Revista Brasileira de Cartografia
ISSN 1808-0936 | https://doi.org/10.14393/revbrascartogr
Sociedade Brasileira de Cartografia, Geodésia, Fotogrametria e Sensoriamento Remoto

Land Use and Land Cover Trajectory Classification and Analysis Methods in the Amazon: Implications for Forest Regeneration Studies

Métodos de Classificação e Análise de Trajetórias de Uso e Cobertura da Terra na Amazônia: Implicações para Estudos de Regeneração Florestal

Mariane Souza Reis [1], Maria Isabel Sobral Escada [2], Sidnei João Siqueira Sant'Anna [3] e Luciano Vieira Dutra [4]

1 Instituto Nacional de Pesquisas Espaciais, PPGCST, São José dos Campos/SP, Brasil. mariane.reis@inpe.br
ORCID: https://orcid.org/0000-0001-9356-7652
2 Instituto Nacional de Pesquisas Espaciais, DIOTG, São José dos Campos/SP, Brasil. isabel.escada@inpe.br
ORCID: https://orcid.org/0000-0002-5822-8265
3 Instituto Nacional de Pesquisas Espaciais, DIOTG, São José dos Campos/SP, Brasil. sidnei.santanna@inpe.br
ORCID: https://orcid.org/0000-0001-7557-3215
4 Instituto Nacional de Pesquisas Espaciais, DIOTG, São José dos Campos/SP, Brasil. luciano.dutra@inpe.br
ORCID: https://orcid.org/0000-0002-7757-039X

Received: 08.2020 | Accepted: 11.2020

Abstract: The analysis of forest regeneration processes provides information used to estimate atmospheric carbon assimilation, soil fertility recovery, hydrological cycles and biodiversity maintenance, among other environmental services. These studies require information that is usually found in land use and land cover trajectories mapped in long time intervals and with annual observations. These trajectories are usually obtained by processing remote sensing image time series. In this review article we first identify and describe the main methods used to classify and analyze land use and land cover trajectories based on orbital remote sensing data. We then discuss these methods based on their applicability in forest regeneration studies in the Amazon. Throughout this process we observe that analyzing land use and land cover trajectories in the Amazon is not a trivial task. Traditional change detection methods result in invalid trajectories or require many classification steps. Given the large volume of data, it is common to simplify the information contained within the trajectories to the point that analyses are reduced to one or two observed times. In these cases, important information about regeneration processes is lost, such as persistence of secondary vegetation and time of use before abandonment. Among the main observed limitations, we highlight the lack of available data, such as cloud free images and reference data.
Keywords: Forest regeneration. Amazon. Land use and land cover trajectories. Remote sensing time series.

Resumo: A análise de processos de regeneração florestal provê informações que permitem estimar serviços ecossistêmicos como a fixação de carbono atmosférico, a recuperação da fertilidade dos solos, a manutenção do ciclo hidrológico e da biodiversidade, entre outros. Esses estudos demandam informações usualmente contidas em trajetórias de uso e cobertura da terra com resolução temporal anual, em intervalos de tempos longos. Comumente, esses dados são obtidos a partir do processamento de séries temporais de imagens de sensoriamento remoto. O objetivo deste artigo de revisão é identificar e descrever os principais métodos utilizados para classificar e analisar trajetórias de uso e cobertura da terra a partir de dados de sensoriamento remoto orbital. Esses métodos foram então discutidos em função de sua aplicabilidade na região Amazônica para análise de regeneração florestal. Observou-se que a análise de trajetórias de uso e cobertura da terra na Amazônia não é trivial. Métodos tradicionais de detecção de mudanças resultam em trajetórias inválidas ou compreendem vários passos de classificação. Pelo grande volume de dados analisados, muitas vezes a informação da trajetória é simplificada ao ponto de se tornar uma análise que envolve apenas um ou dois tempos observados, perdendo-se informações importantes para a análise de regeneração florestal, como a persistência da vegetação secundária ou o tempo de uso antes do abandono, por exemplo. Dentre as principais limitações observadas, destaca-se a baixa disponibilidade de dados, sejam imagens livres de nuvens ou dados de referência.
Palavras-chave: Regeneração florestal. Amazônia. Trajetórias de uso e cobertura da terra. Séries temporais de sensoriamento remoto.

1 INTRODUCTION

The Amazon basin is considered one of the most important ecological systems on the planet (FOLEY et al., 2007), covering more than 6 million km², of which approximately 5.5 million km² are covered by tropical forests. The Amazon rainforest is the biggest tropical forest in the world and is responsible for important ecosystem services, such as biodiversity maintenance, carbon storage, regulation of water flux, and regulation of the regional and global climates (FOLEY et al., 2007; COE et al., 2013). In Brazil the Amazon biome is commonly referred to simply as the Amazon. This biome occupies almost half of the Brazilian territory and extends over the North, Northeast, and Center-West regions. For legal and planning purposes, the Brazilian government also instituted the Brazilian Legal Amazon. It includes the States of Acre, Amapá, Amazonas, Mato Grosso, Pará, Rondônia, Roraima, and Tocantins, and part of the state of Maranhão (BRASIL, 1966; BRASIL, 2007).

Despite its importance, the Amazon has been under constant local and regional pressure for its natural resources. This pressure is reinforced by the type of economic development practiced in the region, as well as the current and inefficient control, conservation, and forest management policies. These elements are commonly reflected in land use and land cover changes, notably the deforestation of primary forest (FEARNSIDE, 1990; COE et al., 2013). Among the potential impacts of deforestation are: biodiversity loss, greenhouse gas emissions, surface albedo modification, soil productivity loss, and hydrological regime alterations (FEARNSIDE, 2005). Some of these impacts can be offset by forest regeneration processes, i.e., the growth of secondary vegetation in previously deforested areas (BROWN; LUGO, 1990; CORLETT, 1995). During forest regeneration, carbon is assimilated from the atmosphere and either transformed into biomass or fixed in the soil (RAMANKUTTY et al., 2007). Secondary vegetation areas provide important ecosystem services, such as soil erosion prevention, soil fertility recovery, hydrological cycle maintenance, and the formation/connection of ecological corridors (CHAZDON et al., 2009; MEYFROIDT; LAMBIN, 2011).

Details on the spatial-temporal distribution and the intensity of forest regeneration processes over long periods are important information to estimate greenhouse gas emissions and support territorial planning (VIEIRA et al., 2014; PARÁ, 2015). However, these details are still poorly understood. The Amazon is extensive with varied histories of land occupation. Therefore, the dynamics of land use and land cover (LULC) change are heterogeneous in space and time, affecting forest regeneration in distinct ways (MORAN et al., 2000; PERZ; SKOLE, 2003; WANDELLI; FEARNSIDE, 2015). These differences in forest regeneration processes result in varied dynamics of biomass accumulation and carbon absorption rates (STEININGER, 2000; AGUIAR et al., 2012).

Forest regeneration can occur throughout different exploitation cycles. Thus, studying this process requires information usually represented as LULC trajectories, defined as the succession of types (i.e., classes) of land use and/or land cover in a given spatial unit of analysis at three or more observed times (MERTENS; LAMBIN, 2000; MENA, 2008). Land cover refers to the biophysical state of the land surface, including the amount and type of vegetation cover, water, and other materials and structures of natural or anthropic origins. Land use refers to the set of activities carried out on the land and the purpose of manipulating the land cover for activities of human interest (TURNER; MEYER, 1994).

Commonly, LULC trajectories are obtained by processing time series data of orbital remote sensing images[1]. In recent years, new techniques have emerged to analyze remote sensing time-series data, as a result of computational and methodological advances, the unprecedented availability of data from different sensors, and improvements in data processing/format standardization (WULDER et al., 2018). Some of these techniques have been reviewed by Banskota et al. (2014), Gómez et al. (2016), and Zhu (2017). The latter studies are comprehensive and more general and, therefore, do not detail important specificities when it comes to analyzing LULC trajectories in forest regeneration studies in the Amazon. Thus, the objective of the present manuscript is to identify and describe the main methods used to classify and analyze LULC trajectories based

[1] Information about land use is not directly derived from remote sensing data. However, land use can be attributed by the analyst according to the knowledge of the study area, in association with the land cover class, and/or using auxiliary data.

on orbital remote sensing data. Given the high degree of complexity in forest regeneration processes, the clear definition of objectives, LULC classes, and the spatial-temporal resolution and extension of the study is crucial. These factors influence both data selection and methods in forest regeneration analyses in the Amazon, as discussed in this manuscript. In this discussion we will examine both the potential and limitations of the most common methods, tools, and available remote sensing products.

1.1 Adopted definitions and review scope

There are different expressions used as synonyms for secondary vegetation in the literature. The most common expressions, as well as selected variations in the definition, are presented in Table 1. Other definitions are discussed in Chokkalingam and Jong (2001).

Table 1 - Definitions of secondary vegetation found in the literature.

Expression	Definition and authors
Secondary vegetation	Forests formed as a consequence of human impact on forest lands, particularly as a result of abandoned cleared forest lands, generally for agriculture, and excluding planted forests and forests resulting from natural disturbances (BROWN; LUGO, 1990)
	Clear-cut areas detected by the Program for Deforestation Monitoring in the Brazilian Legal Amazon (PRODES), where vegetation has regenerated after the land has been abandoned (ALMEIDA et al., 2010)
	"Originally forested areas that had been clear-cut, used for silviculture, agriculture or pasture and then left to regenerate, taking on a forest appearance again" (ALMEIDA et al., 2016)
Secondary forest/Second- growth forest	"Forests regenerating largely through natural processes after significant human and/or natural disturbance of the original forest vegetation at a single point in time or over an extended period, and displaying a major difference in forest structure and/or canopy species composition with respect to nearby primary forests on similar sites" (CHOKKALINGAM; JONG, 2001)
	Forests that develop after complete deforestation (CORLETT, 1995; PUTZ; REDFORD, 2010; VIEIRA et al., 2014; WANG et al., 2020)
	Vegetation that emerges on abandoned farmland or planted estates where the original forest was clear-cut before agricultural use (KAMMESHEIDT, 2002)
	Forests that occur "when a pixel classified as anthropic cover (e.g., pasture or agriculture) in a given year is replaced in the following year by a pixel of forest cover (excluding mangroves and plantations)" (SILVA JUNIOR et al., 2020)
Capoeira	Secondary vegetation that grows after the clearing of primary forests (IBGE, 2004)
	"Areas with secondary vegetation that are either temporarily or permanently removed from agricultural production. (…) Land areas in different stages of natural regeneration after having been radically altered by human activity" (COSTA, 2016)
	Areas of varying dimensions, in different stages of spontaneous regeneration of forest cover in ecosystems radically altered by human actions (COSTA, 2009)
	Secondary vegetation in the intermediate stage of succession (SALOMÃO et al., 2012)
Capoeirão	*Capoeira* in a more advanced stage of succession (IBGE, 2004)
	Secondary vegetation in an advanced stage of succession (SALOMÃO et al., 2012)
Capoeirinha/ Juquira	Secondary vegetation in the initial succession stage (SALOMÃO et al., 2012)

Source: the authors (2020).

The presented definitions agree on the idea that secondary vegetation, secondary forests, or *capoeiras* are types of vegetation that regenerate after the original forest cover has suffered some type of disturbance. The main observed differences among the definitions relate to:

a) the type of disturbance: whether the disturbance is of a natural or anthropic origin, or both;
b) the intensity of the disturbance: whether it occurred only in areas where the forest had been clear-cut or in areas with a given level of forest degradation;
c) the land use after disturbance: some definitions incorporate specific types of land use before secondary vegetation;
d) the vegetation structure and composition: whether the resulting vegetation presents similar characteristics to the original forest cover;
e) the regeneration process: whether it is natural or a result of human intervention;
f) the successional stage: in some cases, some expressions refer to different successional stages, whereas these same expressions may also be used in a general way, as is the case with the expression

capoeira;

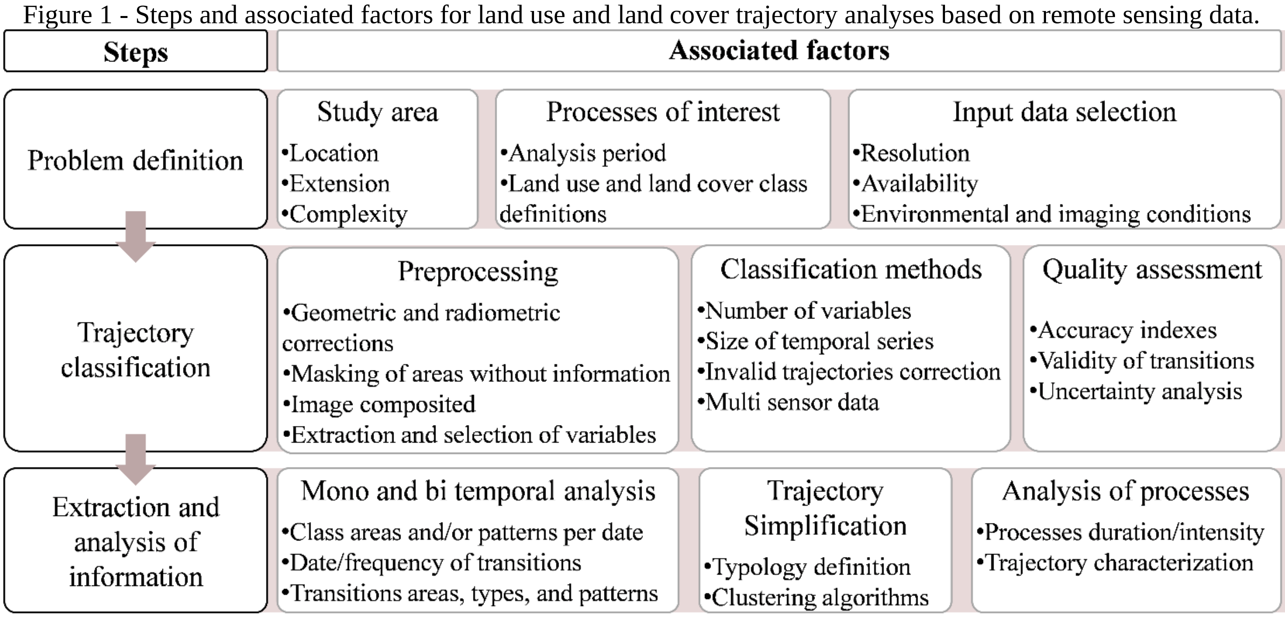
g) the characteristics of the data used: certain definitions are associated with the capacity to identify secondary vegetation with remote sensing data, such as those adopted by Almeida et al. (2010) and Silva Junior et al. (2020).

To delimit the scope of this review article, the expression secondary vegetation was reserved to describe the vegetation that grows without human direct interference in areas with complete removal of the original forest cover, without distinction as to the cause of the removal of this cover or the types of intermediate use. The regeneration of degraded forests was not included in the present discussions.

2 LAND USE AND LAND COVER TRAJECTORY ANALYSES

The methods and procedures used to analyze LULC trajectories based on remote sensing data were summarized in three basic steps: 1) problem definition, 2) trajectory classification, and 3) information extraction and analysis. These steps are as illustrated in Figure 1 and discussed in the context of specific characteristics of forest regeneration studies as follows.

Figure 1 - Steps and associated factors for land use and land cover trajectory analyses based on remote sensing data.



Source: the authors (2020).

2.1 Problem definition

The study objectives are defined in this step, as well as the location and extent of the studied area, the period of the analysis, the LULC classes, and the required level of accuracy (LU; LI; MORAN, 2014). Both the data and methods to be used in the analysis are selected according to the problem definition. Nonetheless, both the availability (or lack thereof) of remote sensing data and methods to process and extract different types of information often limit and/or shape the objectives of the study. Inadequate spatial and temporal resolution in the used data, difficulties discriminating between different LULC classes, and a lack of available time series data for long periods with dense observations are among the main limitations.

2.1.1 STUDY AREA AND PROCESSES OF INTEREST

Forest regeneration processes in the Amazon occur in different ecological, social, and political contexts (VIEIRA et al., 2014; CHAZDON et al., 2020). Studies seeking to examine these processes must consider existing different land management systems and regeneration cycles with varying time lengths. According to Costa (2016), the presence of secondary vegetation in the Brazilian Amazon can be associated with three types of land use decisions: 1) the use of techniques that adopt the regeneration of fallow areas to restore soil fertility, such as the shifting agriculture carried out by riverside and traditional populations; 2) the abandonment of degraded and/or unproductive areas after exhausting the soil and climatic conditions needed for production; and 3) the intensification of land use that lead to production in smaller areas, causing secondary vegetation to regenerate on excess lands. In the latter case, the land surplus can be incorporated into the production process again, thereby leading to deforestation of secondary vegetation. Additionally, Mello and Alves (2011) mention a type of secondary vegetation that results from the abandonment of a recently deforested area that has never been involved in the production process. These characteristics may affect the definition of the analysis period and LULC classes.

According to Wang et al. (2020), secondary vegetation areas are commonly deforested within 2 years after the start of the regeneration process. Therefore, forest regeneration can involve abrupt or subtle changes in both the short or long terms (NUNES et al., 2020). Riverside regions, for example, may present agricultural activities with fallow and regeneration periods that vary between less than four and more than 15 years (STEININGER, 2000; AFFONSO et al., 2016; JAKOVAC et al., 2017). LULC trajectories can also be used to estimate the age of secondary vegetation (NUNES et al., 2020; SILVA JUNIOR et al., 2020). In the state of Pará, Normative Instruction 08 of October 28, 2015 states different rules for vegetation suppression depending on the age of the secondary vegetation. These rules are stratified as follows: no older than five years, five to 20 years, and older than 20 years (PARÁ, 2015). The categorization between secondary vegetation areas that are less than 20 years old and those that are more than 20 years old is also used to estimate carbon absorption rates (SILVA JUNIOR et al., 2020). Therefore, at least one observation of LULC trajectories should be mapped per year to improve the accuracy of age estimates and permit abrupt changes to be captured in dynamic areas. Analyses carried out at intervals of more than 20 years are also recommended to study forest regeneration in the Amazon, to allow full observation of regeneration cycles. Such analyses also enable age estimates of older vegetation.

Defining LULC classes is a particularly important step in LULC studies given that different class definitions can result in quite different analyses. For example, the “forest” class sometimes encompasses areas of primary forest, degraded forest, and also secondary vegetation, which is not compatible with forest regeneration studies (PUTZ; REDFORD, 2010). When it comes to defining LULC classes in the Amazon, it is also interesting to obtain information on areas devoted to agriculture, pasture, urban areas, and mining to better understand the influence of different land use histories. There are three basic ways to define LULC classes. The first is to arbitrarily define the used classes. The second is to derive classes from a standard classification or legend system. A classification system is a logical framework that retains class names, the criterion for class separation, and the relationship among classes (MCCONNELL; MORAN, 2001). A legend is a subset of classes, which may or may not be obtained from a classification system (MCCONNELL; MORAN, 2001; HEROLD et al., 2006). Among the commonly used classification systems are: *Sistema Básico de Classificação da Cobertura e do Uso da Terra* (IBGE, 2013), Anderson et al. (1976), and CORINE (COOrdination of INformation on the Environment) Land Cover (CLC) (EEA, 2019). The third way is to define LULC classes based on empirical analyses of the data (PEREIRA et al., 2018) and/or image classification results (PANTALEÃO; DUTRA; SANDRI, 2012). The main advantages and disadvantages of each method are discussed in Reis et al. (2018). It should be noted that in all three methods any classes defined using subjective criteria can compromise both the reproducibility of a study and eventual comparisons between results. A solution to decrease subjectivity in the class definition is to describe these classes based on quantifiable elements of land cover, as proposed by the Land Cover Meta Language (LCML), initially called Land Cover Classification System (LCCS) (DI GREGORIO; JANSEN, 2005). LCML is a flexible system focused on standardizing the terminology used to describe the classes, rather than describing the classes themselves. It has been used to describe the legends of different locations, including the Amazon (COUTINHO et al., 2013; REIS et al.; 2018). As LULC trajectories necessarily imply the classification of LULC over time, it is also essential that the correspondence among the legends used on each date is known.

2.1.2 INPUT DATA SELECTION

The selection of input data generally occurs considering the resolution characteristics of the available sensors. The selected data should be suitable to identify the LULC classes in the study scale. The characteristics of the main remote sensors with open archives are compiled in Table 2.

Table 2 - Characteristics of the main remote sensors with open archives.

Satellite /Sensor	**Resolution**				**Footprint (km)**	**Operation period**
	Spatial (m)	**Temporal (days)**	**Spectral (μm)**	**Radiometric (bits)**		
NOAA(6-19)/AVHRR(2-3)	1100	< 1	4-6 bands (0,58 to 12,50)	10	2400	1979 to 2019
Landsat(1-5)/MSS	68×83	16-18	4 bands (0,50 to 1,10) [a]	6-8	185	1972 to 1999
Landsat(4-5)/TM	30 [c]	16	7 bands (0,45 to 12,50)	8	185	1982 to 2013 [b]
Landsat-7/ETM+	30 [c,d]	16	8 bands (0,45 to 12,50)	8	183	from 1999 [e]
Landsat-8/OLI	30 [e]	16	9 bands (0,43 to 2,30)	12	185	from 2013
Landsat-8/TIRS	100	16	2 bands (10,30 to 12,50)	12	185	from 2013
(Terra/Aqua)/MODIS	250-1000	1-2	36 bands (0,40 to 14,38)	12	2330	from 1999
Terra/ASTER	15-90	16	15 bands (0,52 to 11,65)	8-12	60	from 1999 [f]
CBERS(1-2b)/CCD	20	26	5 bands (0,51 to 0,89)	8	113	1999 to 2010
CBERS(1-2b)/WFI	260	< 5	2 bands (0,63 to 0,89)	8	890	1999 to 2010
CBERS(1-2)/IRMSS	80-160	26	4 bands (0,5 to 12,50)	8	120	1999 to 2008
CBERS-2b/HRC	2,7	130	1 band (0,50 to 0,80)	8	27	2007 to 2010
CBERS-4/PAN	5-10	26-52	4 bands (0,51 to 0,89)	8	60	from 2014
CBERS-4/IRS	40-80	26	4 bands (0,50 to 12,50)	8	120	from 2014
CBERS-(4-04A)/WFI	55-64	< 5	4 bands (0,45 to 0,89)	10	684-866	from 2014
CBERS(4-04A)/MUX	16,5-20	26-31	4 bands (0,45 to 0,89)	8	95-120	from 2014
CBERS-04A/WPM	2-8	31	5 bands (0,45 to 0,90)	10	92	from 2020
Resourcesat(1-2)/LISS III	23,5	24	4 bands (0,52 to 1,70)	7	141	from 2004
Resourcesat(1-2)/AWiFS	56	5	4 bands (0,52 to 1,70)	10	370-810	from 2004
Sentinel-2/MSI	10-60	5	13 bands (0,43 to 2,32)	12	290	from 2015
ALOS/PALSAR	10-100 [g]	n.d.	band L (23 cm) [h]	32	30-350 [g]	2006 to 2011
Sentinel-1	5-40 [g]	6-12	band C (5,5 cm) [i]	10	20-410 [g]	from 2014

[a] The sensor carried a thermal band in Landsat 3. [b] Significant drops in number of observations after 2011. [c] 120 m for the thermal band. [d] 15 m for the panchromatic band. [e] Detection failures from May 2003. [f] Saturation of infrared band from April 2008. [g] Depending on the acquisition mode. [h] 1 to 4 polarizations, depending on the acquisition mode. [i] 1 to 2 polarizations, depending on the acquisition mode.

Source: EMBRAPA (2018), ASF (2020), ESA (2020), INPE (2020a), INPE (2020b), NASA (2020a), NASA (2020b) e USGS (2020).

It should be noted that the coverage and period of operation of a satellite/sensor does not guarantee the availability of data. This can occur because the sensors may not operate regularly in some areas (e.g., the Multispectral Scanner (MSS), which sensed images for the Amazon on a few and sparse dates). Additionally, remote optical sensors are strongly influenced by atmospheric conditions. Given that cloud cover is frequent in the Amazon at certain times of the year, it is possible that an orbital optical image acquired for the desired period and area may not be suitable for analysis. Despite this eventual difficulty of finding cloud-free images for certain dates, the characteristics of data from the Landsat family are appropriate to analyze annual LULC trajectories over long periods. According to Gómez et al. (2016), Landsat images are the basis for land cover classifications, whereas other types of data are used complementarily. Nonetheless, Sentinel-2 data has great potential for future analyses, given the availability of free images, the resolution characteristics of its sensor, cross-calibration with Landsat data, and the prospects of project continuity (WULDER et al., 2018).

Synthetic Aperture Radar (SAR) data are obtained almost independently of weather conditions and are able to capture information about the land surface in cloud covered areas (PARADELLA et al, 2005).

However, SAR data are more difficult to interpret and process than optical data and are freely available for short periods. Despite the arrival of the first global forest analysis products based on SAR data (SHIMADA et al., 2014), analyses based solely on SAR images are still mostly limited to a few dates. With the continuation of the Sentinel-1 project, it is possible that new products based on SAR data, or even multi-sensor approaches, emerge in the future.

2.2 Trajectory classification

The trajectory classification step corresponds to assigning LULC classes to each spatial unit analysis at each time of interest. This step involves three main procedures, which are described in this section.

2.2.1 PREPROCESSING

Once the remote sensing data is selected, it is necessary to ensure that these data are comparable at the unit of analysis level, which is usually the image pixel. In general, this process involves absolute or relative radiometric and geometric correction of the data (COPPIN et al., 2004; RICHARDS; JIA, 2006; WULDER et al. 2018). It is also common to mask and/or remove low-quality pixels, or pixels without any information, from the analysis. One way to solve low-quality pixel problems is to compose a new image from selected pixels from radiometrically calibrated images in the period of interest. The selection of the Best Available Pixel (BAP) can be done by combining different factors, such as low probability of clouds/cloud shadow, distance to clouds, proximity to the date of interest, and quality indexes derived from the images, for example. Different BAP selection techniques have been proposed in recent years (HOLBEN, 1986; GRIFFITHS et al., 2013; WHITE et al., 2014).

Besides the pixel digital values, it is possible to conduct the analysis by using different measurements calculated from the images. Examples of these measurements include indexes derived from the mathematical combination of the image channels, sub-pixel fractions (e.g., fractions of vegetation, soil, and shadow obtained from the Linear Model of Spectral Mixture proposed by Shimabukuro and Smith (1995)), texture, transformed images (e.g., principal components, Tasseled Cap), and fused images. There are also specific metrics that consider the multi-temporal characteristics of the data (FRANKLIN et al., 2015), and statistical metrics used to summarize sets of images from a given time period, such as the median, quartiles, and the standard deviation (RUFIN et al., 2015; SOUZA et al., 2020). According to LU et al. (2004) variable selection should be based on: 1) the capacity to differentiate between classes of interest, 2) the decreasing data dimensionality to improve classification processes and/or to avoid including noises in the analysis, 3) the limitations in the classification methods, such as whether it is possible to use more than one variable/type of data simultaneously, and 4) whether there is an additional need to standardize data, e.g., if the radiometric calibration of data is not enough to minimize differences on multi-sensor data and/or the effects of factors such as illumination and topography.

Data from the Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), Operational Land Imager (OLI), and Multispectral Instrument (MSI) sensors onboard Landsat 4-5, Landsat 7, Landsat 8, and Sentinel-2 satellites, respectively, are available with geometric and radiometric corrections in many platforms, such as the United States Geological Survey (USGS) archives (*https://earthexplorer.usgs.gov/*, *https://glovis.usgs.gov/app*). These corrected data are also available in Google Earth Engine (GEE) (GORELICK et al., 2017) with cloud masks. Other algorithms used to preprocess these images are discussed in Zhu (2017), Frantz (2019), and Sanchez et al. (2020).

2.2.2 CLASSIFICATION METHODS

The most commonly used method to classify LULC trajectories is post-classification comparison. In this method, images for each date are independently classified and then stacked to create a trajectory. Given that classification is carried out independently for each image, there is no need for a radiometric correction step and it is possible to use multi-sensor data (LU et al., 2004). Although it is necessary to have knowledge about the land cover on each date, no prior knowledge about the LULC trajectories is needed. One of the main criticisms of this method is that the quality of the LULC trajectories directly depends on the classification results for each date (FULLER; SMITH; DEVEREUX, 2003; TEWKESBURY et al., 2015). Classification errors can result in invalid trajectories, i.e., LULC trajectories that present inconsistent transitions (AZEREDO et al., 2016; REIS et al., 2020).

It is also possible to directly analyze radiometrically calibrated image time series to detect changes in land cover and then classify the resulting time segments of non-changes into LULC classes. The Continuous Change Detection and Classification (CCDC) algorithm, proposed by Zhu and Woodcock (2014), follows this logic. As such, the CCDC is more suitable for analyses with dense time series data, i.e. those with several observations for each interval of interest. This is not the case with historical analyses in the Amazon, where few (and sometimes none) cloud-free images are found per year. Different algorithms focused on time segmentation of remote sensing time series data are currently available on GEE (*https://developers.google.com/earth-engine/api_docs*). Among them, the Landsat-based detection of Trends in Disturbance and Recovery (LandTrendR) (KENNEDY; YANG; COHEN, 2010) and the Vegetation Regeneration and Disturbance Estimates through Time (VeRDET) (HUGHES; KAYLOR; HAYES, 2017) are particularly interesting to analyze forest regeneration in the Amazon. Both algorithms use image composite-based variables as input data and classify the time segments as "disturbance", "stable" or "regeneration" based on the variation of the analyzed values. However, they do not directly provide LULC trajectories.

The classification of the temporal segments of non-change can be achieved by using supervised classifiers that are capable of handling high-dimensional data, such as Random Forest and the Support Vector Machine (SVM), those based on neural networks, or even algorithms based on distances between time-series. The Dynamic Time Warping (DTW) is among the most well-known algorithms of the latter type. According to Maus et al. (2016), the DTW distorts the time to adjust the two series to be compared. However, the time elapsed between observations is an important attribute in remote sensing analyses. To solve this problem, Maus et al. (2016) proposed a time-weighted extension of the DTW called Time-Weighted Dynamic Time Warping (TWDTW). The TWDTW shows great potential to discriminate between classes of pasture, agriculture, and forests, for example, due to the characteristic variation of the spectral response of the targets of these classes throughout the year. However, TWDTW does not accurately distinguish between primary forest and secondary vegetation areas given that these classes usually present very similar behavior throughout the time series. TWDTW is currently available in the SITS package (Satellite Image Time Series Analysis), developed in the R language (E-SENSING, 2019). In addition to TWDTW, SITS unites its native tools to classify time series of remote sensing images with a large number of observations into LULC trajectories. This package includes tools to import remote sensing time series directly from web services, and view, group, and filter these series, and provides machine learning based methods to classify remote sensing time series. For sparse time series, i.e., those with one image per date of interest, the classifiers contained in SITS tend to behave like traditional supervised classifiers. Currently SITS is not equipped to deal with invalid transitions.

It is common to treat invalid transitions in multitemporal sets of land cover classifications as classification errors that should be masked from analysis or corrected in post-classification steps. Ways to correct these transitions include manual editing and the use of temporal filters (GRIFFITHS; JAKIMOW; HOSTERT, 2018; SOUZA et al., 2020). A relatively simple way to prevent the occurrence of invalid transitions in the classification process is to use masks, as demonstrated by the methodology applied in the Program for Deforestation Monitoring in the Brazilian Legal Amazon (PRODES). Areas previously deforested or that were not originally covered by forests are removed from the annual analysis in PRODES, so only deforestation of primary forests is quantified (CÂMARA; VALERIANO; SOARES, 2006) and invalid transitions, like a deforested area turning into a primary forest, are not mapped.

Another common LULC trajectory classification method is to classify the data from a given date and use it as the base classification to be updated on the next date by using binary bi-temporal change detection techniques (COMBER; LAW; LISHMAN, 2004; XIAN; HOMER, 2010; HUANG et al., 2017). This method may involve several steps, which can demand a lot of time and effort from the analyst when it comes to studies with a large number of observations. Additionally, classification errors are cumulative.

It is also possible to directly classify time series images into LULC trajectories by using supervised classifiers and labeled samples of the trajectories of interest (ZHU, 2017; ANJOS et al., 2015). The selection of samples is usually carried out in a section of the time series of images and used to define the rules to identify the expected trajectories throughout the time series. According to Zhu (2017), this method has a high computational cost and requires prior knowledge about the types of trajectories to be detected.

In addition to these methods, algorithms based on Markov processes have recently been proposed to classify LULC trajectories. These algorithms incorporate both the observed pixel values and information about the probability of joint occurrence between LULC classes ordered over time. Examples of proposals include the Virtual Land Cover Engine (VLCE) (HERMOSILLA et al., 2018) and the Compound Maximum *a Posteriori* (CMAP) (REIS et al., 2020). VLCE is a set of algorithms used to incorporate the temporal dimension in an extension of the well-known spatial context model Iterated Conditional Modes (ICM). This extension allows the incorporation of knowledge on the probabilities of transitions to correct LULC classifications obtained by Random Forest. It is an iterative algorithm that requires several classification steps, including the calculation of probabilities of successions of different classes before and after change events mapped externally to VLCE.

CMAP is a generative classifier that incorporates pixel values observed at all points in the time series and the joint distribution of the classes over time. In CMAP, LULC trajectories are considered to be a Markov chain, so the probabilities between transitions can be globally modeled by a transition probability matrix. This matrix can either be estimated from auxiliary data or defined by the analyst. The CMAP classifies the time series of remote sensing images directly into valid-only LULC trajectories with a single step and in one location at a time. These characteristics provide some specific advantages for forest regeneration studies, such as the possibility to include multi-temporal data to better separate primary forests from secondary vegetation even if the deforestation event is not registered in the data used (REIS et al., 2020). Given that all dates are classified simultaneously, classification errors do not propagate in the trajectories, as observed with post-classification rule-based methods to eliminate invalid trajectories. CMAP also permits the use of multi-sensor data and different tiers of a hierarchical legend for each date and/or data type. The latter is an important characteristic to analyze areas and/or periods with low data availability.

2.2.3 QUALITY ASSESSMENT

This step still presents major implementation challenges. It usually depends on the existence of reference data collected in the field, using images with higher spatial resolutions, and/or based on auxiliary data. These types of data can be difficult to acquire when it comes to multi-temporal studies involving several observations because they depend on the systematic collection of data for the same study area over time (FOODY, 2010; LU; LI; MORAN, 2014). In general, quality assessments of LULC trajectories are based on the calculation of accuracy indices derived from contingency matrices, also known as confusion or error matrices, being common to independently calculate the accuracy of each LULC classification for each date as a proxy to assess the accuracy of the LULC trajectory. Given the lack of reference data for some dates, particularly the oldest dates, the accuracy of one classification is sometimes considered to be the accuracy of the other classifications obtained with the same classes, data, and methods, which may not be correct. According to Sexton et al. (2013), due to the intrinsic variations of each date either in the land cover or the images, classification errors are not constant across the years, even when the same techniques and data are used. To calculate accuracy indices for all dates, some studies have focused on collecting reference samples from the same remote sensing images used in the classification. In such cases, it should be noted that the calculated accuracy indices are likely to be overestimated. Nonetheless, different tools can facilitate the selection process of reference samples, including those specially developed to observe time series data. Some of these tools have been analyzed in Jakimow et al. (2020).

Regardless of the selected tool, a crucial step in analyzing the quality of LULC trajectories is to define which feature of the trajectories is to be evaluated. In some cases, the correct classification of a certain set of transitions is sufficient, regardless of the exact moment that specific classes/changes were observed. Other studies may demand the correct observation of each class for each time. Specifically, attention should be paid to misclassification of areas containing classes under transition. Even when carrying out an analysis of a LULC classification on a single date, the classes used could represent stages in a gradient, with unclear limits between them (POWELL et al., 2004). Powell et al. (2004), for example, analyzed errors sources in LULC classifications based on Landsat 5/TM images in an area in the State of Rondônia, Brazil. According to the authors, the dominant classes in the study area were in a gradient between pasture and secondary vegetation. Reference samples were obtained from high-resolution images and based on the visual analysis of five trained interpreters. These interpreters disagreed in almost 30% of the samples, mainly in those located along borders between targets, in mixed pixels (pixels covering more than one class), in transition areas (classes overlapping the gradient), or due to geometric correction problems (POWELL et al., 2004). Thus, the accuracy of the reference samples must be evaluated and considered in this type of analysis, as demonstrated by Foody (2010) and Olofsson et al. (2014).

In studies that involve many dates, however, this type of problem should not heavily affect the classification of images sensed before and after the transition date(s). If the exact moment when an area has changed from one class to the next on the gradient is not important, the obtained trajectory is similar, regardless of which of the two classes is assigned to the area under transition. Therefore, misclassifications in certain dates do not necessarily imply errors in LULC trajectories. Since forest regeneration is a continuous process, it is natural that the classes involved in the analysis represent a gradient. Fallow agriculture/shrubby pasture areas can be considered transition classes between agriculture/pasture and secondary vegetation, for example. On the other hand, secondary vegetation classes can also be divided into different development stages, and incorrect classification of a stage on a given date may not affect the trajectory analysis. Nonetheless, possible problems regarding class definition (when an area effectively becomes secondary vegetation and at what stage of development) and classification (capacity for discrimination among these classes) can be particularly troublesome in some forest regeneration studies. This characteristic hinders the establishment of the exact time of vegetation formation, even in studies with observations for all dates of interest. Therefore, analyses that seek to quantify secondary vegetation areas on each date or calculate the age of secondary vegetation demand greater care.

Other methods to evaluate trajectory quality involve analyzing LULC trajectories based on logical rules regarding the probability of transitions, without using reference samples (LIU; ZHOU, 2004; AZEREDO et al., 2016). This type of analysis is particularly useful at identifying invalid transitions as classification errors. These errors can be represented by a transition validity map (REIS et al., 2020).

It is also possible to assess the quality of the classifications with uncertainty analyses (REIS et al., 2017) in spite of these not being a direct indicator of accuracy. An example of this type of analysis is to vary the LULC classification approach (classifier, parameters, set of training samples) and account for variations in the LULC classification/trajectory results (i.e., to identify pixels that lead to unstable classifications). Considering supervised classifiers, it is common for algorithms to assign classes to each pixel/object as a function of the lower or higher values of some measurements calculated for each class, such as probability or distance. For results obtained using these classifiers, Wulder et al. (2018) also mention the possibility of generating quality maps with the differences between the highest and second highest values of these measures. In these analyses, smaller differences indicate greater uncertainty in the classification. Other examples of uncertainty indices are presented and discussed in Gonçalves et al. (2009).

2.3 Extraction and analysis of information

LULC trajectories can be used, for example, to identify the date of LULC changes (ZHU et al., 2016); to calculate the percentage of the studied area covered by each class in each date, the percentage of the changed area and/or of types of transitions (YUAN et al., 2005; SEXTON et al., 2013; HERMOSILLA et al., 2015; ZOUNGRANA et al., 2015; FRANKLIN et al., 2015; HERMOSILLA et al., 2018); and to analyze the occurrence and spatial patterns of trajectories (MENA, 2008; MÜLLER-HANSEN et al., 2017). The visual interpretation of results and calculation of indices on the results from one or two consecutive dates are among the usual methods. Some of the commonly used indices are: fragmentation indices, the percentage/area occupied by each LULC and/or change class, the number and shape of features of a given LULC/change class, the distance between features, the area-perimeter ratio of features, and Shannon's diversity index, among others (GILLANDERS et al., 2008). It should be noted, however, that a comparison of information derived for each date or bi-temporal changes is not an analysis of trajectories *per se*. Despite the potential to generate important results, much of the temporal information contained in the trajectories is ignored by the analyst due to this type of simplification.

The study conducted by Carvalho et al. (2019) exemplifies how to use information derived for each date or pair of dates when carrying out a forest regeneration analysis. The authors evaluated changes in the historical patterns of secondary vegetation accumulation in the State of Pará between 2004 and 2014 using data from the Land Use and Land Cover Mapping of Deforested Areas in the Legal Amazon Project (TerraClass). TerraClass data are described in Section 3. According to the authors, the conversion rate of secondary vegetation to clean pastures/mechanized agriculture increased after 2010, which corresponds to a period with a decrease in the rate of primary forest deforestation. For the same period, the authors identified decreased areas of classes with supposed greater regeneration potential: occupation mosaics and regenerating pastures. Thus, the authors point to a possible tendency for secondary vegetation areas to decrease in the years following the analysis. Additionally, the authors found differences in the spatial concentration of secondary vegetation in the northern and southern regions of the State of Pará. These regions present different historical rates of occupation and deforestation of primary forests.

Information on the age of the secondary vegetation (NUNES et al., 2020; SILVA JUNIOR et al., 2020) and the duration and/or intensity of regeneration processes can also be extracted from LULC trajectories. For example, Müller et al. (2016) and Jakovac et al. (2017) extracted the number and duration of forest regeneration cycles from more than 29 years of Landsat time series data. Müller et al. (2016) first detected deforested areas and then classified secondary vegetation areas along the BR-163 highway between the States of Pará and Mato Grosso. The authors observed differences in the duration and frequency of regeneration cycles, depending on the types of predominant land use and the proximity of forests. Jakovac et al. (2017) segmented and classified an image time series from the municipalities of Tefé and Alvarães, in the State of Amazonas, using the Breaks for Additive Season and Trend (BFAST) (VERBESSELT et al., 2010) and Random Forest algorithms. The authors observed an average decrease in the regeneration cycle duration between the periods 1987-2000 and 2001-2014 in areas with shifting agriculture, which indicates that an agricultural intensification process occurred in the region (JAKOVAC et al., 2017).

Nevertheless, one study can analyze information on each date, pairs of dates, and trajectories jointly. Wang et al. (2020) used TerraClass data for the entire Brazilian Legal Amazon between 2000 and 2014 to analyze the deforestation of secondary vegetation. Their analysis consisted of comparing consecutive data pairs, which were stratified according to the age categories of secondary vegetation determined by stacking TerraClass data. The authors observed two distinct phases of secondary vegetation deforestation: 1) between 2000 and 2008, and 2) between 2008 and 2014. In the first period, they observed decreasing secondary vegetation/primary forest deforestation rates. In the second period they observed increasing deforestation of secondary vegetation along decreased deforestation of primary forest. The authors suggest that an increased pressure on forest systems in the second period had been absorbed by areas that were regenerating. The authors also concluded that 91% of secondary vegetation areas had been converted to pasture at some point in time, regardless of the age of that vegetation.

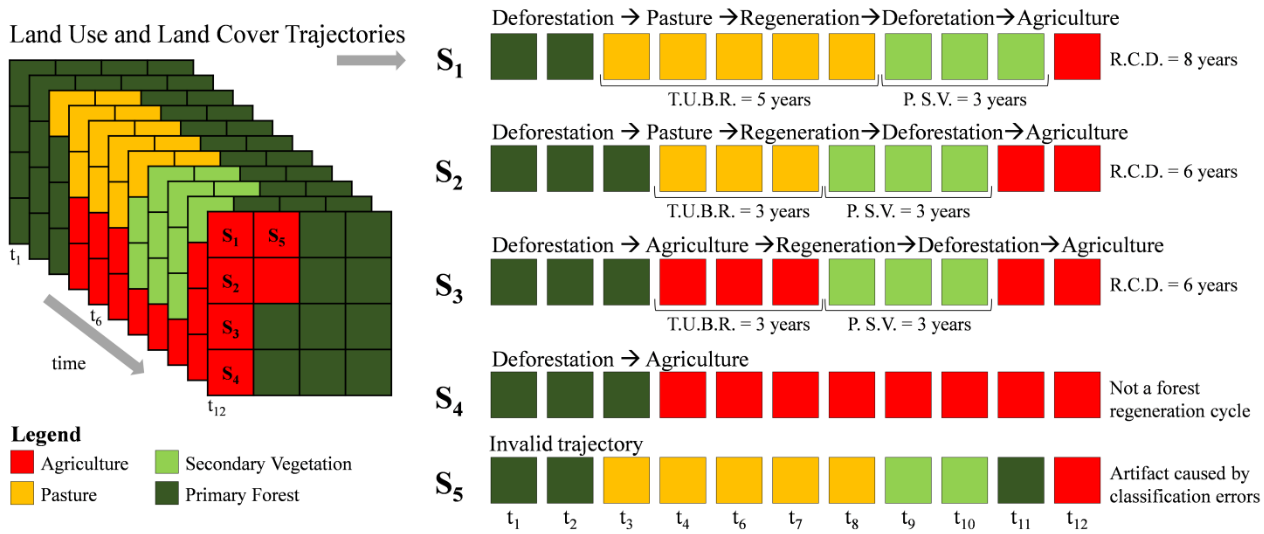
Another common question in LULC trajectory studies is what are the main types of existing trajectories. LULC trajectories can be typified by the duration/intensity of the observed processes or by their composition, i.e., the ordered sequence of LULC classes. We identified two main composition-based methods to define LULC trajectory types. The first method consists of exhaustively defining the typologies based on the observed LULC transitions (PINHEIRO et al., 2016; CORSINI, 2018; ASSIS et al., 2020). The second method is the use of automatic clustering algorithms to identify groups of pixels with the same spatio-temporal pattern (AZEREDO, 2017).

To cite an example of the first composition-based method, Corsini (2018) observed differences in aboveground biomass patterns and how these had been impacted by fire and deficit of water in defined types of forest regeneration trajectories in the Brazilian Legal Amazon. These trajectories corresponded to certain class sequences in TerraClass data for the years 2004, 2008, and 2010. This type of analysis is feasible for a few dates since an increase in the number of analyzed dates generally leads to an even bigger increase in the number of possible trajectories. Given that forest regeneration processes can involve diverse LULC trajectories, identifying all possible typologies *a priori* can be a very complex and expensive task. It can also result in subjective and/or synthetic analyses that focus on only a few previously identified processes.

An example of the second method is the clustering algorithm Grouping by Similarity of Temporal Evolution (GSTE) proposed by Azeredo (2017). The GSTE combines the traditional DTW, Classical Multidimensional Scaling (CMDS), and K-Means Clustering algorithms to analyze how a trajectory behaves over time. According to the author, the GSTE clusters portray characteristics such as the time interval between different processes, the duration of each process, and the classes observed at each given point in time. However, whereas LULC trajectories are generally presented in categories, the current version of GSTE is only applicable for numerical data. LULC classes need to be converted to values associated with different intensities of a single process to carry out a GTSE analysis, which may not be directly feasible when multiple processes are involved. Nonetheless, different clustering methods for categorical data have been proposed in the literature, such as K-Modes (HUANG, 1998), ROBust Clustering using linKs (ROCK) (GUHA; RASTOGI; SHIM, 2000), and Generalized Self-Organizing Maps (GSOM) (HSU, 2006). We were unable to find studies that applied automatic clustering algorithms to analyze forest regeneration trajectories.

Some examples of LULC trajectories are exemplified in Figure 2. In this figure, three LULC trajectories characterize forest regeneration cycles (S_1, S_2, and S_3). From these, we can calculate three chosen attributes: time of use before regeneration, persistence of secondary vegetation, and duration of the forest regeneration cycle. We also exemplified LULC trajectories that do not characterize a forest regeneration cycle (S_4) and invalid trajectories (S_5). Note that some exemplified trajectories present the same sequence of events with different durations, and therefore, different values for each attribute (S_1 and S_2) whereas others present different sequences of events, which may impact the adopted typology and interpretation of results, but identical attribute values (S_2 and S_3). For these hypothetical examples, different methods of analysis may lead to very different interpretations of LULC change processes in the studied area.

Figure 2 Examples of Land Use and Land Cover trajectories.



In which: t_i = year of observation; T.U.B.R. = Time of Use Before Regeneration; P.S.V. = Persistence of Secondary Vegetation; R.C.D. = Duration of the Forest Regeneration Cycle. One Forest Regeneration Cycle begins with a deforestation event (of Primary Forest or Secondary Vegetation) and ends with the deforestation of the Secondary Vegetation. These attributes were defined by the authors for exemplification.

Source: the authors (2020).

Furthermore, new techniques to analyze LULC trajectories have been proposed by Azeredo et al. (2016) and Maciel et al. (2019). Azeredo et al. (2016) adapted some patterns from the mobile objects literature to study LULC trajectories. These patterns have been used in forest degradation analyses.

Although these patterns have not yet been applied to forest regeneration studies, they could be used to identify:

a) trajectories that converge to specific classes that denote forest regeneration processes;
b) trajectories with a given set of LULC classes in specific time windows. This enables secondary vegetation to be identified in certain time windows rather than on individual dates, thus decreasing quantification problems in areas under transition;
c) trajectories that present similar LULC changes, either in the same or different periods. This is useful to identify the deforestation of secondary vegetation for certain types of use;
d) trajectories that present similar process intensities, such as similar fallow/regeneration times;
e) trajectories with inconsistent/invalid transitions.

Maciel et al. (2019) formalized a space-time calculation logic called LUC Calculus. This tool can be used to investigate and characterize LULC trajectories according to four main predicates: conversion (CONVERT), recurrence (RECUR), evolution (EVOLVE), and maintenance (HOLD). These predicates, adapted to the context of forest regeneration analysis, can be interpreted as:

a) CONVERT denotes the change between classes for two consecutive times of observation. Usage example: detection of all secondary vegetation areas that have been converted for agricultural use;
b) RECUR denotes the observation of a recurring class after conversion of that class to another. Usage example: to correct invalid transitions and distinguish secondary vegetation and primary forest areas by the historical analysis of the trajectory;
c) EVOLVE denotes events with one or more different classes interspersed between specific LULC changes. Usage example: to identify deforested primary forests that, after being abandoned, have regenerated to secondary vegetation. These areas can be identified regardless of their intermediate use;
d) HOLD denotes a class that has remained the same throughout all observations over a determined period. Usage example: to identify areas of persistent secondary vegetation.

3 AVAILABLE MAP PRODUCTS

Different programs that monitor tropical forests on either local or global scales have generated LULC change data for the Amazon that can be used as auxiliary data in LULC trajectory analyses. Among these are programs focused on deforestation and/or degradation of primary forests, such as PRODES (INPE, 2020c), both the Deforestation Detection System in Real-Time (DETER) and its incorporated or derivative programs, such as the Forest Degradation Mapping in the Brazilian Amazon (DEGRAD) and intense DETER (INPE, 2020d), the Deforestation Alert System (SAD) of the *Instituto Homem e Meio Ambiente da Amazônia* (IMAZON, 2020), and data from the Global Land Analysis and Discovery (GLAD) laboratory, such as the Global Forest Change dataset (HANSEN et al., 2013). It is also possible to use natural resource maps, such as the pioneers RADAM (Radar in the Amazon) and RADAMBRASIL (VAN ROESSEL; GODOY, 1974), as well as multi-temporal LULC classifications, such as the *Monitoramento de Uso e Cobertura da Terra do Brasil* (IBGE, 2015,2017,2020). However, projects that map deforested areas into LULC classes, among which secondary vegetation necessarily needs to be discriminated, are of particular interest to forest regeneration studies. Examples of such projects in Amazon include TerraClass and the Annual Mapping of Land Cover and Use in Brazil (MapBiomas). Their main characteristics are summarized in this section.

TerraClass is developed by the National Institute for Space Research (INPE) in partnership with the Brazilian Agricultural Research Corporation (Embrapa). In this project, deforested areas mapped by PRODES in the Brazilian Legal Amazon are classified into land cover classes of interest. There are available classifications for years 2004, 2008, 2010, 2012, and 2014. Wang et al. (2020) also mention the use of TerraClass data from 2000, which is not currently available on the project's websites (*http://www.inpe.br/cra/projetos_pesquisa/dados_terraclass.php* or *https://www.terraclass.gov.br*). The TerraClass project is based on classifying images from the Landsat family (or those with similar resolutions) and data from the Moderate-Resolution Imaging Spectroradiometer (MODIS). Different image processing techniques and stages of visual analysis, manual editing, and auditing are used in this project. The results are available with two legend versions, both with 30 m spatial resolution, and with three classes inherited from PRODES data (Hydrography, Non-forest, and Forest). In the first version, 13 land cover classes are mapped by TerraClass: Deforestation of the year, Annual agriculture, Pasture with exposed soil, Clean pasture, Shrubby pasture, Regeneration with pasture, Secondary vegetation, Reforestation (except for the 2008 data), Urban area, Mining, Mosaic of occupations, Others, and Unobserved area (ALMEIDA et al., 2016). Almeida et al. (2016) calculated a Global Accuracy of 76.6% and a Kappa index of 0.67 for the classifications in the States of Pará and Mato Grosso in 2008, with ground samples of the classes Annual agriculture, Mosaic of occupations, Clean pasture, Shrubby pasture, Regeneration with pasture, and Secondary vegetation. The authors observed the greatest misclassification rate among pasture classes. After merging the Clean pasture, Shrubby pasture, and Regeneration with pasture classes, the Global Accuracy and Kappa values increased to 89.7% and 0.79, respectively. In the second legend, the classes are: Natural secondary forest vegetation, Deforestation of the year, Perennial agricultural culture, Semi-perennial agricultural culture, Temporary agricultural culture, Shrub cultivated pasture, Herb cultivated pasture, Silviculture, Urbanized area, Mining, Unobserved, and Others.

Since TerraClass masks deforested areas detected by PRODES, of internationally recognized reliability, secondary vegetation areas can only be identified in previously deforested areas (ALMEIDA et al. 2016). This methodological aspect reduces the misclassification between forested and secondary vegetation areas considerably. However, TerraClass data are not annual and cover a relatively short period. As a result, some longer regeneration cycles would not be entirely observed if one were to only use this data set. Moreover, TerraClass data have misalignment problems inherited from PRODES (INPE, 2017; WANG et al., 2020). These problems must be corrected in order to carry out pixel-level analyses. Therefore, we indicate TerraClass data either to characterize short trajectories, as demonstrated in Corsini (2018) and Wang et al. (2020) and detailed in Section 2.3, or to be used as an auxiliary data for the LULC trajectory classification process, such as a classification mask, base classification to be updated, and/or for collection of reference samples.

The MapBiomas project is produced by a collaborative network of institutions. This project aims to produce annual LULC classifications for the entire Brazilian territory by using automatic techniques to classify Landsat images. In general, mosaics constructed from Landsat image statistical variables (median, amplitude, and standard deviation, etc.) for each year are classified independently. Invalid transitions are then corrected in the post-classification process with spatial and/or temporal filters based on pre-established rules (SOUZA et al., 2020). The images, LULC classes, accuracy, and methodological details vary depending on the MapBiomas collection. The Global Accuracy values are estimated from samples collected from visual interpretation of the images. Only general information on the collection of samples is contained in the documentation of the collections (Algorithm Theoretical Basis Document - ATBD), which is also constantly changing. To the date (November 2020), eight collections have been published. There is no distinction between primary, degraded, or secondary vegetation classes in collection 3.x to 5 (MAPBIOMAS, 2020).

Collection 2.x is the last one that separated the primary forests and secondary vegetation classes. It contains annual data between 2000 and 2016, with Global Accuracy indexes for each year that vary at around 80% for the Amazon biome. Neves et al. (2020) harmonized the legends of the TerraClass (first legend) and MapBiomas collection 2 maps and then compared the classification results between the overlapping areas of the 2004, 2008, 2010, 2012, and 2014 maps. Considering all years in a joint analysis, the authors found that only 3.56% of the areas classified as secondary vegetation in TerraClass products were also classified as such in the MapBiomas 2 products. The remaining areas of secondary vegetation in TerraClass results were mostly classified as Forest (80.34%) and Pasture (13.96%) by MapBiomas. Despite these differences, the agreement among both classifications is around 87% of the pixels. This happens because the predominant class in both maps is forest, which can influence the values of Global Accuracy presented by the MapBiomas data.

Therefore, although the data from MapBiomas collection 2 enables longer and annual analyses, one must consider the possible misclassification between forest and secondary vegetation areas.

Nevertheless, it is possible to reclassify forests that occur in areas with evidence of deforestation as secondary vegetation in more recent MapBiomas collections (NUNES et al. 2020; SILVA JUNIOR et al., 2020). In this case, evidence of deforestation means the observation of a class other than forest in a previous observation. Nunes et al. (2020) used this approach to separate primary forest areas from secondary vegetation areas in the MapBiomas data from collection 3.1, for the Amazon biome. From these data, the authors grouped the pixels of secondary vegetation by estimated age and calculated both the area covered by secondary vegetation in the biome and the area of secondary vegetation deforestation. They also presented carbon capture estimates. It must be highlighted that this approach is unable to identify secondary vegetation areas if there is no evidence of deforestation throughout the time series. Therefore, Nunes et al (2020) found smaller proportions of deforested areas occupied by secondary vegetation than TerraClass for corresponding periods. Using a similar approach, Silva Junior et al. (2020) created a database containing increment, extension, and age of secondary vegetation estimates for the years 1986 to 2018 using data from the MapBiomas collection 4.1. These results were also validated by TerraClass data through a method that compares the proportion of the class in a given regular cell-grid. The authors concluded that although there is statistical evidence that the average proportion of secondary vegetation found by processing MapBiomas data is smaller than that mapped by TerraClass (via Mann-Whitney test and p-values < 0.001) the results of the two data sets are comparable. In addition to these studies, the MapBiomas project is currently working on a native module for forest regeneration analysis. To date, there is no information available about the accuracy of the secondary vegetation classes.

According to Maurano and Escada (2019), variations in each collection of the historical classifications of MapBiomas limit the applicability of this data when it comes to operational and continuous area estimates. In forest regeneration studies, these variations cause the observation of different trajectories, from which different rates of atmospheric carbon absorption can be calculated, for example. The inability to identify secondary vegetation areas without the evidence of deforestation events can also be detrimental to analyses in regions dominated by older secondary vegetation, such as in the northeastern part of Pará State (CAPANEMA et al., 2019). Thus, MapBiomas data are suitable for preliminary analyses and over large areas, which should, subsequently, be refined for more detailed forest regeneration studies.

4 FINAL CONSIDERATIONS

In this manuscript, we reviewed the main data and methods used to classify and analyze LULC trajectories. We also discussed them in the context of their applicability in forest regeneration studies in the Brazilian Amazon. In general, one can either use 1) methods suitable for single images or pairs of images successively or 2) tools focused on the analysis of remote sensing time series images and LULC trajectories.

The studies and remote sensing products reviewed in this paper are based mainly on Landsat images. These images are freely available for use with atmospheric and geometric corrections. Nonetheless, cloud cover continues to present scientific challenges in the Amazon Biome, mainly when it comes to carrying out historical analyses. Given that the combination of radar and optical images constitutes a possible alternative to increase the number of time series observations, methods that combine different types of data are important for LULC trajectories in the Amazon. Therefore, methods capable of dealing with sparse time series, multi-sensor data, and different aggregations of a given legend are of particular interest to forest regeneration studies. Another recurring problem among trajectory classification techniques is that several steps are needed, including a post-classification step to correct invalid trajectories. The CMAP classifier stands out for classifying image time series directly on valid-only LULC trajectories in a single step using multi-sensor data at different tiers of a hierarchical legend. Currently, the computational cost of CMAP is high for large areas and/or long time series, which can limit its operational use. Improvements to the performance of CMAP and the incorporation of new base classifiers to the algorithm, as well as new methods for calculating the probability of transitions within the classifier, are expected shortly.

Despite the diversity of proposed techniques and tools to analyze LULC trajectories, quality assessment methods are mostly based on calculating accuracy indices for each observed time. Similarly, most studies are still based on mono or bi-temporal techniques. One must pay attention to possible overestimations of accuracy values in these studies. This is particularly important when quantifying LULC class/change areas for each date. In this sense, one of the major challenges when it comes to analyzing LULC trajectories is developing methodologies to estimate their accuracy and to allow adequate information extraction.

Forest regeneration studies focused on trajectory information can be summarized into one of the following categories: 1) those that evaluate only a few dates and/or classes and, consequently, only a few types of trajectories or 2) those that calculate the age of secondary vegetation. There is a pressing need to evaluate forest regeneration analysis tools that permit a greater number of dates and classes of interest. Such tools will enable regeneration processes hitherto not discriminated to be identified. Specifically, it is important to quantify specific forest regeneration process characteristics, such as persistence/age of secondary vegetation, and intensity, type, and use time before abandonment in areas with different occupation histories and under the influence of different public policies. These types of studies have the potential to improve the precision and accuracy of carbon emission estimates. They are also important for biodiversity studies because areas of secondary vegetation can connect forest patches. From a socio-economic point of view, such studies can reveal how different forms of occupation produce different landscapes and forest regeneration dynamics, which are important to consider when it comes to elaborating conservation policies, territorial ordering, and sustainable land use practice incentives.

Acknowledgments

This study was supported, in part by, the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) and, in part, by the Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq) under Grant #309135/2015-0. Authors are also thankful to Noeli Aline Particcelli Moreira for the pontual assistance with data summarization, to Eliana Pantaleão for text suggestions, and to Instituto Chico Mendes de Conservação da Biodiversidade (ICMBio) for authorizations #48186-4, #48186-2 and #38157-2, the Large-Scale Biosphere-Atmosphere Experiment in Amazonia (LBA), and the Monitoramento Ambiental por Satélite no Bioma Amazônia Project, Process #1022114003005-MSA-BNDES.

Author’s contributions

Conceptualization: M.S.R, M.I.S.E., S.J.S.S., and L.V.D. Data curation: M.S.R. Formal analysis: M.S.R. Funding acquisition: M.S.R, M.I.S.E., S.J.S.S., and L.V.D. Investigation: M.S.R. Methodology: M.S.R, M.I.S.E., S.J.S.S., and L.V.D. Project administration: M.I.S.E. and S.J.S.S. Resources: M.I.S.E. and S.J.S.S. Software: M.S.R., Supervision: M.I.S.E. Validation: M.S.R, M.I.S.E., S.J.S.S., and L.V.D. Visualization: M.S.R. Writing – original draft: M.S.R. Writing – review & editing: : M.S.R, M.I.S.E., S.J.S.S., and L.V.D.

Conflicts of interest

The authors declare no conflict of interest.

References

AFFONSO, A. G.; ESCADA, M. I. S.; AMARAL, S.; SOUZA, A. R.; SIQUEIRA, J. M.; TORRES, N. C.; CAMILOTTI, V. L.; DAL'ASTA, A. P.; COSTA, L. C. O.; SOARES, F. R. **As comunidades ribeirinhas do Baixo Tapajós (PA): infraestrutura, mobilidade, serviços sócio ambientais e conectividade**. São José dos Campos: [s.n.], 2016. Available in: <http://urlib.net/sid.inpe.br/mtc-m21b/2016/08.02.12.48>. Access in: 21 jul. 2019.

AGUIAR, A. P. D.; OMETTO, J. P.; NOBRE, C.; LAPOLA, D. M.; ALMEIDA, C.; VIEIRA, I. C.; SOARES, J. V.; ALVALA, R.; SAATCHI, S.; VALERIANO, D.; CASTILLA-RUBIO, J. C. Modeling the spatial and temporal heterogeneity of deforestation-driven carbon emissions: the INPE-EM framework applied to the Brazilian Amazon. **Global Change Biology**, v. 18, n. 11, p. 3346–3366, 2012. DOI. 10.1111/j.1365-2486.2012.02782.x.

ALASKA SATELLITE FACILITY (ASF). **ALOS PALSAR**. 2020. Available in: <https://asf.alaska.edu/data-sets/sar-data-sets/alos-palsar/>. Access in: 18 dez. 2020.

ALMEIDA, C. A.; COUTINHO, A. C.; ESQUERDO, J. C. D. M.; ADAMI, M.; VENTURIERI, A.; DINIZ, C. G.; DESSAY, N.; DURIEUX, L.; GOMES, A. R. High spatial resolution land use and land cover mapping of the Brazilian Legal Amazon in 2008 using Landsat-5/TM and MODIS data. **Acta Amazonica**, v. 46, n. 3, p. 291–302, 2016. DOI. 10.1590/1809-4392201505504.

ALMEIDA, C. A.; VALERIANO, D. M.; ESCADA, M. I. S.; RENNÓ, C. D. Estimativa de área de vegetação secundária na Amazônia Legal Brasileira. **Acta Amazonica**, v. 40, n. 2, p. 289–301, 2010.

ANDERSON, J. R.; HARDY, E. E.; ROACH, J. T.; WITMER, R. E. A land use and land cover classification system for use with remote sensor data. **Geologycal Survey Professional Paper 964**. United States Government Printing Office: Washington, Estados Unidos da América, 1976. DOI. 10.3133/pp964.

ANJOS, D.; LU, D.; DUTRA, L.; SANT'ANNA, S. Change detection techniques using multisensor data. In: THENKABAIL, P. S. (Ed.) Remotely **Sensed Data Characterization, Classification, and Accuracies**. London: CRC Press, 2015. v. 1, p. 375–395.

ASSIS, T. O.; AGUIAR, A. P. D.; VON RANDOW, C.; GOMES, D. M. P.; KURY, J. N.; OMETTO, J.; NOBRE, C. A. CO2 emissions from forest degradation in Brazilian Amazonia. **Environmental Research Letters**, v. 15, n. 10, artigo 104035, 2020. DOI. 10.1088/1748-9326/ab9cfc.

AZEREDO, M. **Mineração e análise de trajetórias de mudança de cobertura da terra: explorando padrões comportamentais no contexto da degradação florestal**. 150 f. Tese (Doutorado em Computação Aplicada) — Instituto Nacional de Pesquisas Espaciais (INPE), São José dos Campos, 2017. Available in: <http://urlib.net/sid.inpe.br/mtc-m21b/2017/03.14.13.46>. Access in: 24 maio 2018.

AZEREDO, M.; MONTEIRO, A. M. V.; ESCADA, M. I. S.; FERREIRA, K. R.; VINHAS, L.; PINHEIRO, T. F. Mineração de trajetórias de mudança de cobertura da terra em estudos de degradação florestal. **Revista Brasileira de Cartografia**, v. 68, n. 4, p. 717–731, 2016.

BANSKOTA, A.; KAYASTHA, N.; FALKOWSKI, M. J.; WULDER, M. A.; FROESE, R. E.; WHITE, J. C. Forest monitoring using Landsat time series data: a review. **Canadian Journal of Remote Sensing**, v. 40, n. 5, p. 362–384, 2014. DOI. 10.1080/07038992.2014.987376.

BIG EARTH OBSERVATION DATA ANALYTICS FOR LAND USE AND LAND COVER CHANGE INFORMATION (E-SENSING). **SITS – Satellite Image Time Series Analysis**. 2019. Available in: <https://github.com/e-sensing/sits/blob/master/README.md>. Access in: 05 maio 2019.

BRASIL. Lei nº 5173, de 27 de outubro de 1966. Dispõe sobre o Plano de Valorização Econômica da Amazônia; extingue a Superintendência do Plano de Valorização Econômica da Amazônia (SPVEA), cria a Superintendência do Desenvolvimento da Amazônia (SUDAM), e dá outras providências. **Diário Oficial da União**, Brasília, DF, 31 out. 1966. Section 1, p. 12563.

BRASIL. Lei complementar nº 124, de 3 de janeiro de 2007. Institui, na forma do art. 43 da Constituição Federal, a Superintendência do Desenvolvimento da Amazônia – SUDAM; estabelece sua composição, natureza jurídica, objetivos, área de competência e instrumentos de ação; dispõe sobre o Fundo de Desenvolvimento da Amazônia – FDA; altera a Medida Provisória no 2.157-5, de 24 de agosto de 2001; revoga a Lei Complementar no 67, de 13 de junho de 1991; e dá outras providências. **Diário Oficial da União**, Brasília, DF, 04 jan. 2007. Section 1, p. 1.

BROWN, S.; LUGO, A. E. Tropical secondary forests. **Journal of Tropical Ecology**, v. 6, n. 1, p. 1–32, 1990.

CÂMARA, G.; VALERIANO, D. M.; SOARES, J. V. **Metodologia para o cálculo da taxa anual de desmatamento na Amazônia Legal**. São José dos Campos: INPE, 2006. 24p.

CAPANEMA, V. P.; SANCHES, I. D. A.; ESCADA, M. I. S. Comparação entre os produtos temáticos de uso e cobertura da terra do TerraClass Amazônia e MapBiomas: teste de aderência entre classes. In: SIMPÓSIO BRASILEIRO DE SENSORIAMENTO REMOTO, 19. (SBSR), 2019, Santos. **Anais...** São José dos Campos: INPE, 2019. p. 724–727. Available in: <https://proceedings.science/sbsr-2019/papers/comparacao-entre-os-produtos-tematicos-de-uso-e-cobertura-da-terra-do-terraclass-amazonia-e-mapbiomas--teste-de-aderenci#>. Access in: 06 out. 2020.

CARVALHO, R.; ADAMI, M.; AMARAL, S.; BEZERRA, F. G.; AGUIAR, A. P. D. de. Changes in secondary vegetation dynamics in a context of decreasing deforestation rates in Pará, Brazilian Amazon. **Applied Geography**, v. 106, p. 40–49, 2019.DOI. 10.1016/j.apgeog.2019.03.001

CHAZDON, R. L.; LINDENMAYER, D.; GUARIGUATA, M. R.; CROUZEILLES, R.; BENAYAS, J. M. R.; CHAVERO, E. L. Fostering natural forest regeneration on former agricultural land through economic and policy interventions. **Environmental Research Letters**, v. 15, n. 4, artigo 043002, 2020. DOI. 10.1088/1748-9326/ab97cc.

CHAZDON, R. L.; PERES, C. A.; DENT, D.; SHEIL, D.; LUGO, A. E.; LAMB, D.; STORK, N. E.; MILLER, S. E. The potential for species conservation in tropical secondary forests. **Conservation Biology**, v. 23, n. 6, p. 1406–1417, 2009. DOI. 10.1111/j.1523-1739.2009.01338.x.

CHOKKALINGAM, U.; JONG, W. D. Secondary forest: a working definition and typology. **The International Forestry Review**, Commonwealth Forestry Association, v. 3, n. 1, p. 19–26, 2001.

COE, M. T.; MARTHEWS, T. R.; COSTA, M. H.; GALBRAITH, D. R.; GREENGLASS, N. L.; IMBUZEIRO, H. M. A.; LEVINE, N. M.; MALHI, Y.; MOORCROFT, P. R.; MUZA, M. N.; POWELL, T. L.; SALESKA, S. R.; SOLORZANO, L. A.; WANG, J. Deforestation and climate feedbacks threaten the ecological integrity of south–southeastern Amazonia. **Philosophical Transactions of the Royal Society B: Biological Sciences**, v. 368, n. 1619, p. 1–9, 2013. DOI. 10.1098/rstb.2012.0155.

COMBER, A. J.; LAW, A. N. R.; LISHMAN, J. R. Application of knowledge for automated land cover change monitoring. **International Journal of Remote Sensing**, v. 25, n. 16, p. 3177–3192, 2004. DOI. 10.1080/01431160310001657795.

COPPIN, P. R.; JONCKHEERE, I.; NACKAERTS, K.; MUYS, B.; LAMBIN, E. Digital change detection methods in ecosystem monitoring: a review. **International Journal of Remote Sensing**, v. 25, n. 9, p. 1565–1596, 2004. DOI. 10.1080/0143116031000101675.

CORLETT, R. Tropical secondary forests. **Progress in Physical Geography**, v. 19, n. 2, p. 159–172, 1995. DOI. 10.1177/030913339501900201.

CORSINI, C. R. **Análise multitemporal das mudanças de biomassa da vegetação secundária na Amazônia brasileira**. 106 p. Tese (Doutorado) — Instituto Nacional de Pesquisas Espaciais (INPE), São José dos Campos, 2018. Available in: <http://urlib.net/rep/8JMKD3MGP3W34R/3R44PJP>. Access in: 12 maio 2019.

COSTA, F. A. Dinâmica agrária e balanço de carbono na Amazônia. **Revista EconomiA**, v. 10, n. 1, p. 117–151, 2009.

COSTA, F. A. Contributions of fallow lands in the Brazilian Amazon to CO_2 balance, deforestation and the agrarian economy: inequalities among competing land use trajectories. **Elementa Science of the Anthropocene**, v. 4, 2016. DOI. 10.12952/journal.elementa.000133.

COUTINHO, A.; ALMEIDA, C.; VENTURIERI, A.; ESQUERDO, J.; SILVA, M. **Uso e cobertura da terra nas áreas desflorestadas da Amazônia Legal: TerraClass 2008**. 2013. Available in:< https://www.embrapa.br/busca-de-publicacoes/-/publicacao/971385/uso-e-cobertura-da-terra-nas-areas-desflorestadas-da-amazonia-legal-terraclass-2008>. Access in: 21 jul. 2020.

DI GREGORIO, A.; JANSEN, L. **Land Cover Classification System**. Food and Agriculture Organization of the United Nations: Rome, Italy, 2005.

EMPRESA BRASILEIRA DE PESQUISA AGROPECUÁRIA (EMBRAPA). **Satélites de Monitoramento**. 2018. Available in: <https://www.embrapa.br/satelites-de-monitoramento>. Access in: 18 dez. 2020.

EUROPEAN ENVIRONMENT AGENCY (EEA). **Updated CLC illustrated nomenclature guidelines**. 2019. Available in: <https://land.copernicus.eu/user-corner/technical-library/corine-land-cover-nomenclature-guidelines/docs/pdf/CLC2018_Nomenclature_illustrated_guide_20190510.pdf>. Acesso em 29 set. 2020.

EUROPEAN SPACE AGENCY (ESA). **Sentinel Online**. 2020. Available in: <https://sentinel.esa.int/web/sentinel/home>. Acesso em 18 dez. 2020.

FEARNSIDE, P. M. Environmental destruction in the Brazilian Amazon. In: HALL., A.; GOODMAN, D. (Eds.) **The future of Amazonia**. The Macmillan Press LTD: Houndmills, Basingstoke, Hampshire, London, 1990. p. 179–225.

FEARNSIDE, P. M. Deforestation in Brazilian Amazonia: history, rates, and consequences. **Conservation Biology**, v. 19, n. 3, p. 680–688, 2005. DOI. 10.1111/j.1523-1739.2005.00697.x.

FOLEY, J. A.; ASNER, G. P.; COSTA, M. H.; COE, M. T.; DEFRIES, R.; GIBBS, H. K.; HOWARD, E. A.; OLSON, S.; PATZ, J.; RAMANKUTTY, N.; SNYDER, P. Amazonia revealed: forest degradation and loss of ecosystem goods and services in the Amazon Basin. **Frontiers in Ecology and the Environment**, v. 5, n. 1, p. 25–32, 2007. DOI. 10.1890/1540-9295(2007)5[25:ARFDAL]2.0.CO;2.

FOODY, G. M. Assessing the accuracy of land cover change with imperfect ground reference data. **Remote Sensing of Environment**, v. 114, n. 10, p. 2271-2285, 2010. DOI. 10.1016/j.rse.2010.05.003.

FRANKLIN, S. E.; AHMED, O. S.; WULDER, M. A.; WHITE, J. C.; HERMOSILLA, T.; COOPS, N. C. Large area mapping of annual land cover dynamics using multitemporal change detection and classification of Landsat time series data. **Canadian Journal of Remote Sensing**, v. 41, n. 4, p. 293–314, 2015. DOI. 10.1080/07038992.2015.1089401.

FRANTZ, D. FORCE—Landsat+ Sentinel-2 analysis ready data and beyond. **Remote Sensing**, v. 11, n. 9, p. 1124, 2019. DOI. 10.3390/rs11091124.

FULLER, R.; SMITH, G.; DEVEREUX, B. The characterisation and measurement of land cover change through remote sensing: problems in operational applications? **International Journal of Applied Earth Observation and Geoinformation**, v. 4, n. 3, p. 243–253, 2003. DOI. 10.1016/S0303-2434(03)00004-7.

GILLANDERS, S. N.; COOPS, N. C.; WULDER, M. A.; GERGEL, S. E.; NELSON, T. Multitemporal remote sensing of landscape dynamics and pattern change: describing natural and anthropogenic trends. **Progress in Physical Geography**, v. 32, n. 5, p. 503–528, 2008. DOI. 10.1177/0309133308098363.

GÓMEZ, C.; WHITE, J. C.; WULDER, M. A. Optical remotely sensed time series data for land cover classification: a review**.** **ISPRS Journal of Photogrammetry and Remote Sensing**, v. 116, p. 55–72, 2016. DOI. 10.1016/j.isprsjprs.2016.03.008.

GONÇALVES, L. M.; FONTE, C. C., JULIO, E. N. B. S.; CAETANO, M. Evaluation of remote sensing images classifiers with uncertainty measures. In: DEVILLERS, R.; GOODCHILD, H. (Eds.). **Spatial data quality from process to decisions**. Boca Raton: CRC Press, 2009. p. 163-177.

GORELICK, N.; HANCHER, M.; DIXON, M.; ILYUSHCHENKO, S.; THAU, D.; MOORE, R. Google Earth Engine: planetary-scale geospatial analysis for everyone. **Remote Sensing of Environment**, v. 202, p. 18–27, 2017. DOI. 10.1016/j.rse.2017.06.031.

GRIFFITHS, P.; JAKIMOW, B.; HOSTERT, P. Reconstructing long term annual deforestation dynamics in Pará and Mato Grosso using the Landsat archive. Remote sensing of environment, v. 216, pp. 497-513, 2018. DOI. 10.1016/j.rse.2018.07.010.

GRIFFITHS, P.; VAN DER LINDEN, S.; KUEMMERLE, T.; HOSTERT, P. A pixel-based Landsat compositing algorithm for large area land cover mapping. **IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing**, v. 6, n. 5, p. 2088–2101, 2013. DOI. 10.1109/JSTARS.2012.2228167.

GUHA, S.; RASTOGI, R.; SHIM, K. ROCK: A robust clustering algorithm for categorical attributes. **Information Systems**, v. 25, n. 5, p. 345–366, 2000. DOI. 10.1016/S0306-4379(00)00022-3.

HANSEN, M. C.; POTAPOV, P. V.; MOORE, R.; HANCHER, M.; TURUBANOVA, S. A.; TYUKAVINA, A.; THAU, D.; STEHMAN, S. V.; GOETZ, S. J.; LOVELAND, T. R.; KOMMAREDDY, A.; EGOROV, A.; CHINI, L; JUSTICE, C. O; TOWNSHEND, J. R. G. High-resolution global maps of 21st-century forest cover change. **Science**, v 342, n. 6160, p. 850-853, 2013. DOI. 10.1126/science.1244693

HERMOSILLA, T.; WULDER, M. A.; WHITE, J. C.; COOPS, N. C.; HOBART, G. W. Regional detection, characterization, and attribution of annual forest change from 1984 to 2012 using Landsat-derived time-series metrics. **Remote Sensing of Environment**, v. 170, p. 121–132, 2015. DOI. 10.1016/j.rse.2015.09.004

HERMOSILLA, T.; WULDER, M. A.; WHITE, J. C.; COOPS, N. C.; HOBART, G. W. Disturbance-informed annual land cover classification maps of Canada's forested ecosystems for a 29-year Landsat time series. **Canadian Journal of Remote Sensing**, v. 44, n. 1, p. 67–87, 2018. DOI. 10.1080/07038992.2018.1437719.

HEROLD, M.; WOODCOCK, C.; DI GREGORIO, A.; MAYAUX, P.; BELWARD, A.; LATHAM, J.; SCHMULLIUS, C. A joint initiative for harmonization and validation of land cover datasets. **IEEE Transactions on Geoscience and Remote Sensing**, v. 44, n. 7, p. 1719–1727, 2006. DOI. 10.1109/TGRS.2006.871219.

HOLBEN, B. N. Characteristics of maximum-value composite images from temporal AVHRR data, **International Journal of Remote Sensing**, v. 7 n. 11, p. 1417–1434, 1986. DOI. 10.1080/01431168608948945

HSU, C. C. Generalizing self-organizing map for categorical data. **IEEE Transactions on Neural Networks**, v. 17, n. 2, p. 294–304, 2006. DOI. 10.1109/TNN.2005.863415.

HUANG, S.; RAMIREZ, C.; KENNEDY, K.; MALLORY, J.; WANG, J.; CHU, C. Updating land cover automatically based on change detection using satellite images: case study of national forests in Southern California. **GIScience & Remote Sensing**, v. 54, n. 4, p. 495–514, 2017. DOI. 10.1080/15481603.2017.1286727.

HUANG, Z. Extensions to the k-means algorithm for clustering large data sets with categorical values. **Data mining and knowledge discovery**, v. 2, n. 3, p. 283–304, 1998. DOI. 10.1023/A:1009769707641.

HUGHES, M. J.; KAYLOR, S. D.; HAYES, D. J. Patch-based forest change detection from Landsat time series. **Forests**, v. 8, n. 5, artigo 166, 2017, DOI. 10.3390/f8050166.

INSTITUTO BRASILEIRO DE GEOGRAFIA E ESTATÍSTICA (IBGE). Vocabulário básico de recursos naturais e meio ambiente. 2 ed. Rio de Janeiro, 2004. Available in: <https://ww2.ibge.gov.br/home/presidencia/noticias/vocabulario.pdf>. Access in: 6 mar. 2019.

INSTITUTO BRASILEIRO DE GEOGRAFIA E ESTATÍSTICA (IBGE). **Manual Técnico de Uso da Terra**. Rio de Janeiro, 2013. Available in: <https://biblioteca.ibge.gov.br/visualizacao/livros/liv81615.pdf>. Access in: 29 ago. 2020.

INSTITUTO BRASILEIRO DE GEOGRAFIA E ESTATÍSTICA (IBGE). **Mudanças na cobertura e uso da terra 2000-2010-2012**. Rio de Janeiro, 2015. Available in: <https://biblioteca.ibge.gov.br/visualizacao/livros/liv94724.pdf>. Access in: 21 jul. 2020.

INSTITUTO BRASILEIRO DE GEOGRAFIA E ESTATÍSTICA (IBGE). **Monitoramento da cobertura e uso da terra do Brasil 2000-2010-2012-2014**. Rio de Janeiro, 2017. Available in: < https://biblioteca.ibge.gov.br/visualizacao/livros/liv101469.pdf>. Access in: 21 jul. 2020.

INSTITUTO BRASILEIRO DE GEOGRAFIA E ESTATÍSTICA (IBGE). **Monitoramento da cobertura e uso da terra do Brasil: 2016 - 2018**. Rio de Janeiro, 2020. Available in: < https://biblioteca.ibge.gov.br/visualizacao/livros/liv101703.pdf>. Access in: 27 jul. 2020.

INSTITUTO HOMEM E MEIO AMBIENTE DA AMAZÔNIA (IMAZON). **Monitoramento da Amazônia**. 2020. Available in:< https://imazon.org.br/>. Access in: 02 out. 2020.

INSTITUTO NACIONAL DE PESQUISAS ESPACIAIS (INPE). **Nota Técnica – Correção da máscara do PRODES**. 2017. Available in: <http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/prodes/pdfs/nt_deslocamentomascara.pdf>. Access in: 02 out. 2020.

INSTITUTO NACIONAL DE PESQUISAS ESPACIAIS (INPE). **Satélites**. 2020a. Available in: <http://www.dgi.inpe.br/documentacao/satelites>. Access in: 18 dez. 2020.

INSTITUTO NACIONAL DE PESQUISAS ESPACIAIS (INPE). **CBERS: Satélite Sino-Brasileiro de Recursos Terrestres**. 2020b. Available in: < http://www.cbers.inpe.br/>. Access in: 18 dez. 2020.

INSTITUTO NACIONAL DE PESQUISAS ESPACIAIS (INPE). **Monitoramento do Desmatamento da Floresta Amazônica Brasileira por Satélite**. 2020c. Available in: <http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/prodes>. Access in: 02 out. 2020.

INSTITUTO NACIONAL DE PESQUISAS ESPACIAIS (INPE). **DETER e DETER intenso**. 2020d. Available in: <http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/deter>. Access in: 02 out. 2020.

JAKIMOW, B.; VAN DER LINDEN, S.; THIEL, F.; FRANTZ, D.; HOSTERT, P. Visualizing and labeling dense multi-sensor earth observation time series: The EO Time Series Viewer. **Environmental Modelling & Software**, v. 125, artigo 104631, 2020. DOI. 10.1016/j.envsoft.2020.104631.

JAKOVAC, C. C.; DUTRIEUX, L. P.; SITI, L.; PEÑA-CLAROS, M.; BONGERS, F. Spatial and temporal dynamics of shifting cultivation in the middle-Amazonas river: Expansion and intensification. **PloS one**, v. 12, n. 7, e0181092, 2017. DOI. 10.1371/journal.pone.0181092.

KAMMESHEIDT, L. Perspectives on secondary forest management in Tropical Humid Lowland America. **Ambio**, v. 31, n. 3, p. 243–250, 2002. DOI. 10.1579/0044-7447-31.3.243.

KENNEDY, R. E., YANG, Z.; COHEN, W. B. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr - Temporal segmentation algorithms. **Remote Sensing of Environment**, v. 114, n. 12, p. 2897–2910, 2010. DOI. 10.1016/j.rse.2010.07.008.

LIU, H.; ZHOU, Q. Accuracy analysis of remote sensing change detection by rule-based rationality evaluation with post-classification comparison. **International Journal of Remote Sensing**, v. 25, n. 5, p. 1037–1050, 2004. DOI. 10.1080/0143116031000150004

LU, D.; LI, G.; MORAN, E. Current situation and needs of change detection techniques. **International Journal of Image and Data Fusion**, v. 5, n. 1, p. 13–38, 2014. DOI. 10.1080/19479832.2013.868372.

LU, D.; MAUSEL, P.; BRONDÍZIO, E.; MORAN, E. Change detection techniques. **International Journal of Remote Sensing**, v. 25, n. 12, p. 2365–2401, 2004. DOI. 10.1080/0143116031000139863.

MACIEL, A. M.; CÂMARA, G.; VINHAS, L.; PICOLI, M. C. A.; BEGOTTI, R. A.; ASSIS, L. F. F. G. D. A spatiotemporal calculus for reasoning about land-use trajectories. **International Journal of Geographical Information Science**, v. 33, n. 1, p. 176–192, 2019. DOI. 10.1080/13658816.2018.1520235.

MAPBIOMAS. **MapBiomas General "Handbook"**: Algorithm Theoretical Basis Document (ATBD) - Collection 5, 2020. Available in: <https://mapbiomas-br-site.s3.amazonaws.com/ATBD_Collection_5_v1.pdf>. Access in: 30 det. 2020.

MAURANO, L. E. P.; ESCADA, M. I. S. Comparação dos dados produzidos pelo PRODES versus dados do MapBiomas para o bioma Amazônia. In: SIMPÓSIO BRASILEIRO DE SENSORIAMENTO REMOTO, 19. (SBSR), 2019, Santos. **Anais...** São José dos Campos: INPE, 2019. p. 735–738. Available in: <http://urlib.net/rep/8JMKD3MGP6W34M/3U24J5L>. Access in: 01 jul. 2020.

MAUS, V.; CÂMARA, G.; CARTAXO, R.; SANCHEZ, A.; RAMOS, F. M.; QUEIROZ, G. R. A time-weighted dynamic time warping method for land-use and land-cover mapping. **IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing**, v. 9, n. 8, p. 3729–3739, 2016. DOI. 10.1109/JSTARS.2016.2517118.

MCCONNELL, W.; MORAN, E. **Meeting in the Middle: The Challenge of Meso-Level Integration**, LUCC Report Series No. 5, Land Utilization Coordinating Council: Rome, Italy, 2001. Available in: <http://www.comap.ca/kmland/getdocument.php?F=310836083_4c7195ce74a518.86955292>. Access in: 30 jul. 2020.

MELLO, A. Y. I.; ALVES, D. S. Secondary vegetation dynamics in the Brazilian Amazon based on Thematic Mapper imagery. **Remote Sensing Letters**, v. 2, n. 3, p. 189–194, 2011. DOI. 10.1080/01431161.2010.506206.

MENA, C. F. Trajectories of land-use and land-cover in the northern Ecuadorian Amazon. **Photogrammetric Engineering & Remote Sensing**, v. 74, n. 6, p. 737–751, 2008. DOI. 10.14358/PERS.74.6.737.

MERTENS, B.; LAMBIN, E. Land cover change trajectories in southern Cameroon. **Annals of the Association of American Geographers**, v. 90, n. 3, p. 467–494, 2000. DOI. 10.1111/0004-5608.00205.

MEYFROIDT, P.; LAMBIN, E. F. Global forest transition: prospects for an end to deforestation. **Annual Review of Environment and Resources**, v. 36, n. 1, p. 343–371, 2011. DOI. 10.1146/annurev-environ-090710-143732.

MORAN, E. F.; BRONDIZIO, E. S.; TUCKER, J. M.; SILVA-FORSBERG, M. C.; MCCRACKEN, S.; FALESI, I. Effects of soil fertility and land-use on forest succession in Amazonia. **Forest Ecology and Management**, v. 139, n. 1, p. 93–108, 2000. DOI. 10.1016/S0378-1127(99)00337-0.

MÜLLER, H.; RUFIN, P.; GRIFFITHS, P.; HISSA, L. D. B. V.; HOSTERT, P. Beyond deforestation: Differences in long-term regrowth dynamics across land use regimes in southern Amazonia. **Remote Sensing of Environment**, v. 186, p. 652–662, 2016. DOI. 10.1016/j.rse.2016.09.012.

MÜLLER-HANSEN, F.; CARDOSO, M. F.; DALLA-NORA, E. L.; DONGES, J. F.; HEITZIG, J.; KURTHS, J.; THONICKE, K. A matrix clustering method to explore patterns of land-cover transitions in satellite-derived maps of the Brazilian Amazon. **Nonlinear Processes in Geophysics**, v. 24, n. 1, p. 113–123, 2017. DOI. 10.5194/npg-24-113-2017.

NATIONAL AERONAUTICS AND SPACE ADMINISTRATION (NASA). **MODIS: Moderate Resolution Imaging Spectroradiometer**. 2020a. Available in: <https://modis.gsfc.nasa.gov/>. Acesso em 18 dez. 2020.

NATIONAL AERONAUTICS AND SPACE ADMINISTRATION (NASA). **Terra: the EOS Flagship**. 2020b. Available in: <https://terra.nasa.gov/>. Access in: 18 dez. 2020.

NEVES, A. K.; KÖRTING, T. S.; FONSECA, L. M. G.; ESCADA, M. I. S. Assessment of TerraClass and MapBiomas data on legend and map agreement for the Brazilian Amazon biome. **Acta Amazonica**, v. 50, n. 2, p 170–182, 2020. DOI. 10.1590/1809-4392201900981.

NUNES, S.; OLIVEIRA JR, L.; SIQUEIRA, J.; MORTON, D. C.; SOUZA JR, C. M. Unmasking secondary vegetation dynamics in the Brazilian Amazon. **Environmental Research Letters**, v. 15, n. 3, artigo 034057, 2020. DOI. 10.1088/1748-9326/ab76db.

OLOFSSON, P.; FOODY, G. M.; HEROLD, M.; STEHMAN, S. V.; WOODCOCK, C. E.; WULDER, M. A. Good practices for estimating area and assessing accuracy of land change. **Remote Sensing of Environment**, v. 148, p. 42-57, 2014. DOI. 10.1016/j.rse.2014.02.015.

PANTALEÃO, E.; DUTRA, L. V.; SANDRI, S. A. Scenario analysis for image classification using multi-objective optimization. **InfoComp**, v. 1, n. 3-4, p. 15–22, 2012.

PARÁ. Instrução Normativa nº 08, de 28 de outubro de 2015. Define procedimentos administrativos para a realização de limpeza e autorização de supressão, a serem realizadas nas áreas de vegetação secundária em estágio inicial de regeneração, localizadas fora da Reserva Legal e da Área de Preservação Permanente – APP dos imóveis rurais, no âmbito do Estado do Pará, e dá outras providências. **DOE 33.003**, Belém, PA, 03 nov. 2015. p. 31-33.

PARADELLA, W.; SANTOS, A.; VENEZIANI, P.; CUNHA, E. Radares imageadores nas geociências. **Revista Brasileira de Cartografia**, v. 1, n. 57, p. 56–62, 2005.

PEREIRA, L. O.; FREITAS, C. C.; SANT´ANNA, S. J. S.; REIS, M. S. Evaluation of Optical and Radar Images Integration Methods for LULC Classification in Amazon Region. ***IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing***, v. 11, n. 9, p. 3062–3074, 2018. DOI. 10.1109/JSTARS.2018.2853647.

PERZ, S. G.; SKOLE, D. L. Secondary forest expansion in the Brazilian Amazon and the refinement of Forest Transition Theory. **Society & Natural Resources**, v. 16, n. 4, p.277–294, 2003. DOI. 10.1080/08941920390178856.

PINHEIRO, T. F.; ESCADA, M. I. S.; VALERIANO, D.; HOSTERT, P.; GOLLNOW, F.; MÜLLER, H. Forest degradation associated with logging frontier expansion in the Amazon: the BR-163 region in southwestern Pará, Brazil. **Earth Interactions**, v. 20, n. 17, p. 1–26, 2016. DOI. 10.1175/EI-D-15-0016.1.

POWELL, R.; MATZKE, N.; SOUZA, C.; CLARK, M.; NUMATA, I.; HESS, L.; ROBERTS, D. Sources of error in accuracy assessment of thematic land-cover maps in the Brazilian Amazon. **Remote Sensing of Environment**, v. 90, n. 2, p. 221–234, 2004. DOI. 10.1016/j.rse.2003.12.007.

PUTZ, F. E.; REDFORD, K. H. The importance of defining ‘forest’: Tropical forest degradation, deforestation, long-term phase shifts, and further transitions. **Biotropica**, v. 42, n. 1, p. 10–20, 2010. DOI. 10.1111/j.1744-7429.2009.00567.x.

RAMANKUTTY, N.; GIBBS, H. K.; ACHARD, F.; DEFRIES, R.; FOLEY, J. A.; HOUGHTON, R. A. Challenges to estimating carbon emissions from tropical deforestation. **Global Change Biology**, v. 13, n. 1, p. 51–66, 2007. DOI. 10.1111/j.1365-2486.2006.01272.x.

REIS, M. S.; DUTRA, L. V.; ESCADA, M. I. S.; SANT’ANNA, S. J. S Avoiding invalid transitions in land cover trajectory classification with a Compound Maximum a Posteriori approach. **IEEE Access**, v. 8, p. 98787–98799, 2020. DOI. 10.1109/ACCESS.2020.2997019.

REIS, M. S.; DUTRA, L. V.; SANT'ANNA, S. J. S.; ESCADA, M. I. S. Análise das incertezas envolvidas em classificação multi-legendas da cobertura da terra com suporte de simulação Monte Carlo. **Revista Brasileira de Cartografia**, v. 69, n. 9, p. 1725–1741, 2017.

REIS, M. S.; ESCADA, M. I. S.; DUTRA, L. V.; SANT’ANNA, S. J. S.; VOGT, N. D. Towards a reproducible LULC hierarchical class legend for use in the southwest of Pará State, Brazil: a comparison with remote sensing data-driven hierarchies. **Land**, v. 7, n. 2, artigo 65, 2018. DOI. 10.3390/land7020065.

RICHARDS, J. A.; JIA, X. **Remote sensing digital image analysis: an introduction**. 4. ed. Germany: Springer, 2006.

RUFIN, P.; MÜLLER, H.; PFLUGMACHER, D.; HOSTERT, P. Land use intensity trajectories on Amazonian pastures derived from Landsat time series. **International Journal of Applied Earth Observation and Geoinformation**, v. 41, p. 1–10, 2015. DOI. 10.1016/j.jag.2015.04.010.

SALOMÃO, R. P.; VIEIRA, I. C. G.; BRIENZA JÚNIOR, S.; AMARAL, D. D.; SANTANA, A. C. Sistema capoeira classe: uma proposta de sistema de classificação de estágios sucessionais de florestas secundárias para o estado do Pará. **Boletim do Museu Paraense Emílio Goeldi. Ciências Naturais**, v. 7, n. 3, p. 297–317, 2012.

SANCHEZ, A. H.; PICOLI, M. C. A.; CÂMARA, G.; ANDRADE, P. R.; CHAVES, M. E. D.; LECHLER, S.; SOARES, A. R.; MARUJO, R. F. B.; SIMÕES, R. E. O. ; FERREIRA, K. R.; QUEIROZ, G. R. Comparison of Cloud Cover Detection Algorithms on Sentinel-2 Images of the Amazon Tropical Forest. **Remote Sensing**, v. 12, n. 08, artigo 1284, 2020. DOI. 10.3390/rs12081284.

SEXTON, J. O.; URBAN, D. L.; DONOHUE, M. J.; SONG, C. Long-term land cover dynamics by multi-temporal classification across the Landsat-5 record. **Remote Sensing of Environment**, v. 128, p. 246–258, 2013. DOI. 10.1016/j.rse.2012.10.010.

SHIMABUKURO, Y. E.; SMITH, J. A. Fraction images derived from Landsat TM and MSS data for monitoring reforested areas. **Canadian Journal of Remote Sensing**, v. 21, n. 1, p. 67-74, 1995. DOI. 10.1080/07038992.1995.10874599.

SHIMADA, M.; ITOH, T.; MOTOOKA, T.; WATANABE, M.; SHIRAISHI, T.; THAPA, R.; LUCAS, R. New global forest/non-forest maps from ALOS PALSAR data (2007-2010). **Remote Sensing of Environment**, v. 155, p. 13–31, 2014. DOI. 10.1016/j.rse.2014.04.014

SILVA JUNIOR, C. H. L.; HEINRICH, V. H. A.; FREIRE, A. T. G.; BROGGIO, I. S.; ROSAN, T. M.; DOBLAS, J.; ANDERSON, L. O.; ROUSSEAU, G. X.; SHIMABUKURO, Y. E.; SILVA, C. A.; HOUSE, J. I.; ARAGÃO, L.E.O.C. Benchmark maps of 33 years of secondary forest age for Brazil. Scientific Data, v. 7, n. 1, p. 269-269, 2020. DOI. 10.1038/s41597-020-00600-4.

SOUZA, C. M.; SHIMBO, J. Z.; ROSA, M. R.; PARENTE, L. L.; ALENCAR, A. A.; RUDORFF, B. F. T.; HASENACK, H.; MATSUMOTO, M.; FERREIRA, L. G.; SOUZA-FILHO, P. W. M.; OLIVEIRA, S. W.; ROCHA, W. F.; FONSECA, A. V.; MARQUES, C. B.; DINIZ, C. G.; COSTA, D.; MONTEIRO, D.; ROSA, E. R.; VÉLEZ-MARTIN, E.; WEBER, E. J.; LENTI, F. E. B.; PATERNOST, F. F.; PAREYN, F. G. C.; SIQUEIRA, J. V.; VIERA, J. L.; FERREIRA NETO, L. C.; SARAIVA, M. M.; SALES, M. H.; SALGADO, M. P. G.; VASCONCELOS, R.; GALANO, S.; MESQUITA, V. V.; AZEVEDO, T. Reconstructing Three Decades of Land Use and Land Cover Changes in Brazilian Biomes with Landsat Archive and Earth Engine. **Remote Sensing**, v. 12, n. 17, artigo 2735, 2020. DOI. 10.3390/rs12172735.

STEININGER, M. Secondary forest structure and biomass following short and extended land-use in central and southern Amazonia. **Journal of tropical Ecology**, v. 16, p. 689-708, 2000.

TEWKESBURY, A. P.; COMBER, A. J.; TATE, N. J.; LAMB, A.; FISHER, P. F. A critical synthesis of remotely sensed optical image change detection techniques. **Remote Sensing of Environment**, v. 160, p. 1–14, 2015. DOI. 10.1016/j.rse.2015.01.006.

TURNER, B.; MEYER, W. Global land-use and land-cover change: an overview. In: MEYER, W.; TURNER, B. (Ed.). **Changes in land use and land cover: a global perspective**. Cambridge: Cambridge University Press, 1994.

UNITED STATES GEOLOGICAL SURVEY (USGS). **USGS EROS Archive - Products Overview**. 2020. Available in: <https://www.usgs.gov/centers/eros/science/usgs-eros-archive-products-overview?qt-science_center_objects=0#qt-science_center_objects>. Access in: 18 dez. 2020.

VAN ROESSEL, J. W.; GODOY, R. C. SLAR mosaics for project RADAM. **Photogrammetric Engineering**, v. 40, p. 583-595, 1974.

VERBESSELT, J.; HYNDMAN, R.; NEWNHAM, G.; CULVENOR, D. Detecting trend and seasonal changes in satellite image time series. **Remote Sensing of Environment**, v. 114, n. 1, p. 106–115, 2010. DOI. 10.1016/j.rse.2009.08.014.

VIEIRA, I. C. G.; GARDNER, T.; FERREIRA, J.; LEES, A. C.; BARLOW, J. Challenges of governing second-growth forests: A case study from the Brazilian Amazonian State of Pará. **Forests**, v. 5, n. 7, p. 1737-1752, 2014. DOI. 10.3390/f5071737.

WANDELLI, E. V.; FEARNSIDE, P. M. Secondary vegetation in central Amazonia: Land-use history effects on aboveground biomass. **Forest Ecology and Management**, v. 347, p. 140–148, 2015. DOI. 10.1016/j.foreco.2015.03.020.

WANG, Y.; ZIV, G.; ADAMI, M.; ALMEIDA, C. A.; ANTUNES, J. F. G.; COUTINHO, A. C.; ESQUERDO, J. C. D. M.; GOMES, A. R.; GALBRAITH, D. Upturn in secondary forest clearing buffers primary forest loss in the Brazilian Amazon. **Nature Sustainability**, v. 3, n. 4, p. 290-295, 2020. DOI. 10.1038/s41893-019-0470-4.

WHITE, J. C.; WULDER, M. A.; HOBART, G. W.; LUTHER, J. E.; HERMOSILLA, T.; GRIFFITHS, P., COOPS, N. C.; HALL, R. J.; HOSTERT, P.; DYK, A,; GUINDON, L. Pixel-based image compositing for large-area dense time series applications and science. **Canadian Journal of Remote Sensing**, v. 40, n. 3, p. 192–212, 2014. DOI. 10.1080/07038992.2014.945827

WULDER, M. A.; COOPS, N. C.; ROY, D. P.; WHITE, J. C.; HERMOSILLA, T. Land cover 2.0. **International Journal of Remote Sensing**, v. 39, n. 12, p. 4254–4284, 2018. DOI. 10.1080/01431161.2018.1452075.

XIAN, G.; HOMER, C. Updating the 2001 National Land Cover Database impervious surface products to 2006 using Landsat imagery change detection methods**. Remote Sensing of Environment**, v. 114, n. 8, p. 1676–1686, 2010. DOI. 10.1016/j.rse.2010.02.018.

YUAN, F.; SAWAYA, K. E.; LOEFFELHOLZ, B. C.; BAUER, M. E. Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing. **Remote Sensing of Environment**, v. 98, n. 2, p. 317–328, 2005. DOI. 10.1016/j.rse.2005.08.006.

ZHU, Z. Change detection using landsat time series: A review of frequencies, preprocessing, algorithms, and applications. **ISPRS Journal of Photogrammetry and Remote Sensing**, v. 130, p. 370–384, 2017. DOI. 10.1016/j.isprsjprs.2017.06.013.

ZHU, Z.; FU, Y.; WOODCOCK, C. E.; OLOFSSON, P.; VOGELMANN, J. E.; HOLDEN, C.; WANG, M.; DAI, S.; YU, Y. Including land cover change in analysis of greenness trends using all available Landsat 5, 7, and 8 images: a case study from Guangzhou, China (2000-2014). **Remote Sensing of Environment**, v. 185, p. 243–257, 2016. DOI. 10.1016/j.rse.2016.03.036.

ZHU, Z.; WOODCOCK, C. E. Continuous change detection and classification of land cover using all available Landsat data. **Remote Sensing of Environment**, v. 144, p. 152–171, 2014. DOI. 10.1016/j.rse.2014.01.011.

ZOUNGRANA, B. J.-B.; CONRAD, C.; AMEKUDZI, L. K.; THIEL, M.; DA, E. D.; FORKUOR, G.; LÖW, F. Multi-temporal Landsat images and ancillary data for land use/cover change (LULCC) detection in the Southwest of Burkina Faso, West Africa. **Remote Sensing**, v. 7, n. 9, p. 12076–12102, 2015. DOI. 10.3390/rs70912076.

Author's biographies

Mariane Souza Reis received the B.S. degree in environmental engineering from the Pontifícia Universidade Católica de Campinas, Campinas, in 2011, and the M.Sc. degree in remote sensing from the National Institute for Space Research (INPE), São José dos Campos, Brazil, in 2014, where she is currently pursuing the Ph.D. degree in Earth System Science. From 2014 to 2016, she held a scholarship to work with INPE in land cover monitoring and collection of field data (Amazon), and the development of image processing algorithms. Her research interests include land use and land cover analysis and image processing techniques.

 DOI: http://dx.doi.org/10.14393/rbcv72nespecial50anos-56535

Maria Isabel Sobral Escada received the B.S. degree in ecology from the Universidade Estadual Paulista `Júlio de Mesquita Filho', Brazil, in 1987, and the M.Sc. and Ph.D. degrees in remote sensing INPE, Brazil, in 1992 and 2003, respectively. She has experience with using remote sensing technologies and spatial analysis techniques applied to landscape studies through the analysis of land use and land cover change patterns and processes in Amazon. She is currently a Senior Researcher with the Earth Observation and Geoinformatics Division and a Professor with the Graduate Programs in Earth System Science and Remote Sensing, INPE.

Sidnei João Siqueira Sant'anna received the B.S. degree in electrical and electronic engineering from the Universidade Federal do Rio de Janeiro, Rio de Janeiro, Brazil, in 1993, the M.Sc. degree in remote sensing from INPE, São José dos Campos, Brazil, in 1995, and the Ph.D. degree in electronic engineering and computing from the Aeronautical Technological Institute (ITA), São José dos Campos, in 2009. He is currently a Researcher with INPE. His research interests include image analysis and processing techniques for remote sensing, SAR image filtering, statistical methods, robustness, and so on.

Luciano Vieira Dutra received the B.S.E.E. degree from ITA, São José dos Campos, Brazil, in 1976, and the M.Sc. and Ph.D. degrees in computer science from INPE, São José dos Campos, in 1981 and 1989, respectively. He has been with INPE, since 1977, working in several national and international large-scale remote sensing projects. He is currently a Lecturer with the Computer Science and Remote Sensing Graduate Programs, INPE, where he has been In-Charge of the Image and Signal Processing, the Pattern Recognition, and the Radar Image Processing Courses.