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Characterization of the dynamics of the successional stages of the Amazon forest using Google Earth Engine

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Abstract

Aim of study: This study evaluates the potential of the Google Earth Engine tool, supported by fine-scale information obtained by Unmanned Aerial Vehicle, to apply and characterize the dynamics of the successional stages of the Amazon Forest in the state of Rondônia over ten years.

Area of study: The study was carried out in the state of Rondônia located in the North Region of Brazil (Western Amazon).

Materials and methods: The data and its by-products were derived from the Landsat Level 1 - TOA collection of the United States Geological Survey, specifically Landsat 5 and 8. The mapping also used Phantom 4 Pro UAV images. We used the supervised classifier Random Forest to map the primary forest/advanced regeneration, medium regeneration, initial regeneration, and classes, and, subsequently, we crossed and quantified the successional advance and vegetation loss.

Main results: It was observed that the state lost forest area even with the successional advance that occurred throughout the period, implying that the forest succession was insufficient in the face of forest deforestation.

Research highlights: This study contributed to understanding the dynamics of the Amazon Forest, which goes through a process of deforestation and forest regeneration simultaneously.

Additional key words: regeneration; tropical forests; deforestation; unmanned aerial vehicle.

Abbreviations used: AR (advanced regeneration); EVI (enhanced vegetation index); GEE (google earth engine); IR (initial regeneration); MR (medium regeneration); NDVI (normalized difference vegetation index); NDWI (normalized difference water index); NF (non-forest); OU (other uses); PF (primary forest); PRODES (Project for Monitoring Deforestation in the Legal Amazon); SAVI (soil adjusted vegetation index); SR (simple ratio index); UAV (unmanned aerial vehicle); WR (water resources).

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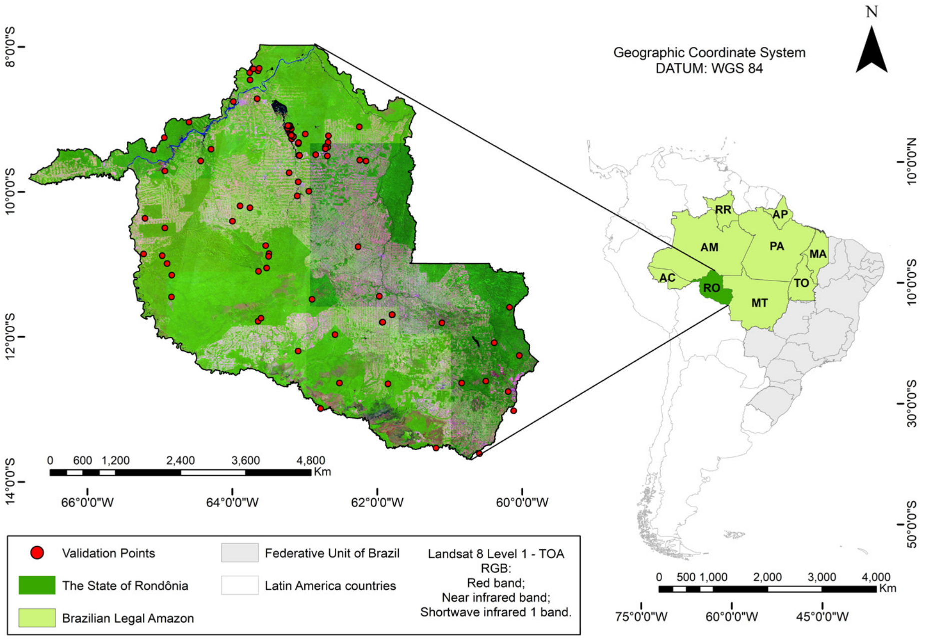


Figure 1. Location map of the state of Rondônia (Landsat 8 satellite image from 2018).

Introduction

The Amazon Forest is the largest tropical forest in the world (Haddad et al., 2015), counting on rich biodiversity (Fearnside, 2021) and playing an essential role in regional and global climate (Baker & Spracklen, 2019; Covey et al., 2021). It is one of the most important tropical ecosystems in the world and provides various ecosystem services.

However, the economic activities developed in this region are strongly linked to forest degradation and illegal deforestation, such as livestock, agriculture, and logging (Sampaio et al., 2007; Arima et al., 2011; Costa et al., 2017). The disorderly and illegal deforestation of the Amazon Forest and its degradation over the years have transformed an immense area of primary forest into fragments of the most diverse levels of vegetation regeneration, pasture, and agriculture (Almeida et al., 2016).

Rondônia is one of the Brazilian states located in the Amazon biome. It is part of the territory called Amazônia Legal (Legal Amazon) – which encompasses the Brazilian states of Acre, Amapá, Amazonas, Mato Grosso, Pará, Rondônia, Roraima, and Tocantins, as well as part of the state of Maranhão – and it is the third state of this territory with the highest deforestation rates (INPE, 2021). The illegal deforestation in Rondônia also occurs in protected areas, such as indigenous lands and conservation areas (Araújo et al., 2017; Paiva et al., 2020).

Secondary forests or Capoeiras are areas of forest regeneration essential in the process of change in the soil. These areas increase with deforestation in the Amazon, eventually becoming predominant in the landscape (Vieira et al., 2008). This secondary vegetation in different development stages represents 150,800 km² (21%) of the total deforested area in the Amazon – 13,300 km^2 is located in the state of Rondônia (Almeida et al., 2016). In general, successional vegetation is grouped into three developmental classes: early, intermediate, and advanced (Lu et al., 2003).

The secondary forest has gained increasing importance over time, contributing to biodiversity restoration, soil conservation, and the maintenance of hydrological systems (Lennox et al., 2018; Matos et al., 2020; Montfort et al., 2021). The successional advance of forests has increased the supply of most ecosystem services (Cortés-Calderón et al., 2021), and it works as an important carbon sink (Heinrich et al., 2021). However, mapping land use and land cover in the humid tropical regions of the Brazilian Amazon is a challenge due to the complexity of the biophysical environment (Lu et al., 2012).

The development of knowledge about Remote Sensing and the evolution of the power of computational techniques have led to the explosive growth of Remote Sensing data (Akturk et al., 2023). The Google Earth Engine (GEE) geospatial technology represents a major improvement for monitoring and evaluating land use and coverage changes over large geographic areas with greater detail (Zurqani et al., 2018). Today, the GEE proposes overcoming the barriers of large-scale mapping by providing a high-performance cloud processing infrastructure and spatial data catalog and algorithms (Gorelick et al., 2017).

The engine's library features over 20 types of supervised classification, linear and nonlinear regression, and unsupervised clusters (Gorelick et al., 2017). Among them, the Random Forest machine learning technique, which is being increasingly applied in land cover classification, proving to be efficient in land use and land cover mapping (Gislason et al., 2006; Rodriguez-Galiano et al., 2012;

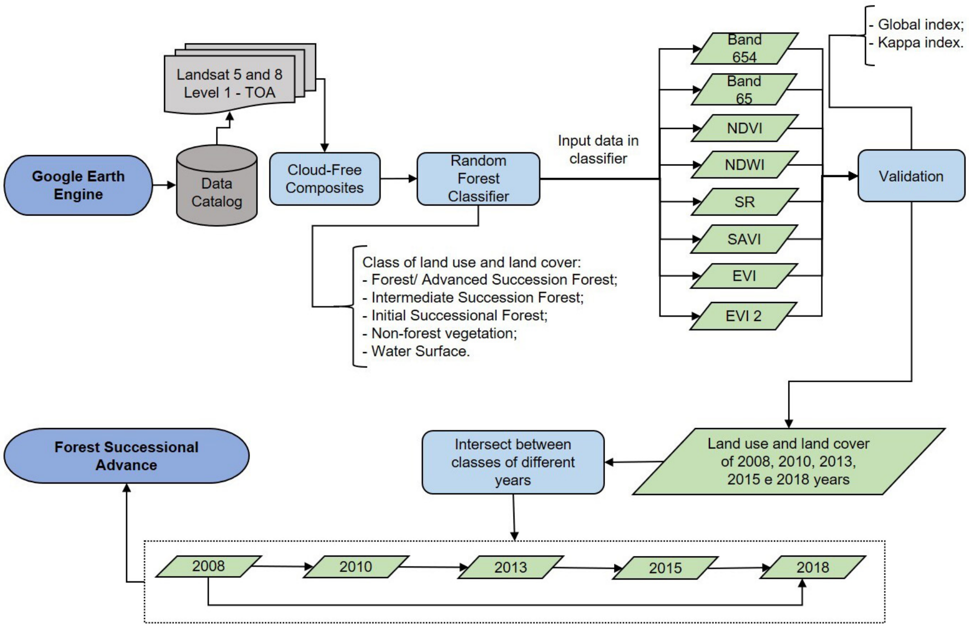


Figure 2. Methodology flowchart.

Feng et al., 2015). The results obtained using this technique show it is efficient in handling high-dimensional data on a regional and planetary scale (Gislason et al., 2006; Belgiu & Drăgut, 2016), such as the state of Rondônia.

Therefore, mapping forest succession and loss in one of the states with the most deforestation in the Legal Amazon provides important analyses of the dynamics between the stages of forest development and the gains from regenerated forest growth against the advance of deforestation that occurs in the state of Rondônia. Thus, this study aims to evaluate the potential of the GEE tool, supported by fine-scale information obtained by an Unmanned Aerial Vehicle (UAV), for the application and characterization of the dynamics of the successional stages of the Amazon Forest in the state of Rondônia over ten years (2008-2018). We tested the possibility of this tool to provide a more comprehensive understanding of the dynamics of tropical forests.

Material and methods

Area of study

The state of Rondônia is located in the North Region of Brazil (Western Amazon), central geographic coordinates 62°50’27.253” W and 10°56’44.217” S, capital Porto Velho, limited to the north by the state of Amazonas, to the northwest by the state of Acre, to the west and south by Bolivia, to the east and southeast by the state of Mato Grosso (Fig. 1). The state has a tropical-hot and humid climate. The average annual rainfall is 1896.5 mm (Franca, 2015), and latosol and argisol soils are predominant (Santos et al., 2011). The territory has low altitudes and no major irregularities, so about 94% of its terrain is between 100 and 600 m (Franca, 2015).

The state is in the Amazon floristic region. The dominant vegetation type in the state is (i) the Open Ombrophilous Forest, which is characterized by three facies dominated by typical genera, located suggestively in the less humid areas: palm forest, bamboo forest, and forest-with-cipó; (ii) Dense Ombrophylous Forest characterized by high temperatures and high rainfall, well-distributed throughout the year; and (iii) Seasonal Forest whose seasonal climate determines the semi-deciduity of forest canopy foliage. Non-forest vegetation of Savannah was removed from the study.

Spatial data

The research used the database available on the GEE online platform. The platform gives access to an extensive collection of geospatial data. The data and its by-products were derived from the Landsat Level 1 - TOA collection of the United States Geological Survey, specifically Landsat 5 and 8. The mapping also used Phantom 4 Pro UAV images from 2018 provided by the Centro de Estudos RIOTERRA. The institute covers a large territory of the state of Rondônia, so images from several areas within the state were provided.

Rondônia is constituted by areas of forest and areas called non-forest (NF) vegetation – as designated by the Project for Monitoring Deforestation in the Legal Amazon (PRODES), which provides data from areas identified in the images as consisting of vegetation different from the forest physiognomy (INPE, 2021). The NF spatial data was adopted as a mask, identifying the NF areas present in the state.

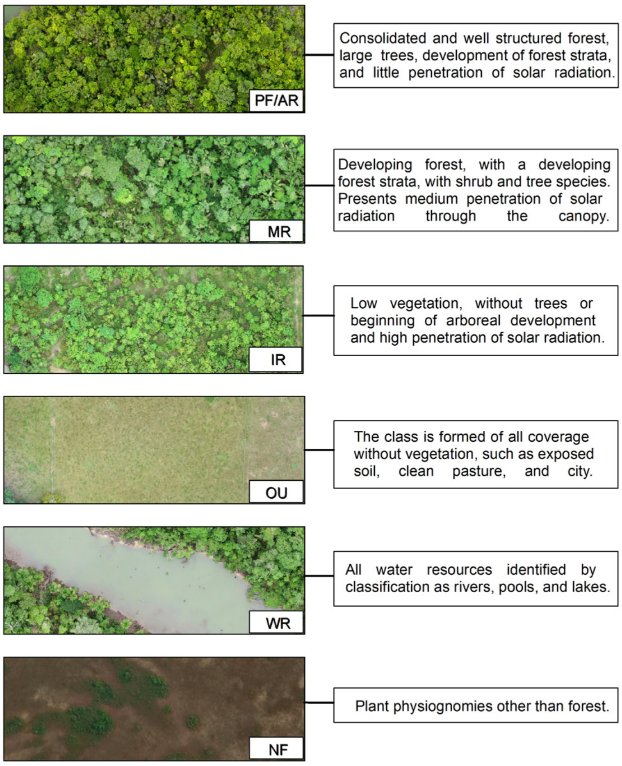


Figure 3. Classes of land use and land cover (images of the UAV Phantom 4 Pro for 2018). PF/AR: primary forest/advanced regeneration. MR: medium regeneration. IR: initial regeneration. OU: other uses. WR: water resources. NF: non-forest.

Field data

The field data were obtained in December 2018 during a field visit by the Centro de Estudos RIOTERRA around the state of Rondônia. The institute covers a large territory in the state of Rondônia, about 20% of the state.

The field collection of the points obtained on the ground regarding the land use and land cover classes to perform the cartographic validation was done during the field visit in the year 2018 in the area that the institute covers. The tool used was the Garmin GPSMAP 62S navigation device. However, part of the points class primary forest/advanced regeneration points was obtained from the Google Earth Pro platform due to sampling insufficiency in the class.

Flights were conducted by Phantom 4 Pro UAV in December 2018 and orthophotos were obtained from 18 forest succession areas of different ages and development that are monitored by RIOTERRA. The orthophoto was one of the bases for differentiating the classes in the mapping.

Data processing

Digital image processing and land use and land cover classification for 2008, 2010, 2013, 2015, and 2018 were performed on the GEE platform using the JavaScript computational language and transferred to the Arcgis 10.5 program only to analyze the successional advance and vegetation loss (Fig. 2).

Digital image processing and classification

Data processing was based on the Landsat level 1 TOA series images free of cloud and cloud shadow with 30 m of spatial resolution. The cloud/shadow removal script uses the Quality Assessment band and the median of the image collection from the period May 1 to October 30. The Quality Assessment band quality control values improve data integrity, indicating pixels affected by artifacts or subject to cloud contamination. The GEE was instructed to obtain the median of each pixel of the stack of images collected from May 1 to October 30 to form a single image with median value pixels. The process was repeated for the years 2008, 2010, 2013, 2015, and 2018, using an average of 201 images per year.

For mapping land use and occupation, the supervised machine learning classifier Random Forest was used (Breiman, 2001). The classifier can achieve higher accuracy compared to other classifiers in large study areas (Belgiu & Drăgut, 2016). Random Forest is structured in a collection of decision trees producing results from the predictions generated in the trees (Breiman, 2001). The final classification was defined by the arithmetic mean of the class assignment probabilities calculated by all trees produced, i.e., a new input of unlabeled data was evaluated against all decision trees created in the set, and each tree votes in a class association. Thus, the class of association with the maximum number of votes was selected (Belgiu & Drăgut, 2016).

The vegetation indices were generated based on the function “expression”: Simple Ratio Index (SR) (eq. 1), Soil Adjusted Vegetation Index (SAVI) (eq. 2), Normalized Difference Water Index (NDWI) (eq. 3), Normalized Difference Vegetation Index (NDVI) (eq. 4), Enhanced Vegetation Index (EVI) (eq. 5), and Enhanced Vegetation Index 2 (EVI 2) (eq. 6). Vegetation indices were used as input attributes in the classifier and bands in the red, near-infrared, and mid-infrared regions of the electromagnetic spectrum. Thus, generating eight classifications with different input attributes for validation, the choice of the best classification was made based on the input attribute.

Eq. 1 $$SR = \frac{\text{band near infrared}}{\text{band red}}$$

Eq. 2 $$SAVI = \left(\frac{(\text{band near infrared- band red})}{(\text{band near infrared+band red+0.5})}\right)\times(1+0.5)$$

Eq. 3 $$NDWI = \left(\frac{(\text{band near infrared- band short wave infrared})}{(\text{band near infrared+band short wave infrared})}\right)$$

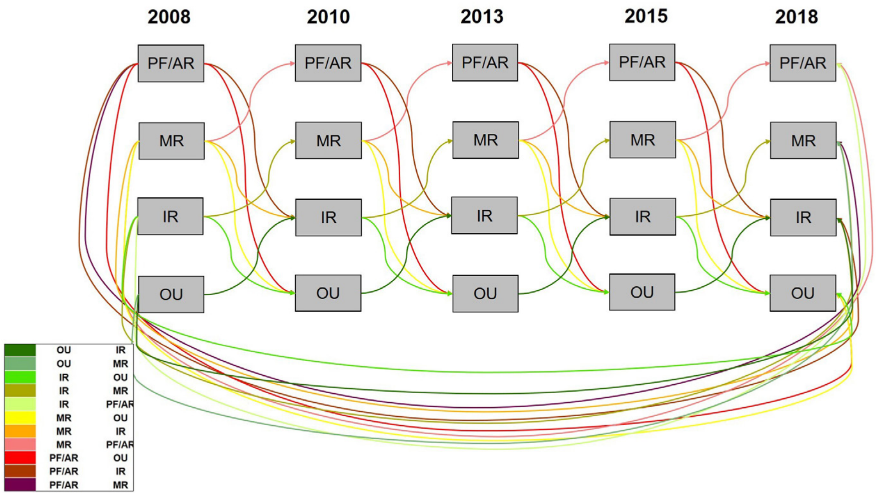


Figure 4. Process of crossing classes to analyze the dynamic of the successional advance and vegetation removal. PF/AR: primary forest/advanced regeneration. MR: medium regeneration. IR: initial regeneration. OU: other uses. WR: water resources. NF: non-forest.

$$\text{Eq. 4} \quad \text{NDVI} = \left(\frac{(\text{band near infrared- band red})}{(\text{band near infrared+band red})}\right)$$

$$\text{Eq. 5} \quad \text{EVI} = 2.5\times\left(\frac{(\text{band near infrared- band red})}{(1+\text{band near infrared}+(6\times\text{band red})-(7.5\times\text{band blue}))}\right)$$

$$\text{Eq. 6} \quad \text{EVI 2} \quad 2.5\times\left(\frac{(\text{band near infrared- band red})}{(\text{band near infrared}+(2.4\times\text{band red})+1)}\right)$$

In all eight classifications, the same training limit of 2,000 to 3,000 randomized points was used in the sample acquisition process, and the number of decision trees was equal to 100. According to Rodriguez-Galiano et al. (2012), the number of trees is directly proportional to the classifier's precision until reaching a certain stabilization (100 trees), changing from there, only slightly, the producer's accuracy.

The samples of each class were refined based on UAV images from different areas of the state of Rondônia. Thus, from the parameters inserted in the classifier and the classes sampling, three classes of forest development were differentiated: primary forest/advanced regeneration (PF/AR), medium regeneration (MR), initial regeneration (IR). Another two classifications obtained were the classes other uses (OU) and water resources (WR). As mentioned before, the non-forest (NF) vegetation class was adopted as a mask, removing all areas with non-forest physiognomy (Fig. 3).

Validation

Validation was performed on eight classifications generated from the following input attributes: mid-infrared, near-infrared, and red spectral bands (B654); mid-infrared, near-infrared spectral bands (B65); SR; SAVI; NDWI; NDVI; EVI; and EVI 2. We used 458 true field points covering the entire state, 50 from PF/AR, 156 from MR, 42 from IR, 181 from OU, 29 from WR (Fig. 1).

The validation points (true class) and the predicted class are compared through the confusion matrix, generating the accuracy indices. Global accuracy index informs the possibility that a sample chosen at random within the classification is correct, as does the Kappa index (Cohen, 1960). Kappa is widely used to validate land use and land cover mapping (Ruiz Hernandez & Shi, 2018; Vale et al., 2018; Diniz et al., 2019; Guloglu et al., 2021). The Kappa coefficient associates a certain range of rating quality values that goes from less than zero (poor) to 0.81 to 1.0 (excellent) (Landis & Koch, 1977).

The confusion matrix generated the user's and producer's accuracy. The generated columns correspond to the producer's perspective (the role of an accurate database producer is to avoid different classes entering a sample of a specific class). The rows are the user's perspectives, which inform what the database content actually means on the ground (Longley et al., 2013).

Analysis of successional advance

The dynamics of successional advance, vegetation removal, and forest degradation over a 10-year period were performed by superimposing the classes PF/AR, MR, IR, OU for each year and evaluating the intersection between the classes using the "Union" tool, that computes a geometric intersection of the input data. The polygons that showed a difference in class of land use and land cover from one year to another were scored as they changed, quantifying in area the changes from 2008 to 2010, 2010 to 2013, 2013 to 2015, 2015 to 2018 and, finally, 2008 to 2018 (Fig. 4).

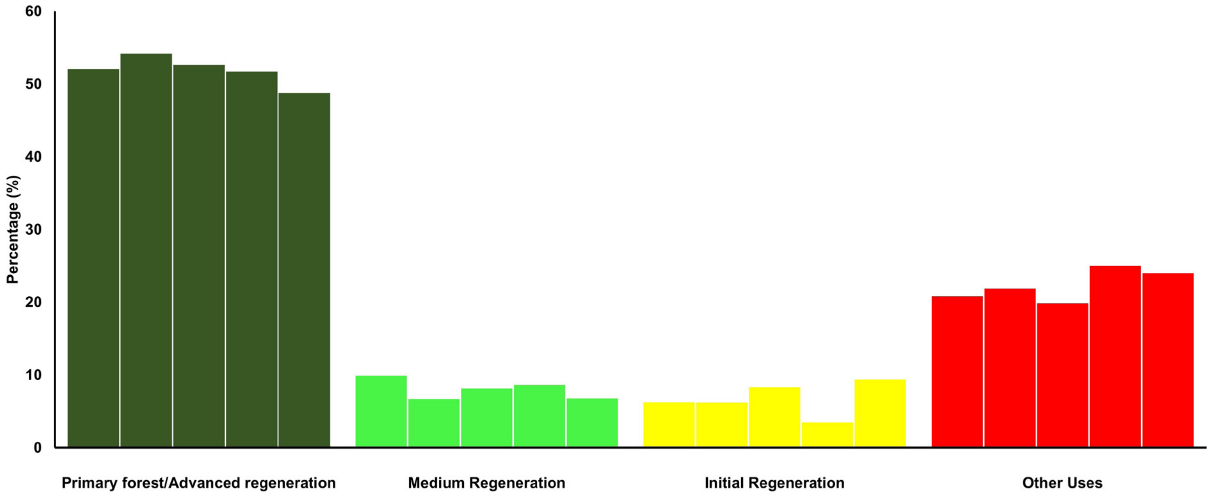


Figure 5. Vegetation coverage in the Brazilian state of Rondônia over ten years.

Results

Validation

The validation results verified that the highest values input attributes were the bands combinations, and the lowest were the six vegetation indices. The input attribute B654 resulted in a Kappa index of 0.87, classified as excellent, and a global accuracy index of 0.91, showing lower accuracy in the IR class, which presented user's accuracy of 0.59 and a high producer's accuracy (0.81). The input attribute B65 presented a Kappa value of 0.83, classified as excellent, a global accuracy index of 0.88, and a lower user's accuracy for class IR, similar to the B654 input attribute.

Therefore, classifications using vegetation indices as input attribute resulted in Kappa indices ranging from 0.60 to 0.44 and a global accuracy index from 0.70 to 0.59. The input attribute with the lowest accuracy was SAVI, which had a Kappa index of 0.44 and a global accuracy index of 0.59.

Mapping of the Amazon Forest successional stages from 2008 to 2018

Fig. 5 shows the percentage coverage of the PF/AR, MR, IR, and OU classes in intervals of two and three years over ten years. Detecting during the study period demonstrated that the quantity of vegetation in the classes PF/AR, MR, and IR increased and reduced, oscillating. However, these vegetation classes were reduced at the end of the period, increasing the class OU.

Fig. 6 shows the classification of each year for the state of Rondônia and in an approximate fraction of the area. The maps help to visualize the advance of deforestation in the state and the transformations in land use and occupation over the ten years. Visually, it is possible to perceive the transformation of the PF/AR class into other land use and land cover in the enlarged map area and the transformations of the class PF/AR in the northern region of the state of Rondônia.

Soil covered with more developed vegetation such as PF/AR and MR decreased in the period. In 2008, the state was covered by 52.02% of PF/AR and 9.88% by MR, whereas in 2018, less than half of the state was covered by the class PF/AR, and MR covered only 6.78% of the state. The area with PF/AR increased only in 2010, gaining 2% and reaching 54.16% of the state.

The sum of the three successional vegetation classes occupied 68.17% of the state in 2008, 67.05% in 2010, 69.06% in 2013, 63.78% in 2015, and 64.85% in 2018, showing increases and decreases in the area with vegetation. At the end of the period, a reduction of about 3.3% in the amount of area covered by vegetation was observed, considering the three successional classes (PF/AR, MR, and IR).

Forest succession from 2008 to 2018

Fig. 7 shows the process of change of successional classes (in percentage) of the total area of Rondônia. From 2008 to 2010, a process of successional advance from MR to PF/AR of 2.55%, from OU to IR of 3.57%, and IR to MR of 1.04% was observed. However, there was a 3.67% loss from IR to OU and 0.87% from MR to OU. In addition, there was a transformation of an area of 1.03% of MR class into IR, restarting the succession process.

The 3-year interval from 2010 to 2013 showed an expressive successional advance of two classes (Fig. 7). The biggest successional advance occurred in 5.53% of the territory, from the class OU to IR, followed by a 2.05% successional advance from IR to MR. Finally, there was a reduction from IR to OU in 2.33% of the area.

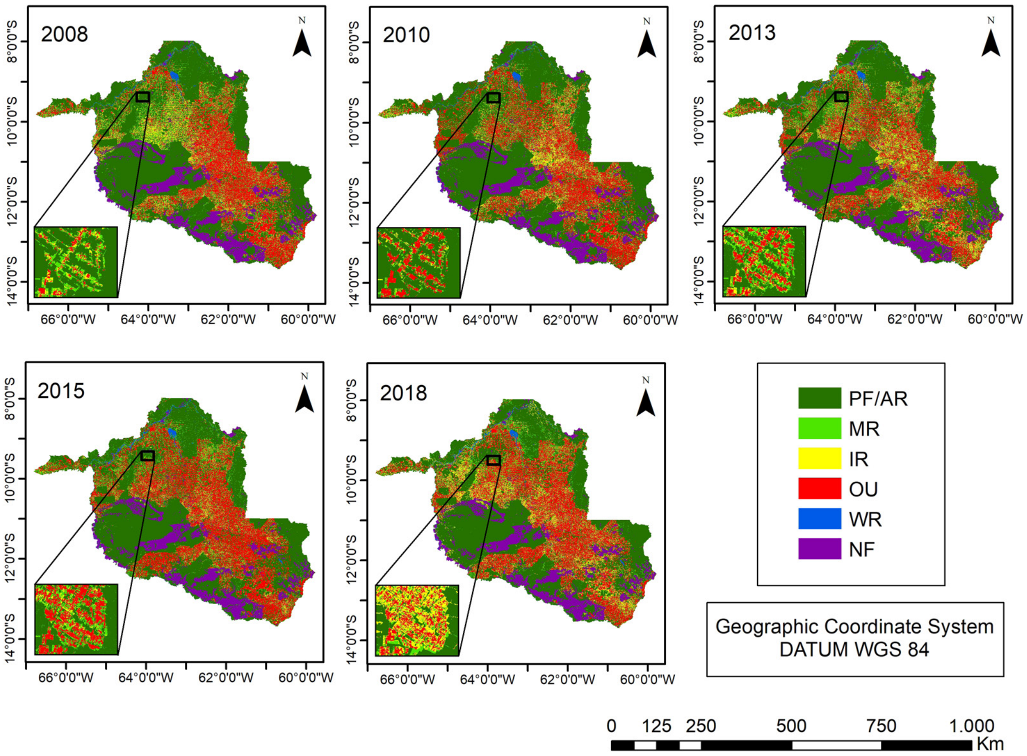


Figure 6. Map of the vegetation coverage in the Brazilian state of Rondônia over ten years. PF/AR: primary forest/advanced regeneration. MR: medium regeneration. IR: initial regeneration. OU: other uses. WR: water resources. NF: non-forest.

The period from 2013 to 2015 presented lower percentages of successional advances (Fig. 7). The most significant successional advance was an area of 1.13% from OU to IR, an area of 1.88% from IR to MR, and 1.66% from MR to PF/AR. The successional advance to the most advanced stage of succession was extremely important due to the relevance of forests in the highest succession stage. However, an expressive reduction (an area of 4.96%) from IR to OU was observed.

A more expressive transformation from OU to IR occurred from 2015 to 2018 (4.55%), a trend observed in previous periods. A successional evolution was verified from MR to PF/AR encompassing an area of 1.31%. Vegetation loss occurred mainly in the transformation from MR to OU (1.54%), with the removal of the MR and a restart of succession in 3 years to IR in an area of 1.80%, and loss of PF/AR transformed to IR (1.43%) (Fig. 7).

In addition, the change process was carried out during the 10-year interval, from 2008 to 2018 (Fig. 7). At the end of the period, an important successional evolution from MR to PF/AR of 2.72% is presented, with the most expressive transformation in succession from OU to IR (3.84%). At the end of the study period, there was also higher loss of vegetation, loss of 3.80% of IR to OU, loss of 2.45% of MR to OU, the transformation of 1.86% from MR to IR, loss of 1.41 % from PF/AR to OU and, finally, the transformation of 1.82% from PF/AR to IR.

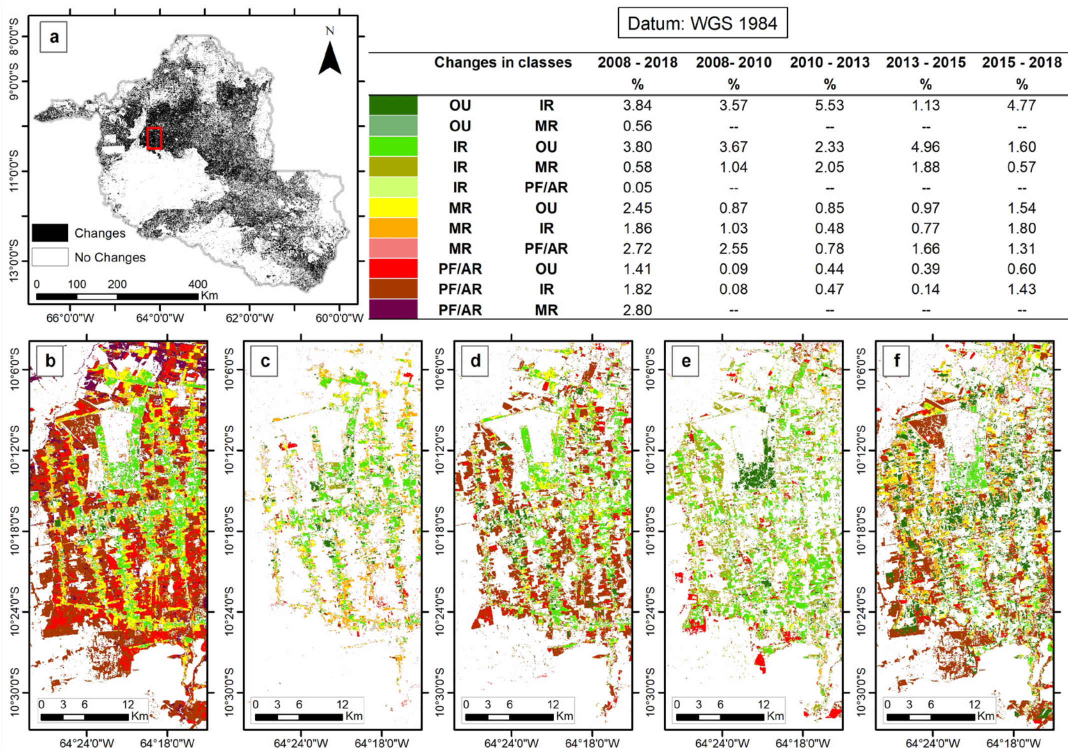
Discussion

Validation of the differentiation between the successional stages of the Amazon Forest

Land use and occupation mapping are subjected to errors; hence the importance of validation tests assessing how much the classes selected in the process are correlated to the surface analyzed. The mapping quality was measured by the global accuracy index, Kappa, producer's accuracy, and user's accuracy. According to the four indices, the higher the value, the greater the correlation between the maps and the surface.

The classification with the input attribute B654, which combines bands from the red, near-infrared, and mid-infrared region, obtained a Kappa index considered excellent according to Landis & Koch (1977). It also had a high global accuracy index, ensuring that the chance of correct classification in a randomly selected sample is above 90%. Therefore, the B654 input attribute was applied to all classifications.

According to Jensen (2009), the accuracy of each classification is highly dependent on the existence of significant spectral differences between the chosen classes. For this author, the regions of the red, near-infrared, and mid-infrared spectrum are efficient to differentiate vegetation. The near-infrared region has a direct relationship with the increase in biomass and leaf



	Changes in classes		2008 - 2018 %	2008- 2010 %	2010 - 2013 %	2013 - 2015 %	2015 - 2018 %
	OU	IR	3.84	3.57	5.53	1.13	4.77
	OU	MR	0.56	--	--	--	--
	IR	OU	3.80	3.67	2.33	4.96	1.60
	IR	MR	0.58	1.04	2.05	1.88	0.57
	IR	PF/AR	0.05	--	--	--	--
	MR	OU	2.45	0.87	0.85	0.97	1.54
	MR	IR	1.86	1.03	0.48	0.77	1.80
	MR	PF/AR	2.72	2.55	0.78	1.66	1.31
	PF/AR	OU	1.41	0.09	0.44	0.39	0.60
	PF/AR	IR	1.82	0.08	0.47	0.14	1.43
	PF/AR	MR	2.80	--	--	--	--

Figure 7. Map of changes in successional classes in the Amazon Forest. All changes between classes during the ten years (a); changes between classes occurred from 2008 to 2010 (b), 2010 to 2013 (c), 2013 to 2015 (d), 2015 to 2018 (e), and 2008 to 2018 (f).

area, whereas the red region has an inverse relationship. The mid-infrared region informs about the water present in the leaf. Thus, the three regions of the electromagnetic spectrum together were enough to differentiate the three successional stages in the B654 input attribute.

The input attribute B65 also obtained a Kappa index considered excellent according to Landis & Koch (1977) and a high global accuracy index. Thus, it can be adopted to classify the images, especially when high computational demand is required and it is necessary to reduce the size of the processed data – which is not the case in this study since data processing was performed within the GEE platform.

The biggest error was observed in the class IR, with a lower user's accuracy value compared to the other classes because of the inclusion of the MR and OU classes within the IR class. However, the producer's accuracy was higher, suggesting that the class was well represented in the sample. The confusion between the classes IR and OU may have occurred because these classes presented significant dynamics during the period, affecting the capture of images (carried out two months before the validation through field verification). Finally, the confusion between IR and MR occurred since they present similar spectral characteristics.

The vegetation indices highlight part of the scenes that present varying densities of vegetation cover (Meneses et al., 2019). However, low accuracy was observed in all indices, which is explained since the spectral reflectance of the forest canopy in certain parts of the electromagnetic spectrum reaches an asymptotic spectral reflectance. This phenomenon makes the indices less effective, reducing the ability to differentiate the vegetation (Mutanga & Skidmore, 2004). Thus, the indices in tropical forests are saturated, influenced by high precipitation (Nicholson & Farrar, 1994) and vegetation density (Hueter et al., 1997; Almeida et al., 2015).

Dynamics in the vegetation's successional stages

The Brazilian state of Rondônia presents high rates of Amazon Forest deforestation. However, part of the deforested area enters the process of forest succession, either through the abandonment of areas after exploitation or due to restoration projects – around 405 restoration projects were carried out from 1950 to 2017 in 191 municipalities in the Brazilian Amazon (Denis et al., 2021). The successional evolution increased vegetation cover area, but not enough since a loss of this area was observed at the end of the period analyzed (2008 to 2018).

The transformation of PF/AR to other classes of land cover and use occurs mainly in the north of the state of Rondônia (Fig. 6) due to the increase in predatory economic activity in the region, for example, livestock, agriculture, and logging. In this sense, Costa et al. (2017) indicate that farmers and ranchers are increasingly moving from the consolidated regions of southern Rondônia to areas in the north of the state. The threat to the forest in that region is significant; for example, the Machadinho river basin already had a reduced forest area of more than 50% from 1984 to 2011 (Souza et al., 2019). In addition, the construction of two dams in the north of the state (Jirau and Santo Antônio, on the Madeira river and Ribeirão waterfall) increased the demand for land in the region (Ochoa-Quintero et al., 2015).

To the best of our knowledge, there is no previous mapping of the state of Rondônia with the three successional classes in the period presented in this study. However, the mapping can be compared to that carried out by the PRODES project (INPE, 2021), which has been mapping deforestation in the region for more than 30 years. The project recorded approximately 50% of its original forest in 2018, and a similar value of PF/AR was detected in this study in 2018. Although the two mappings use different methodologies, there is a similarity in the amount of area mapped as forest.

Another mapping used was the MapBiomas project (2020), which adopts methodologies similar to this study and presents similar results. In this sense, MapBiomas (2020), using the same platform and the same classifier, mapped 13,682,574.88 ha in 2018, 14,640,334.55 ha in 2008 of forest formation in Rondônia. This value is close to that obtained in this study in the sum of the PF/AR and MR classes (Fig. 5). Such differences are connected to the different classes and filters used later to group the pixels. The different post-classification filters can result in disagreements. Therefore, some differences can occur in the final result.

The successional evolution from MR to PF/AR at all time intervals within the period expresses the vegetation restoration capacity for the most advanced levels of forest succession. It also shows the successional evolution from IR to MR at all intervals within the period. The greatest dynamics occurred between the OU and IR classes, with expressive values of loss and gain in the IR area for the study period. The removal and growth of this vegetation are characteristic in the region. The IR can be fallow areas between agricultural activities, well-developed agricultural plantations, and dirty pastures, all subject to early removal of vegetation.

In contrast to deforestation, the areas that underwent successional evolution are significant. Vegetation restoration after clearcutting is important in carbon sequestration (Chazdon et al., 2016; Mora et al., 2018), soil recovery (Van Hall et al., 2017; Nunes, 2019), and maintenance of biodiversity (Almeida & Vieira, 2010; Brito & Carvalho, 2014). Even natural regeneration, which does not have a treatment for better successional evolution, is already effective in providing ecosystem services (Cortés-Calderón et al., 2021).

However, as expected, it showed a significant loss in total areas of vegetation from 2008 to 2018, the sum of the PF/AR, MR, and IR classes (Fig. 5). Mainly decreasing PF/AR area from 2008 to 2018; currently, less than half of the state is covered by this class of vegetation. The economic crisis Brazil has been going through in recent years has influenced these results leading to a decrease in the resources that control the Amazon region and putting pressure on natural resources to produce commodities destinated for exportation to increase income (Pereira et al., 2019).

Economic management is heavily influenced by politics in the region, a phenomenon that is reflected in the mapping data. The PF/AR area increased only in the period from 2008 to 2010, a period in which the MR was significantly transformed into PF/AR, and low rates of deforestation were recorded. The data from PRODES (INPE, 2021) corroborate this finding, with a drop in deforestation rates and an increase in the area of the forest formation class mapped by MapBiomas (2020). This was the result of the creation of Decree 6321 of December 21, 2007 (Brasil, 2007), which established actions to protect areas at risk of degradation and to rationalize land use to prevent, monitor, and control illegal deforestation activity in the Amazon Biome, increasing the siege to deforestation in the Amazon region.

At the end of the study period, there was a reduction in PF/AR, which showed a gain in area only in 2010. The MR during the whole period oscillated in increase and decrease in area. At the end of the period, it presented a loss in the area and PF/AR, whereas the IR was the largest area in 2018. However, when totaling all classes of vegetation development in 2018, the vegetation area in the state decreased.

The Amazon Forest can show a rapid recovery of the species diversity in up to two decades, depending on the influence of events disturbing expected natural processes (Villa et al., 2018). It is essential to promote environmental policies and actions that use planning in restoration projects that promote socioeconomic development and ecological enrichment. Primary forest conservation policies, mainly because the recovery of intact primary forest species composition takes much longer and may never return to the same species composition (Villa et al., 2018).

This study was limited to mapping the forest succession in the state of Rondônia, considering that the state is one of the most affected by illegal deforestation and limitations on accessing state-only UAV images and data used in mapping validation collected only within the state. However, high-performance cloud processing tools are available nowadays, helping to process data on a planetary scale, such as the GEE platform that should be increasingly used for the benefit of the Amazon rainforest, as a tool in future research, policies, and actions in the Brazilian Legal Amazon.

Conclusions

GEE provided excellent tools for mapping Rondônia in different regions of the state, offering high-performance cloud processing. The platform made it possible to map 100% of the state by removing clouds and cloud shadows from the study area. It also enabled the testing of eight classifications with different input attributes in a more agile way only modifying the parameter in the algorithm. Finally, it allowed the inclusion of high-resolution images obtained by UAV within the platform to refine the samples of each class inserted in the Random Forest classifier.

Among all the input attributes tested, the one that obtained the best accuracy was the combinations of the mid-infrared, near-infrared, and red bands. Differently, the vegetation indices tested showed lower values in all accuracy indices. In all classifications, the most significant error occurred in the IR class, which may be explained by spectral confusion with the class MR and the greater dynamics between IR and OU. Also, the field validation was carried out two months after the dates of the orbital images of the Landsat series.

The analysis of the change in development classes showed that even with the successional advance from MR to PF/AR in all periods, the high rates of forest removal continued to result in the loss in the total area of the most advanced development class (PF/AR) at the end of the study period. Likewise, among all the classes, the greatest dynamics were the OU and IR with the loss and gain of younger vegetation, which can be fallow areas between agricultural activities, well-developed agricultural plantations, and dirty pastures.

This study contributed to understanding the dynamics of the Amazon Forest, which goes through a process of deforestation and forest regeneration simultaneously. The study proves that even with the successional advance existing in the Brazilian state of Rondônia, it is not enough to face the removal of vegetation through illegal deforestation. However, the study was limited to the analysis of the state, and future studies may expand the analysis of the dynamics between the successional stages of the forest for the entire Legal Amazon.

The work of non-governmental organizations, private companies, research institutes, and the government is crucial in the Legal Amazon, jointly conducting environmental projects to raise awareness, slow down deforestation, and restore the forest in activities involving landowners and communities in the region and disseminating the social benefits of forest conservation.

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