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RESEARCH

The role of land use and rural property characteristics to forest integrity in a fragmented landscape in the eastern amazon

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Abstract The integrity of native vegetation remnants in fragmented landscapes depends on various factors. The land use and surrounding landscape characteristics are expected to have a substantial impact. However, a comprehensive understanding of the role of productive activities and rural property characteristics to integrity of forest remnants in the Amazon region remains limited. This study assessed whether land-use types and three other specific rural properties influence forest integrity in the Guamá microregion, northeastern Pará. Data on permanent crops and forests were integrated into annual land use and land cover mapping from the MapBiomas Brazil Project. Three variables were used as proxies for forest integrity: the Normalized Difference Infrared Index (NDII), vegetation height, and aboveground biomass, derived from Global Ecosystem Dynamics Investigation (GEDI) data. We analyzed seven predictors: property size (log_TPR), proportion of agriculture (AGRI_PR), native vegetation area (FOR), proportion of native vegetation (FOR_PR), forest percentage in the landscape (%FP), fire frequency (FIRE), and fragment age (IVEG). Four predictors (FOR_PR, FIRE, IVEG, and log_TPR) explained 10% of the variation in aboveground biomass ($r^2 = 0.10$; $p < 0.05$). All predictors accounted for 28% of the variation in the vegetation height ($r^2 = 0.28$; $p < 0.05$). For the NDII, all predictors were significant, explaining 13% of the variation ($r^2 = 0.13$; $p < 0.05$). These results highlight the importance of understanding land use and rural property characteristics to conserve Amazonian forest remnants and support sustainable management and policy development in the Eastern Amazon.

Keywords Forest degradation · Forest integrity · Permanent agriculture · Rural environmental registry

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Introduction

Human interventions have significant environmental impacts, especially when activities related to land-use change lack adequate supervision and oversight (Leite et al., 2019). In the Amazon region, primary forests are being degraded and replaced by other land uses, especially agricultural activities. In the last five years, approximately 20% of the Amazon rainforest has been removed, directly affecting the biodiversity and ecosystem functioning (Santos, 2019). Among all the states with this type of forest, Pará has emerged as an important hub for the expansion of agricultural, mining, energy, and forestry activities, which has contributed to its prominence in the context of deforestation in the Legal Amazon (INPE, 2017).

In this context, the northeastern region of Pará has emerged as a prominent area because it has the oldest colonization frontier in the state (Cordeiro et al., 2018). The dynamics of the occupation and transformation in this region have been widely documented. The high population density has led to the replacement of primary forests with areas dedicated to agriculture and livestock, as well as uncontrolled logging. These activities have also resulted in the regeneration of secondary forests in abandoned and unmanaged areas (Santos, 2019). According to data from MapBiomas (2024), since 1985, the net loss of forests in Brazil has been 67 million hectares (15.2%), and most of the suppressed natural vegetation have been converted to pasture. In 2020, a total of 21,257 km^2 of forest was cleared in the Amazon, and Pará alone was responsible for 36% of this deforestation, ranking as the leading deforesting state in the region (IMAZON, 2022).

Given the current land use scenario, it is important to understand land-use dynamics through the characteristics of productive landscapes, as well as the socio-economic factors that influence change. This understanding can help identify management practices that reduce the degradation of the native forest remnants (Di Toro, 2019). However, there are still uncertainties regarding the negative impacts of land-use practices, such as intensive agriculture, on forest biodiversity and landscape dynamics (Branco et al., 2021; Ferreira et al., 2019a; Safar et al., 2020). Within this context, the complex interaction between production practices and the preservation of forest areas poses a challenge in achieving a sustainable balance between economic development and environmental conservation (Garcia et al., 2021).

To understand the dynamics of land use in the Amazon, it is necessary to use accessible technological tools, such as remote sensing, to identify and map the agents involved in this process. This technique, based on obtaining information about the Earth's surface through images captured by satellites or drones, is an essential resource for municipal, state, and federal administration. This makes it possible to monitor vast areas, map land use and occupation, and analyze environmental impacts (Garcia et al., 2021). In the last 30 years, there has been a significant increase in the use of and investment in remote sensing technologies, which has been considered by several studies to be an effective tool for monitoring human pressures on the environment (Horning et al., 2010; Ritter et al., 2017). Thus, remote sensing plays a strategic role in environmental management, offering accurate and up-to-date data on natural resources and environmental changes.

This study investigates how productive activities on rural properties influence the conservation of forest remnants in the Eastern Amazon to identify more sustainable land use strategies. We hypothesized that the degree of integrity of native vegetation does not vary significantly between properties, regardless of their characteristics or productive activities. In this context, we used advanced remote sensing techniques to assess the relationship between land-use practices and the structural integrity of native vegetation across different properties. The results contribute to a deeper understanding of how land use affects surrounding forest areas, offering support for the development of public policies that reconcile economic productivity with environmental conservation.

Material and methods

Study area

We conducted this study in the Guamá microregion, located in northeastern Pará, Brazil, which encompasses approximately 28,235.6 km^2 (Fig. 1). It stands out for its high diversity of agricultural practices, with a high density of family farmers and traders, favoring intense economic activity in the region, such as the cultivation of permanent crops, including citrus, palm oil and black pepper. The climate of the Guamá microregion is classified as AM according to the Köppen system, with average annual precipitation ranging from 1250 to 2500 mm (Alvares et al., 2013).

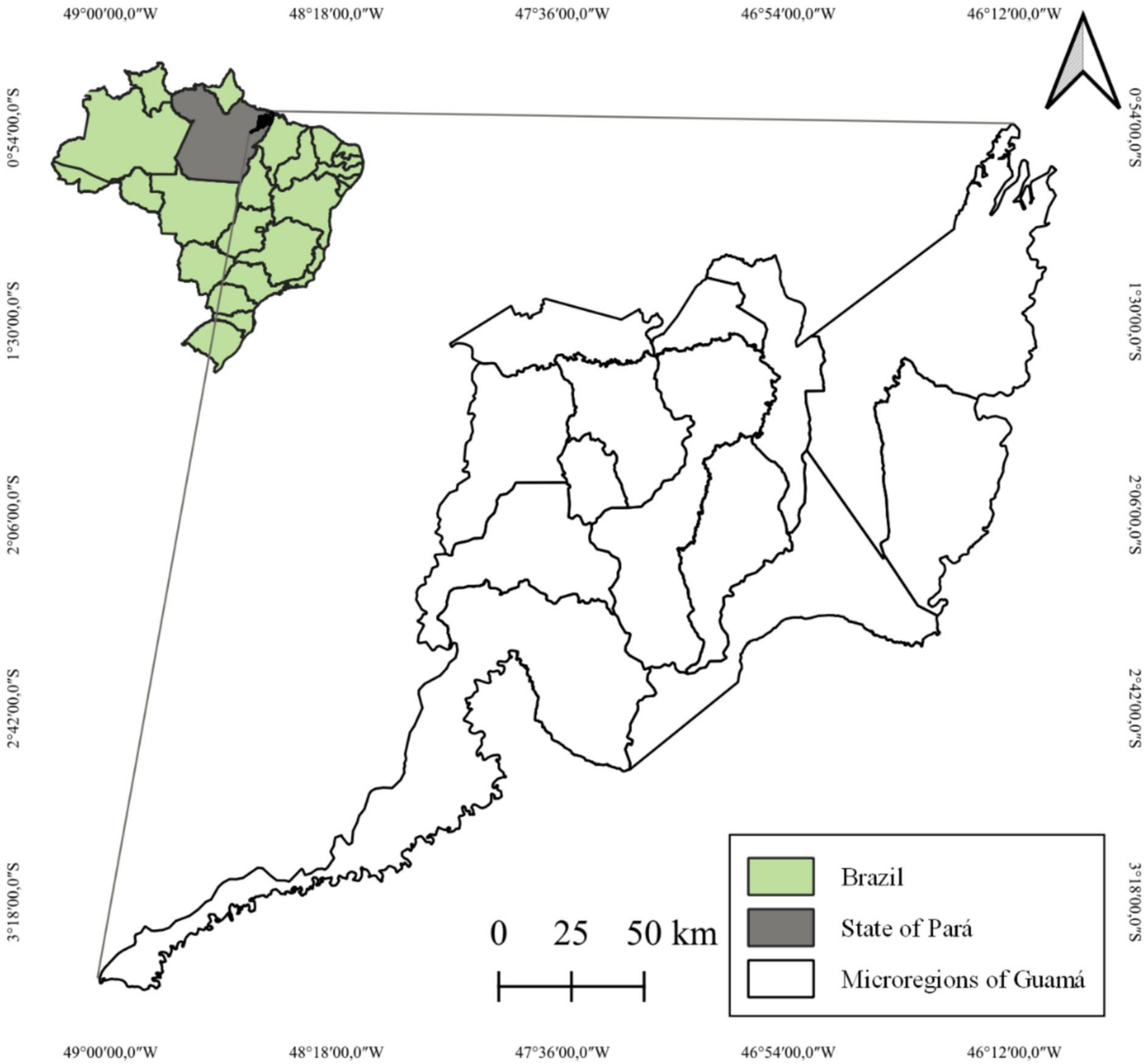

Fig. 1 Geographic location of the Guamá microregion, Pará, Brazil

Mapping of permanent crops (citrus, black pepper and palm oil)

We mapped permanent crops and forest areas within the study region using high-resolution Maxar satellite imagery (spatial resolution < 1 m; Maxar Technologies, 2023). These images, accessed via Google Satellite through the QuickMapServices plugin in QGIS and dated between 2018 and 2022, supported visual interpretation and land cover validation. Although Maxar imagery does not have a fixed revisit interval, it typically provides updates every 1–3 days, depending on cloud cover and regional acquisition priorities. We performed the mapping by visually interpreting the images, considering the specific characteristics of the spacing and shape of the crop canopies. For citrus crops, a regular spacing of 6–7×4 m was identified. For black pepper, the spacing varied between 0.5 and 2.5 m. In the case of the palm oil plantations, we observed canopies with a star-shaped pattern and a regular spacing of 9×9 m. We used QGIS 3.34 software (QGIS Development Team, 2024) to analyze and process the images. This methodology has been used to map and validate land use (Silvério et al., 2022).

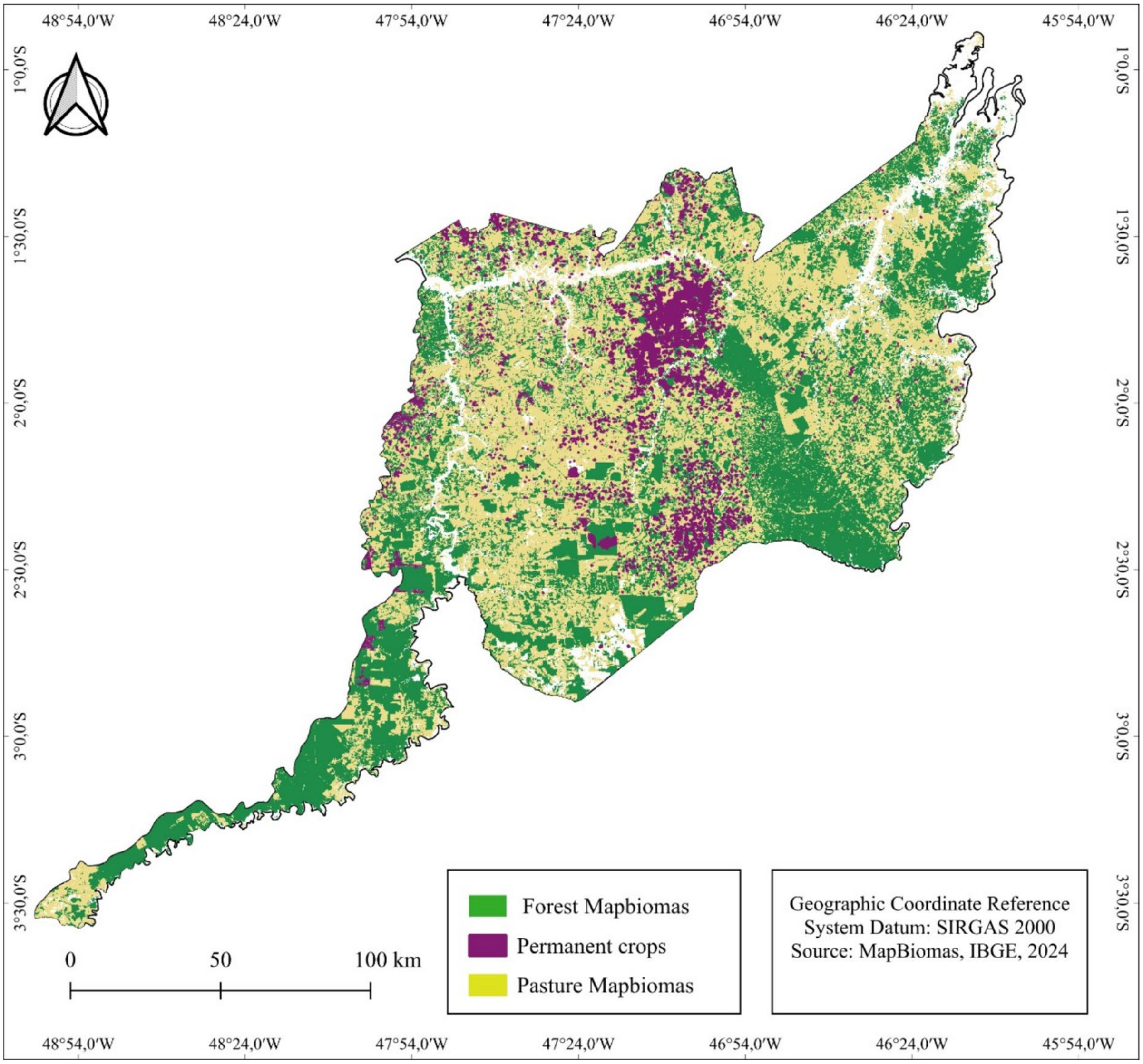

Fig. 2 Classification map of permanent crops and forest and pasture areas (MapBiomas) in the Guamá microregion, Pará, Brazil

Land use and land cover classification

We compared the permanent crop maps generated for the Guamá region—covering citrus, black pepper, and oil palm—with the corresponding land use classes from MapBiomas Collection 8 (MapBiomas, 2024) to assess classification consistency. When discrepancies were identified, we prioritized our manually interpreted data for permanent crops and retained the original MapBiomas classifications for all other land cover types (Fig. 2).

Dataset of rural properties

We characterized rural properties using data from the Rural Environmental Registry (Cadastro Ambiental Rural – CAR), available on the SICAR-PA platform. We selected only records with active cadastral status, which are valid for technical analysis and access to public policies (Pará, 2023). Approximately 90% of the study area is covered by CAR registration. Selected CAR polygons were intersected with forest fragments to identify forested areas within each rural property. Forest fragments smaller than 1 ha were

Table 1 Characteristics of predictor variables used in the degradation analysis, including acronyms, definitions, and units

Acronym	Full Name	Description	Unit
Log_TPR	Rural property size	Total size of rural property	Hectares (ha)
AGRI_PR	Proportion of Permanent Agriculture	Proportion of rural property occupied by permanent agriculture	-
Log_FOR	Native Vegetation Area	Total area of native vegetation on the rural property	Hectares (ha)
FOR_PR	Proportion of native vegetation	Proportion of rural property occupied by native vegetation	-
%FP	Percentage of Forest in the Landscape	Proportion of the landscape occupied by forest fragments	Percentage (%)
FIRE	Average number of fires	Average number of times the forest fragment was burned between 1985 and 2022	Number of events
IVEG	Average age of fragments	Average age of forest fragments on the rural property	Years

excluded from the analysis to reduce the noise from small or transitional patches.

Forest integrity metrics: biomass, canopy height, and NDII

We assessed forest integrity based on the degree to which the forest structure, composition, and function aligned with their natural range of variation (Andreasen et al., 2001; Parrish et al., 2003; Wurtzebach & Schultz, 2016). In this study, we considered forests with higher aboveground biomass, taller canopy height, and greater vegetation vigor—reflected by higher Normalized Difference Infrared Index (NDII) values—to have greater integrity. These three metrics capture key structural and functional attributes of forest ecosystems and serve as proxies for their overall health and resilience. Vegetation vigor was assessed using the NDII (Hunt & Rock, 1989), derived from Landsat 8 imagery processed on the Google Earth Engine platform (GEE, 2024). NDII measures vegetation water content using near-infrared (NIR) and shortwave infrared (SWIR) bands. It is calculated as (NIR – SWIR)/(NIR + SWIR), resulting in values ranging from –1 to 1, where higher values indicate more vigorous vegetation. For this study, we used average NDII values for forested areas between 2019 and 2024.

Structural metrics were derived from the Global Ecosystem Dynamics Investigation (GEDI), version 2.1, provided by NASA and processed in the Google Earth Engine environment (NASA, 2024; GEE, 2024). GEDI is a full-waveform LiDAR (Light Detection and Ranging) sensor that provides detailed vertical profiles of forest canopies based on 25 m ground footprints. From the GEDI Level 2 A (L2A) product (Dubayah et al., 2020), we extracted relative canopy height metrics and calculated the mean tree height. Height values were adjusted based on data quality and vegetation degradation indicators to ensure measurement reliability. Aboveground biomass was also estimated from GEDI v2.1 data. To ensure the accuracy of the estimates, we applied a rigorous filtering process that included: (i) exclusion of low-quality observations, (ii) removal of measurements with high relative uncertainty (i.e., relative standard error > 50%), and (iii) elimination of records collected in areas with slopes greater than 30 degrees. These procedures were adopted to reduce the influence of signal degradation and topographic distortion, thus ensuring robust estimates of forest structure and integrity.

Classification of fire frequency, average vegetation age and percentage of forest in the landscape

We analyzed environmental degradation by focusing on fire frequency using data from the MapBiomas platform, following a systematic sequence of steps. First, we extracted temporal data on land use and vegetation cover from MapBiomas (Collection 8), and fire frequency from MapBiomas Fire, accessed through high-resolution satellite images. Spatial analysis was then applied using Geographic Information Systems (GIS) to map areas affected by fires in different periods, allowing temporal and spatial patterns to be identified. Degradation was quantified by calculating indices that correlated the frequency of fires with the loss of forest cover and its impacts on biodiversity.

The average age of forest fragments was calculated for each rural property. To do this, we

Table 2 Model selection using the predictors: age of vegetation (IVEG), proportion of agriculture (AGRI_PR), average number of times the forest fragment on the property has been burned (FIRE), proportion of permanent agriculture (FOR_PR), percentage of forest in the landscape (%FP), logarithm of native vegetation area (log_FOR), and logarithm of the property area (log_TPR)

Intercept	IVEG	AGR_PR	FIRE	FOR_PR	%FP	Log_FOR	Log_TPR	df	AICc	delta	weight
Biomass (Mg/ha)											
31.61	1.229		−2.197	19.50			−0.999	6	117532.7	0.00	0.398
31.15	1.228		−2.193	19.69			−0.895	7	117534.5	1.72	0.169
31.40	1.226		−2.213	19.27			−1.007	7	117534.6	1.92	0.153
31.58	1.229		−2.194	19.52			−0.998	7	117534.7	1.99	0.147
27.63	1.226		−2.275	20.86				6	117536.2	3.51	0.069
Vegetation height (m)											
−0.5094	0.224	3.098	−0.863			−1.200	2.015	9	24147.1	0.00	0.826
1.2280	0.226	3.074	−0.885			−0.288	1.105	8	24151.7	4.65	0.081
−0.3837	0.223		−0.875			−1.211	2.029	8	24152.6	5.53	0.052
1.4530	0.224	3.199	−0.875				0.856	7	24154.4	7.34	0.021
1.6100	0.225	3.135	−0.883				0.837	8	24155.2	8.09	0.014
NDII											
0.383	0.000	0.023	−0.002		0.016			9	−49957.8	0.00	0.994
0.381	0.000	0.023	−0.001		0.016			8	−49947.5	10.31	0.006
0.380	0.000	0.024			0.016			8	−49940.9	16.96	0.000
0.378	0.000	0.024	−0.001		0.016			7	−49930.9	26.90	0.000
0.385	0.000				0.015			8	−49923.9	33.91	0.000

analyzed 37 years of secondary vegetation age classification maps generated using the FloreSer methodology (Nunes et al., 2020), based on land use and land cover data derived from Landsat 5, 7 e 8 (30 m spatial resolution), available on the MapBiomas platform (Collection 8) from 1986 to 2022. To generate the average age of the forest fragments, we considered primary vegetation pixels as 40 years old and then cross-referenced the vegetation age map with the forest fragments of the rural properties.

The methodology for generating the percentage of forest in the landscape followed specific steps. First, we generated 10 km radius buffers around the centroids of each property registered in the Rural Environmental Registry (CAR), allowing for a consistent analysis area. Next, we cropped the images obtained from the MapBiomas platform using these buffers to isolate the regions of interest. Finally, we quantified the number of pixels corresponding to the forest class within these areas, which allowed us to calculate the percentage of forest cover and assess degradation as well as monitor changes in vegetation over time.

Data analysis

We used three linear models (multiple regression) to assess how each variable associated with forest integrity (NDII, biomass, and vegetation height) varied as a function of the predictors related to land use and cover, as well as the characteristics of particular rural properties. Initially, we developed a global model, including seven predictors, the descriptions of which are presented in Table 1.

We performed model selection to identify which combination of predictors best explained the variation in each response variable. The best-performing models were those with the lowest Akaike Information Criterion (AIC) values (Zuur, 2009). Model selection was conducted using the *dredge* function from the *MuMIn* package (Burnham & Anderson, 2002; R Core Team, 2024).

Results

We analyzed 13,202 rural properties across the Guamá microregion. On average, permanent agriculture occupied 2% of the property area, although

Table 3 Linear models of biomass, vegetation height, and NDII; R^2 = coefficient of determination; R^2a = adjusted coefficient of determination

Variable	Estimate	Standard error	T-value	*p*-value
Biomass (Mg/ha); $R^2=10.22$; $R^2_{\text{Adjusted}}=0.102$				
Intercession	31.610	2.3947	13.200	< 2e-16
IVEG	1.229	0.0528	23.277	< 2e-16
FIRE	−2.197	0.6315	−3.479	0.000
FOR	19.501	1.8622	10.472	< 2e-16
Log_FOR	−0.999	0.4155	−2.404	0.016
Vegetation height (m); $R^2=28.91$; $R^2_{\text{Adjusted}}=0.288$				
Intercession	−0.509	0.775	−0.658	0.51085
IVEG	0.224	0.008	26.440	< 2e-16
FIRE	−0.863	0.093	−9.249	< 2e-16
AGRI_PR	3.098	1.129	2744	0.006
Log_TPR	2.015	0.374	5.389	7.48e-08
FOR	2.115	0.820	2.580	0.010
Log_FOR	−1.120	0.378	−3.177	0.002
%FP	−0.037	0.005	−7.571	4.50e-14
NDII; $R^2=13.8$; $R^2_{\text{Adjusted}}=0.137$				
Intercession	3.827e-01	1.723e-03	222.100	< 2e-16
IVEG	2.917e-04	3.423e-05	8.520	< 2e-16
FIRE	−1.719e-03	3.947e-04	−4.354	1.35e-05
AGRI_PR	2.286e-02	3.813e-03	5.995	2.09e-09
%FP	1.561e-02	1.323e-03	11.806	< 2e-16
Log_TPR	3.797e-03	2.992e-04	12.690	< 2e-16
FOR_PR	1.920e-06	5.472e-07	3.508	0.000
FOR	1.561e-02	1.323e-03	11.806	< 2e-16

some properties were almost entirely dedicated to permanent crops. We mapped 55,447 hectares of permanent crops in 2,591 properties. Of this total, 24,485 hectares were cultivated with citrus (orange, lemon, and tangerine), 24,828 hectares with oil palm, and 6,135 hectares with black pepper. Forest remnants covered, on average, 38% of the property area, though this proportion varied significantly among properties (Fig. 2). We found that the average vegetation height across forest fragments was 10 m, ranging from 1 to 22 m. NDII values varied between 0.25 and 0.47, with an average of 0.38, indicating moderate vegetation vigor. Aboveground biomass averaged 45.5 Mg/ha. Fire frequency varied considerably across the region. According to MapBiomas Fire data, many properties experienced at least one fire event between 1985 and 2022, with some showing up to 6 fire occurrences.

Analysis of predictors to explain variation in biomass, vegetation height and NDII

The model selection analysis (Table 2) revealed that the variation in aboveground biomass (Mg/ha) was best explained by predictor variables such as the proportion of forest relative to property size (FOR_PR), the frequency of fires in forest fragments (FIRE), the average vegetation age (IVEG), and the logarithm of property size (log_TPR). Table 3 presents the linear regression results for the selected predictors. These findings highlight the relevance of land use and landscape characteristics in maintaining forest integrity.

All seven predictors of vegetation height (m) were significant (Table 3). However, for graphical representation, we selected the four variables with the highest standardized regression coefficients (β): the average number of times the forest fragment was burned (FIRE), the average age of the vegetation (IVEG), the logarithm of the area of native vegetation within the rural property (log_FOR), and the logarithm of total property size (log_TPR). These variables contributed most strongly to explaining the variation in forest height.

In addition, NDII showed a significant relationship with all predictors (Table 3). For graphical representation, we selected the four most influential variables based on their standardized coefficients: the proportion of rural property occupied by permanent agriculture (AGRI_PR), the percentage of forest in the landscape (%FP), the average number of times the forest fragment was burned (FIRE), and the average age of the vegetation (IVEG).

Aboveground biomass (Mg/ha)

Aboveground biomass (Mg/ha) showed a positive relation with the proportion of forest in relation to property size (FOR_PR) (Fig. 3a), indicating that higher percentages of forest resulted in higher biomass values. Similarly, the average age of the vegetation (IVEG) showed a positive relationship (Fig. 3c), with biomass increasing as the vegetation aged, reaching a higher concentration in fragments with an average age of 40 years.

In contrast, the frequency of fires in forest fragments (FIRE) and the logarithm of rural property size (log_TPR) showed a negative relationship with

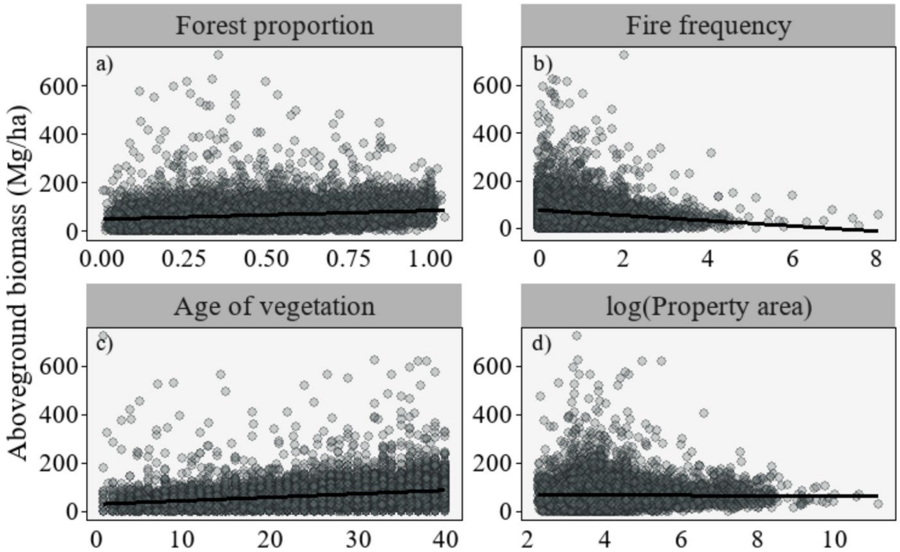

Fig. 3 Relationship between aboveground biomass (Mg/ha) and key predictor variables across rural properties in the Guamá microregion, Pará, Brazil. **a**) proportion of forest, **b**) fire frequency, **c**) average vegetation age, and **d**) logarithm of rural property area

biomass (Fig. 3b, d). This suggests that areas with a higher frequency of fires tend to have lower biomass because of the direct impact of fires on vegetation. In addition, the reduction in biomass with an increase in the logarithm of the property's area may be associated with the history of management of larger properties and human interventions in these areas.

These results indicate that the predictor variables explained 10% of the variation observed in the aboveground biomass data ($R^2 = 0.10$) (Table 3), highlighting the influence of factors such as forest cover, vegetation age, and anthropogenic pressure on biomass variation in the properties analyzed.

Vegetation height (m)

We found that frequent fires in forest fragments negatively affect vegetation height, suggesting that frequent fires can limit tree growth and result in forests with lower heights. The data indicates that a significant reduction in tree height can be observed after four recurrent fires.

In contrast, the positive relationship between the average age of the forest fragments (IVEG) and the height of the forest (Fig. 4b) highlights that as the vegetation ages, the trees tend to reach greater heights. This reflects the natural development of older forests, where trees have more time to grow, as evidenced by the trend line showing a consistent increase in height with advancing age.

In addition, a positive relationship was observed between the logarithm of the area of native vegetation on rural properties (log_FOR) and vegetation height (Fig. 4c), suggesting that a greater proportion of forest has a positive influence on vegetation height. Similarly, the logarithm of the total area of the rural property (log_TPR) also showed a positive relationship (Fig. 4d), indicating that larger properties are associated with taller forests. These results reinforce the importance of property characteristics for vegetation development, with the predictor variables explaining 28% of the variation observed in the vegetation height data ($R^2 = 0.28$) (Table 3).

Normalized difference infrared index (NDII)

Our analysis revealed a positive relationship between NDII and the proportion of land used for agriculture (Fig. 5a). A possible explanation for this positive relationship between these variables may be related to plant growth as well as irrigation, which increases water content, resulting in higher NDII values in agricultural areas. In contrast, the percentage of forests in the landscape (%FP) showed a negative relationship (Fig. 5b). This relationship can be explained by factors related to the functioning and structure of forests compared with agricultural areas.

The frequency of fires in forest fragments (FIRE) showed a negative relationship with NDII (Fig. 5c), indicating that vegetation vigor tends to decrease with

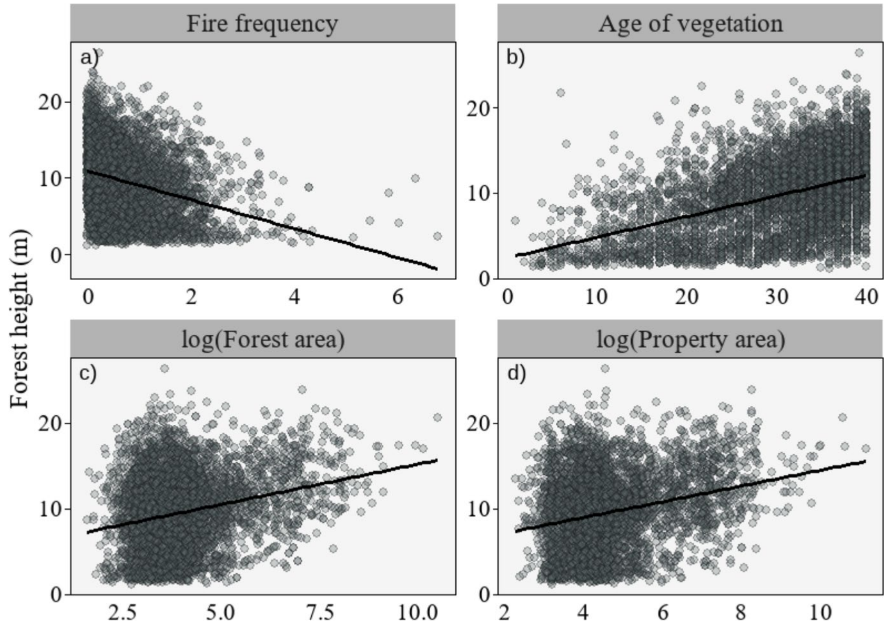

Fig. 4 Relationship between forest height (m) and key predictor variables across rural properties in the Guamá microregion, Pará, Brazil. **a**) fire frequency, **b**) average age of vegetation, **c**) logarithm of forest (area/ha) and **d**) logarithm of property area

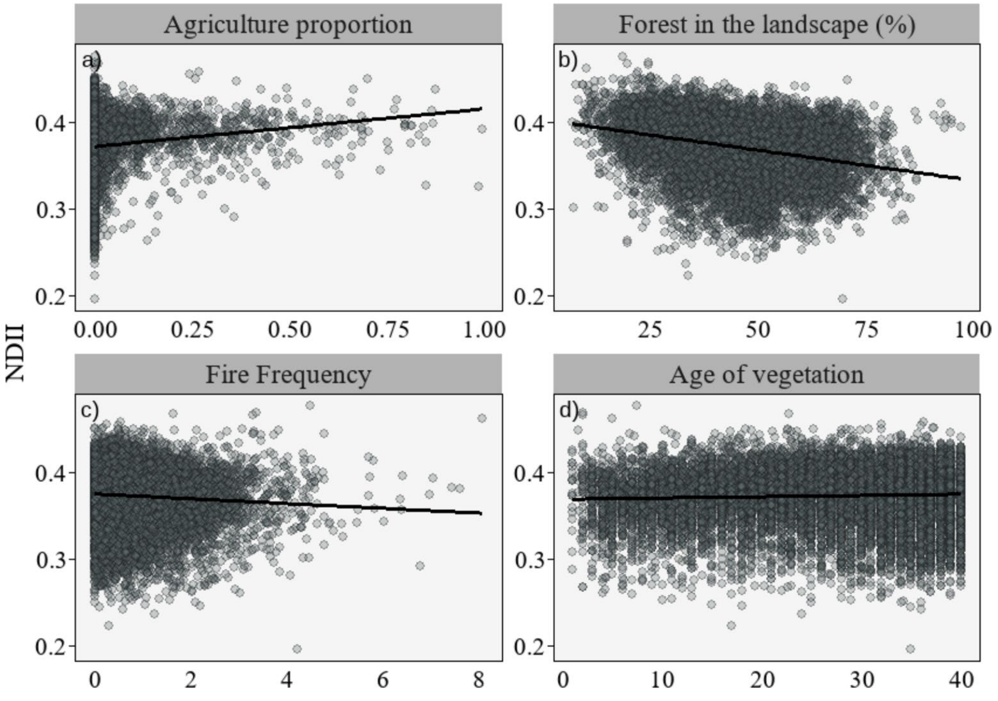

Fig. 5 Relationship between NDII and key predictor variables across rural properties in the Guamá microregion, Pará, Brazil. **a**) area dedicated to agriculture (%), **b**) forest in the landscape (%), **c**) average number of times the forest fragment on the property has been burned and **d**) average age of the fragments

increasing fire frequency. This relationship can be explained by various reasons, as forest fires cause direct damage to vegetation, leading to a decrease in vegetation cover. Although the relationship between NDII and the average age of forest fragments (Fig. 5d) was statistically significant ($p<0.001$), the effect size was very small (coefficient = 0.00029; R^2 adjusted = 0.137), indicating that vegetation age has limited influence on NDII values.

These results highlight how agricultural practices, the proportion of forest in the landscape, and the frequency of fires affect the vigor of vegetation on rural properties in the region analyzed (Fig. 5). The linear model (Table 3) confirmed that the predictor variables explained 13% of the variation observed in NDII data ($R^2=0.13$).

Discussion

This study partially rejected the initial hypothesis (H0) that the degree of native vegetation integrity would be similar across all properties, regardless of landscape characteristics or land use. The findings underscore a complex interplay between forest remnant integrity, land use type, and property size in the Eastern Amazon. Significant differences were observed in Vegetation Height and NDII across property size classes, while Biomass remained relatively consistent. Notably, all predictor variables significantly influenced Vegetation Height and NDII, whereas only IVEG, FIRE, FOR, and log_FOR were significant for Biomass. These outcomes reveal that the structural and compositional attributes of native vegetation respond differently to environmental and management variables, highlighting the nuanced effects of rural property characteristics and land use practices on forest conservation.

The initial hypothesis, which suggested a similarity in the degree of native vegetation integrity regardless of property characteristics, was only partially corroborated. Evidence indicates that factors such as the percentage of forest, history of burning, and size of properties are important predictors in determining the variation in forest integrity, highlighting the need for public policies adapted to local specificities.

Biomass

The importance of aboveground biomass accumulation in forests is widely recognized, especially in the context of preserving and mitigating climate change (Baccini et al., 2017; Pan et al., 2011; Walker et al., 2014). Biomass accumulation plays a crucial role in carbon storage, since biomass-rich forests are able to capture large amounts of carbon dioxide (CO2) from the atmosphere, helping to reduce the greenhouse effect (Breunig et al., 2011). Preserving forest remnants ensures that this natural process continues to function effectively, contributing to the global climate balance.

The evident relationship between a higher percentage of forest and higher aboveground biomass values (Fig. 3a) suggests that areas with greater forest cover tend to be more efficient in sequestering and storing carbon, as well as playing a crucial role in maintaining ecosystem services and climate regulation (Ribeiro et al., 2009). According to the studies carried out by Sanquetta et al. (2018), which estimated biomass and carbon stocks in various biomes, there was a significant reduction in biomass stocks during the period of analysis as a result of the loss of forest cover. This finding is in line with the results of this research, which also identified that the percentage of forest influences biomass stock, reinforcing the importance of forest preservation for maintaining these stocks.

The results showed that the age of vegetation had a positive relationship with the accumulation of aboveground biomass (Fig. 3c). This corroborates the findings of Almeida et al. (2019), which demonstrated the accumulation of biomass over time in secondary forests. However, when compared to the reference dataset used in our study, Almeida et al. (2019) overestimated biomass accumulation. His results suggest that secondary forests older than 14 years can accumulate, on average, 46.4% of the biomass of mature forests in the same regions. These findings indicate that although biomass accumulation is slower in the early stages of succession, it intensifies over time. This pattern is supported by studies showing rapid increases in aboveground biomass during early forest regrowth. For instance, Silver et al. (2000) reported that tropical secondary forests accumulate biomass at rates of up to 6.2 Mg ha^{-1} yr^{-1} during the first 20 years, with accumulation continuing for decades. Similarly, Letcher and Chazdon (2009) found that secondary forests in northeastern Costa Rica reached aboveground biomass levels comparable to old-growth forests after 21–30 years of succession. These results reinforce the critical role of older secondary forests in carbon sequestration and highlight their value in climate change mitigation strategies.

The relationship observed between the lower frequency of fires and the higher aboveground biomass values (Fig. 3b) suggests the importance of management practices that prevent the occurrence of fires, thus preserving forest biomass stocks. Forest fires are widely recognized as risk factors for carbon sequestration in forests. Studies indicate that extreme climatic events, such as droughts resulting from the El Niño phenomenon and warming of the Atlantic, can significantly increase the occurrence of fires, release large quantities of greenhouse gases, and accelerate global warming (Fernandes et al., 2023). Therefore, management strategies that minimize fires are essential for conserving biomass and mitigating climate impacts.

Furthermore, the finding that larger properties imply a reduction in biomass (Fig. 3d) is particularly relevant in the Brazilian context, where the expansion of agricultural activities and forest fragmentation are directly related to deforestation and the use of fire as a management tool. Recent studies have highlighted that Brazilian tropical forests are facing intense anthropogenic pressures, resulting in the loss of forest cover, increased fragmentation, and damage to essential ecosystem services, such as carbon stocks and water regulation (Ferrante & Fearnside, 2020; Silva Junior et al., 2022). These processes not only reduce forest cover but also increase the vulnerability of the remaining forest areas to fire. The combination of deforestation, fragmentation, and prolonged droughts intensifies the region's susceptibility to fires, amplifying the negative impacts on forests and their ecological functions (Dutra, 2023). Thus, the relationship identified in this study between the reduction in biomass and fire frequency reinforces the urgency of management policies that preserve forest areas, especially on larger properties, which, due to intensive use, may suffer greater degradation and consequent loss of biomass.

Vegetation height

Tree height is a crucial indicator of forest structure and reflects the health and dynamics of forest ecosystems. Our results showed a negative relationship between fire frequency and forest height (Fig. 4a). This indicates that a higher incidence of fires is associated with lower forests, suggesting that recurrent fires can limit tree growth or result in the death of taller trees, leading to a reduction in the average vegetation height. Previous studies have corroborated these findings, showing that frequent fires alter the structure of forests, particularly affecting large trees, resulting in a decrease in biomass (Barlow et al., 2012; Brando et al., 2014).

The conversion of forests into agricultural areas is one of the main causes of biodiversity loss in the tropics (Newbold et al., 2015). However, other less visible anthropogenic factors contribute to this loss, such as predatory logging and forest fires, which can occur alone or in combination (Barlow et al., 2016). In Brazil, fires in rural areas are closely linked to agricultural management and are used as a quick and economical solution for production, particularly in agriculture and livestock (May, 2019). Inappropriate use of fire contributes significantly to deforestation and is associated with an increase in fires in the Amazon (Fuchs, 2020).

Forest fires also have serious consequences for the hydrological cycle, affecting the transportation of moisture from forests to agricultural regions in southern and southeastern Brazil, which results in reduced rainfall not only in these areas but also in other regions of South America (Fearnside, 2005). In addition, Amazonian forests are not adapted to fire (Cochrane & Schulze, 1999; Nóbrega et al., 2019), leading to high tree mortality (Brando et al., 2014; De Andrade et al., 2019a, b; Xaud et al., 2013). Fire acts as a selective pressure, favoring species with specific characteristics that can alter forest composition (Nóbrega et al., 2019), directly influencing the vertical structure of forests and resulting in a decrease in height.

The recurrence of fires over short periods poses an even greater threat to forest resilience as it reduces forest biomass, mainly due to the loss of large trees (DBH > 50 cm) (Martins et al., 2012). In states such as Mato Grosso and Pará, where fires are more frequent, deforestation and land conversion for agriculture and mining increases the vulnerability of these areas. This calls for comprehensive environmental monitoring and stricter public policies to mitigate these effects (Da Silva et al., 2023; Jesus et al., 2020).

Another important variable that explains the variation in forest height is the age of the vegetation. The results showed that older forests tend to have taller trees (Fig. 4b), as these trees have more time to grow and occupy vertical space. As trees age, their diameter at breast height (DBH) and total or commercial height tend to increase, resulting in a greater accumulation of organic matter in the plant (Ferreira et al., 2019a).

Large trees play a fundamental role in forest functioning. Because of their size, these trees intercept greater amounts of sunlight, which favors photosynthesis and enables them to sequester high rates of carbon (Andrade & Higuchi, 2009; Hubbel et al., 1999).

The positive relationship between vegetation height and forest size (Fig. 4c) is a crucial factor for the functioning of forest ecosystems. In large areas of undisturbed native forests, trees tend to grow taller because of favorable conditions, such as the availability of space, water resources, and ecological stability. This increase in height is important not only because it allows trees to access more sunlight, which increases their ability to carry out photosynthesis and sequester carbon, but also because it promotes the accumulation of biomass and the cycling of nutrients, which are essential for the balance of the ecosystem (Ali & Wang, 2021; Bordin et al., 2021; Pinho et al., 2020).

In addition, the protection of large areas of intact forest is fundamental for the conservation of biodiversity (Watson et al., 2018). In landscapes where the forest remains untouched, structural and functional diversity increases, favoring both the vertical growth of trees and preservation of species that depend on these complex habitats. However, large areas of undisturbed forests are extremely rare today, which makes their preservation even more crucial for maintaining vital ecological processes (Edwards, 2016). Therefore, maintaining these forests allows trees to reach great heights, strengthening the role of forests in regulating climate, storing carbon, and supporting biodiversity.

We found a positive relationship between property size and forest height (Fig. 4d), suggesting that larger properties tend to have taller vegetation. This pattern may be associated with the size of the forest remnants, which are generally more extensive on larger properties. Large forest areas offer favorable conditions for the development of trees, allowing them to grow freely and reach greater heights. This favorable environment may be the result of lower levels of fragmentation and greater continuity of vegetated areas, which benefits the vertical growth of vegetation.

NDII

Although NDII is commonly used as a proxy for vegetation vigor and water content, our findings suggest that its effectiveness as an indicator of forest integrity should be interpreted with caution. Our results showed that NDII was positively associated with agricultural areas, likely due to irrigation and higher crop vigor. In intensive agricultural areas, irrigation increases the water content of plants, reflecting a higher NDII, because growing leaves capture water directly by maintaining higher levels of humidity (Sellers et al., 1997; Szilagyi, 2000). This result is reinforced by the positive relationship observed between the NDII and the percentage of agricultural area, suggesting that both irrigation and crop vigor contribute to raising the index (Fig. 5). While forested areas often exhibited lower NDII values, this pattern may result from factors such as higher canopy density, species diversity, and reduced transpiration in mature forests (Marques et al., 2024). Therefore, while NDII can provide insights into vegetation conditions, its use as a standalone measure of forest integrity may be limited. We recommend combining NDII with structural metrics, such as canopy height and aboveground biomass, to obtain a more comprehensive assessment of forest integrity in tropical landscapes.

However, the negative relationship between the percentage of forest and NDII (Fig. 5b) reflects a more complex phenomenon, which is not limited to leaf water content. In forests, high canopy density limits light penetration, which can reduce the transpiration rate and consequently NDII (Datt, 1999). In addition, the diversity of species in forests, each with distinct patterns of water response and drought tolerance (Hinckley et al., 1978; McDowell et al., 2008), suggests that factors such as leaf structure, chlorophyll concentration, and water-holding capacity in leaves can affect the spectral response, resulting in lower NDII values compared with irrigated agricultural areas (Peñuelas et al., 1993; Zhang & Zhou, 2015).

Additionally, the negative relationship between fire frequency and NDII (Fig. 5c) in forest fragments can be attributed to the direct impact of fire on vegetation structure, which degrades leaves and stems, decreases vegetation cover, and reduces the photosynthetic surface and water retention (Chuvieco et al., 2004). This also compromises the ability of vegetation to maintain hydraulic functionality, limit water storage, and increase the vulnerability of trees, especially in scenarios of drought and extreme heat (Allen et al., 2015; Garcia & Tague, 2015).

Finally, the weak relationship between fragment age and NDII (Fig. 5d) indicates that the index is more influenced by management factors, water stress, and variable environmental conditions than age. This suggests that NDII reflects a set of factors related to land use and management, including agricultural practices and environmental impacts in fragmented ecosystems, which are essential for maintaining the ecological integrity of forests in the Amazon. These findings emphasize the importance of a multifactorial approach when using the NDII to understand the health and integrity of ecosystems in regions where the interaction between agriculture and forest conservation is intense and dynamic.

Conclusion

This study demonstrates that rural property characteristics and land use practices significantly influence forest integrity in the Eastern Amazon. In this context, integrating sustainable agricultural practices with the conservation of native forests is essential to promote more balanced productive landscapes. Strategies such as strict control of burning, incentives for forest restoration, and financial compensation for ecosystem services can contribute to the region's environmental and productive resilience.

Therefore, it can be concluded that maintaining biodiversity and ecosystem services in the Eastern Amazon depends not only on the size of the properties and their land-use practices, but also on integrated territorial planning. Sustainable management strategies that align economic development with environmental conservation are essential to preserve forest remnants and ensure their contribution to climate regulation, carbon sequestration, and regional biodiversity.

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Authors'contributions JCS and DVS were responsible for the conceptualization and methodology of the study. JCS performed the formal analysis, investigation, and wrote the original draft of the manuscript. DVS also contributed to writing the original draft, visualization, and project administration. FE, HA, and EM reviewed and edited the manuscript. All authors reviewed and approved the final version of the manuscript.

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Data availability Access to research data:

The data used in this manuscript were obtained from public sources and are available at the following links:

Global Ecosystem Dynamics Investigation (GEDI): Aboveground height and biomass data were accessed via GEE. Available at: https://developers.google.com/earth-engine/datasets/catalog/LARSE_GEDI_GEDI04_A_002.

Landsat 8: Satellite images were obtained from the Landsat 8 collection through the Google Earth Engine (GEE) platform. Available at: https://developers.google.com/earthengine/datasets/catalog/LANDSAT_LC08_C02_T1_L2

MapBiomas Project: Land use and land cover data in Brazil were obtained from MapBiomas Collection 8. Available at: https://www.mapbiomas.

Rural Environmental Registry (CAR): Information on rural properties in the Guamá region was extracted from the National Rural Environmental Registry System (SICAR-PA). Available at: https://www.car.gov.br/publico/imoveis/index.

Declarations

Ethical responsibilities of authors All authors have read, understood, and have complied as applicable with the statement on"Ethical responsibilities of Authors"as found in the Instructions for Authors.

Competing interests The authors declare no competing interests.

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