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Looking beyond forest cover: an analysis of landscape-scale predictors of forest degradation in the Brazilian Amazon

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Abstract

While forest degradation rates and extent exceed deforestation in the Brazilian Amazon, less attention is given to the factors controlling its spatial distribution. No quantified correlation exists between changes of forest structure due to anthropogenic disturbances and dynamics of land use and cover change occurring at broader spatial levels. This study examines the influence of multi-scale landscape structure factors (i.e. spatial composition, configuration and dynamic of land use/cover) on primary forest's aboveground biomass (AGB), spanning from low to highly degraded, in Paragominas municipality (Pará state). We used random forest models to identify the most important landscape predictors of degradation and clustering methods to analyze their distribution and interactions. We found that 58% of the variance of AGB could be explained by metrics reflecting land use practices and agricultural dynamics around primary forest patches and that their spatial patterns were not randomly distributed. Forest degradation is mainly driven by fragmentation effects resulting from old deforestation and colonization events linked with cropland expansion (e.g. soybean and maize) coupled with high accessibility to market. To a lesser extent, degradation is driven by recent and ongoing (1985–2015) deforestation and fragmentation in slash-and-burn agricultural areas, characterized by heterogeneous mosaics of pastures and fallow lands combined with high use of fire. Our findings highlight the potential of landscape-level framework and remotely sensed land cover data for a thorough understanding of the distribution of forest degradation across human-modified landscapes. Addressing these spatial determinants by looking at agricultural dynamics beyond forest cover is necessary to improve forest management which has major implications for biodiversity, carbon and other ecosystem services.

1. Introduction

Forest degradation provokes a reduction in the capacity of the forest to provide goods and services (Vásquez-Grandón *et al* 2018). It denotes damages in structure, composition and function with no change in land use (Putz and Redford 2010, Morales-Barquero *et al* 2014). Forest degradation accounts for 68.9% of overall carbon losses from tropical forests (Baccini *et al* 2017) and impacts biodiversity (Broadbent *et al* 2008, Barlow *et al* 2016) and ecosystem services, especially related to hydrological

and soil properties and non-timber forest resources (Thompson *et al* 2009, Lewis *et al* 2015). Forest degradation often exceeds deforestation such as in the Brazilian Amazon (respectively 337 427 km^2 vs 308 311 km^2 from 1992 to 2014; Matricardi *et al* 2020). However, unlike drivers of deforestation which have long been studied (Geist and Lambin 2002, Curtis *et al* 2018, de Sy *et al* 2019), our current understanding of the drivers of forest degradation appears limited to implement urgently needed sustainable forest management and land-use planning that both ensure climate change mitigation (Malhi *et al* 2014) and conservation/restoration of ecosystem functions and biodiversity (Nelson *et al* 2006, Goldstein 2014).

Most remote sensing studies on forest degradation focused on pixel-based mapping and monitoring of disturbances in forested areas (e.g. unsustainable logging and understory fires; Asner *et al* 2009, Souza *et al* 2013, Wang 2019, Bullock *et al* 2020). Yet, forest degradation also results from surrounding land change dynamics that shaped landscapes into complex land use mosaics where remaining primary forests (i.e. forests that have never been cleared) span from conserved to highly degraded (Longo *et al* 2016, Rappaport *et al* 2018). Indeed, forest degradation is non-randomly distributed (Matricardi *et al* 2020) in hotspots (Baccini *et al* 2017) corresponding to agricultural frontiers with high rates of deforestation, habitat fragmentation and infrastructure development (Tyukavina *et al* 2016). In this regard, scientific knowledge on the influence of landscape structure (i.e. composition and configuration of land cover/use) on the status of remaining forests remains scattered and incomplete.

A large body of literature focuses on the relationship between degradation and deforestation pattern, emphasizing the importance of fragmentation that increases edge effects and decreases forest fragment size (Hansen *et al* 2020). Almost 20% of tropical forests are within 100 m of a non-forest edge (Haddad *et al* 2015, Brinck *et al* 2017). This edge effect reduces the amount of carbon stored at forest edges from 25% lower within the first 500 m up to 10% reduction within the first 1.5 km (Chaplin-Kramer *et al* 2015). Age of forest edges and fragment size also significantly influence canopy structure and aboveground biomass (AGB) (Shapiro *et al* 2016, Almeida *et al* 2019, Ordway and Asner 2020, Silva Junior *et al* 2020). Fragmentation impacts the status of remaining forest patches as it facilitates accessibility to forest resources (Asner *et al* 2005, Broadbent *et al* 2008) but also increases the flow of disturbances from the surrounding landscape, leading to higher tree mortality. For instance, wind increases canopy desiccation or fire frequency (Broadbent *et al* 2008, Briant *et al* 2010, Laurance *et al* 2011).
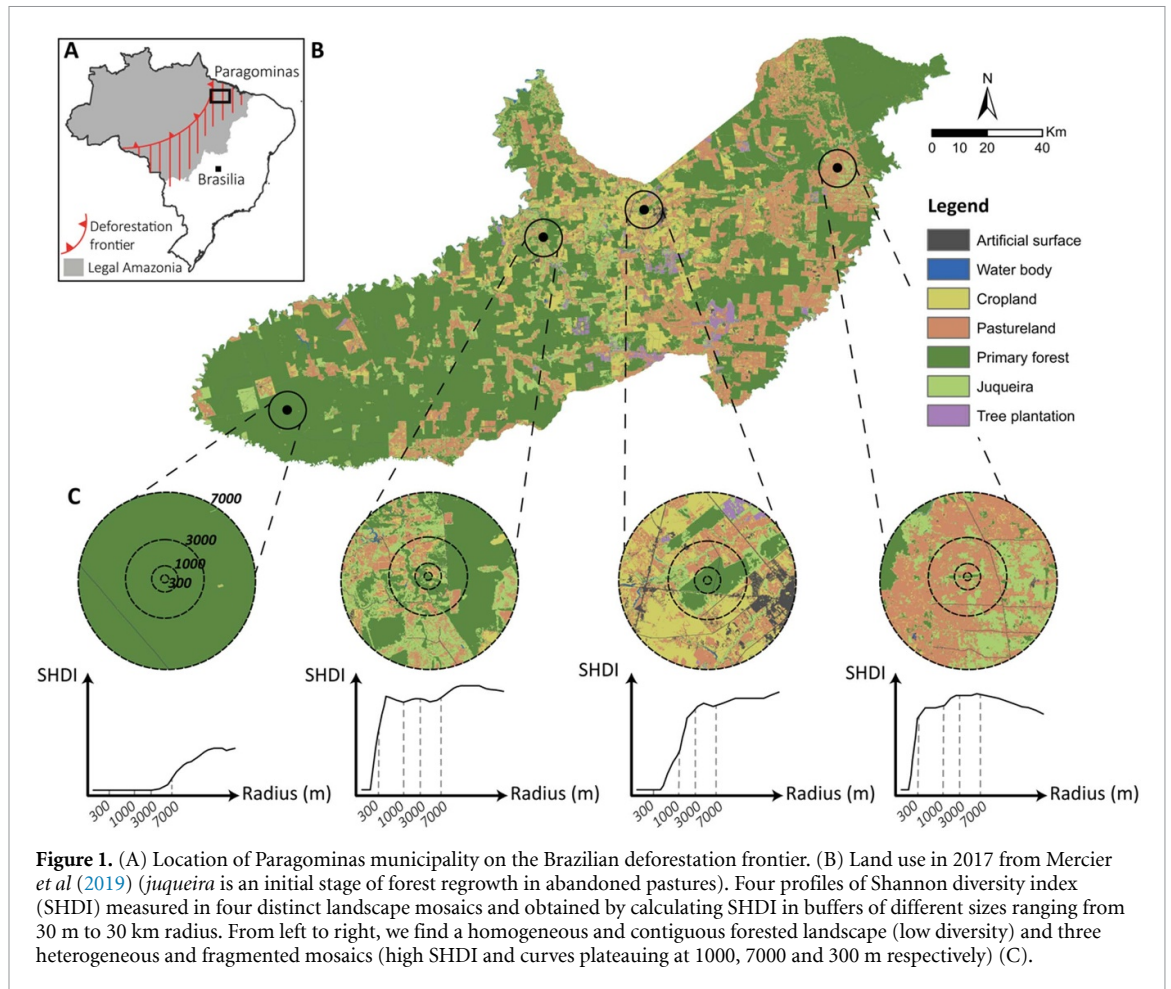
Fragmentation studies rarely consider land use dynamics in the surrounding of forest patches, thus preventing the integrative understanding of exogenous pressures (Ordway and Asner 2020). Yet, land use conflicts between the protection of forest resources and growing pressure from the agricultural sector may trigger severe forest degradation, especially in areas where agricultural expansion is strictly limited (Nepstad *et al* 2008). In addition, agricultural land management through specific agricultural practices may influence forest status (e.g. fire used in slash-and-burn agriculture or in pastureland management affecting proximate forest structure). As a consequence, there is a poor understanding of the impacts of landscape structure and dynamic resulting from land use planning decisions, feedback loops and legacy effects on forest degradation. We consider this may be due to the lack of a landscape-level framework that encompasses complex anthropogenic gradients of degradation while existing frameworks only focus on natural variation of forest structure (Melito *et al* 2017).

This study aims at assessing the performance of spatially explicit metrics of landscape structure and dynamics to explain the spatial distribution of forest degradation. The definition of degradation is restricted in this study to the changes in AGB within remaining forest patches following anthropogenic disturbances. Landscape structure relates to the composition (the relative proportion of habitat types) and the spatial configuration (the spatial arrangement of these habitat) of a given area. The landscape dynamic refers to land use and land cover changes as a result of agricultural expansion. We first identify and examine the influence of landscape structure and dynamic metrics on forest degradation at multiple scales and then analyze the spatial distribution of these metrics and their interdependencies.

2. Study area

The study area is the municipality of Paragominas located in the northeastern part of Pará State (figure 1). The municipality is located in the deforestation frontier and comprises 19 342 km^2 with a total population of 108 547 inhabitants (IBGE 2018). The eastern part of the municipality includes an indigenous reserve. The western part is covered by forests logged by the CIKEL Brasil Verde Madeiras Ltda private company. Smallholders mainly practicing subsistence agriculture (cassava) but also small-scale cattle breeding, cash crops cultivation (pepper) and açai extraction (Laurent *et al* 2017a) can be found in the eastern and northern parts of the municipality. The progress of the pioneer frontier was based on successive development cycles (cattle ranching in the 1960s, the logging industry boom in the 1980s and the agribusiness expansion in 2000s). That resulted in a heterogeneous landscape mosaic ranging from preserved to highly degraded forests associated with different land uses, mainly pasture and crop commodities, including soybean and maize (Piketty

Figure 1. (A) Location of Paragominas municipality on the Brazilian deforestation frontier. (B) Land use in 2017 from Mercier *et al* (2019) (*juqueira* is an initial stage of forest regrowth in abandoned pastures). Four profiles of Shannon diversity index (SHDI) measured in four distinct landscape mosaics and obtained by calculating SHDI in buffers of different sizes ranging from 30 m to 30 km radius. From left to right, we find a homogeneous and contiguous forested landscape (low diversity) and three heterogeneous and fragmented mosaics (high SHDI and curves plateauing at 1000, 7000 and 300 m respectively) (C).

et al 2015, Viana *et al* 2016, Bourgoin *et al* 2018, Mercier *et al* 2019). Since 2008, the municipality is involved in a green development agreement that aims to improve land and environmental regularization with a focus on reducing forest encroachment. However, forest degradation continues to exert increasing pressure on the remaining primary forests through unsustainable selective logging and fires (Hasan *et al* 2019, Bourgoin *et al* 2020a).

3. Materials and methods
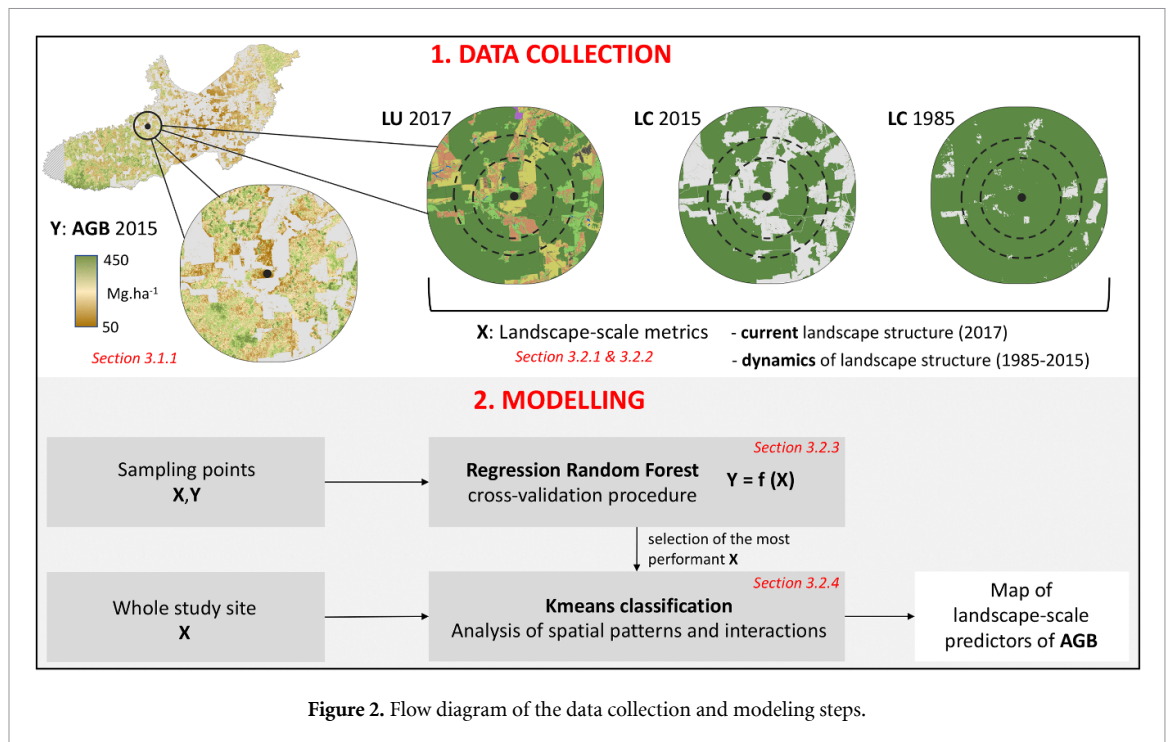
3.1. Materials
3.1.1 2015 map of AGB
We used the AGB of primary forest as indicator of forest degradation (Gao *et al* 2020) and as response variable (Y) in our statistical analyses. We used the AGB map from Bourgoin *et al* (2018) since it provides spatial information on the state of forest structure in 2015 resulting from the accumulation of anthropogenic disturbances over time at 20 m spatial resolution (figure 2). It was produced from multi-source remote sensing and calibrated using *in-situ* field inventory AGB data sampled along gradients of undisturbed, selectively logged and/or burned forests (Berenguer *et al* 2014). A total of 21 000 AGB plots were allocated using a stratification random sampling

approach in order to capture the diversity of primary forest status, from highly degraded (<180 Mg ha^{-1}), degraded (180–300 Mg ha^{-1}) and low degraded (>300 Mg ha^{-1}). We extracted the geographical position of each sampled plots and the average value of AGB within 4×4 pixels radius to minimize local variations.

3.1.2. Land use/cover maps
Current land use was obtained using a supervised random forest (RF) classification that strictly followed the methodology by Mercier *et al* (2019). We used 2017 Landsat images (preprocessed to surface reflectance, presenting less than 10% cloud cover, and acquired in the dry season) and 328 field sample points acquired in September 2017 in different locations in the municipality to train and validate the classification model (see Mercier *et al* 2019 and appendix 1 and 2 (available online at stacks.iop.org/ERL/16/114045/mmedia)). The land uses classification discriminated seven classes: artificial surfaces, water bodies, croplands, pasturelands, tree plantations, primary forests and *juqueira* land uses (initial stage of regrowth in abandoned pastures) and revealed an overall accuracy of 0.87 and kappa index of 0.86 (more details in appendix 3). Due to the lack of field data to produce historical classifications using

Figure 2. Flow diagram of the data collection and modeling steps.

archived Landsat images, we used forest-non forest classifications in 1985, 1995, 2005 and 2015 (key years of main cycles of socio-economic development) from the Brazilian Land Cover and use Collection 5.0 Map Series of the MapBiomas project (Souza *et al* 2020).

3.2. Methods

We developed a two-steps approach to explore the relationships between forest degradation and landscape structure and dynamics (figure 2). First, we measured AGB in sampling points of primary forests in 2015 and calculated metrics of structure and dynamics of the landscape in buffers around each sampling point. We defined four different buffer sizes around each sampling point (i.e. landscape scales). These buffers are named hereafter 'landscape-scale metrics'.

In a second step, we modeled the AGB with the data extracted from the buffers. The modeling had two main objectives. First, we applied RF regression models to (a) identifying and examining the influence of landscape-scale metrics on forest degradation at multiple scales. Then, we applied a kmeans unsupervised classification to (b) analyzing the spatial distribution of these metrics and their interdependencies.

3.2.1. Defining landscape scales of analysis

Landscapes are complex mosaics of land use/cover elements with specific spatial heterogeneity (HET). They result from various human-environment processes and interactions acting at different scales (Burel and Baudry 2003, Messerli *et al* 2009). To define appropriate landscape scales, we calculated the Shannon diversity index (SHDI) based on 2017 land use map in ten different regions throughout the study

area and spanning along gradients of land use intensity (e.g. forest dominated landscapes, small/large scale agriculture dominated landscapes, mosaic landscapes). SHDI allow to measure the diversity of landscape elements in a given area (Burel and Baudry 2003). SHDI were calculated in buffer zones whose radius ranged from 30 m to 30 km around each region of interest. We estimated the plateauing of the average curve based on the resulting profiles of SHDI (figure 1). Depending on specific land use history and current landscape structure, we recorded four different distances where no further spatial HET was captured by the SHDI metric (i.e. four distinct saturation points). These saturation points are observed for buffer radius of 300 (L1), 1000 (L2), 3000 (L3) and 7000 (L4) meters for respectively highly fragmented elements and low diverse mosaics up to heterogeneous mosaics composed of larger elements. These four distances were used as landscape scales, ranging from L1 to L4, for the landscape analysis.

3.2.2. Landscape metrics

We computed landscape-scale metrics surrounding AGB sampled plots at the four landscape scales using Chloe 4.0 (Boussard and Baudry 2017) (table 1). Metrics based on the 2017 land use classification characterized current agricultural practices based on the concepts of HET, connectivity and fragmentation of forest-agricultural mosaics (Burel and Baudry 2003). Metrics calculated from each historical land cover classification were merged into a single variation metric that combined the amplitude between 1985 and 2015 with the average at each date of the analysis. Variation metrics characterize deforestation and fragmentation dynamics (Wang *et al* 2014). These

Table 1. Landscape-scale metrics as indicators of landscape structure and dynamics.

Metrics of current landscape structure—reflects current agricultural practices

Metric name	Abbreviation	Formula	Rationale
Proportion of land use (LU) type 'i'	Proportion LU i (e.g. proportion cropland)	$p(i)$ = percentage of pixels of land use type 'i'	Metric of landscape composition
Interface between paired land uses i and j	Interface LU i/LU j (e.g. interface forest/cropland)	$p(i,j)$ = percentage of edge pixels between paired land use types 'i' and 'j'	Metric of landscape configuration between two specific land uses
Landscape heterogeneity	Heterogeneity	With $i \neq j$	Synthetic metric of landscape configuration reflecting the heterogeneity of a given landscape limited only to non-homogeneous couples of land use (Burel and Baudry 2003)

Metrics of landscape structure dynamics—reflects deforestation and fragmentation dynamics

Metric name	Abbreviation	Formula	Rationale
Variation of primary forest proportion	Variation Forest	Variation in the percentage of pixels of forest between date $t1$ and $t2$	Metric of change in the landscape composition of primary forest. Reflects deforestation dynamic.
Variation of primary forest-non forest interface length	Variation interface	Variation in the percentage of edge pixels between forest and non-forest between $t1$ and $t2$	Metric of change in the landscape configuration. Reflects fragmentation through the dynamic of forest edge length.
Variation of primary forest patch aggregation	Variation aggregation	Variation in the aggregation between $t1$ and $t2$. Aggregation = with ni = number of pairs of adjacent forest pixels	Aggregation is the ratio between the number of pairs of adjacent forest pixels and the number of pairs in case all forest pixels are gathered in a compact form. Reflects fragmentation through forest patches isolation.
Variation of primary forest number of patches	Variation number patches	Variation in the number of patches between $t1$ and $t2$.	Metric of change in the landscape configuration. Reflects fragmentation though the increase in the number of patches.
Variation of mean primary forest patch size	Variation mean patch size	Variation in the mean patch size between $t1$ and $t2$.	Metric of change in the landscape configuration. Reflects fragmentation though the decrease in mean patch size.

metrics calculated at the four landscape-scales are used as input (i.e. explanatory variables) in the RF models.

3.2.3. Regression analysis: identifying landscape-scale predictors of forest degradation

We used RF regression models to better understand the potential relationship between the selected landscape-scale metrics and forest AGB (Breiman 2001). This modeling approach was selected for its predictive performance, its build-in measures to rank the relative importance of explanatory variables. As a matter of fact, such approaches have been frequently adopted to explore drivers of tropical deforestation (Zanella *et al* 2017, Bax and Francesconi 2018). RF model grows multiple trees (500 trees in our study) by randomization of data subsampling to improve the predictive power of regression and to limit overfitting (Liaw and Wiener 2002). The number of variables used for tree nodes splitting were randomly

determined using the tune function implemented in the R randomForest package, version 4.6–14.

A set of 50 pairs of training and validation sets were randomly selected from the database with a 70/30 ratio. Incremental regression analyzes quality as the type and number of variables used are added, thus, determining at what combination and number of variables the regression reaches an acceptable quality (Mercier *et al* 2019). For each pair, a RF model was applied to all the variables (i.e. multi-scale metrics of current and historical landscape structure) to rank them in order of importance based on the increase in mean-squared error (percentage of IncMSE), which quantifies how much MSE increases when each independent variable is randomly permuted. This error measures the relative importance of each variable, where a low IncMSE implies that the variable does not have much weight on the model prediction and vice-versa (Mascaro *et al* 2014). The rank of importance of each variable was derived by adding up

all the 50 ranks obtained from the 50 pairs of training and validation samples. We then ran RF starting with the two most important variables and then adding the less important variables until the top 20 features was processed. The determination coefficient (R^2) and root mean square error (RMSE) were calculated for each regression to evaluate the performance of the models. Two outputs of the incremental regression—ranking of the 20 most important variables and mean R^2 and RMSE according to number of variables—were used to select the relevant variables (called hereafter 'landscape-scale predictors') to use in the final model (50 cross-validation of RF regression). Analysis of partial dependence plots for each of the landscape-scale predictors was carried out to estimate its direction and magnitude on the forest AGB variable.

3.2.4. Cluster analysis: distributions and interactions analysis of landscape-scale predictors

We analyzed the spatial variability and interdependencies between the landscape-scale predictors of forest degradation identified in the previous step. Cluster analysis by kmeans was used to identify areas with similar sets of landscape-scale predictors. The optimal number of clusters was identified using the elbow method, which calculates the total intra-cluster variation or total within-cluster sum of squares (WSS) for a range of cluster sizes varying from 1 to 15 (Charrad *et al* 2014). Principal component analysis (PCA) in R was also used to analyze quantitatively the variation and interdependencies in all landscape-scale predictors across the study area. Finally, we analyzed the distribution of infrastructure development, agricultural and environmental factors within each cluster. Infrastructure development are the distance to market (Euclidean distance to Paragominas city) and the road network (derived from OpenStreetMap). The proxy for modeling agricultural practices is the fire occurrence between 2000 and 2018 from MODIS fire products MOD14A2 and MYD14A2 (Giglio *et al* 2016). Environmental factors are elevation (SRTM 90 m Digital Elevation Database v4.1; Jarvis *et al* 2008) and soil texture separated into clay (fertile soils) and loamy sand (less suitable for agriculture; Laurent *et al* 2017b).

4. Results

4.1. Identification of landscape-scale predictors of forest degradation

The incremental regression provided ranking of the most explanatory and robust variables over the 50 RF model iterations. Figure 3(A) shows the average percentage of IncMSE for the top 20 landscape metrics. Most of the explanatory variables characterized the L4 buffers. It performed best to capture landscape structure and dynamic in the study area.

The variable selection procedure ranked the proportion of cropland measured at L4 buffers (7000 m of radius) as the top ranked variable, i.e. the most robust and explanatory landscape composition metric. We found two specific landscape configuration metrics (length of interfaces between forest and pastureland and between forest and juqueira) and three metrics of landscape dynamics that capture fragmentation (variation of interface, variation of the number of forest patches and variation of mean patch size) and deforestation (variation of forest cover proportion). Aggregation metrics ranked lower but still showed effects on AGB. Similarly, metrics similar than the top ranked ones but processed at L3 scale affected the AGB. The only metric calculated at the L1 scale was the overall landscape HET which captures at that scale forest edge effects on AGB values.

Figure 3(B) shows the R^2 increasing from 0.36 using the top two variables to 0.58 using six variables (vertical dashed line). After that, adding variables, up to 15 variables contributed to increase slightly the R^2 until its stabilization over 0.6. The RMSE curve dropped from 0.56 to 0.45 (six input variables) and then continued to slightly decrease but globally stabilized around 0.44 Mg ha^{-1}. Six variables is therefore the minimum number of input variables statistically required to get the smallest model that fits the data and optimize the bias-variance trade-off.

The final RF model was built on the six most explanatory variables. The final model showed that 58% of the variance in forest AGB could be explained with a RMSE of 45.66 Mg ha^{-1} (table 2). The low standard deviation of R^2 (0.006) and RMSE (0.35 Mg ha^{-1}) shows the robustness of the model performance over the 50 cross-validation procedures.

Among the six selected variables, the proportion of cropland and the interface length between forest/-pastureland were identified as the most important landscape-scale predictors, reflecting the current landscape composition and configuration (figure 4(A)). In terms of landscape dynamics, the variation of the number of forest patches and forest/non-forest edge length reflecting fragmentation were more explanatory than deforestation measures alone (average of 155 and 85 in % of IncMSE respectively). Partial dependence plots were generated to interpret the effect of single variables on forest AGB (figure 4(B)). They show that AGB decreases as the proportion of cropland, the interface length between forest/pastureland and forest/juqueira increase with an absence of negative influence (plateauing) when high values of these variables are reached. We also found that an increase in deforestation triggers a decrease in AGB of remaining forest patches. The variation in forest/non forest edge length and number of forest patches also triggers a sharp decrease in AGB.
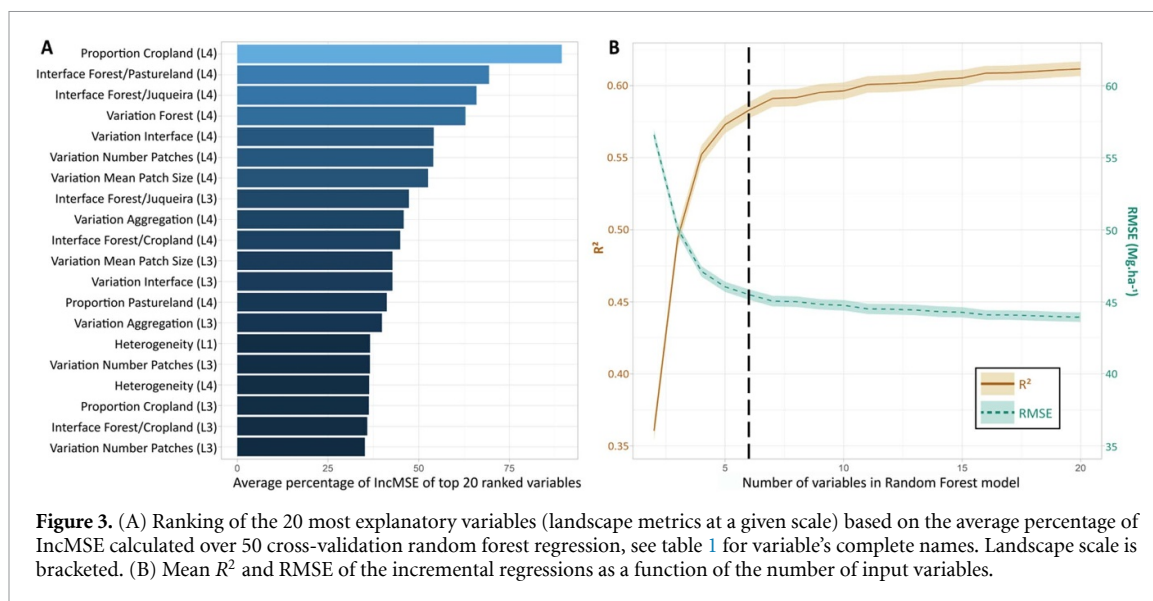
Figure 3. (A) Ranking of the 20 most explanatory variables (landscape metrics at a given scale) based on the average percentage of IncMSE calculated over 50 cross-validation random forest regression, see table 1 for variable's complete names. Landscape scale is bracketed. (B) Mean R^2 and RMSE of the incremental regressions as a function of the number of input variables.

Table 2. Average and standard deviation of the global model performance with the six most important landscape metrics and over the 50 datasets.

	Average	Standard deviation
R^2	0.58	0.006
RMSE (Mg ha^{-1})	45.66	0.35
rRMSE	0.65	0.005

4.2. Spatial patterns and interactions among landscape-scale predictors

The spatial distribution of landscape-scale predictors of forest degradation show that these predictors were clumped on the study area rather than being randomly distributed (figures 5(a)–(f)). The proportion of cropland (figure 5(a)) is strongly related with forest degradation in the central corridor of Paragominas. The longest interface length between forest/pastureland (figure 5(b)) are found in the eastern and central southern regions, whereas the longest interface length between forest/juqueira are found mainly in the eastern and central northern regions (figure 5(c)). The eastern region overlaps increased the most with areas where the fragmentation variables (variation interface, figure 5(e); and variation of the number of patches, figure 5(f)). Forest variation (figure 5(d)) mostly increased in the eastern part and the western edge of the central corridor while the extreme eastern and western forest landscapes of the study area were better preserved.

Cluster analysis resulted in the creation of five data clusters (corresponding to the location of a bend in the WSS curve), representing five bundles of landscape-scale predictors (see appendix 4 for more details). The five clusters were also geographically clustered on the municipality in distinct areas demonstrating that the landscape-scale predictors act as complementary factors (figure 5).

These interactions are confirmed by the PCA results. Principal component 1 (explaining 51% of the variance) corresponded to an axis that varied from highly deforested and fragmented to undisturbed forested landscape (the higher the values, the less variation in forest proportion). These two dynamics show high correlation with metrics of current landscape configuration. Principal component 2 (explaining 22% of the variance) was only influenced by the current proportion of cropland variable which traduced landscapes dominated by cropland and having no influence from deforestation and fragmentation since 1985. The five clusters of landscape-scale predictors are organized along these two gradients.

- Cluster 1 comprises heterogenous landscapes (combine long forest/pastureland and forest/juqueira interfaces), fragmented landscape (variation interface and variation number patches) and deforested landscapes (variation forest). Landscapes of cluster 1 are located in two distinctive areas of the eastern part of the municipality (figure 5, lower panel).
- Cluster 2 comprises landscapes which are quite similar to cluster 1 except that they are slightly less heterogeneous, fragmented and deforested. Landscapes of cluster 2 are located at the edge of the whole cluster 1 and in four other distinct areas in the central and southern areas of the municipality.
- Cluster 3 comprises landscapes with high crop proportion, moderate HET (between forest, pasture and juqueira), moderate fragmentation and low deforestation. Landscapes of this cluster dominate the central zone of the municipality (Laurent *et al* 2017b).
- Cluster 4 comprises landscapes with no fragmentation, moderate HET (between forest, pasture and juqueira) and low deforestation. Landscapes of
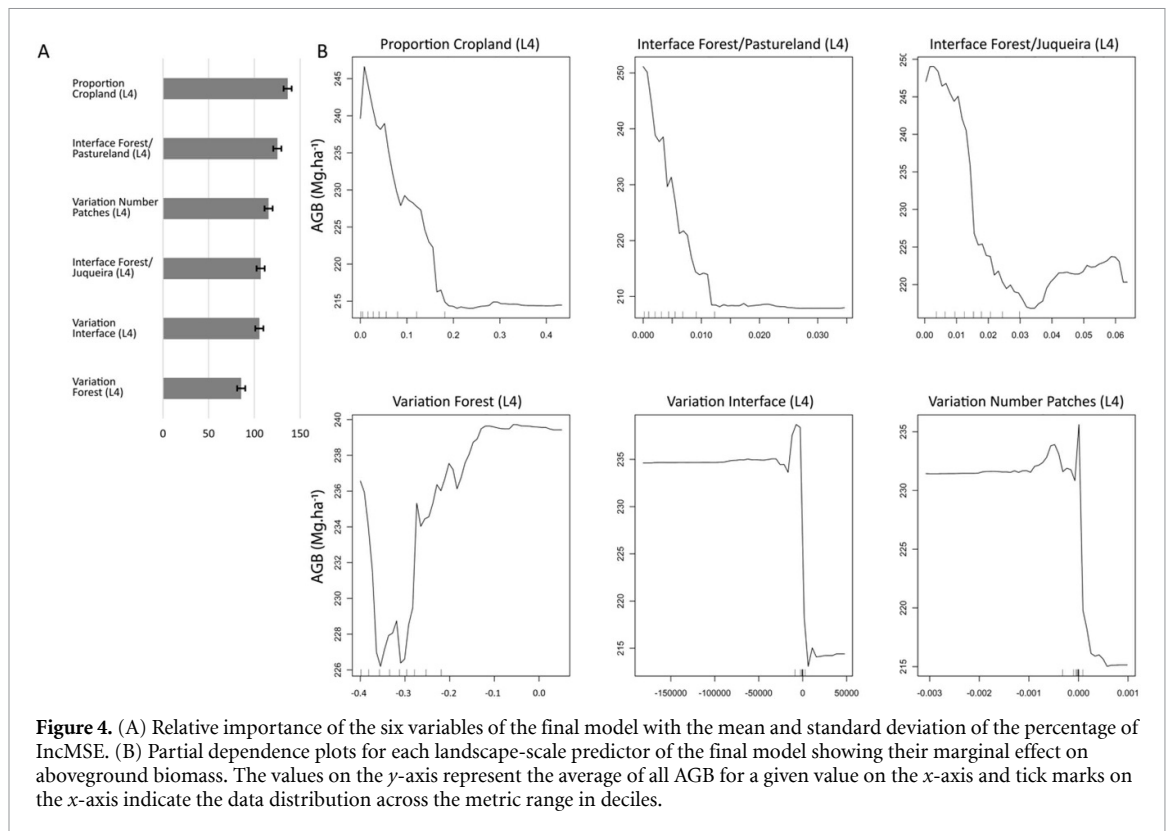
Figure 4. (A) Relative importance of the six variables of the final model with the mean and standard deviation of the percentage of IncMSE. (B) Partial dependence plots for each landscape-scale predictor of the final model showing their marginal effect on aboveground biomass. The values on the *y*-axis represent the average of all AGB for a given value on the *x*-axis and tick marks on the *x*-axis indicate the data distribution across the metric range in deciles.

cluster 4 are the most dominating and widespread landscapes from the east to the west of the municipality.

- Cluster 5 comprises landscapes with no agriculture, no HET, no fragmentation and no deforestation. Landscapes of cluster 5 are mostly located in the extreme western and eastern regions of the municipality.

Landscapes grouped within cluster 3 are significantly closer to the market while landscapes in cluster 5 are significantly further than the other clusters (figure 6). Any cluster showed statistically significant trend in the distance to the road network. Fire occurrence between 2000 and 2018 is significantly higher (two fires in average) in landscapes of cluster 1 and in lesser amount for clusters 2 and 3. Fire occurrence is however absent in clusters 4 and 5. Cluster 3 corresponds to landscapes located in higher elevation areas where soil texture is significantly more dominated by clay which indicates higher soil fertility.

5. Discussion

5.1. How do landscape patterns predict forest degradation?

Most forest degradation across Paragominas is driven by fragmentation effects resulting from old deforestation and colonization events linked with cropland expansion (e.g. soybean and maize) coupled with high accessibility to market. To a lesser extent, degradation is driven by recent and ongoing (1985–2015)

deforestation and fragmentation in slash-and-burn agriculture areas, characterized by heterogeneous mosaics of pasturelands and fallow combined with high use of fire.

Our study informs that landscape-scale metrics explained two third of the variance of AGB in primary forest, i.e. forest degradation is partly explained by land cover dynamics around the forest patches. Cluster analysis also evidenced high significant spatial overlap and co-occurrence among the identified landscape-scale metrics that spatially differ across the study area. Five distinct clusters were identified in the municipality. This attests to their spatial covariation and inter-dependency and reveals specifically localized land use history and management practices. Each cluster is characterized by a particular relation between forest degradation and a particular set of landscape-scale metrics reflecting land use practices and agricultural dynamics (figure 7).

In the central part of the study area, the landscapes of the cluster 3 are in the oldest deforestation region of the municipality where colonization started in the late 60s (Laurent *et al* 2017a). In this region, forest degradation is mainly associated with high cropland proportion during the study period (1985–2015, figure 7). Cash crops, e.g. soybean and maize are produced on large plateaus with clay soils suitable for large scale mechanized agriculture (Pinillos *et al* 2020). Agriculture for cash crop started in the early 2000s on former deforested land previously used as pastures. These landscapes could be named as 'large scale landscape agriculture' (figure 7) where forests
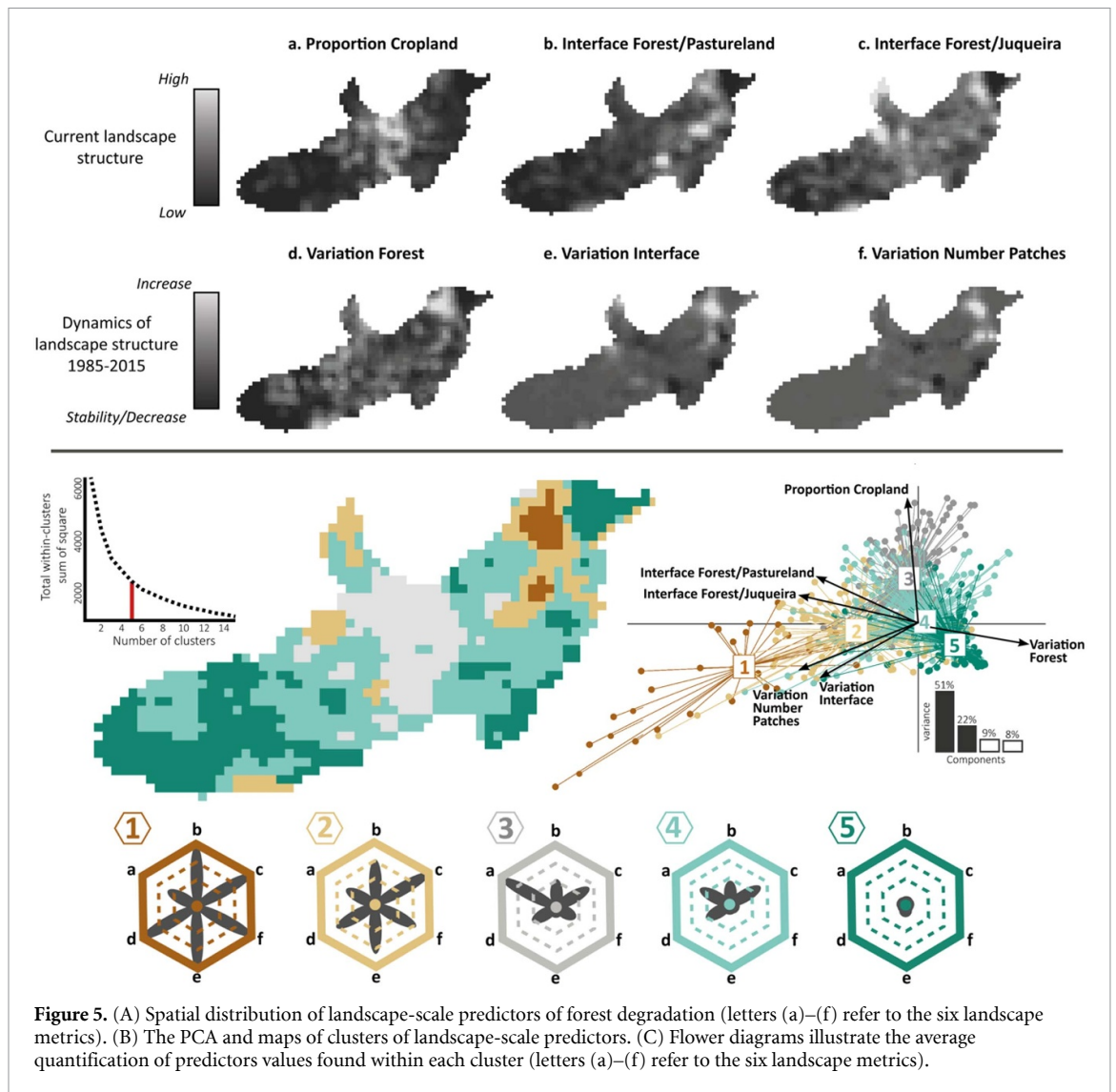
Figure 5. (A) Spatial distribution of landscape-scale predictors of forest degradation (letters (a)–(f) refer to the six landscape metrics). (B) The PCA and maps of clusters of landscape-scale predictors. (C) Flower diagrams illustrate the average quantification of predictors values found within each cluster (letters (a)–(f) refer to the six landscape metrics).

are highly degraded (180 Mg ha^{-1} of averaged AGB). Interestingly, forest degradation in this area is moderately associated with recent dynamics of deforestation, landscape HET and fragmentation. Therefore, forest degradation is here a secondary result of deforestation that occurred before 1985 (now stabilized) and occurs through cumulative factors of (a) high exposition to selective logging since the beginning of the colonization phase (1965) as the accessibility to forest resource is facilitated (close distance to market) and that most of the logging industry (1980s) was concentrated along the BR-010 road (Piketty *et al* 2015); (b) degradation depending on old deforestation events and thus increased isolation of forest patches and edge effects. Similar conclusions on the dominant drivers of degradation were found in this particular region by Matricardi *et al* (2020).

The landscapes of clusters 1 and 2 correspond to heterogeneous and fragmented mosaics of pasturelands, juqueira, forest patches reflecting complex and small-scale agricultural systems. Indeed, those clusters are located in areas dominated by

small-scale farmers practicing slash-and-burn agriculture (Mercier *et al* 2019). These two clusters are spatially coupled because forest degradation is predicted by similar large-scale metrics. Forest degradation is related to recent deforestation and fragmentation dynamics (from 1985 to 2015). However, landscapes in cluster 1 have been more fragmented and are subject to more fires. Accordingly, we identified and differentiated 'small scale fragmented agriculture landscape' (landscapes of cluster 1) from 'small scale agriculture landscape' (landscapes of cluster 2). Degradation process is thus integrated with broader dynamics of forest encroachment and is the result of cumulative effects linked with fragmentation enhancing edge effects and forest resource accessibility (Broadbent *et al* 2008) but also the use of fire in agricultural expansion or slash-and-burn agriculture (Osis *et al* 2019).

In cluster 4, we observed the same trend as in 'large scale landscape agriculture' (cluster 3): forest degradation area is not much associated with recent dynamics of deforestation or fragmentation as no
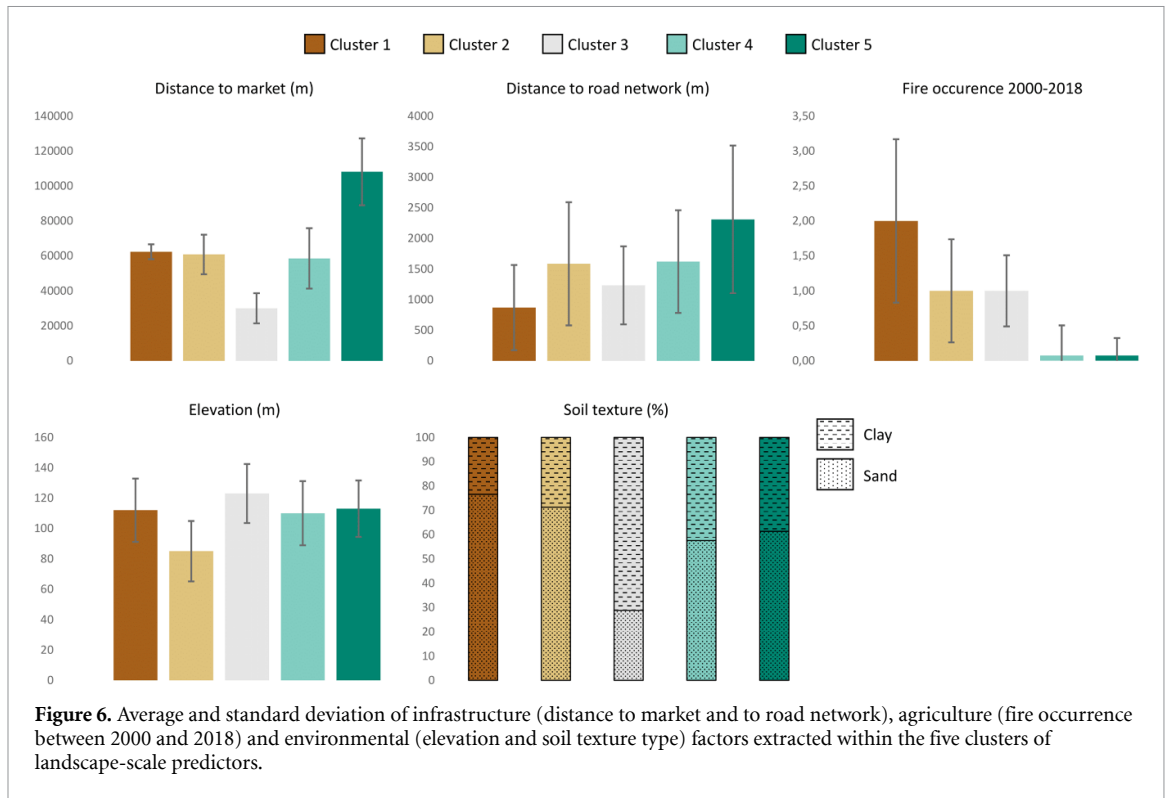
Figure 6. Average and standard deviation of infrastructure (distance to market and to road network), agriculture (fire occurrence between 2000 and 2018) and environmental (elevation and soil texture type) factors extracted within the five clusters of landscape-scale predictors.
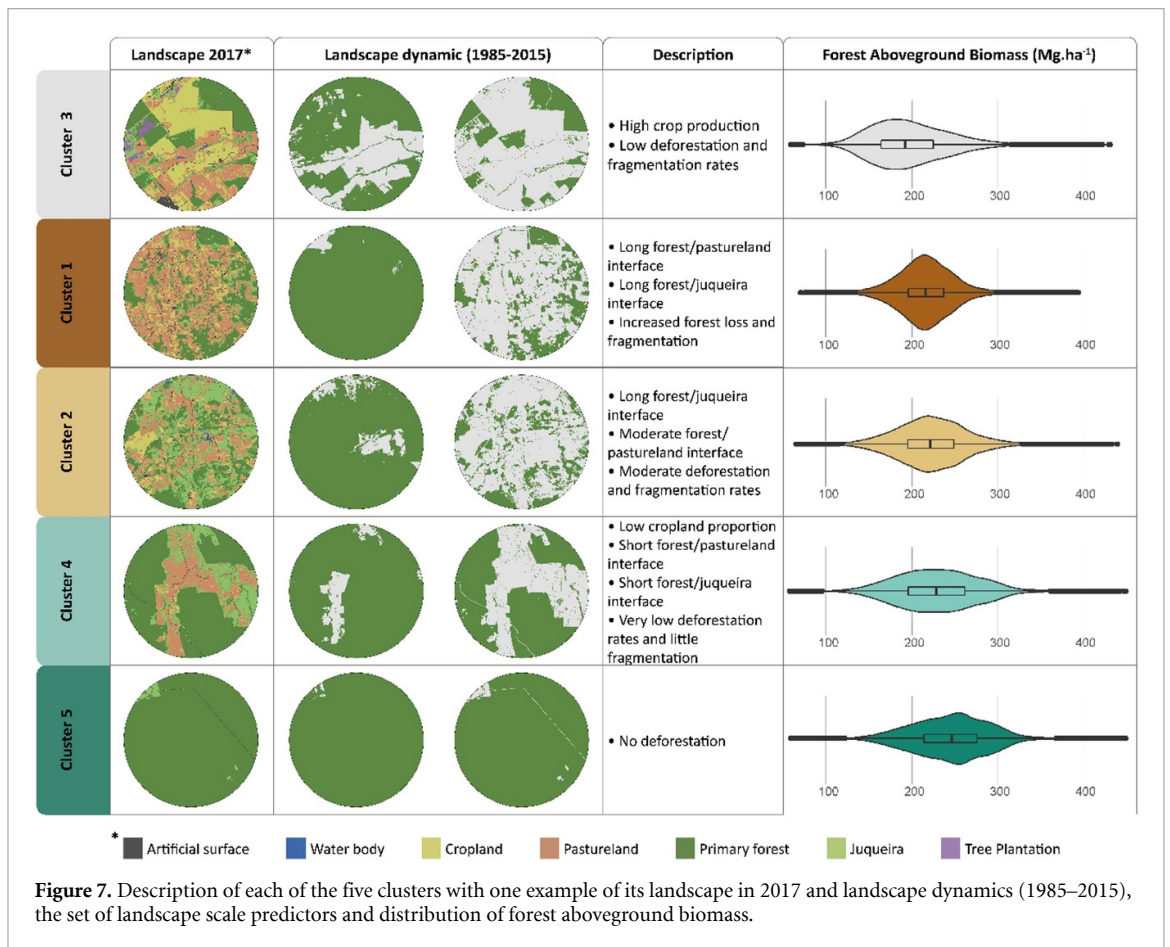

Figure 7. Description of each of the five clusters with one example of its landscape in 2017 and landscape dynamics (1985–2015), the set of landscape scale predictors and distribution of forest aboveground biomass.

significant trend was found since 1985. However, compared to the 'large scale landscape agriculture', this region, away from the main road was not subject to high deforestation in the first decades of colonization and to agriculture conversion in the 2000s because of less favorable soil conditions (figure 6).

These landscapes are now dominated mainly by primary forests with *juqueira* and pastures. These landscapes are identified as 'pastureland landscapes'. In these pastureland landscapes, mean forest biomass value is slightly higher than in the 'small scale fragmented agriculture landscape' (cluster 1) or in the 'small scale agriculture landscape' (cluster 2) but the variability is much higher. As the use of fire is rare, we conclude that these forests have been heavily depleted mainly by over-logging.

Finally, landscapes in cluster 5 showed low to absent proportion of any landscape scale metrics. These 'forest landscapes' correspond to areas characterized by large and connected patches of primary forest showing less degradation and are commonly called intact forest landscapes (Tyukavina *et al* 2016) or slightly degraded forests. These areas reflect specific conditions of land tenure in forested areas, e.g. forest logged by a private company (respecting reduced impact logging guidelines) in the westerner part of Paragominas (Mazzei *et al* 2010) and forest located in the indigenous land in the eastern part. Unsurprisingly, the AGB is the highest in these 'forest landscape'.

5.2. Addressing the causes of degradation to prioritize tailored forest management

Understanding the causes of forest degradation is crucial for the development of policies and measures for effective but sustainable management of degraded forests at the landscape scale to guarantee the conservation of their ecological values (Goldstein 2014). Data concerning both the severity of degradation and the causes of degradation provide key information to enable decision makers prioritize and tailor interventions at the landscape scale (Chazdon and Guariguata 2018). Our study provides a spatially explicit understanding on the determinants of forest degradation distribution in human-modified landscapes which appeared to be mostly driven by land use and land management at large scales.

Firstly, we can assume that forest degradation has been driven by three main factors. First, forests have been exposed to selective logging since the beginning of the colonization phase (1965) as the accessibility to forest resource was facilitated (close distance to market) and that most of the logging industry (1980s) was concentrated along the BR-010 road (Piketty *et al* 2015). Then, old deforestation events (before 1985) increased isolation of forest patches and edge effects. Finally, forests have been degraded by fires used either as a process of clearing primary forest or for pasture maintenance.

Secondly, landscape-scale predictors of forest degradation are clustered in specific areas and thus require spatially targeted forest management. This is particularly important as regions experiencing increasing exposure to the causes of forest degradation are regions where forests are already highly degraded and fragmented making forests more vulnerable to further disturbances (Bourgoin *et al* 2020b). Policy reinforcement is crucial to prevent illegal logging and forest encroachment but also to support intensification of agriculture/ livestock activities in areas with high fragmentation and HET. The collective engagement of local people, especially in highly degraded and fragmented landscapes, is essential to efficiently reduce fire risks (Cammelli *et al* 2019). Reducing the negative effects of forest fragmentation should be a major priority in future land use planning. Besides the two large patches of forests in the western and eastern part of Paragominas, the remaining forest patches are small and isolated and have an increased likelihood to shrink due to the continuous increase of fragmentation due to agricultural expansion (Hansen *et al* 2020, Montibeller *et al* 2020).

Given the difficulty to detect and monitor direct causes of forest degradation (e.g. selective logging or fire) due to limitations of remote sensing data (Gao *et al* 2020), the proposed landscape-scale approach can provide a set of relevant proxies to assess forest status based on the spatiotemporal patterns of landscape structure. With accessibility, global coverage and temporally rich archives of land use and cover maps, this study paves the way for replicating and scaling out the proposed framework to other agricultural frontiers for generalizing the analysis between forest degradation and landscape structure (Bégué *et al* 2018, Bourgoin *et al* 2020a).

5.3. Limitations and future outlook

Although the identification and mapping of the landscape-scale predictors of forest degradation yielded good results, we identified several limitations that need to be discussed. Firstly, all results presented here rely on the accuracy and validity of the forest AGB map presented by Bourgoin *et al* (2018). Novel remote sensing technologies combining very high-resolution sensors and 3D mapping of forest structure (using aerial or satellite LiDAR) have shown high capabilities in assessing AGB (Asner *et al* 2018, Csillik *et al* 2019, Meyer *et al* 2019). For instance, the upcoming Global Ecosystem Dimension Investigation and BIOMASS sensors are promising data sources that will improve the mapping and monitoring of forest structure. The modeling approach can successfully evaluate the spatial correlation between forest degradation and the explanatory variables but can hardly assess the interactions among these variables. There is room for improving the analysis of interactions of landscape metrics among the different scales of computation. Our results showed that the largest landscape scale dominates the variable selection procedure and was relevant for synthesizing landscape structure dynamics in spatial and temporal dimensions. This is consistent with hierarchy theory that predicts that higher levels constraint the functioning of lower ones (Allen and Starr 2017).

The analysis of forest degradation within the framework of land use and cover change as conceptualized by Geist and Lambin (2002) could be expanded on in future studies. For example, additional proximate causes should be considered such as (a) wood extraction by integrating forest disturbances (e.g. selective logging) as spatial-temporal relationships between agricultural expansion, forest disturbances and degradation have not been explicitly quantified (Matricardi *et al* 2020) and (b) environmental factors such as climate change that may amplify feedback loops between fragmentation effects (Briant *et al* 2010, Laurance *et al* 2011), fire occurrences (Morton *et al* 2011, Rappaport *et al* 2018) and forest degradation (Alencar *et al* 2015, le Page *et al* 2017, Silva Junior *et al* 2018, Xu *et al* 2020).

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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Conflict of interest

The authors declare no conflict of interest.

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