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The Amazon Deforestation Calendar: Unveiling the role of marked seasonal patterns.

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Highlights

- Using a spatial-temporal approach, identified deforestation patterns in the Amazon.
- Regions 1 and 2 stand out as critical areas despite covering only 4% of the biome.
- A marked seasonal pattern was observed, influencing the mode and dynamics of deforestation.

Abstract

The Amazon biome has experienced significant changes in its landscape, similar to other tropical forests, primarily due to changes in land use in the area. Despite previously established strategies to contain the advance of deforestation, we have observed an increase in deforestation rates recently. Our objective was to analyze deforestation in the biome using clustering and spatial analysis methods to understand deforestation patterns and spatio-temporal dynamics. Regions 1 and 2 stood out as priority areas for monitoring and combating deforestation. Human settlements, agricultural land, and undesignated public forests characterize these areas. Deforestation in these areas presents a significant level of seasonality in its mode and dynamics. The results emphasize that annual deforestation changes require strategies addressing territorial differences. Therefore, prevention and intervention measures must be adapted to seasonal variations and the specific characteristics of each region to combat deforestation in the Amazon biome effectively.

Keywords: clusters; deforestation patterns; land categories; seasonality.

Introduction

The increasing scarcity of land suitable for agricultural expansion emerges as a global challenge[1–3]. This phenomenon intensifies in tropical regions, where the expansion of the agricultural frontier has found its primary focus[4–6]. The outcome of this expansion manifested as a notable increase of approximately 36% in cultivated areas in tropical regions from 1961 to 2021[7]. Although this expansion has contributed to some countries consolidating themselves as the leading exporters of commodities in the world, this growth model has opposed the conservation and maintenance of natural resources, given the impact that changes in land use and land cover have on natural forests, especially the Amazon rainforest[8–10].

Tropical forests have experienced significant alterations in recent decades[8,10–12]. The tropical forests of South America, especially the Amazon, are not impervious to this situation; they are gradually changing due to diverse human factors that have substantially altered the environment[13]. The impact of these recent transformations goes beyond changing the landscape. Biogeochemical cycles, biodiversity, and hydrological and climate regulatory systems face significant challenges due to these changes, even influencing global levels [14–19], as well as land conflicts and threats to indigenous populations[10,20–23]. These transformations contribute to the impoverishment of ecosystems, thus affecting socio-environmental relations at different scales.

The current deforestation scenario in the Brazilian Amazon illustrates this problem. Around 20% of forest cover has already undergone modification, according to the Project for Monitoring Deforestation in the Legal Amazon by Satellite (PRODES)[24], whose data is available on the TerraBrasilis platform[25]. In the wake of a decrease between 2012 and 2014, subsequent years revealed a significant surge in the deforestation rate, reaching more than 13,000 km^2/year in 2021[24].

The complex spatio-temporal heterogeneity of the deforestation process in the Amazon requires preventive approaches based on understanding its dynamics and the factors that drive changes in land cover and use[26–29]. This understanding is especially crucial in defining solid indicators to support policies that identify areas susceptible to deforestation.

According to Souza and De Marco (2014), effectively addressing deforestation includes using satellite data for deforestation measurement, identifying key factors and responsible parties, and creating models to guide prevention efforts. In summary, the effectiveness of these models hinges on their foundation in a comprehensive understanding of the intricate interplay of socioeconomic, political, and environmental factors that drive deforestation [14].

In this context, spatial-temporal analysis dynamics presents a powerful tool for the agile and precise identification of priority areas that demand interventions, as highlighted by Harris et al. (2017). The authors also highlight that, in the context of forest conservation, this approach makes it possible to reveal trends in forest loss without relying exclusively on prior information about the underlying factors that drive or shape these trends.

The central objective of this study is to craft a methodological approach for discerning and evaluating deforestation patterns and trends within the Amazon. The method combines deforestation alerts from the Real-Time Deforestation Detection System (DETER) with information on land categories (environmental protection area (APA), settlements (ASS), rural properties (CAR), undesignated public forests (FPND), indigenous lands and conservation units (UC)). The integration of this data will enable the identification of areas at risk of deforestation, strengthening inspection and control activities aimed at combating deforestation in the Amazon.

Results

From the clustering analysis considering the entire period (2017 to 2020), four internally homogeneous but externally heterogeneous regions were identified (wss=141.374, k=n, and R^2=0.57). Fig. 1 presents the spatially explicit distribution of clusters/regions obtained considering a) deforested area (km^2), b) alert counts, and c) the number of quarters in which deforestation alerts were recorded. It is observed that deforestation in the biome exhibits a strong spatial concentration pattern. According to Aguiar et al. (2007) and Alves (2001), this occurs because deforestation tends to happen closer to previously opened areas.

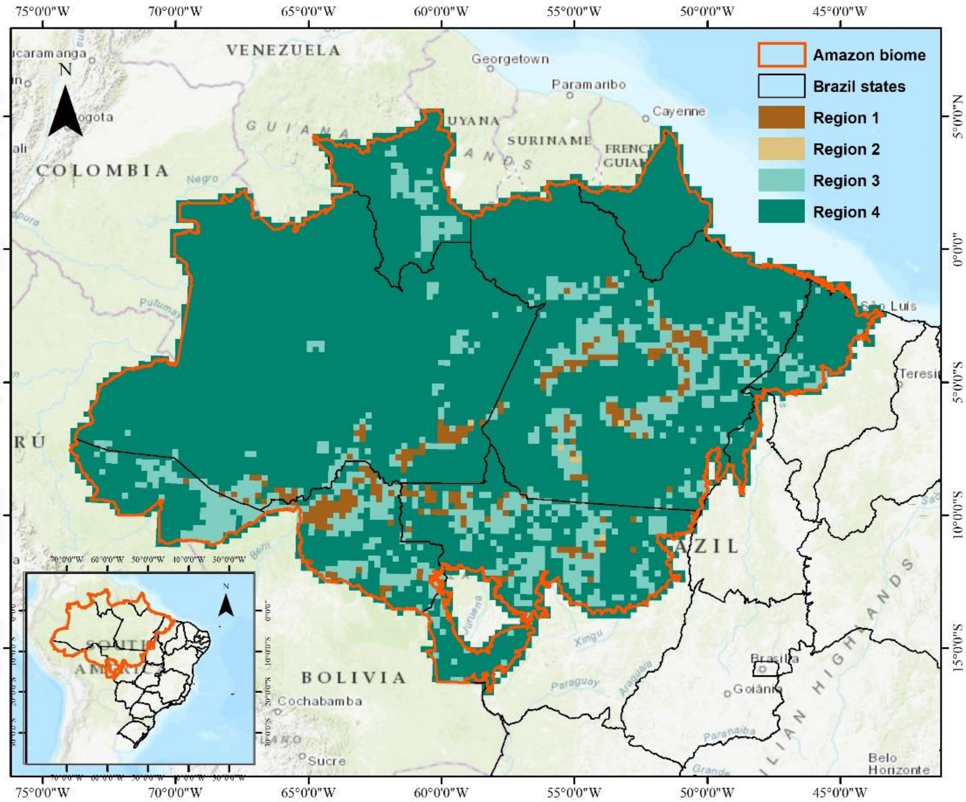

Fig. 1. Spatial distribution of regions according to the cluster analysis (k-means) considering deforestation alerts between the period of 2017 to 2020, aggregated by quarters.

In the context of the spatial distribution of regions, it can be observed that Region 4 covers the majority of the biome, approximately 82.47%, followed by Region 3 (14.07%), Region 1 (3.36%), and Region 2 (0.10%). Despite covering a smaller percentage of areas, Regions 1 and 2 have higher values in terms of area, the number of alerts, and the number of quarters with alert occurrences (Fig. 2). In Regions 1 and 2, the average deforested area is around 3 and 5 km², respectively. However, it was observed that in some areas, the deforested area reached 44 km² in Region 1 and 67 km² in Region 2.

In addition to having more extensive areas of deforestation alerts, Regions 1 and 2 also presented a higher frequency of deforestation alerts during the analyzed period, with an average of 4 and 3 alerts per cell. The cells are the units of analysis and have a 25 x 25 km resolution. Furthermore, there was a higher prevalence of deforestation occurrence regardless of the region. However, the highest prevalence was observed in Region 1, where, on average, 84% of the analyzed period showed recurring alerts. Region 1 encompasses the states of Pará (56,676.20 km²), Rondônia (37,000.47 km²), Mato Grosso (28,884.85 km²), Amazonas (28,250.34 km²), and Acre (877.60 km²).

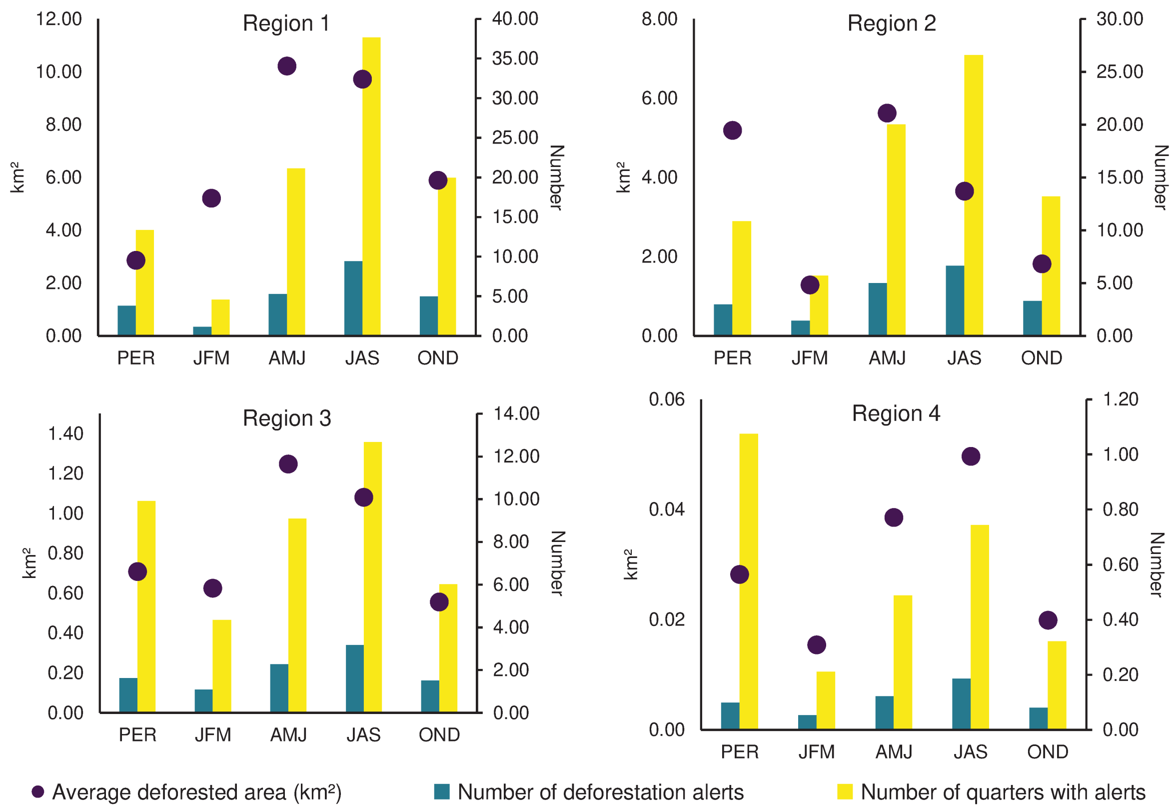

Fig. 2. Descriptive analysis of the data used in the determination of regions. PER - Period between 2017 to 2020; JFM - January, February, and March; AMJ - April, May, and June; JAS - July, August, and September; and OND - October, November, and December.

Fig. 3 presents the characterization of the regions described earlier based on land categories. Region 1 is characterized by the predominance of rural properties (CAR), settlements (ASS), and undesignated public forests (FPND), and to a lesser extent, conservation units (UC), indigenous lands (TI), and environmental protection areas (APA). In this region, the agrarian structure (ASS and CAR) is a crucial factor to consider in deforestation dynamics. This result corroborates with previous studies [31–34] that identified a clear and strong relationship between deforestation hotspots and land appropriation. Region 2 is characterized by a higher presence of CAR, FPND, and UC, with less representation (or absence) of other land categories. In this context, the pressure on FPND and UC appears to be more intense in this region compared to others. Region 3, closer to consolidated agricultural frontier areas, is primarily characterized by the presence of ASS and CAR, with a smaller proportion of FPND. Region 4 has the lowest deforestation values but mainly encompasses TI and UC. Similar to the other regions, CAR and FPND areas, albeit in smaller proportions, are also present in this region. In all regions, some areas with a high percentage of APA were observed.

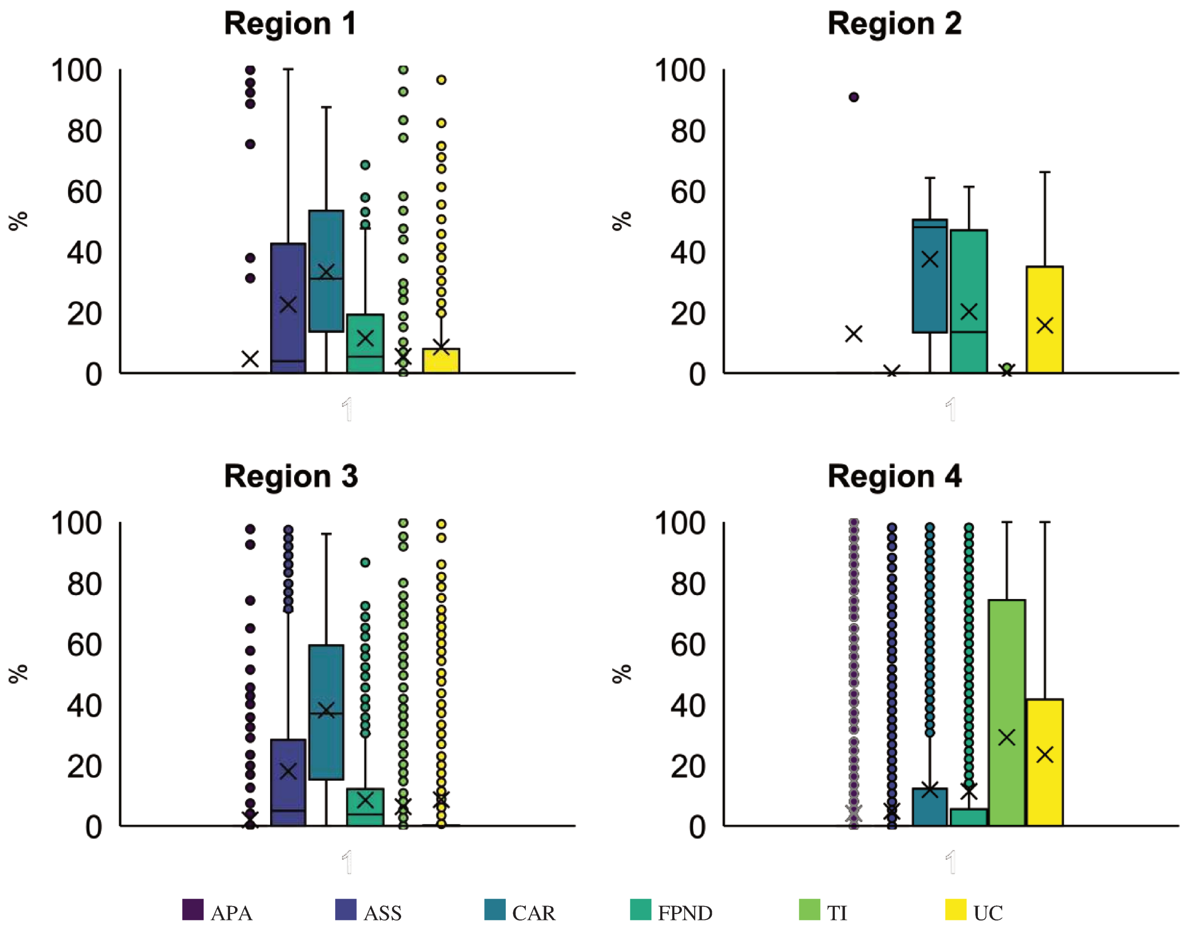

Fig. 3. Boxplots of the selected determining factors for the spatiotemporal analysis of deforestation patterns and dynamics. These factors include Environmental Protection Area (APA) (%), Settlement Area (ASS) (%), Rural Property Area (CAR) (%), Undesignated Public Forest Area (FPND) (%), Indigenous Land Area (TI) (%), and Conservation Unit Area (UC) (%)

When analyzing the data grouped by quarters, a strong influence of seasonality on the distribution of regions was observed (Fig. 4). In the first quarter, the most critical regions were dispersed but concentrated in the states of Pará and Mato Grosso. In the second quarter, these areas are mainly found in the states of Pará, Amazonas, Rondônia, and Mato Grosso. In the third quarter, there is an intensification of critical areas in the regions of Pará, Amazonas, Rondônia, and Mato Grosso, with a notable focus on the western region of Rondônia. In the last quarter, there was a higher concentration in the state of Pará.

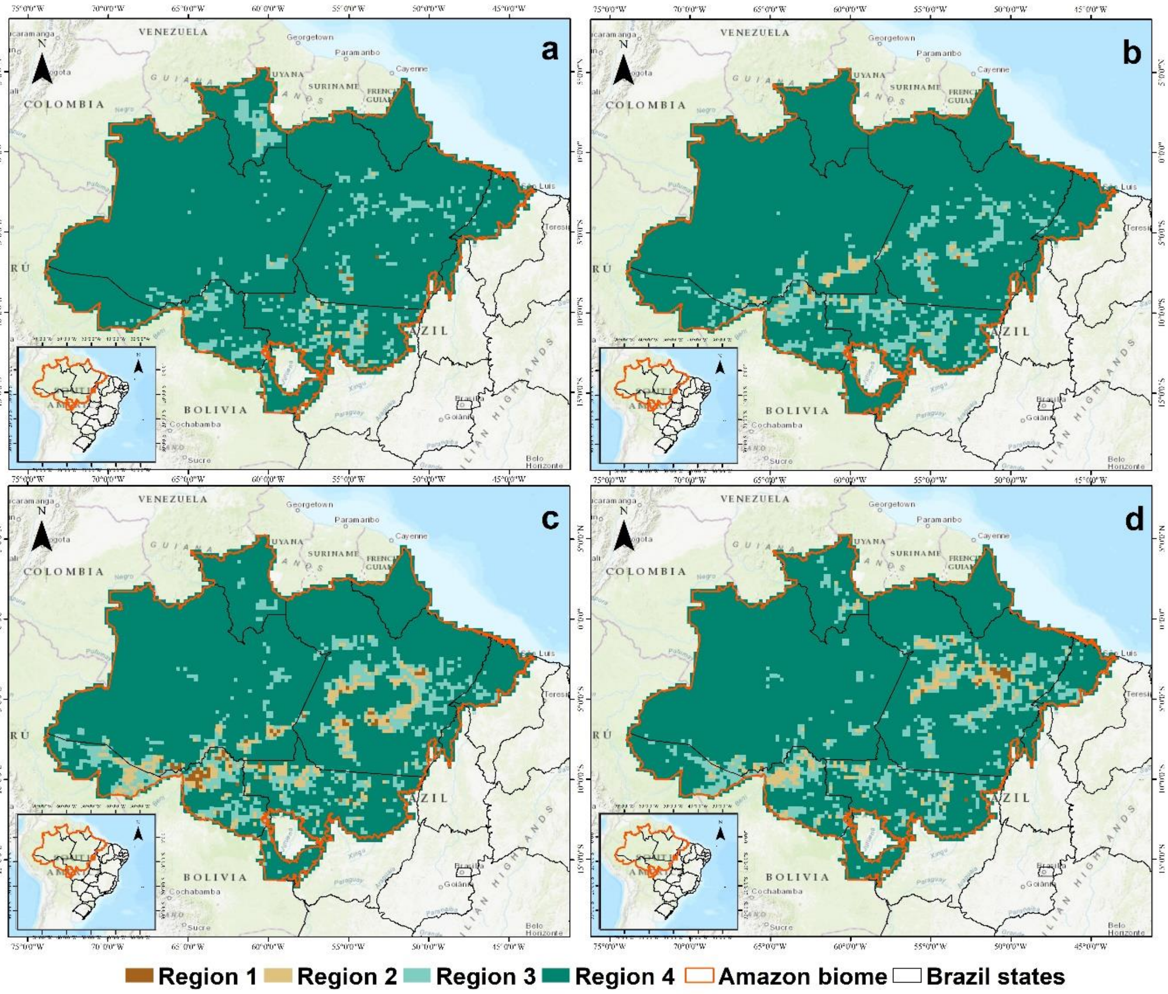

Fig. 4. Spatial distribution of regions according to the cluster analysis (k-means) considering deforestation alerts between the period from 2017 to 2020, based on the analyzed quarter: a) JFM - January, February, and March; b) AMJ - April, May, and June; c) JAS - July, August, and September; and d) OND - October, November, and December.

Partially, this seasonal behavior is related to the dry season in the Amazon, which shows spatiotemporal variability [35]. When comparing the most critical regions (1 and 2) with the work conducted by Carvalho et al. [35], it was observed that in the quarters with the highest deforestation alert rates (AMJ and JAS), the regions coincide either entirely or partially with the beginning and end of the dry season.

After the clustering analysis and the identification of regions that are similar in terms of deforestation patterns and dynamics, a comparison was made between the most critical regions (1 and 2) and the deforestation alert data observed in 2021. Fig. 5 presents the spatial overlap of deforestation alerts in 2021, categorized by area in square kilometers versus Regions 1 and 2. The data were analyzed according to the period and seasonality. Based on this verification, it is observed that the highest deforestation alerts observed in 2021 occurred in Regions 1 and 2 or the surrounding areas.

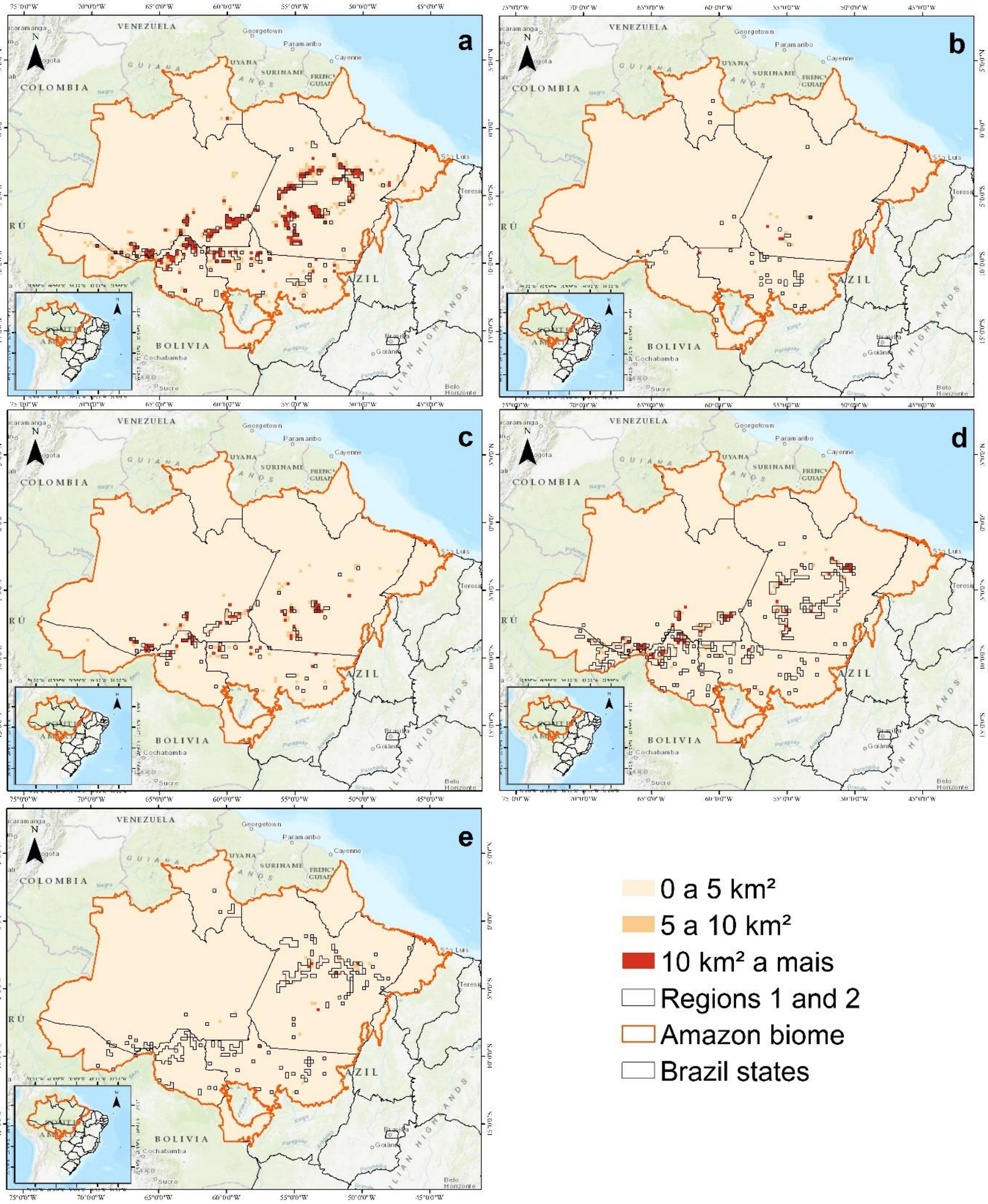

Fig. 5. Spatial distribution of the overlap between deforestation alert data in 2021 and Regions 1 and 2 identified by the clustering analysis: a) Period - considering the entire period between 2017 and 2020; b) JFM - January, February, and March; c) AMJ - April, May, and June; d) JAS - July, August, and September; and e) OND - October, November, and December.

According to Table 1, the regions identified as critical (1 and 2) encompassed, on average, 55% of alerts with an area greater than 10 km² and 36% between 5 and 10 km². The highest similarity values between Regions 1 and 2 and the 2021 alerts occurred in the 3rd quarter - JAS, approximately 84.62%, considering alerts larger than 10 km², and 75.63% for alerts with an area less than 10 km² and greater than or equal to 5 km². The 1st quarter presented the lowest similarity values; however, this behavior should correlate with the fact that, during this period, the number and extent of alerts were smaller and more random.

Table 1. Number of deforestation alerts in 2021 and the percentage of occurrence (similarity) in Regions 1 and 2.

	Number of alerts 2021		Region					
			1		2		1+2	
	Intervals							
	$5 \leq x \leq 10$ km²	$x > 10$ km²	$5 \leq x \leq 10$ km²	$x > 10$ km²	$5 \leq x \leq 10$ km²	$x > 10$ km²	$5 \leq x \leq 10$ km²	$x > 10$ km²
	Nº		%					
Period	263	208	22.81	61.54	0.38	1.92	23.19	63.46
JFM	14	6	0.00	16.67	7.14	0.00	7.14	16.67
AMJ	93	59	2.15	6.78	23.66	37.29	25.81	44.07
JAS	119	52	12.61	50.00	63.03	34.62	75.63	84.62
OND	28	6	21.43	33.33	28.57	33.33	50.00	66.67

The cross-analysis observed that deforestation patterns tend to occur in regions where the process occurs historically, reinforcing the theory of spatial concentration of solids [36,37]. However, it stands out that these patterns may change with changes in agricultural frontiers and the advancement of specific activities (such as soybean production and mining). Another factor that can influence the pattern is the dynamics/behavior of the process itself. Like the location of alert occurrences, the quantity also showed new patterns.

Fig. 6 shows the distribution of the local spatial association index of deforestation alert areas in the analyzed period (2017 to 2021). The spatial autocorrelation observed over the years ($I = 0.40$, on average) indicates that deforestation occurs regionally and is related to neighbors' behavior. From 2017 to 2021, there is a prevalence of areas where the analysis unit (cell) exhibits high values and its neighboring cells. These areas mainly encompass Regions 1 to 3 and are near consolidated deforestation areas. However, these areas are increasing in the state of Roraima. When analyzing the surrounding areas, it is possible to see that they have low deforestation values but are adjacent to areas with high values, which may become deforestation expansion areas in the medium and long term due to neighborhood pressure. Additionally, there is a change in the spatial pattern of primary forest with an increase in scattered deforestation that does not exhibit spatial autocorrelation.

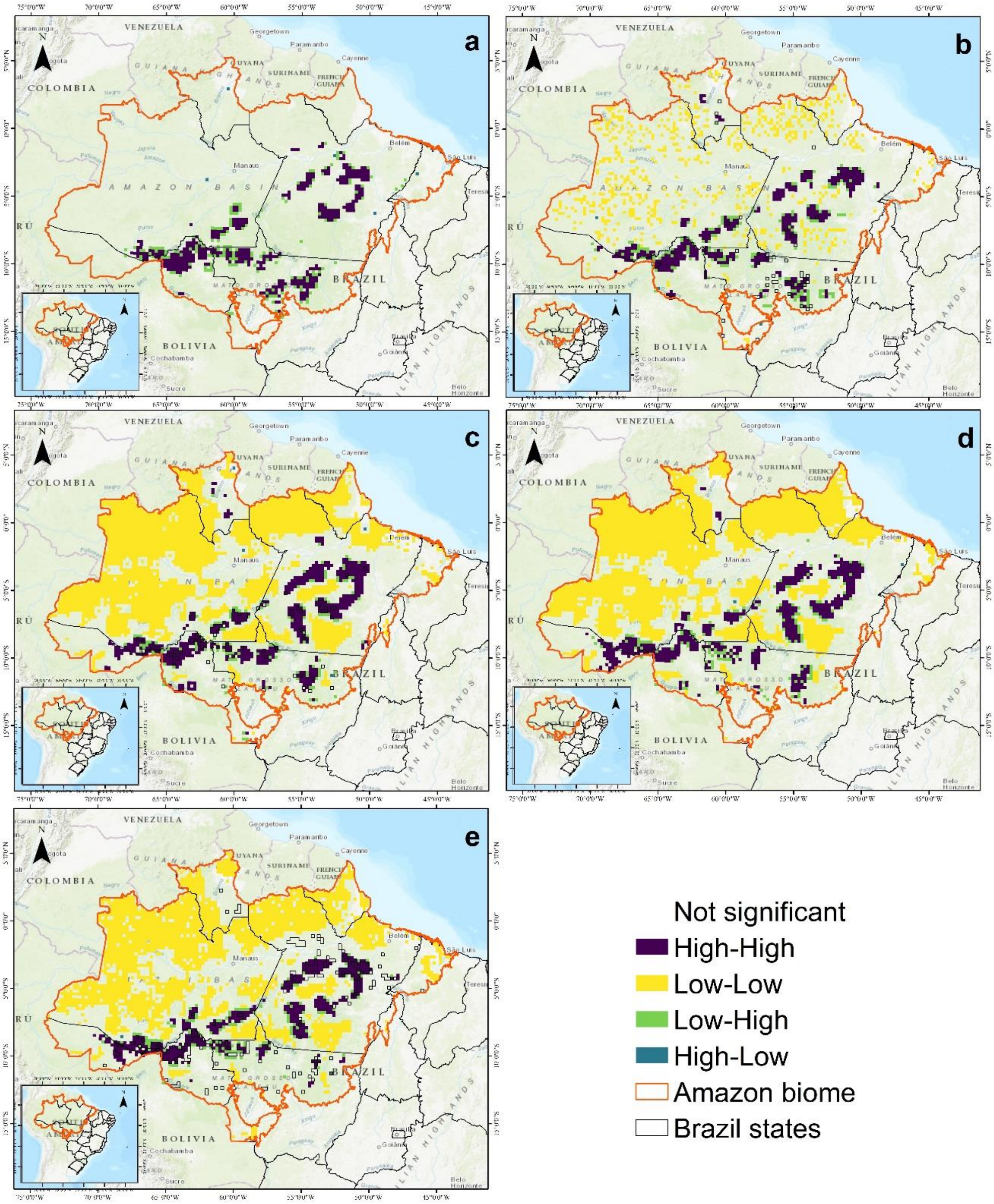

Fig. 6. Distribution of the local spatial association index for deforestation alert areas in the analyzed years: a) 2017, b) 2018, c) 2019, d) 2020, and e) 2021.

Discussion

The spatially explicit and temporal approach proposed in this study contributes to global efforts to combat deforestation and address climate change. Differing from other studies [38–42] that also sought to understand deforestation in the Amazon, this study uniquely integrated deforestation data and land information to identify areas potentially at greater risk of deforestation events based on both space and time.

The results emphasize the need to formulate deforestation control strategies that consider heterogeneity between territories and at different times of the year. Interannual seasonal variability emerges as a critical consideration since the patterns and trends reveal that regions with higher occurrence and recurrence of deforestation events change according to the analyzed period. In this context, emerging systems that monitor and assess deforestation risks can benefit significantly from this proposed approach. By enabling the identification of priority areas for deforestation control and insights into its dynamics, this approach can strengthen such monitoring and intervention structures.

Furthermore, the dynamic and complex interaction between socioeconomic factors [43], ecological dynamics [44], and climatic influences [45] requires a holistic approach to combat deforestation effectively. The variations identified in critical deforestation hotspots throughout the year emphasize the importance of adaptive strategies that can accommodate spatial and temporal changes in deforestation patterns.

In light of these findings, policymakers, conservation organizations, and local communities can adjust their efforts more effectively, recognizing the multifaceted nature of deforestation dynamics. Integrating this approach into existing conservation initiatives can enhance their accuracy and impact, ultimately contributing to protecting the Amazon biome and its vital role in global climate regulation and biodiversity preservation. However, Barlow et al. (2016) emphasize that policy interventions should go beyond mere forest cover maintenance, as maintaining forest cover alone does not necessarily reduce anthropogenic forest disturbances.

As we move forward, integrating real-time monitoring systems, predictive modeling, and collaborative stakeholder engagement can further expand the practical application of these findings. As our understanding of deforestation dynamics evolves, incorporating these insights into policy frameworks and sustainable land use practices can collectively shape a more resilient and sustainable future for the Amazon and the planet.

Materials and Methods

Study area

The Amazon, a biome of continental proportions with a tropical climate, covers an area of approximately 4 million km² [47,48], which corresponds to 49.5% of Brazil's total territory. This region encompasses nine states in whole or in part, with the states of Amazonas and Pará standing out for occupying the most extensive areas, at 37% and 29% of the biome, respectively. The territorial structure of the Amazon is marked by the presence of dense forests, predominantly the ombrophilous dense (48%) and open (24%) forests, as well as an extensive network of rivers and floodplain areas [48]. Regarding land ownership, the region showcases a broad spectrum of properties, ranging from small family holdings to large-scale commercial farms where soybean, corn, and cattle farming.

Agricultural activities in the Amazon face significant challenges, notably associated with deforestation and transforming forested areas into lands for agriculture and livestock. Historically, since the 1960s and 70s, there has been a considerable loss of forest cover in the Amazon, initially concentrated in the area known as the "Deforestation Arc" and later spreading along new roads and colonization projects, especially during the military period [34,49–53]. More recently, this deforestation trend has shifted to the central region of the biome.

Data source: Deforestation and Land Categories

In addition to the alert data from the DETER system, from the National Institute for Space Research (INPE) through the TerraBrasilis platform [25], land category information was compiled, enabling an understanding of deforestation patterns and dynamics. Table 2 presents the data utilized in the spatiotemporal analysis of deforestation patterns in the Amazon biome.

Table 2. Selected factors for the spatiotemporal analysis.

	Factors	Description	Source
Deforestation	Deforestation alerts (DETER)	Notifications of evidence of forest cover change in the Amazon to support surveillance and control of deforestation and forest degradation.	INPE [24]
Categorias Fundiárias	Indigenous lands (TI)	Lands traditionally inhabited by indigenous communities, including those used for permanent residence, productive activities, the preservation of essential environmental resources for their well-being, and their physical and cultural reproduction per their customs and traditions.	BRASIL[54]
	Conservation units (Federal and State) (UC)	Protected natural areas established by law have unique characteristics related to the local fauna and flora.	
	Settlements (Federal and State) (ASS)	Set of agricultural units created by Incra on a rural property. For each family of farmers or rural workers without the economic conditions to acquire a rural property, Incra allocates an agricultural unit.	
	Environmental Protection Area (APA)	Natural area intended to protect and conserve biotic attributes (fauna and flora). Allows a certain degree of human occupation. It aims to protect biodiversity by reconciling the occupation process and the sustainable use of natural resources.	
	Rural Environmental Registry (CAR)	The Rural Environmental Registry is a mandatory national electronic public record for all rural properties. It aims to integrate environmental information from rural properties, creating a database for environmental and economic planning, monitoring, and combating deforestation.	SICAR [55]
	Public Forests Not Designated (FPND)	Public forests, mainly owned by states or the federal government, have yet to be designated for use by society.	BRAZIL [56]

Integrating deforestation alert data with land category information enables a comprehensive method for comprehending deforestation processes. While DETER alerts provide information about the location and magnitude of changes in forest cover, land categories offer insights into the involved agents and underlying reasons for deforestation.

Integration of data

Analysis unit

The data was organized into a cell-based information plan (cellular space) at a resolution of 25 x 25 km using the FillCell plugin [57,58], following the steps described in Fig. 7. The definition of this resolution was determined by on previous studies [36,47,59], as well as the web tool "Situation Room" [60], which aims to support territorial intelligence actions through the synoptic visualization of deforestation critical area indicators, integrating alerts from the Near Real-Time Deforestation Detection system. The use of cellular space allowed for data standardization regardless of its original format (vector data, raster data, among others), aggregating them into the same spatiotemporal database using operators (e.g., Percentage of each class, Minimum distance) applied according to the geometric representation and semantics of the input data attributes.

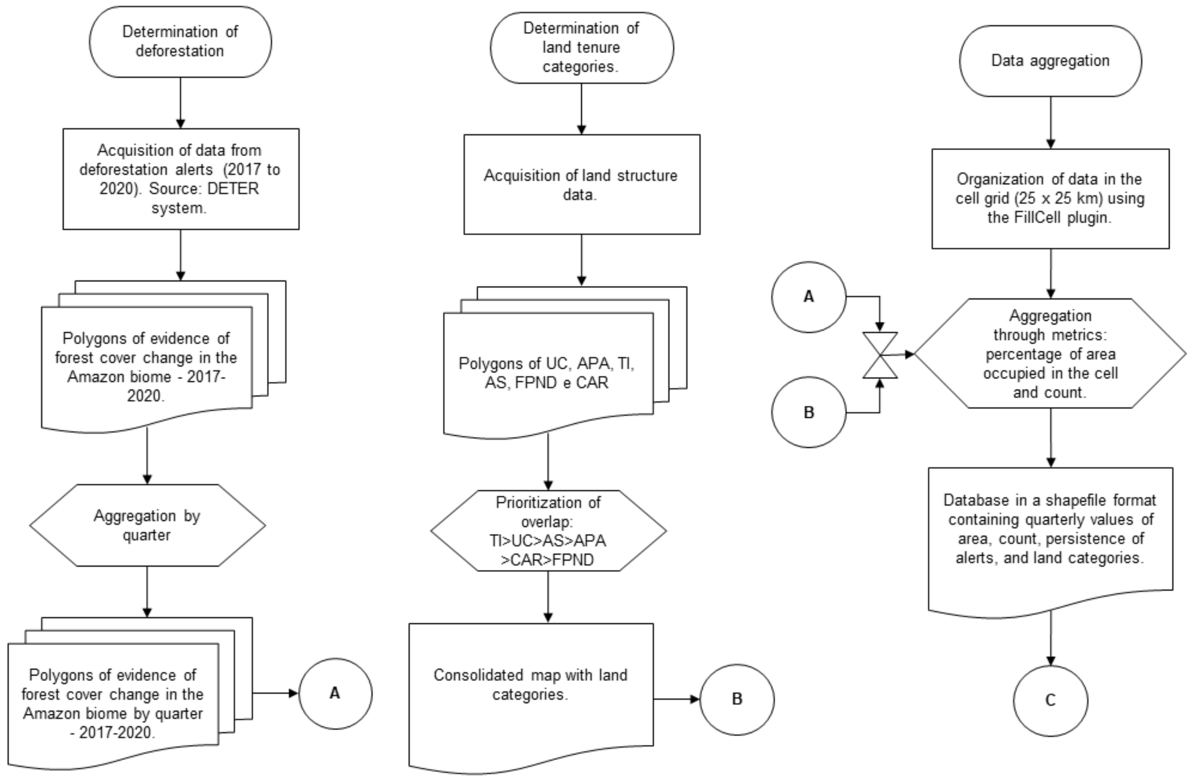

Fig. 7. Flowchart of the data preparation and database setup for the spatiotemporal analysis of deforestation patterns. A detailed description of the aggregation metrics used is available at http://www.terrame.org/packages/doc/terralib/doc/files/Layer.html

Spatiotemporal analysis of deforestation patterns in the Amazon biome

Cluster analysis: determination of regions

Cluster analysis (Fig. 8a) aimed to identify and segment deforestation alert observations from 2017 to 2020. Segmentation divided them into internally homogeneous groups but heterogeneous among themselves. The groupings were determined using the k-means method (non-hierarchical clustering), as this method performs well and is easy to understand when working with a large set of observations [61–66]. The number of clusters was determined using the Elbow method [67]. This method suggests that the number of groupings with the most significant bend should be chosen as the optimal number of clusters, thus minimizing the total variation inside the groups (or the total sum of squares). Additionally, we compared the optimal number of clusters determined by the Elbow method with the values of the one-way analysis of variance (ANOVA) coefficient of determination (R^2), calculated from the ratio of the sum of squares between groups to the sum of all the squares for each of the variables used in the analysis [62].

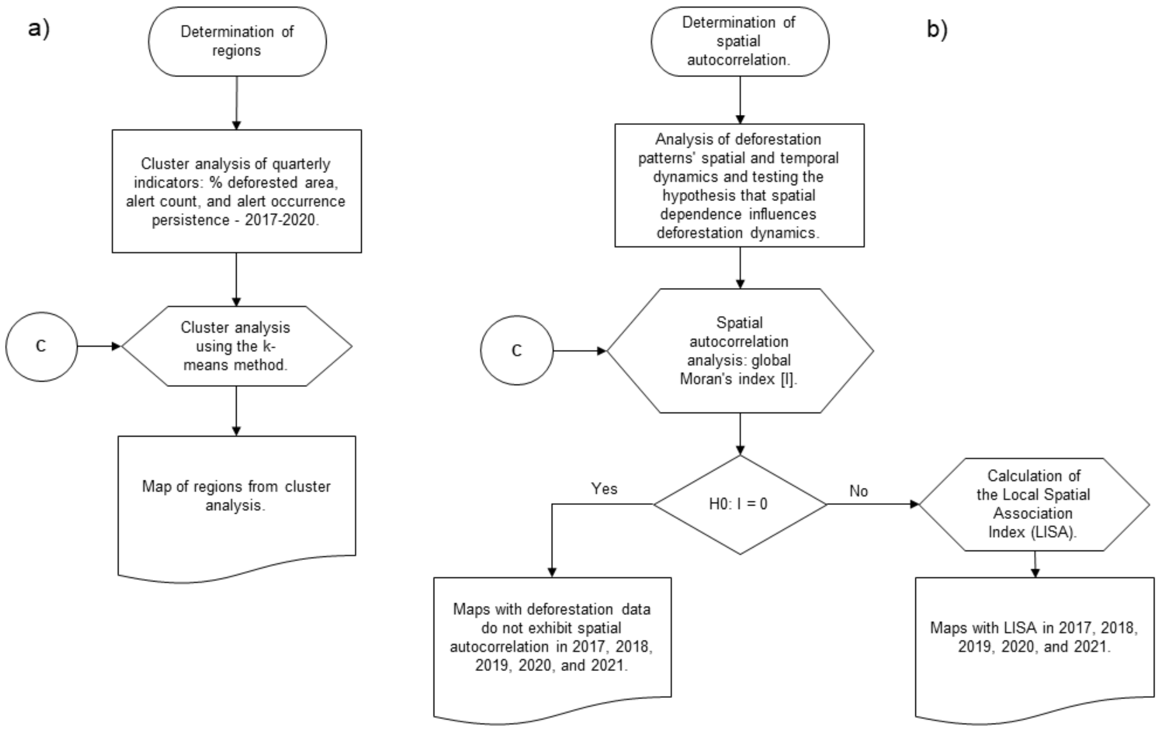

Fig. 8. Flowchart of the cluster analysis stage (**a**). Flowchart of the spatial dependence analysis stage (spatial autocorrelation) of the dynamics of deforestation patterns (**b**).

Analysis of the spatiotemporal relationship of deforestation patterns.

Fig. 8b illustrates the development of this stage, which aims to analyze the spatial and temporal dynamics of deforestation patterns, test the hypothesis that spatial dependence influences deforestation dynamics, and determine whether deforestation distribution occurs randomly or follows some systematic spatial pattern.

Based on the analysis, spatial autocorrelation statistics, including the Global Spatial Association Index (I) by Moran, which provides an overall measure of spatial association, and the Local Spatial Association Index (LISA) [68]. The latter identifies similar clusters and outliers and allows for creating a map of local spatial dependence.

To calculate the Moran Index (I), equation (1) [69] was used:

$$I^{(k)}=\frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}^{(k)}(z_i-\bar{z})(z_j-\bar{z})}{\sum_{i=1}^{n}(z_i-\bar{z})^2} \tag{1}$$

Where **n** is the number of evaluated cells; **zi** represents the attribute value of area *i*; **zj** is the attribute value of area *j*; **z** is the mean value of the attribute across all cells; $\mathbf{w_{ij}^{k}}$ represents the elements of the normalized spatial proximity matrix of order *k*.

The Moran's index takes values between -1 and 1. Values close to the extremes, whether negative or positive, represent the existence of spatial autocorrelation. Values close to zero indicate the absence of spatial autocorrelation. In this analysis, the tested hypotheses were as follows:

H0: I = 0 (There is no spatial dependence));

H1: I > 0 (There is spatial dependence).

The calculation of the Local Spatial Association Index (LISA) used equation (2) [69]:

$$I_i=\frac{z_i\sum_{j=1}^{n}w_{ij}z_j}{\sum_{j=1}^{n}z_j^2} \tag{2}$$

Where **n** is the number of cells studied; **zi** represents the normalized attribute value in cell *i*; **zj** is the attribute value of cell *j*; $\mathbf{w_{ij}}$ represents the normalized spatial proximity matrix elements.

Validation of the developed approach.

The effectiveness of the proposed approach was verified by crossing the most critical regions and the deforestation alert data observed in 2021. The 2021 deforestation data served as test data.

Conclusion

The present study focused on proposing a methodological approach that would enable the determination and spatialization of deforestation patterns, aiming to contribute to discussions on priority areas in deforestation combat and their dynamics through the spatial analysis of deforested areas over the analyzed period.

The approach holds relevance in the context of efforts to understand and define strategies to combat deforestation, which has risen in recent years. The results demonstrated that the pattern and dynamics of deforestation in the biome are not homogeneous and have undergone changes during the analyzed period. However, it was possible to identify priority areas (Regions 1 and 2) in deforestation control and monitoring. Furthermore, the approach allowed for assessing the effect of seasonality on deforestation dynamics and, consequently, on the definition of critical areas.

The methodological approach proved useful, timely, and efficient in establishing deforestation risk areas. Although this approach has proven useful, it is essential to establish relationships that allow the projection of future deforestation areas.

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