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Spatial Distribution of Secondary Forests by Age Group and Biomass Accumulation in the Brazilian Amazon

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Abstract: Secondary forests provide essential ecosystem services, especially in helping to mitigate climate change with the storage of carbon in the aboveground biomass of tree species. In this context, the present research aimed to analyze the spatial distribution of secondary forests and estimate the aboveground biomass accumulation of land cover of different ages in the state of Pará. The spatial patterns of the secondary forests in Pará state were evaluated with hot spot analysis algorithms using data from the TerraClass project for the 2004–2014 time period. The results showed that the spatial distribution of the secondary forests did not occur randomly in space, but suggested local geopolitical influences. The younger secondary forests had the most deforested areas during the study period. Approximately 5% of Pará had its secondary forests deforested in 2014. In general, the balance of the secondary forests was positive. The aboveground biomass accumulation differed according to the secondary forest ages during the study period as evaluated in two pilot areas. It was observed that the secondary forests > 10 years old in pilot area A had an average of 23% of old-growth forest aboveground biomass in the same area, while in pilot area B, the secondary forests > 10 years old had an average of 32.7% of old-growth forest aboveground biomass.

Keywords: secondary forests; Amazon; carbon; aboveground biomass

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1. Introduction

Secondary forests have expanded worldwide in recent decades, mainly in regions with a deforestation history [1]. In the Brazilian Legal Amazon (BLA), the dynamics of secondary forest growth is strongly correlated with agricultural and pastoral activities, which is related to the rise of illegal logging in the last decade [2–4]. Furthermore, this type of forest regenerates in previously deforested areas and is seen as a component of the landscape, potentially generating ecosystem services, especially for climate change mitigation [4–7]. Within this context, this study sought to broaden the understanding of the role of secondary forest regeneration in the current land use and land cover (LULC) change process in the BLA.

Secondary forests are understood as natural vegetation in regeneration. They feature tree species densification, which have already suffered total suppression of the native vegetation since deforestation monitoring began in the Amazon [8,9]. In addition, it is meaningful to understand the dynamics of secondary forest expansion and how these forests are spatially distributed according to the official Brazilian monitoring systems in the Amazon. For this reason, it is helpful to expand the knowledge about the role of the dynamics of the gain, remanence and loss of the secondary forests in the current process of changing the land use and cover in the Brazilian Legal Amazon.

In the BLA, the old-growth forest losses have surpassed the gains for three decades [10]. However, according to the data provided by the Brazilian national land use and land cover monitoring system (TerraClass), the secondary forest areas accounted for 150,800 km^2 in the BLA in 2008, which highlights secondary forest regeneration as a potential mitigation for deforestation [9]. As an ecological consequence, the ombrophilous forests are replaced by savanna vegetation [11], causing a large-scale loss of biodiversity and affecting part of the local people's livelihoods [12]. However, these impacts can lead to lost opportunities for the sustainable use of forests and the production of traditional goods for timber forest management and sustainable non-timber products [13].

In the current scenario, deforestation has been a major environmental problem in the Amazon. Until 2020, the accumulated deforestation rates in the BLA corresponded to 457,237 km^2, with the state of Pará being the most significant contributor with 157,374 km^2 of deforestation [10]. In 2001, Pará registered an old-growth forest deforestation rate of about 16,728 km^2 [10], the highest in the last 20 years for this state. In this context, the secondary forests emerged from previously deforested areas with different land use.

Recent studies show that secondary forests in the BLA may mitigate climate change by sequestering carbon up to 20 times faster than old-growth forests [7]. According to MapBiomas [14], in 2004 the state of Pará had 79.1% of its entire territory covered by forest, and in 2020 this reduced to 74.91%, representing a loss of around 30,000 km^2 of the forest, including different types of forest formation. Given the importance of monitoring forest loss and gain, this study selected a land use coverage dataset from the TerraClass project in the state of Pará in the BLA, to analyze a time series from 2004, 2008, 2012 and 2014.

Land coverage monitoring systems are important for understanding the dynamics of forest changes and mapping the forest age. For example, in the Amazon, secondary forest age is the primary driver to estimate aboveground carbon [7]. Within these spatial information policies, decision makers can take actions to mitigate carbon emissions [15], forest management planning and change environmental laws for sustainable use.

Several studies have been attempted to map and quantify the area of the forests in the Amazon for decades, historically based on satellite imagery and monitoring the age of abandoned areas from land use change [4,16–20]. The aboveground biomass storage and carbon sequestration specifically encompassing the forest areas were initially studied using allometric equations and permanent plots [17,21], and later combined with remote sensing technologies and fieldwork [22,23]. Currently, the secondary forests are expanding over more than 129,000 km^2, the majority represented by $\leq$60 year old forests [4,24]. The carbon storage in these forests is about 294 Tg C of storage [7], which represents 45 Mg of aboveground biomass per hectare (using 0.5 g C as the carbon factor conversion from the IPCC; 129,361 km^2 based on Smith et al., 2020 [24]).

The biomass of tropical forests has been taking an important role in the global carbon cycle as a source of carbon stock and potential for carbon dioxide emissions in deforested areas. Secondary forest aboveground biomass has been identified as one of the main factors in the global carbon cycle due to the high amounts of carbon that it can stocks for forest successional processes [4,5,25,26]. The aboveground biomass in secondary forests has been estimated using multi-sensor platforms of remote sensing data [5,27,28]. Some studies have contributed to the great importance of the age factor in estimating the aboveground biomass in secondary forests [25,29] but this needs to be further investigated in different regions.

In this context, the present study seeks to answer how the distribution of secondary forests and deforestation occur in two pilot areas in the state of Pará according to the estimation of forest age and aboveground biomass. Based on the above, we tested the hypothesis that Complete Spatial Randomness (CRS) drives the spatial distribution patterns of the secondary forests. For this, we used the TerraClass dataset in a time series analysis to understand how secondary forest distribution occurs in the state of Pará and the dynamics of land use and land cover changes in the region.

2. Materials and Methods

2.1. Study Area

The state of Pará is located in the northern region of Brazil, with an approximate area of 1,248,000 km^2 [30], located between the parallels of 2°60′ N and 9°85′ S and the meridians of 58°90′ and 46° W (Figure 1). The state of Pará was selected for this study because it presents a wide variety of vegetation cover and land use, especially secondary forest, resulting in a formation with great complexity and spatial and temporal variability. In 2020, around 74.91% of the entire state was covered by forest, 3.3% by non-forest natural formations, 17.8% by farming, 0.001% by non-vegetated areas and 3.5% by water [14].

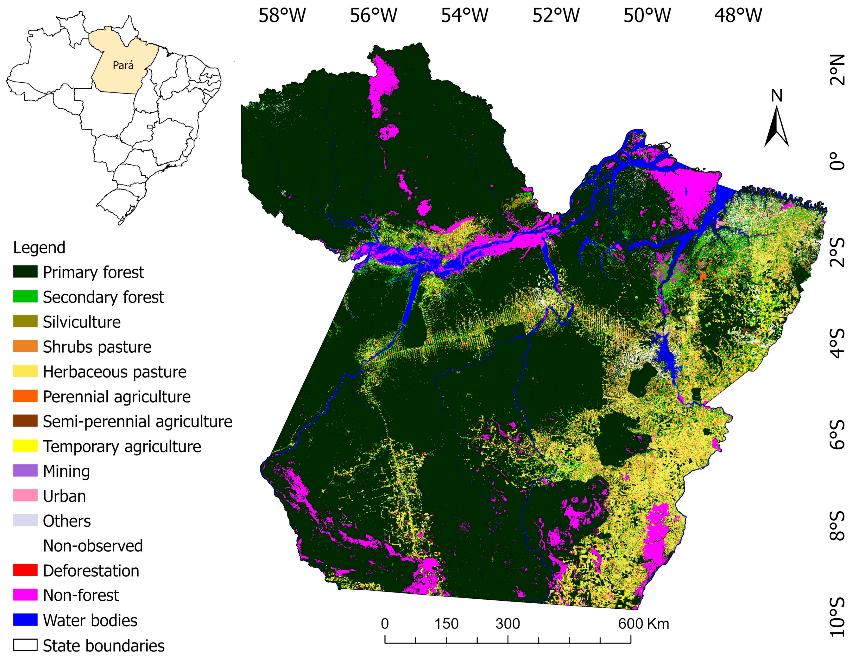

Figure 1. Land use and land cover map of Pará state according to TerraClass for 2014.

Pilot Areas

Two pilot areas were selected for the aboveground biomass estimation, specifically for secondary forest land cover. The first one, named in this paper as region A, is mostly located within the municipality of Paragominas (3°15′ S and 47°30′ W) (Figure 2). This municipality is known for its heavy logging activities from sustainable forest practices since 1960. With the decline in logging activity, the agricultural frontier expanded, mainly with monocultures such as soy and pasture areas. As of 2008, the municipality adopted policies to reduce the environmental impact of the economic activities, which led to a decline in deforestation for the first time in the history of Pará [31]. The second, named region B, is located in the municipality of Belterra (3°5′ S and 54°56′ W), near the Tapajós National Forest (Figure 2). Region B has a history of degradation, logging, anthropic occupation, pasture and agriculture.

More details about the pilot areas are described in the Supporting Information for "Aboveground biomass variability across intact and degraded forests in the Brazilian Amazon" [23].

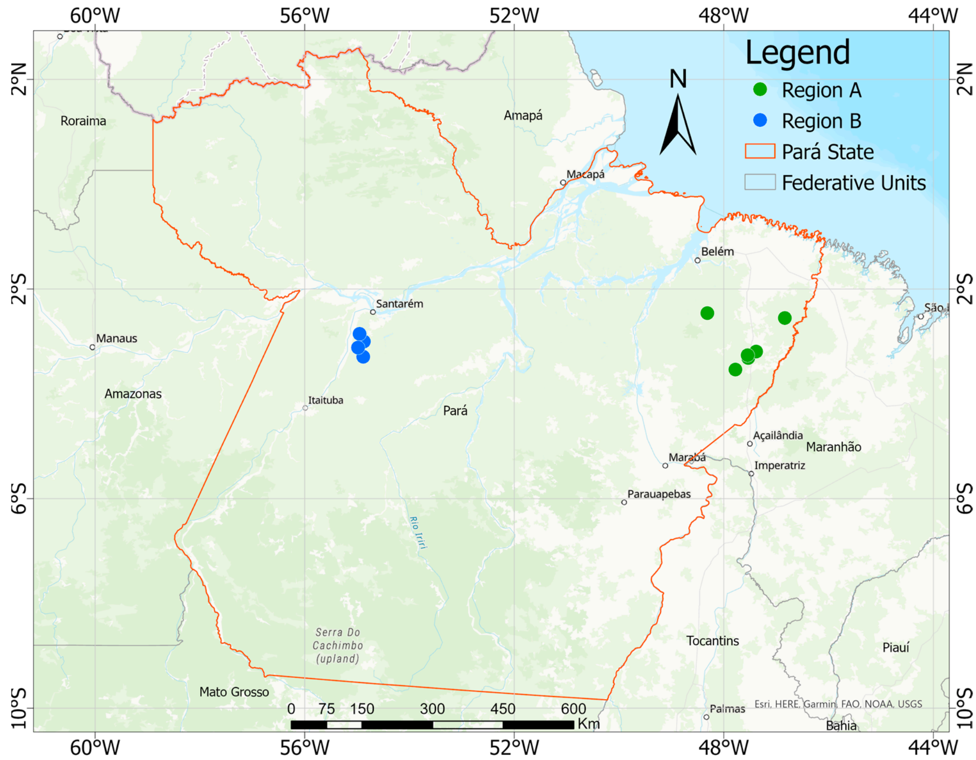

Figure 2. Pilot study areas in Pará state.

2.2. Methodological Approach

Figure 3 shows the general flowchart of the methodological approach developed for this study.

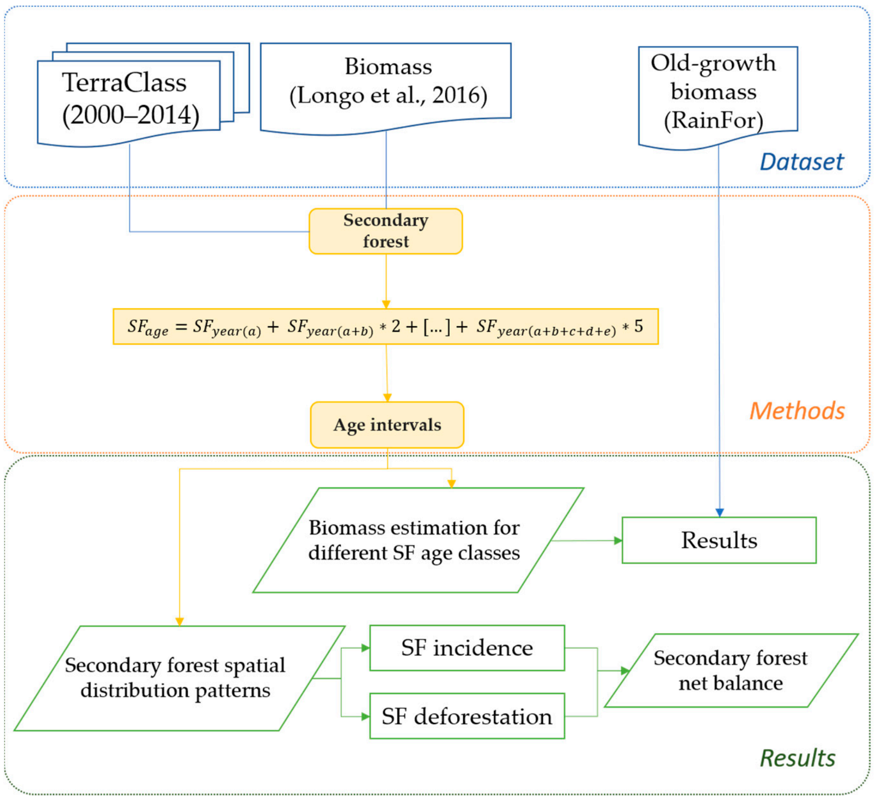

Figure 3. Flowchart of the methodological approach [23].

2.3. Land Use Change and Secondary Forest Age

Land use and land cover maps were generated for every year under analysis, using the TerraClass thematic classes. The dataset was derived from medium-resolution Landsat-5 TM and MODIS images through supervised classification [8,9], and it was freely available on INPE's website. The global accuracy of TerraClass mapping was 76.64%, with a 21.5% omission error and a 20.2% commission error for secondary vegetation classes [9]. Then, we imported and preprocessed land use data from the Google Earth Engine (GEE) platform into a raster format. Different rasters were then generated for secondary forest age classes based on previous land use.

Using cartographic modelling [32], rasters with binary values for the absence or presence of secondary forest in each year were used to classify the age interval per pixel of secondary forest. The last year in our time series was 2014. Prior to that, we mapped the 2012 LULC, meaning the minimum age interval for secondary forest was 0 to 2 years old according to the previous LULC. The age classes were based on the difference in the age interval for each year studied, assigning a range from 1 to 5 to each interval, according to Equation (1):

$$SF_{age} = SF_{year(a)} + SF_{year(a+b)} * 2 + [\ldots] + SF_{year(a+b+c+d+e)} * 5, \quad (1)$$

where SF_{age} refers to the secondary forest age class from 1 to 5 for determining the age interval estimation, and SF_{year} refers to the mapped permanent year of secondary forest multiplied by the age class.

An exploratory data analysis was performed using the age classes and the previous land use for each secondary forest was mapped (Table 1).

Table 1. Classification of secondary forest age in age interval.

Age Interval (Years)	Class	2004	2008	2010	2012	2014
0 to 2	1	Non-Secondary Forest	Non-Secondary Forest	Non-Secondary Forest	Non-Secondary Forest	Secondary Forest
2 to 4	2	Non-Secondary Forest	Non-Secondary Forest	Non-Secondary Forest	Secondary Forest	Secondary Forest
4 to 6	3	Non-Secondary Forest	Non-Secondary Forest	Secondary Forest	Secondary Forest	Secondary Forest
6 to 10	4	Non-Secondary Forest	Secondary Forest	Secondary Forest	Secondary Forest	Secondary Forest
>10	5	Secondary Forest	Secondary Forest	Secondary Forest	Secondary Forest	Secondary Forest

For each year, every pixel classified as secondary forest was checked against its previous classification to determine the age interval. According to the previous land use and land cover, the age range of secondary forest was classified to fit the age range estimation of the forest.

2.4. Aboveground Biomass Estimation Data

The aboveground biomass carbon density (AGBCD) estimation data were collected from the literature [23]. The data were estimated using airborne LiDAR and calibrated using forest inventory measurements. For the chosen pilot areas, the estimated AGBCD-selected LiDAR metrics were collected between 2012 and 2015 using parametric modelling [23]. The uncertainty of the aboveground carbon density was described for each plot in the pilot areas in the Supporting Information for "Aboveground biomass variability across intact and degraded forests in the Brazilian Amazon" [23]. The data were acquired from the Sustainable Landscapes Brazil project, supported by the Brazilian Agricultural Research Corporation (EMBRAPA), the US Forest Service, USAID and the US State Department in nearby areas with characteristics similar to the pilot area. In addition, the old-growth aboveground biomass data were acquired from plots provided by ForestPlot.net [33].

2.5. Data Analysis

2.5.1. Hot Spot Analysis of Spatial Distribution of Secondary Forests

The geopolitical influence on the variation in the spatial distribution of secondary forests was analyzed and mapped using TerraClass. For this, we applied the Optimized Hot Spot Analysis algorithm from ArcGIS Pro. This algorithm associates an attribute of each feature to the corresponding neighboring elements by mapping locations with statistically higher (hot spot) or lower (cold spot) values than the expected value of the attribute for the total area analyzed [34].

The secondary forest fragments of each age class in raster format with 30 m of the spatial resolution were converted into points to enable the fragment area measurement based on the projected coordinate system South America Albers Equal Area Conic. Each point was assigned the area of its respective polygons given the municipal boundaries. This dataset was used as an input file in the first hot spot analysis, which considered the incidence (density of points) and forest fragment (ha) area with 90, 95 and 99% confidence levels by spatial location on the map. In addition, according to the secondary forest fragments, descriptive statistics for the secondary forest fragments were used to consider the number and area of polygons within every age class.

2.5.2. Hot Spot Analysis of Spatial Distribution of Deforestation in Secondary Forests

To map deforestation, To map deforestation, we subtract the secondary forest area in two different periods along the time series to detect the loss of secondary forest. Then, we applied the Optimized Hot Spot Analysis algorithm using the area of secondary forest deforestation as input for each year in the time series. We considered the area of secondary forest deforestation (ha) with 90, 95 and 99% confidence levels by spatial location on the map, including areas where the deforestation occurred more than once.

2.5.3. Secondary Forest Net Balance

We selected the secondary forest incidence and deforestation areas to calculate the balance in the study period. Then, the data were analyzed in pairs to verify the cumulative secondary forest (accumulated SF mapped in the final year of analysis), the gain (new secondary forest mapped), the remaining (permanent SF), the loss (remain subtracted from the previous cumulative year) and the net balance (total secondary forest mapped: Remain + Gain − Loss).

2.5.4. Aboveground Biomass Estimation for Different Secondary Forest Age Classes

To estimate the aboveground carbon density, we selected the secondary forest fragments for each plot with the aboveground biomass estimation data collected from the literature. Then, after applying the method described to estimate the age interval for the time series we interpolated the aboveground biomass data with the secondary forest fragments. The old-growth aboveground biomass data for the nearby regions were then considered to compare the aboveground biomass accumulation results. According to the secondary forest fragments, a descriptive statistic was also used to collect information the interpolation of the aboveground biomass data for every age class. We applied a Kolmogorov–Smirnov test to check the normality of the data and computed a two-way analysis of variance (ANOVA) for unbalanced designs to test the null hypothesis that the mean aboveground biomass for different age intervals in the secondary forest had no difference in the two pilot areas. Finally, we applied a Tukey multiple comparisons test at a 95% family-wise confidence level to verify which classes differed in aboveground biomass accumulation.

3. Results

3.1. Secondary Forest Spatial Distribution Patterns

Using hot spot analysis, we detected the hot and cold spots for secondary forest incidence in Pará state, according to the age classes (Figure 4). In general, the spatial distribution of the secondary forests in Pará presented a hot spot pattern in the northeast region of the state, and also along the main highways and harbor areas of the state. The oldest mapped secondary forests in Pará state (Figure 4A,B) presented similar patterns of cold and hot spots. These areas of hot spots were regions with long historic LULC changes. Compared with the other age intervals, the secondary forests of 4 to 6 years in age (Figure 4C) had very defined locations across the state. On the other hand, the youngest mapped secondary forest incidence connected the eastern side of the state with the Baixo Amazonas mesoregion (Figure 4D,E). To summarize the incidence of the secondary forests, Figure 4F grouped the entire time series representing hot spot and cold spot areas.

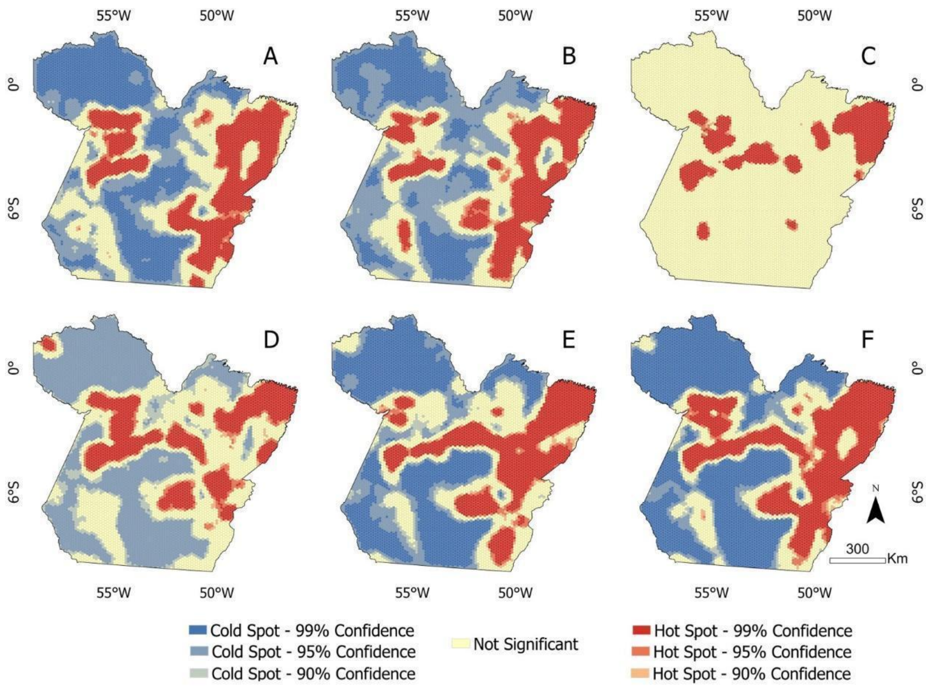

Figure 4. Hot spot analysis of secondary forest incidence in Pará state by age class. (**A**) >10 years old; (**B**) 6 to 10 years old; (**C**) 4 to 6 years old; (**D**) 2 to 4 years old; (**E**) 0 to 2 years old; (**F**) total incidence between 2004 and 2014.

The same analysis was performed for secondary forest deforestation (Figure 5). A specific age interval could not define the pattern of deforestation for the study area. The regions with the highest incidence of secondary forests presented the hottest spot areas for deforestation. On the other hand, the map showed a few parts where deforestation occurred more than once in the time series. Further, the cold spot areas were primarily located in the protected areas, highlighting the importance of environmental protection laws.

The total area of secondary forest deforested in 2014 was 64,396.91 km^2, which represented around 5% of Pará's territory. The youngest age interval of 0–2 years old had the most deforested area of 23,465.4 km^2, which represented the fast changes in land use and land cover in a short period. The oldest secondary forest (>10 years old) had 16,653.2 km^2 deforested in 2014 (Figure 6).

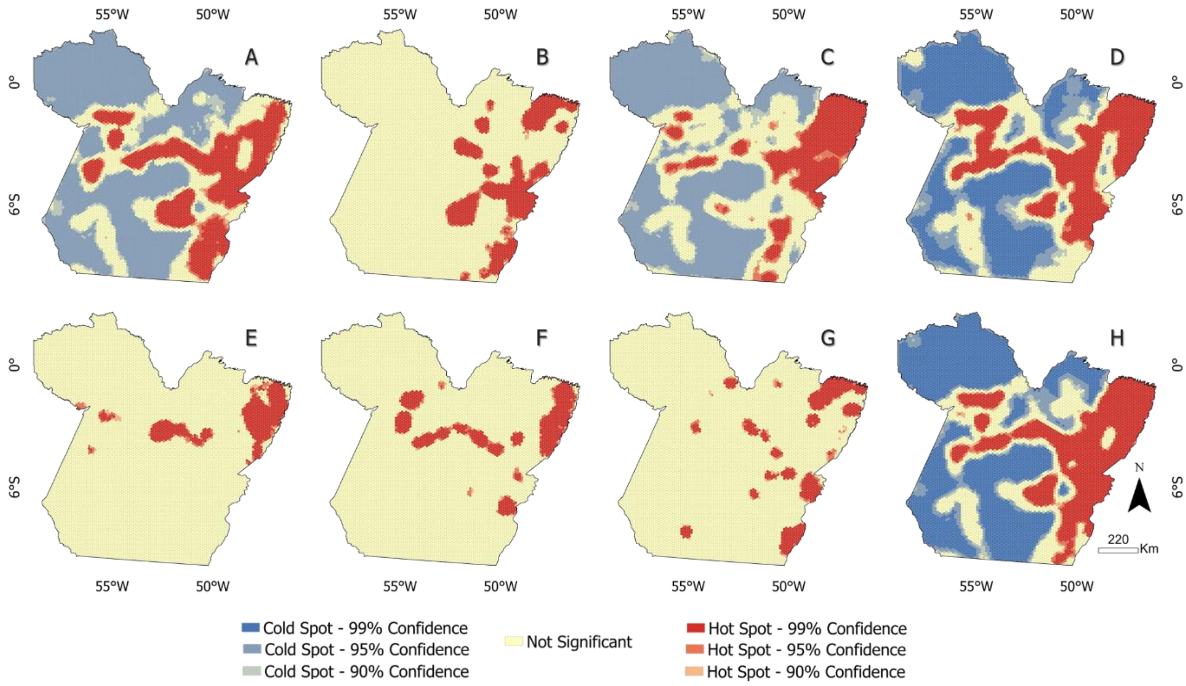

Figure 5. Hot spot analysis of secondary forest deforestation in a time series. (**A**) Deforestation in 2008; (**B**) Deforestation in 2010; (**C**) Deforestation in 2012; (**D**) Deforestation in 2014; (**E**) Repeated deforestation in 2008 and 2012; (**F**) Repeated deforestation in 2008 and 2014; (**G**) Repeated deforestation in 2010 and 2014; (**H**) Accumulated deforestation for the time series.

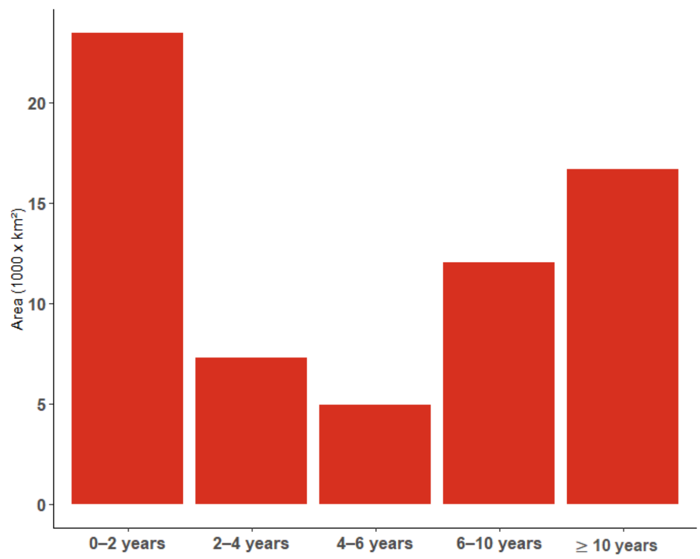

Figure 6. Deforestation of secondary forest in Pará state (2014).

3.2. Secondary Forest Net Balance

We divided the temporal data into different intervals according to the available data to extract the area of secondary forest balance mapped for the study period. The cumulative area did not vary much along the time series; the average for the time interval of analysis was 65,275.0 km^2 of secondary forest (Figure 7A). As shown in the balance (Figure 7B), a considerable proportion of the area remained growing during the time series, with some gains (new secondary forest mapped) and losses. Therefore, the secondary forest balance was still positive with a higher net balance in 2008–2010 (Figure 7C).

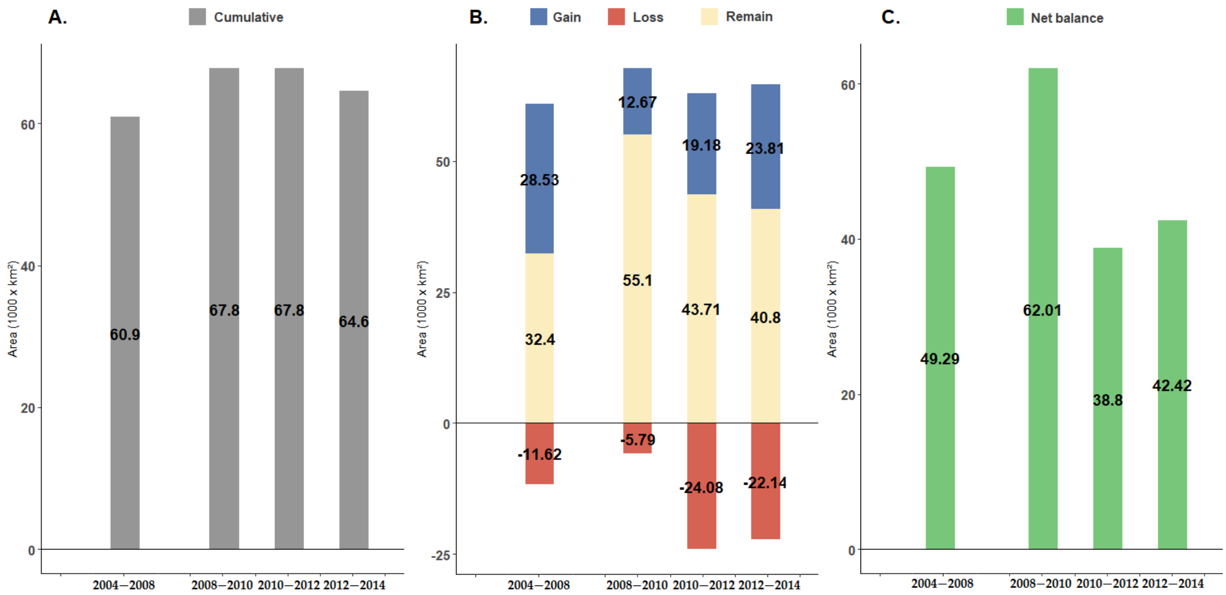

Figure 7. Secondary forest balance in Pará. (**A**) Cumulative = Accumulated SF mapped in the final year of analysis; (**B**) Gain = New secondary forest mapped, Remain = Permanent SF, Loss = Remain-previous cumulative year; (**C**) Net balance = Total secondary forest mapped (Remain + Gain − Loss).

3.3. Aboveground Biomass Estimation for Different Secondary Forest Age Classes

To point out the deforestation of secondary forests, it was essential to understand how this has impacted the aboveground biomass recovery over the years. We analyzed the carbon density in the aboveground biomass (MgC.ha^{-1}) in two municipalities in the state of Pará (regions A and B). Similar findings were observed in the age classes, where the accumulation of aboveground biomass in the two municipalities was different over time. Over the years, the secondary forests stored different amounts of carbon per hectare/year according to their age classes. It was observed that the secondary forests > 10 years old in pilot area A had an aboveground biomass average of 23% of old-growth forest in the same region, while the secondary forests > 10 years old in pilot area B had an average of 32.7% of old-growth forest aboveground biomass (Figure 8).

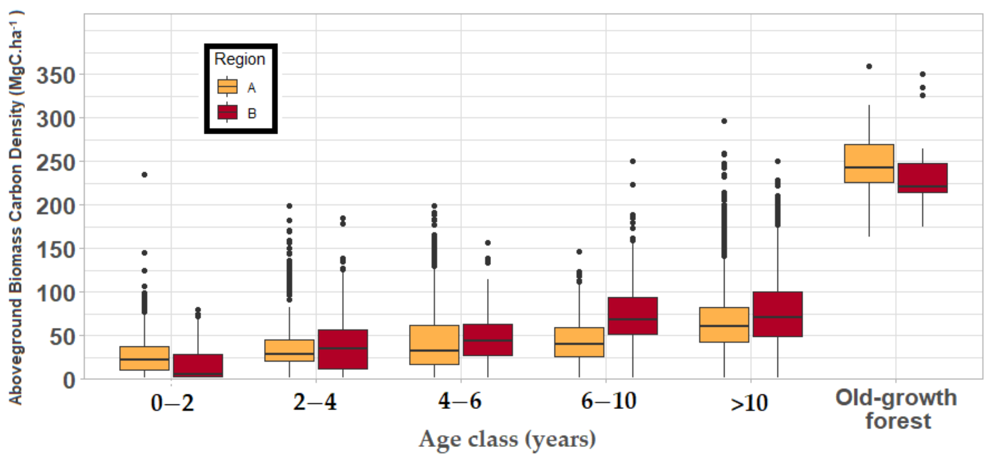

Figure 8. Distribution of aboveground biomass carbon density by secondary forest age class group.

The lowest aboveground biomass estimates by age group occurred in the 0−2 years old interval with a mean and standard deviation of 27.10 ± 20.98 and 17.18 ± 19.67 MgC.ha^{-1} for region A and region B, respectively. On the other hand, the age class that grouped the secondary forests over 10 years old had the highest mean aboveground biomass with

66 ± 37 and 77.01 ± 39.22 MgC.ha^{-1} (Table 2). Region A presented a higher aboveground biomass in the early age groups (0−4 years old), while region B presented a higher mean as the secondary forest aged (≥4 years old).

Table 2. Descriptive statistics for aboveground biomass carbon density (MgC.ha^{-1}).

Age Interval (Years)	Region A				Region B			
	$\bar{X}$	σ	σ^2	N	$\bar{X}$	σ	σ^2	N
0 to 2	27.11	20.98	439	2326	17.18	19.67	387	155
2 to 4	43.48	38.67	1492	545	38.17	31.46	990	478
4 to 6	45.96	40.67	1654	1333	46.18	32.57	1061	141
6 to 10	43.97	24.03	576	1835	75.86	43.72	1911	284
>10	66.00	37.00	1369	4508	77.01	39.22	1538	2828
Old-growth forest	287.07	95.50	9120	13	235.50	41.78	1745	29

$\bar{X}$ = mean; σ = standard deviation; σ^2 = variance; N = number of observations.

Using a two-way analysis of variance (Table 3), we verified that there was a significant accumulation of aboveground biomass ($p < 0.001$) over time in the age classes of the secondary forests. Moreover, it could be stated that there was a significant difference ($p < 0.001$) between the aboveground biomass in the two regions (A and B) related to the accumulation of aboveground biomass in the period studied, denoting that regional variations (quality of the site) might influence the recovery of the aboveground biomass.

Table 3. Analysis of variance test (ANOVA).

Source of Variation	Df	Sum Sq	F_{value}	Pr (>F)
(Intercept)	1	1,709,123	1454.573	$<2.2 \times 10^{-16}$ ***
Age class	5	32,15,260	547.279	$<2.2 \times 10^{-16}$ ***
Region	1	14,319	12.187	0.0004828 ***
Age class + Region	5	282,406	48.069	$<2.2 \times 10^{-16}$ ***
Residuals	14,469	16,995,190		

Signif. codes: 0 '***'.

Furthermore, we applied a Tukey test at a 95% family-wise confidence level and found that for both regions in the same age interval, class 2 (2–4 years old) and 3 (4–6 years old) did not show a significant difference in the aboveground biomass accumulation (Table 4). The results showed that, in general, region B (western Pará) presented a higher aboveground biomass accumulation as the secondary forests aged when compared with region A, except for class 4 (4–6 years old) in region B, which did not show the mean difference with class 3 (4–6 years old) in region A.

Table 4. Tukey multiple comparisons of mean test at 95% family-wise confidence level.

Interaction	diff	lwr	upr	*p* adj
B−A	8.311	7.054	9.569	0.000
A−1−A−2	16.374	11.042	21.706	0.000
A−1−A−3	18.855	15.007	22.703	0.000
A−1−A−4	16.862	13.364	20.360	0.000
A−1−A−5	38.895	36.034	41.755	0.000
A−1−A−7	259.966	228.805	291.127	0.000
B−1−A−1	−9.927	−19.221	−0.632	0.024
B−1−A−2	11.067	5.440	16.693	0.000

Table 4. *Cont.*

Interaction	diff	lwr	upr	*p* adj
B−1−A−3	19.071	9.354	28.789	0.000
B−1−A−4	48.757	41.715	55.800	0.000
B−1−A−5	49.899	46.763	53.035	0.000
B−1−A−7	208.398	187.463	229.333	0.000
A−2−A−3	2.481	−3.215	8.177	0.959
A−2−A−4	0.488	−4.977	5.954	1.000
A−2−A−5	22.521	17.440	27.602	0.000
A−2−A−7	243.592	212.149	275.035	0.000
B−2−A−1	−26.300	−36.499	−16.101	0.000
B−2−A−2	−5.307	−12.328	1.714	0.359
B−2−A−3	2.698	−7.888	13.284	1.000
B−2−A−4	32.384	24.184	40.583	0.000
B−2−A−5	33.525	28.284	38.767	0.000
B−2−A−7	192.024	170.673	213.376	0.000
A−3−A−4	−1.993	−6.024	2.039	0.904
A−3−A−5	20.040	16.548	23.532	0.000
A−3−A−7	241.111	209.886	272.337	0.000
B−3−A−1	−28.781	−38.289	−19.274	0.000
B−3−A−2	−7.788	−13.761	−1.816	0.001
B−3−A−3	0.217	−9.705	10.138	1.000
B−3−A−4	29.903	22.581	37.225	0.000
B−3−A−5	31.045	27.323	34.766	0.000
B−3−A−7	189.543	168.513	210.574	0.000
A−4−A−5	22.033	18.930	25.135	0.000
A−4−A−7	243.104	211.920	274.288	0.000
B−4−A−1	−26.789	−36.160	−17.417	0.000
B−4−A−2	−5.795	−11.549	−0.042	0.046
B−4−A−3	2.209	−7.582	12.001	1.000
B−4−A−4	31.895	24.751	39.040	0.000
B−4−A−5	33.037	29.679	36.396	0.000
B−4−A−7	191.536	170.567	212.505	0.000
A−5−A−7	221.071	189.952	252.190	0.000
B−5−A−1	−48.821	−57.974	−39.669	0.000
B−5−A−2	−27.828	−33.217	−22.439	0.000
B−5−A−3	−19.823	−29.405	−10.241	0.000
B−5−A−4	9.863	3.008	16.717	0.000
B−5−A−5	11.005	8.317	13.692	0.000
B−5−A−7	169.503	148.631	190.375	0.000
B−7−A−1	−269.892	−302.244	−237.541	0.000
B−7−A−2	−248.899	−280.393	−217.405	0.000
B−7−A−3	−240.894	−273.370	−208.419	0.000
B−7−A−4	−211.209	−242.986	−179.431	0.000
B−7−A−5	−210.067	−241.212	−178.921	0.000
B−7−A−7	−51.568	−88.964	−14.172	0.000
B−1−B−2	20.993	10.637	31.349	0.000
B−1−B−3	28.998	15.959	42.037	0.000
B−1−B−4	58.684	47.495	69.873	0.000
B−1−B−5	59.826	50.583	69.068	0.000
B−1−B−7	218.325	195.656	240.993	0.000

Table 4. *Cont.*

Interaction	diff	lwr	upr	*p* adj
B−2−B−3	8.005	−2.733	18.742	0.381
B−2−B−4	37.691	29.297	46.085	0.000
B−2−B−5	38.833	33.292	44.373	0.000
B−2−B−7	197.331	175.904	218.759	0.000
B−3−B−4	29.686	18.143	41.228	0.000
B−3−B−5	30.828	21.160	40.496	0.000
B−3−B−7	189.327	166.482	212.172	0.000
B−4−B−5	1.142	−5.832	8.116	1.000
B−4−B−7	159.641	137.799	181.482	0.000
B−5−B−7	158.499	137.587	179.410	0.000

Region: A, B; Age classes: 1−5.

4. Discussion

This study proposed using the national land use and land cover system (TerraClass) to classify secondary forest age and to estimate the aboveground biomass accumulation in the Amazon region (Pará state). The results emphasized the need for mapping and understanding the dynamics of secondary forests in the regional carbon balance. The dynamics of the LULC changes in tropical regions shift the carbon balance. Furthermore, the knowledge of aboveground biomass dynamics in secondary forests in the context of changes in LULC has an essential role in the global carbon cycle [5,35,36] and needs to be further investigated.

Pará's eastern region has had municipalities with great economic activity in logging activities and forest management since the 1960s. With the decline in wood activity, the agricultural frontier expanded, mainly with monocultures such as soy and pasture areas. As of 2008, a few municipalities adopted policies to reduce the environmental impact of the economic activities, which led to a decline in deforestation for the first time in the history of Pará state [31].

According to the biennial report of the Green Municipalities Program 2013−2014 [37], the reasons for the reduction in deforestation were: (i) the restriction on rural credit, (ii) the list of embargoed areas, (iii) the list of municipalities that most deforested the Amazon due to the imposition of various administrative restrictions in these municipalities, (iv) the accountability in the meat production chain; and, last but not least, (v) the strengthening inspection operations. However, in 2008 about 45% of the municipality's natural vegetation area had already been deforested [38].

We performed the hot spot analysis to test the CRS. The spatial distribution patterns of the secondary forests did not present CRS, although the occurrence of secondary forests was mostly along the main roads and harbors, regions where the old-growth forest had historically been deforested. The spatial distribution of secondary forest might be influenced by climate [7,36], the history of LULC [27,39] and other environmental factors [40,41].

The net balance of the secondary forest demonstrated the need for forest management improvement. In Pará state, there were municipalities that had already deforested almost all of their old-growth forests; therefore, they sought resources from other LULC such as secondary forests. The need to protect secondary forests is something that has to be discussed in different spheres of society, and its loss can occur for several reasons, even due to the lack of an official definition of when a forest begins to be considered as secondary forest [2].

Moreover, the result obtained using the proposed method corroborated with what was found in the literature [6], where in secondary forests in the neotropical region, different amounts of aboveground biomass accumulated in distinct areas. Secondary forests sequester carbon as one of its ecological functions. Some studies state that secondary forests can sequester carbon in tropical regions up to 20 times faster than old-growth forests. These studies indicate that the pressures influencing carbon sequestration vary within sites, age, environmental conditions, and regrowth rates [7,42,43]. These findings show the importance of monitoring secondary forest sites in the Amazon region. However, the old-growth forests are still the most important driver in the Brazilian Amazon carbon balance [22,24].

In general, region B, located in western Pará, accumulated more aboveground biomass compared to region A (eastern Pará). A recent study found that young secondary forests (<20 years old) from the western Amazon regions absorb ~60% higher rates when compared to the eastern regions [7]. The drivers of the aboveground biomass changes were usually explained by previous land use [27,39], age [2,15,26] environmental factors [7,40,44] and mainly the climate, which could influence the occurrence and the quality sites of secondary forests, and thus impact the aboveground biomass accumulation [7].

In the Amazon, previous land use and land cover may have a negative impact on the secondary forest aboveground biomass if the area has suffered repeated burning events. The growth rate can also be affected by the LULC history [39]. The history of LULC also has an impact on the aboveground biomass estimates. A study conducted in the Amazon using L-band Synthetic Aperture Radar found that the LULC history information explained 71% of the AGB when used in the input model [27]. Furthermore, the LULC information is crucial in determining the secondary forest age using cartographic modeling, and for consideration in discussions of the aboveground biomass accumulation in different sites.

Secondary forest age has been considered as one of the most important variables influencing aboveground carbon in the BLA [2,7]. The age may affect the rates that secondary forests in tropical regions can accumulate carbon. The younger secondary forests have higher aboveground biomass rate variation [5,29], but as the forest succession process occurs these rates are downgraded [25]. Thus, mapping the secondary forest age allows further investigation into the accumulation of the aboveground biomass. In our study, the data limitation did not allow us to investigate longer time series and estimate aboveground biomass for a higher range of secondary forest ages. Therefore, improving LULC mapping is an important tool to estimate age in the longer time series and to explore more information about the secondary forests.

Further, as the secondary forests are not officially protected by any specific Brazilian environmental legislation, national monitoring systems such as TerraClass and MapBiomas are crucial for surveying the data and beginning new discussions on the environmental panel. This would also benefit the Brazilian Amazon by reducing the emissions from deforestation and forest enhancements (REDD+) programs improving forest carbon stocks, following the Intergovernmental Panel on Climate Change (IPCC) [45–47]. On the other hand, it is unusual to have dense airborne LiDAR data available in the Amazon region or repeated acquisitions to monitor the changes in the forest structure, which makes it difficult to estimate AGB with high spatial resolution and monitoring efforts for REDD+ [48].

New data products and sensors with a high potential to estimate biomass, such as the Global Ecosystem Dynamics Investigation (GEDI) [49] and the Biomass European Space Agency's forest mission [50] with active sensors, are able to measure the structure of the forest and have a huge potential to monitor the forest carbon and contribute to the IPCC reports. To attend to the demands of REDD+ with the results based on actions fully measured, reported and verified (MRV), we need to have a better understanding of the spatial distribution of the forests and local data to calibrate the estimates. Here, we presented two pilot areas with restricted data that have the potential to upscale using orbital sensors and have continuous monitoring if related to temporally continuous data. These areas can also assist aboveground biomass estimation models for secondary forests.

5. Conclusions

The land use and land cover monitoring system revealed cold and hot spots in the distribution of the secondary forest in Pará state. Although the balance of the secondary forests was positive, the gains and losses varied over the period studied. In addition, the aboveground biomass accumulation differed according to the secondary forest ages during the study period as evaluated in the two pilot areas. As the old-growth forest was cleared in the Brazilian Amazon, the new LULC changes were mostly used for agriculture and pasture, then after years of exploring these LULC, new secondary forests regenerated from those areas. For this reason, new environmental legislation and official monitoring systems are crucial to develop strategies to protect the secondary forests in the Brazilian Amazon.

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