Mosaic of Occupations* class for 2000 and 2010, considering that part of the Secondary Vegetation area may be inserted in the context of SSA. In 2000, TerraClass *Non-observed Area* class was also refined to identify SSA areas, using 1999 TM images, specifically in places where there was cloud cover in 2000. The procedures proposed for the refinement of the TerraClass classes for the two years, as well as for the evaluation of the resulting map, are schematized in step 1 of Figure 3.

The first step for the refinement consisted of the registration between TerraClass data and the TM/Landsat images. In this procedure, control points were manually acquired, and the registration was performed based on TerraClass data, Landsat images, using the KNN method for interpolation.

In the second step of refinement, multiresolution segmentation was performed in each of the scenes (Figure 2). The parameters considered for segmentation were determined empirically for each of the scenes given their specific spatial and spectral patterns. For classification, training samples (segments) of each class were selected and then the adapted object-oriented, K-Nearest Neighbor (KNN) classifier was applied. This classifier establishes an attribute space, including all segments in the training samples. When classifying each segment, the algorithm assigns it to the most similar or closest class, considering the attributes indicated by the analyst. In this work, the spectral attributes chosen were brightness and band average, and the spatial attributes were area and shape index. Therefore, the classifier considers spectral characteristics of the targets and their spatial attributes (TRIMBLE, 2021).

The maps resulting from the TerraClass refinement for the two years were evaluated using sample points acquired through TM/Landsat images with the aid of the Google Earth Pro platform. For the year 2000, 150 points were collected randomly distributed in the area of the refined classes. For the year 2010, 100 points were collected. The difference between number of points obtained in 2000 and 2010 is due to a smaller area of the Occupation Mosaic class in 2010.

In order to perform land use and land cover classification for the year 2019, 4 scenes from the OLI/Landsat 8 satellite were analyzed, covering the basin area (Figure 2). In the first step of the classification process, multiresolution segmentation was performed in each of the scenes, similarly to the approach presented for the refinement of previous years. The same legend adapted from the 2000 and 2010 maps was used in the classification of the OLI/Landsat images for the year 2019, including SSA class refinements.

Note that, although the basin area is composed of four images from the same sensor, they present different spatial patterns that influenced the choice of thresholds for segmentation. For example, scene 22762 (Figure 2) has large polygons that characterize LSA areas, then the thresholds defined for segmentation were higher than those of scene 22662, which does not have LSA areas. Thus, without loss of information in the classification of the scenes, we decided to perform individual segmentations and classifications using specific thresholds for each scene.

The images were classified using the adapted K-Nearest Neighbor (KNN) algorithm. After each scene was segmented and classified, they were appended, composing the total area of the basin. After the classification was completed, the Forest, Non- Forest, and Water classes from PRODES 2019 were aggregated together with Urban Area from TerraClass 2014, called "Prodes Mask" to ensure that there were no inconsistencies in the mapping in relation to the 2000 and 2010 TerraClass maps.

In order to evaluate the 2019 classification, images from Google Earth Pro, the Planet image mosaic (5 m), and images from the Landsat scenes were used. This process consisted of the selection of points throughout the extension of the classified scenes, which enabled the generation of four confusion matrices for each part of the basin, obtaining classes' accuracy rates and global accuracy rates.

The results obtained with the methodology developed allowed the Curuá-Una Basin to be characterized regarding mainland use and land cover in stage 3. The generated maps were combined using an intersection operation, two by two, to obtain the transition matrices for 2000-2010, 2010-2019, and 2000-2019. From the result of the intersection and the transition matrices, analyses of the transitions were performed using graphs of gain and loss of land use and land cover classes areas, in addition to the Sankey diagram.

3 RESULTS AND DISCUSSION

3.1 TerraClass Refinement

The evaluation of the refinement process for the maps in 2000 and 2010 was performed by inspection of a sample of locations using Landsat and Google Earth Pro images. From this result, it was possible to generate two confusion matrices to estimate accuracy values per class, as presented in Table 2. The accuracy of the results for SSA class, which comes from the refinement of the Occupation Mosaic class, is satisfactory regarding to the multiresolution segmentation procedure and object-oriented classification (KNN) in the discrimination of this class.

Table 2- Accuracy by class of the 2000 and 2010 occupancy mosaic class refinements.

2000			**2010**		
Overall Accuracy 98%			**Overall Accuracy 96%**		
Accuracy:	**Consumer**	**Producer**	**Accuracy:**	**Consumer**	**Producer**
LSA	100%	100%	LSA	100%	100%
SSA	100%	100%	SSA	100%	100%
Sec. Veg.	96%	96%	**Sec. Veg.**	88%	92%
Dirty Pasture	96%	96%	**Dirty Pasture**	96%	96%
Clean Pasture	96%	96%			

Source: The authors (2022).

3.2 2019 Classification

In order to evaluate the result of the 2019 land use and land cover mapping, four confusion matrices were generated, one for each scene that composes the Curuá-Una river basin area. From these matrices, it was possible to obtain the accuracy metrics per class for each part of the classified scene (Table 3).

Table 3 - Accuracy measures by class of each scene that composes the basin for the year 2019.

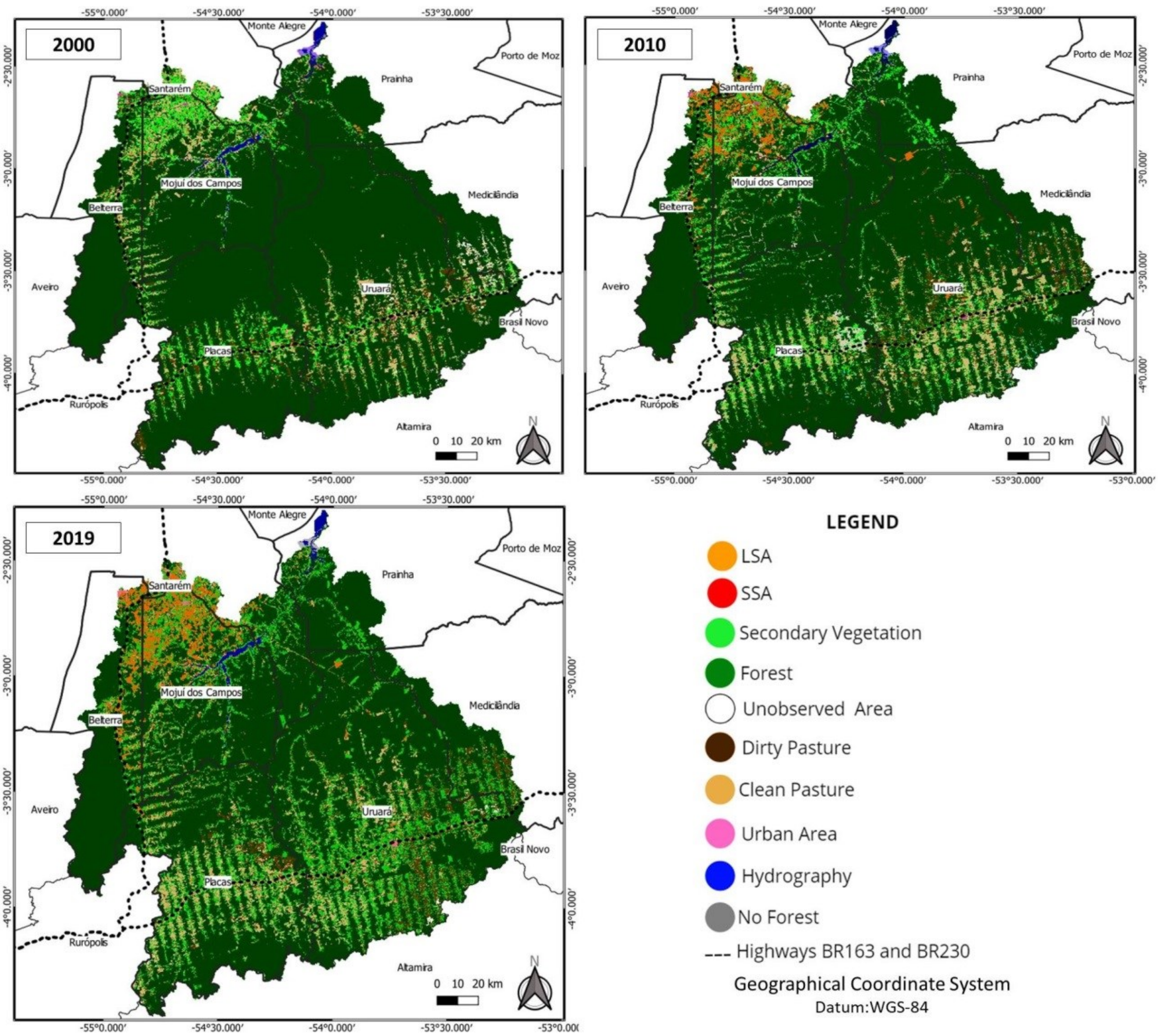
2019					
22762 Overall Accuracy 88%			**22662 Overall Accuracy 96%**		
Accuracy:	**Consumer**	**Producer**	**Accuracy:**	**Consumer**	**Producer**
LSA EXP. GROUND	98%	100%	**Sec. Veg. Init.**	93%	100%
LSA PLANTED	96%	96%	**Sec. Veg. Adv.**	86%	100%
SSA	56%	96%	**Dirty Pasture**	100%	84%
Sec. Veg. Init.	88%	70%	**Clean Pasture**	87%	100%
Sec. Veg. Adv.	76%	80%	**22663 Overall Accuracy 96%**		
Dirty Pasture	86%	87%	**AGPE**	76%	100%
22763 Overall Accuracy 98%			**Sec. Veg. Init.**	100%	100%
Sec. Veg. Init.	92%	100%	**Sec. Veg. Adv.**	100%	88%
Sec. Veg. Adv.	100%	92%	**Dirty Pasture**	100%	93%
Dirty Pasture	100%	100%	**Clean Pasture**	93%	93%
Clean Pasture	100%	100%			

Source: The authors (2022).

Table 3 shows that, although the classifications were performed using different parameters, given the particular conditions of each scene, all evaluations showed agreement between the classes and overall accuracy between 96% and 98%. The lowest overall accuracy value was 88%, for scene 22762. That result was expected, because this scene covers the most part of the basin and, for this reason, presents a greater variability of reflectance, which can result in greater confusion. Even though, the producer and consumer accuracy indexes per class show that the classes presented satisfactory agreement, obtaining indexes that ranged between 76% and 100%.

The results of the refinement and classification for the years 2000, 2010, and 2019 are presented in Figure 4. Notice that in the northern portion of the basin, the LSA class was found in 2010, but it was not present in 2000. The land use and land cover patterns found near Santarém are characterized by the strong increasing of the LSA class, in the period between 2010 to 2019, while in the lower portion of the Curuá-Una basin, in the neighborhood of the Transamazon Highway, the classes found are mainly related to Pasture. Also, Figure 4 shows the expansion of land use and land cover classes over forested areas in the central portion of the basin and on the side roads transverse to the Transamazon highway, which begins in the period from 2000 to 2010 and continues in the following period.

Figure 4 - Land use and land cover maps of the analyzed years.

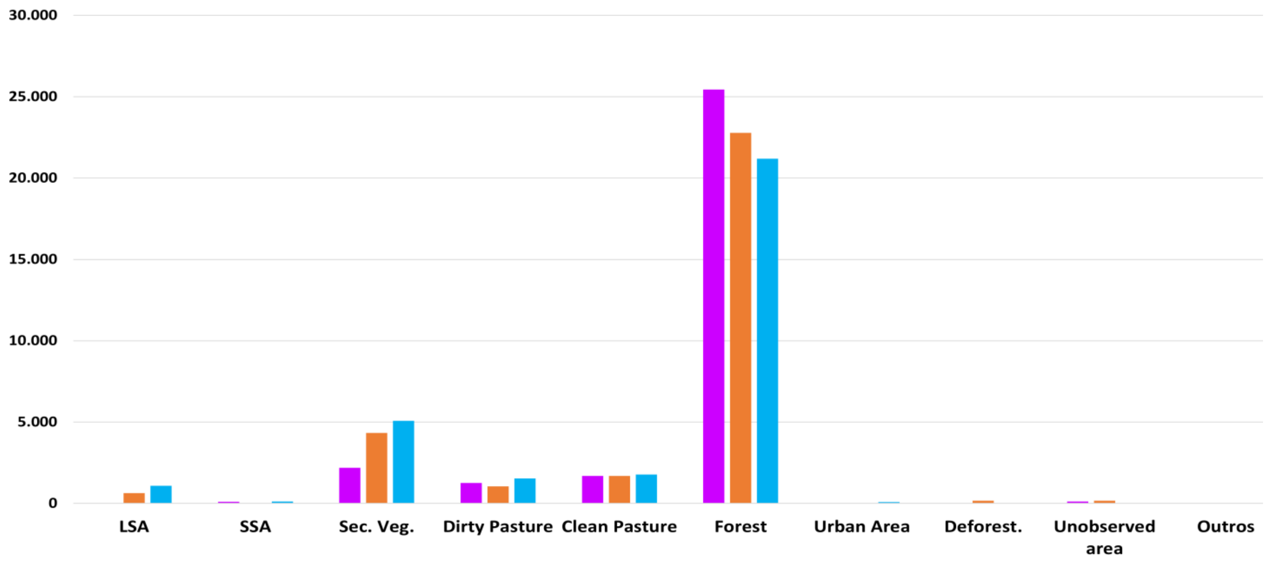


Source: The authors (2022).

3.3 Analysis of land use and land cover transitions in the period 2000 to 2019

The resulting maps allow analyzing the areas and the transitions that occurred between land use and land cover classes in the period of analysis, 2000 to 2010, 2010 to 2019, and 2000 to 2019. Figure 5 and Tables 4, 5, and 6, show the estimated transition matrices that describe the main dynamics of land use and land cover that have occurred in this region since soybeans entered the Curuá-Una basin in the late 1990s. Notice that "mining" and "reforestation" classes were aggregated into the class "Others", since they are relatively small and not prominent areas in this region.

Figure 5 - Dynamics of the land use and land cover classes in the period of 2000 to 2019.



	LSA		SSA		Sec. Veg.		Dirty Pasture		Clean Pasture		Forest		Urban Area		Deforest.		Unobser. area		Others	
	Km^2	%	Km^2	%	Km^2	%	Km^2	%	Km^2	%	Km^2	%	Km^2	%	Km^2	%	Km^2	%	Km^2	%
2000	23	0.07	93	0.30	2.192	7	1.264	4	1.696	5	25.438	82	23	0.07	1	0	123	0.3	33	0.1
2010	642	2	20	0.06	4.329	14	1.047	3	1.693	5	22.781	73	23	0.07	176	0.5	177	0.5	0	0
2019	1.093	3	121	0.39	5.079	16	1.528	4	1.770	5	21.183	68	76	0.24	0	0	37	0.11	0	0

Source: The authors (2022).

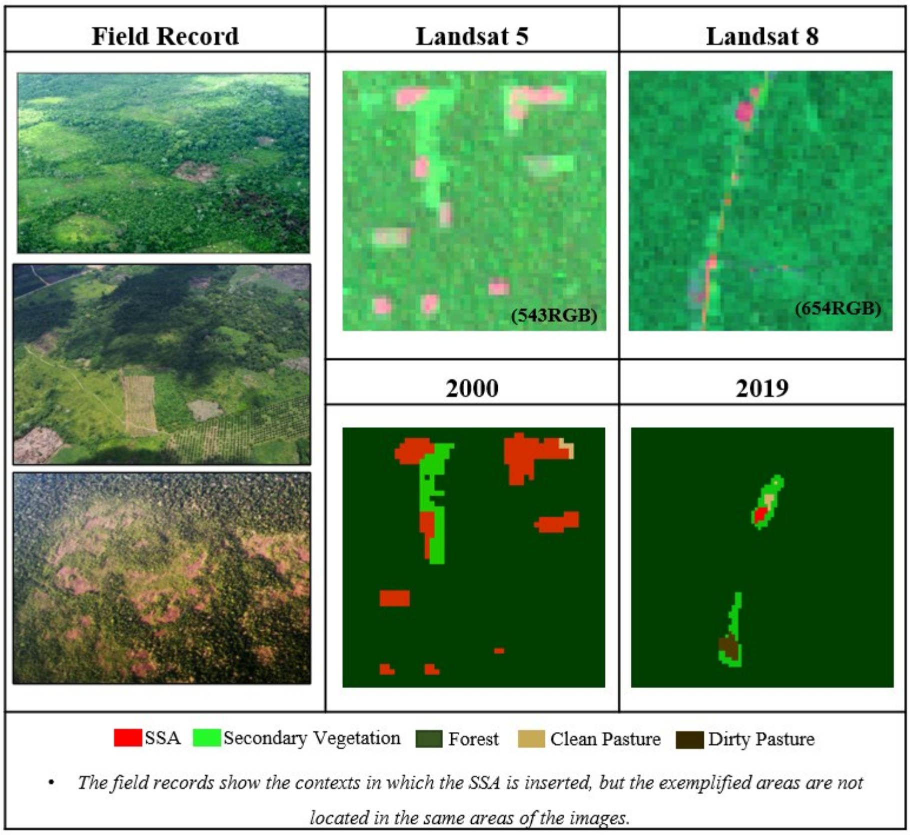
Table 4 - Transition matrix of land use and land cover classes from 2000 to 2019. The % refer to the loss values (line). Source: The authors (2022).

		2019																	
	TRANSITION	**LSA**		**SSA**		**Sec. Veg.**		**Dirty Past.**		**Clean Past.**		**Forest**		**Urban Area**		**Unobs. Area**		**Total**	
		KM^2	**%**	**KM^2**	**%**	**KM^2**	**%**	**KM^2**	**%**	**KM^2**	**%**	**KM^2**	**%**	**KM^2**	**%**	**KM^2**	**%**	**KM^2**	**%**
2000	**LSA**	12	(49)	0	(2)	6	(27)	1	(5)	2	(8)	1	(6)	0	(2)	0	(0)	23	*(100)*
	SSA	24	(25)	2	(2)	42	(45)	7	(7)	11	(12)	7	(7)	1	(1)	0	(0)	93	*(100)*
	Sec. Vegetation	336	(15)	22	(1)	1.026	(47)	215	(10)	287	(13)	282	(13)	18	(1)	4	(0)	2.191	*(100)*
	Dirty Pasture	90	(7)	12	(1)	556	(44)	228	(18)	302	(24)	59	(5)	12	(1)	5	(0)	1.263	*(100)*
	Clean Pasture	326	(19)	19	(1)	637	(38)	284	(17)	329	(19)	69	(4)	23	(1)	7	(0)	1.695	*(100)*
	Forest	298	(1)	65	(0)	2.737	(11)	752	(3)	826	(3)	20.735	(82)	7	(0)	19	(0)	25.439	*(100)*
	Urban Area	2	(10)	0	(1)	4	(20)	1	(4)	1	(4)	1	(4)	13	(57)	0	(0)	23	*(100)*
	Deforestation	0	(0)	0	(17)	0	(57)	0	(3)	0	(6)	0	(16)		(0)		(0)	1	*(100)*
	Unobs. Area	2	(1)	0	(0)	50	(41)	39	(31)	10	(8)	20	(16)	1	(1)	2	(1)	124	*(100)*
	Others	3	(8)	1	(1)	19	(55)	1	(4)	3	(7)	8	(23)	0	(1)	0	(0)	34	*(100)*
	Total km^2	1.093		121		5.079		1.528		1.770		21.183		76		37		30.886	

Observing Figure 5 and Table 4 a few findings can be made about land use and land cover transitions over the 19 years of analysis. About half (49%) of the LSA areas mapped in 2000 remained in 2019. However, this class area was very small and non-substantial in 2000 (23 km^2). In 2019, 298 km^2 (27%) of the LSA area comes from areas mapped as Forest class in 2000, while 416 km^2 (38%) comes from Pasture areas and 336 km^2 (31%) comes from Secondary Vegetation (Table 4). In the study by Coelho et al. (2021) similar results are presented, however, with different proportions, which are expected since the category of analysis in this work is family farming and not SSA. In Large-Scale grain production, whose goal is to expand the area of cultivation to ensure greater profit, it is a common practice to replace Pasture or other land designated to agriculture of crops for soybean cultivation. At the same time, usually in areas far away from these fields, to sustain a herd of cattle, the Pasture advances over forested land (GOLLNOW et al., 2018), a process called Indirect Land Use Change (ILUC).

As mentioned earlier, 31% of the LSA area in 2019 (Table 4) came from Secondary Vegetation areas in 2000, and only 24 km^2 (2%) of LSA expanded over SSA areas. However, LSA areas in 2019 represent 25% of the total SSA area in 2000. Note that part of the SSA may be within Secondary Vegetation class, which is part of these shifting cultivation systems, representing the fallow areas. In order to better understand this process, it is necessary to look beyond the limits of the SSA areas, as this cropping system is constituted by mosaics of land use and land cover, in which cropping areas are interspersed with patches of Secondary Vegetation (shifting cultivation) in various stages, as can be seen in Figure 6.

Figure 6 - Example of SSA-related Occupation Mosaic from field records and Landsat images.

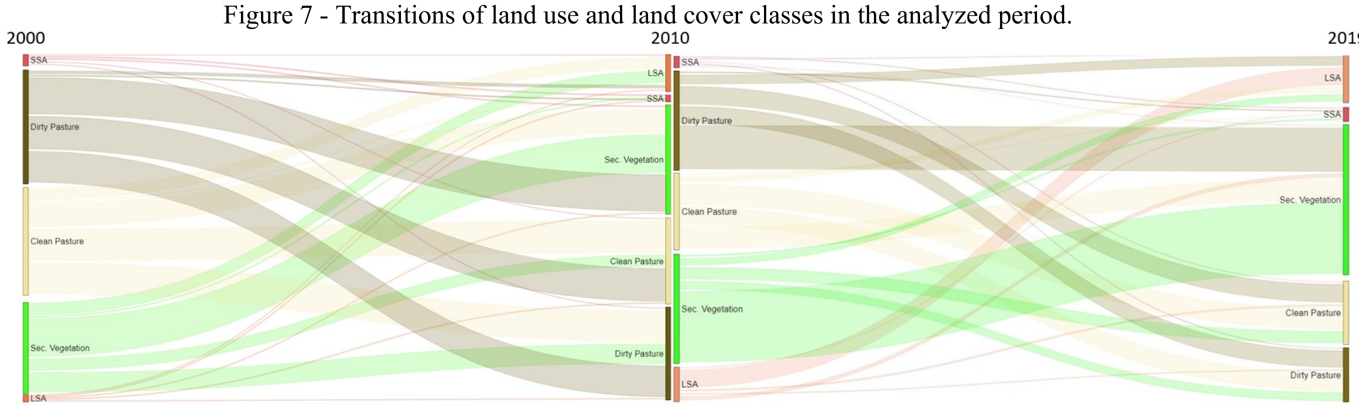


Source: The authors (2022).

The area of SSA that persisted in the period from 2000 to 2019 represented 2% of the SSA area in 2000, showing great instability (Table 4). This instability can be explained by the SSA agricultural practices in this region, mainly in cassava cultivation. These systems are dynamic, changing the cultivation locations every one or two years and are characterized by the presence of patches of Secondary Vegetation in various stages, and may also contain small areas of Pasture (DAL'ASTA et al., 2017) (Figure 6).

Additionally, 45% of the SSA area in 2000 became Secondary Vegetation in 2019 (Table 4), indicating that this type of agriculture is associated with fallow practices (FOURQUIN, 1972; BOSERUP, 2011; JAKOVAC et al., 2017). Table 4 also shows that 65 km² (53%) of the SSA class mapped in 2019 came from forest class in 2000. In order to facilitate the understanding of the dynamics presented in Table 4, Figure 7 shows the Sankey diagram, which illustrates transition schemes of land use and land cover in the period of analysis. Note that Forest class was removed from Figure 7, despite its importance, because it presented a much larger area than the other classes, preventing an adequate visualization of the transitions.

Figure 7 - Transitions of land use and land cover classes in the analyzed period.



Source: The authors (2022).

Evaluating the transitions of land use and land cover classes in greater detail, we decompose the transition analyses into two periods, 2000 to 2010 and, 2010 to 2019.

Table 5 and Figure 8 show the transitions in land use and land cover classes from the period 2000 to 2010. There is a total of 23 km^2 of LSA area in 2000, representing 0.4% of deforested areas. This class showed a large increase in 2010 to 642 km², representing 8% of the 2010 deforested areas. Since the Soy Moratorium started in 2008, a large part of the deforested area occupied by LSA might have formed before that year. According to data from IBGE (2010), the increase in soybean production in Brazil, in the period of 2000 to 2010, occurred predominantly through an increase in planted areas, of which 22.4% occurred in the Northern region of the country. Santos (2020) reports that in the study area, much of the soybean production expanded over Pasture and SSA areas. Since this region still has large areas of forested land, the author suggests that migratory population processes might have led to the advance of farming and ranching activities over forested areas.

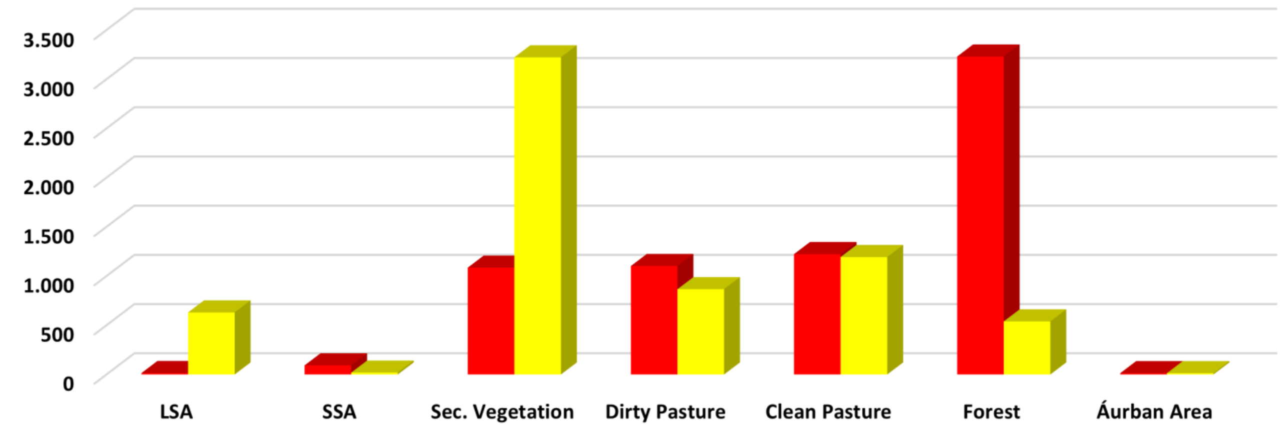
In the current study, the results show that the classes that had the highest proportions of area conversion to LSA in 2010 were Secondary Vegetation (33%) and Pasture (37%), which is consistent with the field surveys carried out by Santos (2020). Figures 8 clearly shows these transitions, through estimates of area loss and gain of land use and land cover classes. Note that forest class showed the greatest area loss, while Secondary Vegetation and LSA showed areas of gain far greater than loss from 2000.

Table 5- Land Transition among classes in km² and percentage (%) from 2000 to 2010. The % refer to the loss values (line).

		2010																			
	TRANSITION	LSA		SSA		Sec. Veg.		Dirty Past.		Clean Past.		Forest		Urban Area		Desfor.		Unobs. Area		Total	
		KM²	%	KM²	%	KM²	%	KM²	%	KM²	%	KM²	%	KM²	%	KM²	%	KM²	%	KM²	%
2000	LSA	9	(38)	0	(1)	7	(28)	4	(16)	2	(9)	2	(7)	0	(1)	0	(0)	0	(0)	23	(100)
	SSA	13	(14)	1	(1)	49	(53)	8	(9)	12	(13)	9	(10)	0	(0)	0	(0)	0	(0)	93	(100)
	Sec. Vegetation	209	(10)	4	(0)	1.107	(50)	178	(8)	293	(13)	342	(16)	4	(0)	12	(1)	43	(2)	2.192	(100)
	Dirty Pasture	43	(3)	1	(0)	553	(44)	162	(13)	377	(30)	88	(7)	3	(0)	5	(0)	32	(3)	1.264	(100)
	Clean Pasture	192	(11)	5	(0)	652	(38)	229	(14)	473	(28)	97	(6)	5	(0)	4	(0)	39	(2)	1.696	(100)
	Forest	171	(1)	9	(0)	1.883	(7)	446	(2)	507	(2)	22.208	(87)	1	(0)	151	(1)	61	(0)	25.438	(100)
	Urban Area	2	(9)	0	(1)	6	(25)	1	(4)	2	(8)	1	(5)	9	(40)	0	(0)	2	(8)	23	(100)
	Deforestation	0	(0)	0	(0)	0	(68)	0	(6)	0	(7)	0	(19)	0	(0)	0	(0)	0	(0)	1	(100)
	Unobs. Area	1	(1)	0	(0)	54	(44)	17	(14)	23	(19)	25	(20)	0	(0)	3	(2)	0	(0)	123	(100)
	Others	1	(4)	1	(1)	18	(55)	2	(5)	3	(8)	9	(26)	0	(0)	0	(0)	0	(1)	33	(100)
	Total km²	642		20		4.329		1.047		1.693		22.781		23		176		177		30.887	

Source: The authors (2022).

Figure 8 - Area losses and gains for the period 2000 to 2010.



Km²	LSA	SSA	Sec. Veg.	Dirty P.	Clean P.	Forest	Urban Area
LOSS	14	93	1.085	1.102	1.223	3.230	13
GAIN	630	19	3.222	866	1.193	539	13

Source: The authors (2022).

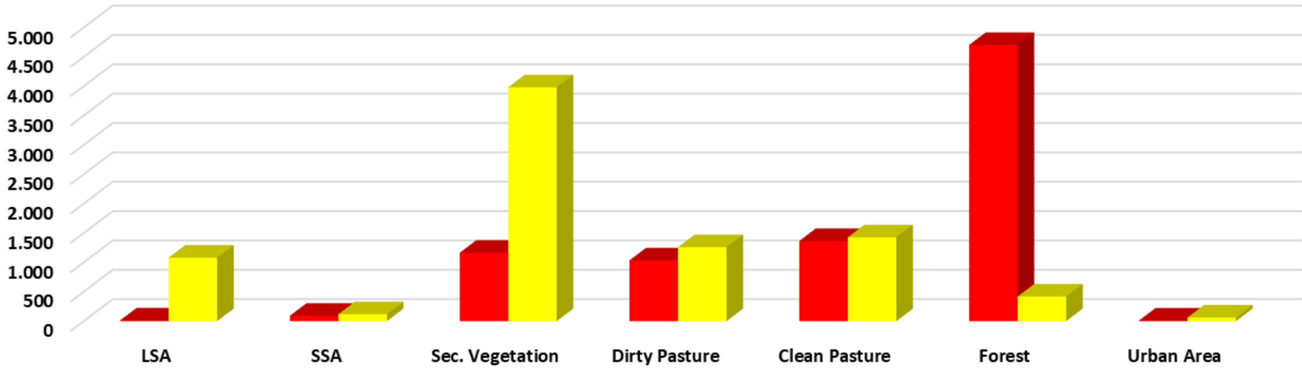
For the period between 2010 and 2019, Table 6 and Figure 9 show that, 70% of LSA area persisted in the period, occupying 11.5% of the deforested areas in 2019. This class proved to be quite stable, losing only to the Urban and Forest classes that showed stability of more than 90%. The LSA class showed an increase in its total area of 71%, going from 641 km² to 1,093 km². In 2019, LSA contained 305 km^2 (27%) of its area from the conversion of Secondary Vegetation, 247 km^2 (22.6%) from the Pasture area, 81km^2 (7.8%) from the Forest class, and 3 km² (3%) from SSA. The areas of SSA converted to LSA represented about 15% of the total SSA area of 2010, while 7% of the total Secondary Vegetation mapped in 2010, was converted to LSA. In this period, SSA shows an expressive growth (121 km^2) over the previous period (20 km^2). According to Santos (2020) this may have occurred due to low soybean prices in the period, which led to crop diversification of medium and small producers, who also leased part of their land for soybean farming. Souza et al. noted a similar process in 2012, the occurrence of Small-Scale Agricultural production, with Forest remnants and Secondary Vegetation in the interstices of LSA. The diagram in Figure 9 shows a large loss of forested land, of 2,018 km^{2,} and a large gain of area of LSA, Secondary Vegetation, an overgrown Pasture, while the other classes showed balance between losses and gains of land.

Table 6- Transition matrix of land use and land cover classes from 2010 to 2019. The % refer to the loss values (line).

		2019																	
	TRANSITION	LSA		SSA		Sec. Veg.		Dirty Past.		Clean Past.		Forest		Urban Area		Unobs. Area		Total	
		KM²	%	KM²	%	KM²	%	KM²	%	KM²	%	KM²	%	KM²	%	KM²	%	KM²	%
2010	LSA	448	(70)	4	(1)	95	(15)	23	(4)	44	(7)	18	(3)	8	(1)	1	(0)	641	*(100)*
	SSA	3	(15)	1	(3)	10	(47)	2	(11)	4	(21)	1	(3)	0	(1)	0	(0)	20	*(100)*
	Sec. Vegetation	305	(7)	52	(1)	2.586	(60)	467	(11)	617	(14)	268	(6)	19	(0)	12	(0)	4.327	*(100)*
	Dirty Pasture	114	(11)	10	(1)	437	(42)	214	(20)	188	(18)	72	(7)	6	(1)	4	(0)	1.044	*(100)*
	Clean Pasture	133	(8)	16	(1)	518	(31)	447	(26)	518	(31)	32	(2)	16	(1)	10	(1)	1.691	*(100)*
	Forest	81	(0)	33	(0)	1.278	(6)	302	(1)	320	(1)	20.770	(91)	2	(0)	8	(0)	22.796	*(100)*
	Urban Area	0	(1)	0	(0)	1	(3)	0	(1)	0	(1)	0	(0)	21	(93)	0	(0)	23	*(100)*
	Deforestation	6	(4)	2	(1)	88	(50)	28	(16)	30	(17)	20	(11)	0	(0)	1	(1)	176	*(100)*
	Unobs. Area	3	(2)	2	(1)	64	(36)	45	(25)	49	(28)	11	(6)	4	(2)	0	(0)	177	*(100)*
	Total km²	1.093		121		5.077		1.529		1.770		21.193		76		37		30.895	

Source: The authors (2022).

Figure 9 - Loss and gain area among classes from 2010 to 2019.



Km²	LSA	SSA	Sec. Veg.	Dirty P.	Clean P.	Forest	Urban Area
LOSS	192	20	1.728	827	1.163	2.018	2
GAIN	636	116	2.339	1.242	1.174	392	51

Source: The authors (2022).

4 CONCLUDING REMARKS

In the period of analysis, large-scale grain agriculture expanded in the plateau region of Santarém in a concentrated and intense manner, especially in the period from 2000 to 2010. Regarding this process of LSA expansion, over the analyzed period, we can synthesize some of the main findings of this study:

In the period from 2000 to 2010, Large-Scale Agriculture that was incipient in 2000, evidenced in the mapping with 23km², increased considerably in 2010, concentrated on the Santarém plateau, reaching an area of 642 km². This area advanced primarily over areas of Pasture, Secondary Vegetation, Forest, and land designated for Small-Scale Agriculture. SSA persists and coexists in the same regions where LSA is established.

In the period from 2010 to 2019, the expansion of LSA was steady, still concentrated in the Santarém plateau, but in an expanded region, getting closer to the BR-163 highway. In 2019, LSA covered 1,093 km², and incorporated more areas of Secondary Vegetation, Pasture, Forest, and SSA. Less forested land was converted directly to LSA compared to the period from 2000 to 2010. The SSA area increased and persisted on the Santarém plateau, remaining close to LSA fields.

From 2000 to 2019, the total period of analysis, 25% of SSA areas were converted to LSA. While there was an advance of LSA in the Santarém Plateau region, in the central portion of the Curuá-Una basin and in other regions far from urban areas and major highways, there was a conversion of forested land that are in 2019 occupied in large proportion by Secondary Vegetation. That process can also be seen in neighbor areas around the Transamazon highway, in locations somewhat far from the axis of this highway. This phenomenon should not be evaluated in isolation, the high prices of land due to the expansion of grain production unable access of small and medium producers to land, forcing migration to increasingly more distant regions, in general, to areas with little infrastructure, with large forest cover. The expansion of LSA over forested land was more intensive in the period from 2000 to 2010. However, the results indicate that the expansion of LSA may have caused indirect changes through forest conversion in remote areas, such as the central portion of the basin.

A more complete analysis, with field interviews, is necessary to investigate this process in greater detail. The results obtained by this research reinforce the importance of establishing policies that enhance and strengthen the local economy, enabling these agents and their production practices to persist in the region. It is known that the balance between large and small scale production is fragile, presenting great asymmetries in their purchasing power, institutional arrangements, and the technologies employed.

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Authors' contribution

The first author (Danielle Silva de Paula) was responsible for Conceptualization, Research and Methodological, Visualization and Writing – draft. The second author (Maria Isabel Sobral Escada) was responsible for Conceptualization, Supervision and Writing – revision and editing. The third author (Jussara de Oliveira Ortiz) was responsible for Conceptualization, Supervision and Writing – revision and editing.

Conflict of interest

The authors declare no conflict of interest.

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Biography

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