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ORIGINAL ARTICLE

Spatial distribution of population and forest cover in extractive reserves in the Amazon biome, Brazil

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This study relates spatial measures of forest cover with measures of the spatial distribution of the population in the 31 Extractive Reserves (ERs) within the Amazon biome, Brazil, in 2010. We integrated layers of information on the ERs, forest cover, and spatial distribution of the population in a Geographic Information System. We produced 24 variables in three groups: population; external conditions (both as predictor variables); and land cover (predicted variables). We assessed the correlation between predictor variables and forest cover and fragmentation variables. Linear regression analyses based on cooperative game theory were conducted to evaluate the significance of the predictor variables in explaining the number of forest fragments and the percentage of forest cover in the models. We found that the size, concentration, dispersion, and geometry of the population contributed to a better understanding of deforestation and the landscape structure. However, forest fragmentation and forest cover extent are not necessarily defined by the same population aspects. The models suggest that forest cover change is primarily driven by population concentration within the ER, while forest fragmentation is strongly shaped by population dispersion. External conditions such as surrounding forests and protected areas also played a significant role. Our study highlights the importance of incorporating forest spatial distribution measures into Population and Environment research, going beyond the usual focus on forest extent. Additionally, it highlights the value of working with spatial demographic variables, extending beyond the conventional approach centered on population size.

Keywords: Spatial distribution. Protected areas. LUCC. Forest fragmentation. Linear regression. Shapley value.

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Introduction

The Amazon Biome, renowned for its biodiversity and endemism, spans eight South American countries, with approximately 60% located in Brazil (RAISG, 2022). The forest plays a central role in carbon balance, rainfall regulation, and planetary climate maintenance, making Land Use and Land Cover Change (LUCC) in the region a globally significant phenomenon (Mitchard, 2018; Mu; Jones, 2022). The continuous forest conversion process intensifies impacts due to habitat loss and changes in landscape structure, as evidenced by forest cover reduction and fragmentation, i.e., isolated forest patches that disrupt forest ecosystem functions (Fahrig, 2017; Laurance *et al.*, 2012).

In Brazil, after a period of relative control over deforestation rates in the early 21st century (Hansen *et al.*, 2013), concerns about the destruction of the forest cover have resurfaced. Attacks on federal public monitoring and control agencies have weakened the management of protected areas (Begotti; Peres, 2019; Escobar, 2019). The vulnerability of these areas, particularly that resulting from human activity (Laurance *et al.*, 2012), poses a serious problem as they are critical for the protection of biodiversity and forest cover in different countries (Bruner *et al.*, 2001; Yang *et al.*, 2021).

Brazil has one of the largest networks of protected areas in the world, especially those located in the Amazon: 357 Conservation Units and 387 Indigenous Lands covering more than 210 million hectares (IPAM, 2018; INPE, 2022; Brasil, 2022). The National System of Nature Conservation Units (SNUC) defines two types of conservation units: *Integral Protection and Sustainable Use* (Brasil, 2000). While residence is prohibited within integral protection units, such as national parks, traditional populations are allowed to reside in sustainable use units, such as Extractive Reserves (ERs) (Brasil, 2000, Article 2, item IX and XI). ERs aim at environmental conservation associated with resource management, consistent with Category VI of Protected Areas, as defined by the International Union for Conservation of Nature (Dudley, 2013).

According to estimates based on official data from the Brazilian Institute of Geography and Statistics (IBGE), the Amazon's ERs were the federal conservation units with the largest population in 2007: 227,000 people lived within the reserves, accounting to 70% of the total residents in all federal conservation units, while 690,000 people lived in the surrounding area across a 10 km buffer zone (D'Antona *et al.*, 2013). The ER model was first proposed by Chico Mendes, an environmentalist and social activist who advocated for the rights of traditional populations dependent on the rainforest for their livelihood. However, studies have identified deforestation processes associated with specific occupation dynamics, such as the introduction of livestock (Kröger, 2020; Spínola; Carneiro-Filho, 2019).

Studies examining the potential impact of populational spatial distribution patterns on forest cover within areas designated for environmental preservation are scarce. This study aimed to assess the influence of population size and spatial distribution on the extent of forest cover and fragmentation across all 31 ERs in the Amazon Biome in Brazil in 2010.

The hypothesis is that forest cover is not solely dependent on population size, but also influenced by the spatial arrangement of the population. Furthermore, we hypothesize that both population size and spatial distribution significantly affect forest fragmentation and the distribution of forest patches

The distinctive contribution of this study lies in the application of population spatial distribution measures comparable to those used in landscape ecology to analyze land cover (Metzger *et al.*, 2021). In the field of Population and Environment studies, this article seeks to enhance the understanding of the relationship between population and forests by analytically integrating the spatial distribution of population into the model. This approach differs from conventional studies on population and land cover in the Amazon, which often prioritize population size and growth. Additionally, the research highlights the impact of population on forest spatial distribution, diverging from studies that traditionally prioritize forest extent over fragmentation.

Background

Deforestation in the tropics is a complex, multicausal and multiscale phenomenon (Magliocca *et al.*, 2015), with anthropogenic forces recognized as key factors influencing forest change. Some probable causes of deforestation include the extension of infrastructure, such as roads, agricultural expansion, and colonization projects (Assunção; Chiavari, 2015; França *et al.*, 2021; Milien *et al.*, 2021; Perz *et al.*, 2013; Yanai *et al.*, 2020). While demographic factors are acknowledged as underlying driving forces (Lambin; Geist, 2006), they do not typically represent the primary drivers, usually categorized as control variables or associated with other deforestation drivers (Ferretti-Gallon; Busch, 2014). This observation stems from the fact that studies addressing the relationship between population and LUCC often yield results with limited convergence due to a high variability in association outputs, contingent upon the territorial unit of analysis or methodological framework (Côrtes; D'Antona, 2014).

Most studies, whether conducted at micro-level (focusing on households), or macro-level (examining regional or continental perspectives), tend to analyze deforestation through the lens of population size, generally applying growth or density variables (Bremner *et al.*, 2010; Defries *et al.*, 2010; Geist; Lambin, 2001; Jorgenson; Burns, 2007; Maja; Ayano, 2021; Martin, 2023). In household life cycle studies, additional variables are incorporated, such as gender, age, and population mobility (Barbieri, 2023; Barbieri *et al.*, 2021; Barbieri; Carr, 2005; Guedes *et al.*, 2017; Perz *et al.*, 2006; Walker *et al.*, 2002; VanWey *et al.*, 2007).

Patterns of deforestation linked to population spatial settlement have been discussed in the literature. Notable examples include the fishbone pattern, associated with colonization projects (Becker, 2001; De Filho; Metzger, 2006), as well as urbanization and expansion of urban patches (Browder; Godfrey, 1997; Côrtes; Silva Júnior, 2021). Although the spatial dimension is implicitly addressed in these approaches in various ways, none of them proposes to establish a relationship between spatial index measures and deforestation.

The methodological endeavor to incorporate the spatial dimension of population in land cover studies, rather than focusing solely on population size, has the potential to address the gap in the empirically established relationship between population distribution and forest spatial distribution. This also goes beyond the perspective focused solely on the extent of deforestation to analyze fragmentation.

In the field of landscape ecology, it is recognized that varying spatial and temporal patterns of deforestation result in specific configurations concerning the structure of the remaining forests and the intensity of these changes. When deforestation advances continuously, habitat loss occurs in large areas, but the contiguous forest can remain in other large areas. Forest fragments (isolated patches of forest remnants) are created when deforestation occurs in a dispersed manner (Metzger, 2001). Despite possible controversy over its effects (Fletcher *et al.*, 2018; Fahrig *et al.*, 2019), forest fragmentation is usually associated with negative impacts on animal and plant species (Martínez-Ramos *et al.*, 2016). This phenomenon is related to fire events (Soares-Filho *et al.*, 2012), as well as changes in the structure and composition of arboreal communities and reductions in tree diversity associated with the proliferation of invasive species (Laurance *et al.*, 1998). These modifications reduce habitats and their continuities, and can impair the survival of animals, which ultimately compromises the existence of the forest itself (Terborgh *et al.*, 2001; Dirzo *et al.*, 2014).

The diverse combinations of deforestation patterns create landscape mosaics that affect the ecological functions of forests. Forest spatial distribution is mainly influenced by size, distance, and shape of forest fragments, which determine the extent of the fragment's perimeter (Haddad *et al.*, 2015; Metzger, 2001). Reductions in area, isolation and greater edge effect trigger persistent, deleterious, and often unpredictable ecosystem changes. A biodiversity loss of up to 75% is estimated, to the detriment of the landscape configuration via the forest fragmentation process, in addition to changes in ecosystem functions that reduce biomass and alter nutrient cycles (Haddad *et al.*, 2015; Laurance; Vasconcelos, 2009).

In contrast, protected areas are considered the most important strategy for the conservation of forest resources (Bamford *et al.*, 2014; Pfaff *et al.*, 2015). Protected areas can be defined as social-ecological systems, within multi-scale social-ecological functional landscapes (Cumming *et al.*, 2015). Several studies have demonstrated the effectiveness of these units for forest conservation compared to what occurs outside their boundaries (Holland *et al.*, 2014; Miranda *et al.*, 2014). Conservation units act as barriers to the expansion of the agricultural frontier in the Amazon, where they have an expressive portion of old-growth forests (Nolte *et al.*, 2013; Ferretti-Gallon; Busch, 2014). Deforestation in protected areas in the Legal Amazon amounts to less than 10% of the total deforested area between 2002 and 2011 (Assunção; Chiavari, 2015). The average probability of deforestation occurring outside these units is 7 to 11 times higher than within them (Ricketts *et al.*, 2010; Ferreira *et al.*, 2005).

Access conditions to conservation units can be understood as barriers to occupation in the Amazon as Brazilian environmental legislation regulates resident presence. The forms of occupation and activities performed determine the intensity and pattern of deforestation, which depend on the category of the conservation unit. Consequently, the highest rate of deforestation growth between 2002 and 2011 occurred in the sustainable use units, the least restricted areas, thus increasing the suppressed area by 150% (Assunção; Chiavari, 2015). In a regional framework in which protected areas are influenced by the processes of human occupation and LUCC, ERs are particularly important for examining the relationship between population distribution and deforestation.

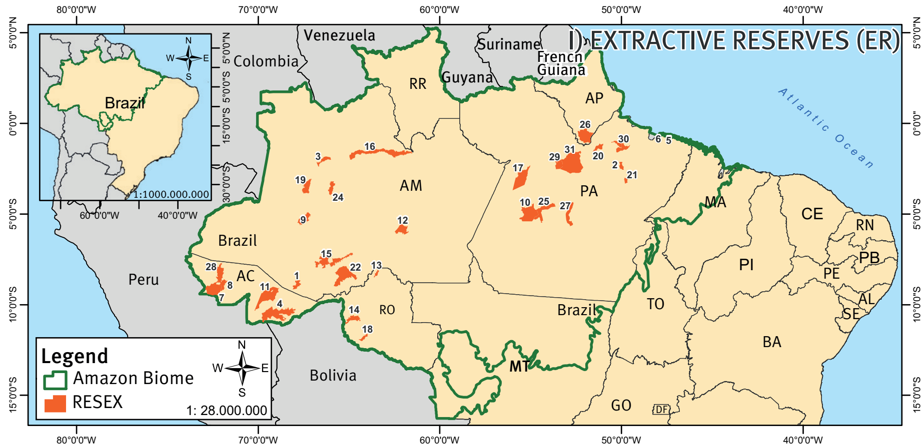
Data and methods

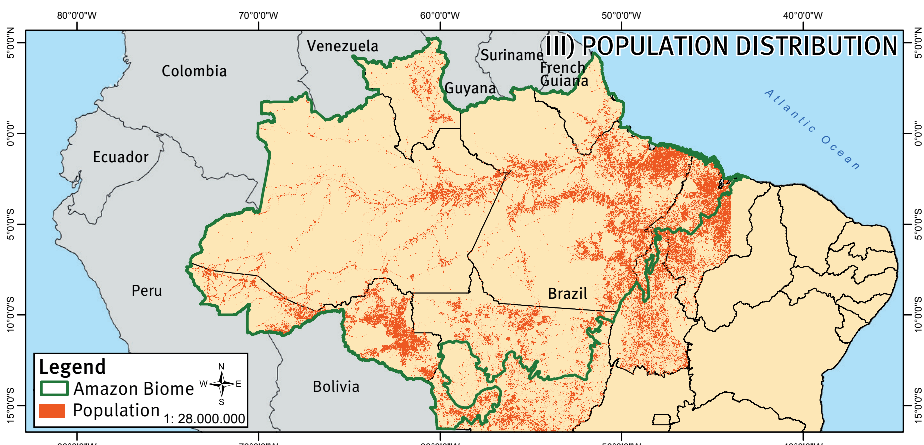
The data from ER (I), forest cover (II), and the spatial distribution of the resident population (III) in the Brazilian Amazon Biome in 2010 were incorporated into a Geographic Information System (GIS) built in ESRI-ARCMAP 10.8 software (Figure 1).

The boundaries of the 31 ER in the Amazon Biome were extracted from the official shapefile containing data for the 132 federal protected areas established in Brazil until 2010 (ICMBIO, 2017). This group excluded ERs that do not properly correspond to the Amazon Biome: marine units and those located in transition areas to other biomes. A layer with a 10 km buffer zone around each extractive reserve (ER) was created. As there are spatially contiguous ERs, we eliminated the buffers overlapping the examined reserves to avoid data duplication. As some Ers are spatially contiguous to other types of conservation units and indigenous land, we calculated the percentage of buffer overlap to other types of adjacent protected areas.

We used the 2010 land cover data from TerraClass in raster format (INPE, 2013, 2022). For forest fragmentation calculations, we reclassified the 15 original classes into: natural cover, anthropogenic use, and no information. The natural cover class included forest (unaltered or slightly altered arboreal vegetation); other non-forest vegetation formations (i.e., savannas); hydrography and others (sand bank and rocky outcrops). This grouping aims to prevent certain configurations, such as watercourses in the middle of forest masses, from being considered anthropogenic fragmentation. Consequently, forest fragments in our approach were defined by patches with original natural cover distinguished from neighboring units, using the limits of conservation units as an analytical limit while disregarding possible continuities of natural cover beyond the perimeter of the reserves.

FIGURE 1
Geographic Information System components





Source: INPE (2022); IBGE (2016); Brasil (2022). Prepared by the authors.

We used an official statistical grid of the 2010 Demographic Census delimited according to the boundaries of the Amazon Biome in Brazil, totaling 4,208,891 regular 1 km x 1 km cells containing the variable resident population and the variable rural or urban situation (IBGE, 2016). The statistical grid was created by IBGE using a hybrid approach (Bueno, 2016) that combines coordinates of households from the 2010 Demographic Census with estimates from techniques like disaggregating census tract data and auxiliary information (e.g., land use and infrastructure distribution) to account for missing coordinates. A grid is an effective tool, as the size and regularity of cells enable spatial compatibility between demographic and environmental data. It aligns well with protected area boundaries and improves understanding of population distribution within them, facilitating the application of spatial statistical measures (Bueno; D'Antona, 2016).

Variables

We calculated 24 continuous variables for each ER, the territorial unit of our analysis, organized into three variable groups: ER population; external conditions; and land cover in ER. Population and external conditions are predictor variables; the forest cover variables in the reserves are the predicted variables.

Group 1, calculated based on the 120,521 cells corresponding to the boundaries of the 31 ERs, includes (Table 1): the number of cells (v1) and the resident population (v2); measures of population concentration (v3 to v7); measures of population dispersion (v8 and v9); and measurements of occupation shape (v10 to v13). The number of occupied cells (v3) expresses the quantity of cells with resident population greater than zero, while the proportion of occupied cells (v4) measures the relationship between the number of cells with population and the total ER cells. We utilized the Gini index as a sparsity measure for population spatial distribution, not for income: v5 includes occupied and unoccupied cells; v6 includes only cells with resident population greater than zero. The index is expressed as a numerical percentage equivalence, ranging from 0 to 1, where 0 corresponds to complete equality (homogeneous population distribution in all cells), and 1 corresponds to the maximum concentration (all people in one cell). Population Density (v7) measures the ratio between population size and the total number of cells corresponding to the ER.

The cells of each ER were classified into two classes: cells with resident population and cells without resident population. We aggregated contiguous cells of each class (*Dissolve* command in the ArcGIS), creating new polygons: patches of occupied cells and patches of unoccupied cells. The patches of occupied cells were exported to the Fragstats software (McGarigal, 1995) to calculate the following: number of patches of occupied cells (v8); median size of patches of occupied cells (v9); mean shape index of patches of occupied cells (v10). A higher number of patches of occupied cells (v8) indicates a more fragmented Reserve occupation. The larger the median patch size (v9), the greater the number of contiguous cells with human occupation. The closer the mean shape index (v10) is to 1, the more square-like the patches of occupied cells; the further away from 1, the greater the difference in patches' shapes.

Variables v11 to v13 were generated from the ellipse overlaid around 63% of the occupied cells in one ER to summarize the dispersion and directional trends of the occupied cells (Standard Deviational Ellipse tool in ArcGIS): v11 corresponds to the perimeter; v12, to the area; and v13, to the eccentricity of the ellipse. Eccentricities close to zero indicate a circular occupation pattern, while values close to 1 suggests the distribution of occupied cells occurs along an axis or vector, such as a watercourse.

TABLE 1
Extractive reserve (ER) population variables, 2010

Theme	Variable (v)		Description
	#	Name	
Area and population size	1	*Cells*	Total number of cells in the Statistical Grid corresponding to the Extractive Reserve.
	2	*Resident population*	Total number of people living in the ER.
Concentration	3	*Occupied cells*	Number of cells with resident population greater than zero.
	4	*Proportion of occupied cells*	Ratio between the number of occupied cells (v3) and the total number of cells in the ER (v1). Number between 0 and 1.
	5	*Gini index - all cells*	Sparsity measure of the spatial distribution of the population, computed based on all cells, including those without population. Number between 0 and 1.
	6	*Gini index – occupied cells*	Sparsity measure of the spatial distribution of the population, computed only with cells with resident population greater than zero.
	7	*Population density*	Ratio between Resident Population (v2) and the total number of cells in the Extractive Reserve (v1). Number between 0 and 1.
Dispersion	8	*Patches of occupied cells*	Number of cells patches with population greater than zero.
	9	*Median patch size of occupied cells*	Median size of the patches of occupied cells.
Occupation shape	10	*Mean shape index of occupied cells*	Measure of the regularity of the shape of the patches. Number equal to or greater than 1. The higher the MSI, the more irregular the shape of each patch.
	11	*Standard deviational ellipse – perimeter*	Perimeter of the ellipse that aggregates 63% of the occupied cells, weighted by the resident population in each cell. The larger the perimeter, the greater the occupation (ArcGIS, Standard Deviational Ellipse - SDE).
	12	*Standard deviational ellipse – area*	Area of the SDE that aggregates 63% of the occupied cells, weighted by the resident population in each cell.
	13	*Standard deviational ellipse – eccentricity*	Ratio between the two axes of the SDE that aggregates 63% of the occupied cells, weighted by the resident population in each cell.

Source: Variables defined and calculated by the authors.

The variables in the External Conditions group (Table 2) were computed for each ER to verify whether the characteristics of the surrounding areas impact land cover within the reserve. The surrounding population (v14) was calculated for the 10km buffer around each reserve, encompassing a total of 79,526 cells from the 2010 demographic statistical grid. The surrounding forest cover (v15) corresponds to the percentage of forest within the 10km buffer zone around the ER, based on the 2010 TerraClass land cover classification. The surrounding protected areas (v16) represent the percentage of the 10km buffer around the ER occupied by some type of protected area (including indigenous lands), as per the 2010 official map of protected areas. The distance to the nearest urban area (v17) measures the shortest straight-line distance from the ER to the nearest urban area (patch of cells classified as urban by IBGE), even if it is outside the 10km buffer. The distance to the five closest urban areas (v18) considers the average distances to these five areas.

TABLE 2
External conditions variables, 2010

Theme	Variable (v)		Description
	#	Name	
Population	14	*Surrounding population*	Resident population in the 10km buffer around the ER.
Forest cover	15	*Surrounding forest cover*	Percentage of the 10km buffer around the ER, with forest cover.
Protected areas	16	*Surrounding protected areas*	Percentage of the 10km buffer around the ER occupied by some type of protected area.
Urban areas	17	*Straight distance to nearest urban patch.*	Straight distance from the ER to the nearest urban patch (ArcGIS, Near Dist.).
	18	*Average distance of the five closest urban patches.*	Average distance from the ER to the five closest urban patches.

Source: Variables defined and calculated by the authors.

The variables in the Land Cover Group (Table 3) included forest fragmentation indicators and forest cover measurements for each ER. Fragmentation measurements, calculated in the Fragstats software, include number of forest patches (v19), the density of forest patches (v20), the number of patches per 100 hectares, the size of the largest patch relative to the size of the ER (v21), and the forest patches mean size (v22). Forest cover variables were calculated directly in ArcGIS in percentual values of the size of the ER: Forest Cover (v23) and Deforested Area (v24).

TABLE 3
ER Land cover variables, 2010

Theme	Variable (v) #	Variable (v) Name	Description
Forest fragmentation	19	*Forest patches*	Number of forest patches
	20	*Density of forest patches*	Number of forest fragments per 100 *hectare*s
	21	*Forest largest patch*	Size of largest forest fragment in relation to the size of the Extractive Reserve
	22	*Forest patches mean size*	Mean of forest fragment size
Forest cover	23	*Forest*	Percentage of the Extractive Reserve with forest cover
	24	*Deforestation*	Percentage of the Extractive Reserve deforested

Source: Variables defined and calculated by the authors.

Statistical analyses

Statistical analyses were performed to test the correlations between the population variables and external conditions (predictor variables) and the forest cover variables (predicted variables). We considered the Pearson linear correlation coefficient $\rho_{x,y}$ (Chen; Popovich, 2002), in which x and y represent a predictor variable (v1 to v18) and a predicted variable (v19 to v24), respectively. The correlation is generally assumed to be strong, moderate, weak, or negligible if:

$$|\rho_{x,y}| \geq 0.7,\ 0.7 > |\rho_{x,y}| \geq 0.5,\ 0.5 > |\rho_{x,y}| \geq 0.3, \text{ or } |\rho_{x,y}| < 0.3, \text{ respectively} \quad (1)$$

Regression analyses were conducted to evaluate the importance of the predictor variables in predicting the Number of Forest Fragments (v19) and Forest Cover Percentage (v23). For this study, we opted for the multiple linear regression model (Montgomery; Runger, 2010), where the regression line was calculated as follows:

$$\hat{y}_i = \alpha + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \ldots + \beta_{18} x_{i,18} \quad (2)$$

In which α represents the intercept with the vertical axis, $\beta_1, \beta_2, \ldots \beta_{18}$ are the regression coefficients, and $x_{i,1}, x_{i,2}, \ldots x_{i,18}$ are the values of the predictor variables (from v1 to v18) in relation to ER i, such that the estimates $\hat{y}_i$ are as close as possible to the actual predictions y_i. Note that $\hat{y}_i$ (as well as y_i) is either the Number of Forest Fragments (v19) or the Forest Cover Percentage (v23). It is worth highlighting that we defined the regression model in Eq. (2) based on all predictor variables v1 to v18.

From a statistical perspective, given the limited samples (31 ER) compared to the number of predictor variables (18), we selected a subset of variables to construct the regression model. To that end, we used multicollinearity observation in the data and performed a combinatorial analysis of several regression models with different compositions of the two groups of predictor variables: Resident Population (v2), Gini Index – all cells (v5), Patches of occupied cells (v8), Median patch size of occupied cells (v9), Mean shape index of occupied cells (v10), and Surrounding Forest cover (v15).

The regression analysis was assessed using the coefficient of determination (R^2), which varies from 0 and 1 and indicates the percentage of variance in the predicted variable explained by the linear model. In addition, it is also common to interpret the importance of predictor variables in the coefficient of determination from the parameters β_1, β_2, ... β_{18} of the regression model. However, in the presence of multicollinearity among the collected data, extracting interpretations from such parameters can be a challenging task that can frequently lead to erroneous conclusions (Kraha, 2012; Daoud, 2017). For instance, multicollinearity increases the likelihood that independent variables are classified as statistically insignificant even when they are important for the regression task.

To understand the importance of each variable in R^2 (Lipovetsky; Conklin, 2001) and overcome this limitation, we adopted an approach based on the cooperative game theory, aiming to provide a more accurate interpretation of the importance of each predictor variable. In cooperative game theory (Peleg; Sudhölter, 2007) a set of players, M, cooperates towards a common goal (e.g., increasing profits or reducing costs of an operation). The worth of a game, defined here as $\upsilon(A)$, indicates the payoff (or gain) when the coalition of players $A \subseteq M$ act cooperatively. Recently, this game theory-based formulation has been borrowed by statisticians and computer scientists to interpret any classification and/or regression model (Lundberg; Lee, 2017; Sundararajan; Najmi, 2020). A similar formulation can be adopted in linear regression models to evaluate the gain obtained in the determination coefficient for different coalitions (or subsets) of variables (Lipovetsky; Conklin, 2001).

In this paper, the set of predictor variables can be viewed as the players in a game. When these variables join in a coalition (i.e., when they are used to predict either v19 or v23), they cooperate to improve the quality of the regression model, measured through R^2. Consider, for example, the use of variables v2, v5, v9, and v10 to predict variable v19. In this case, the subset of variables $A = \{v2, v5, v9, v10\}$ are the players of the game and $\upsilon(A) = R^2(\{v2, v5, v9, v10\})$ is the coefficient of determination achieved when the variables present in A are used to predict variable v19 (i.e., when they join a coalition). For any subset of variables A, there is the associated $\upsilon(A) = R^2(A)$. Furthermore, for the coalition with all the variables (i.e. A=M=$\{v1,v2,...,v18\}$), it follows that $\upsilon(\{v1,v2,...,v18\})$=$R^2(\{v1,v2,...,v18\})$=$R^2$, i.e. the coefficient of determination of the regression model with all the predictor variables. When there is no variable to predict v19 or v24, it is assumed that $\upsilon(\varnothing)$=0.

The advantage of using the game theory formulation to interpret regression models lies in the solution concept known as the Shapley value (Shapley, 1953), which fairly distributes the achieved R^2 among the predictor variables. In the example above and for variable v2 (and the same reasoning applies to all other predictor variables), the associated Shapley value is calculated as follows:

$$\Phi_{v2} = \sum_{A \subseteq M} \frac{|A|!(|M| - |A| - 1)!}{|M|!} [R^2(A \cup v2) - R^2(A)] \qquad (3)$$

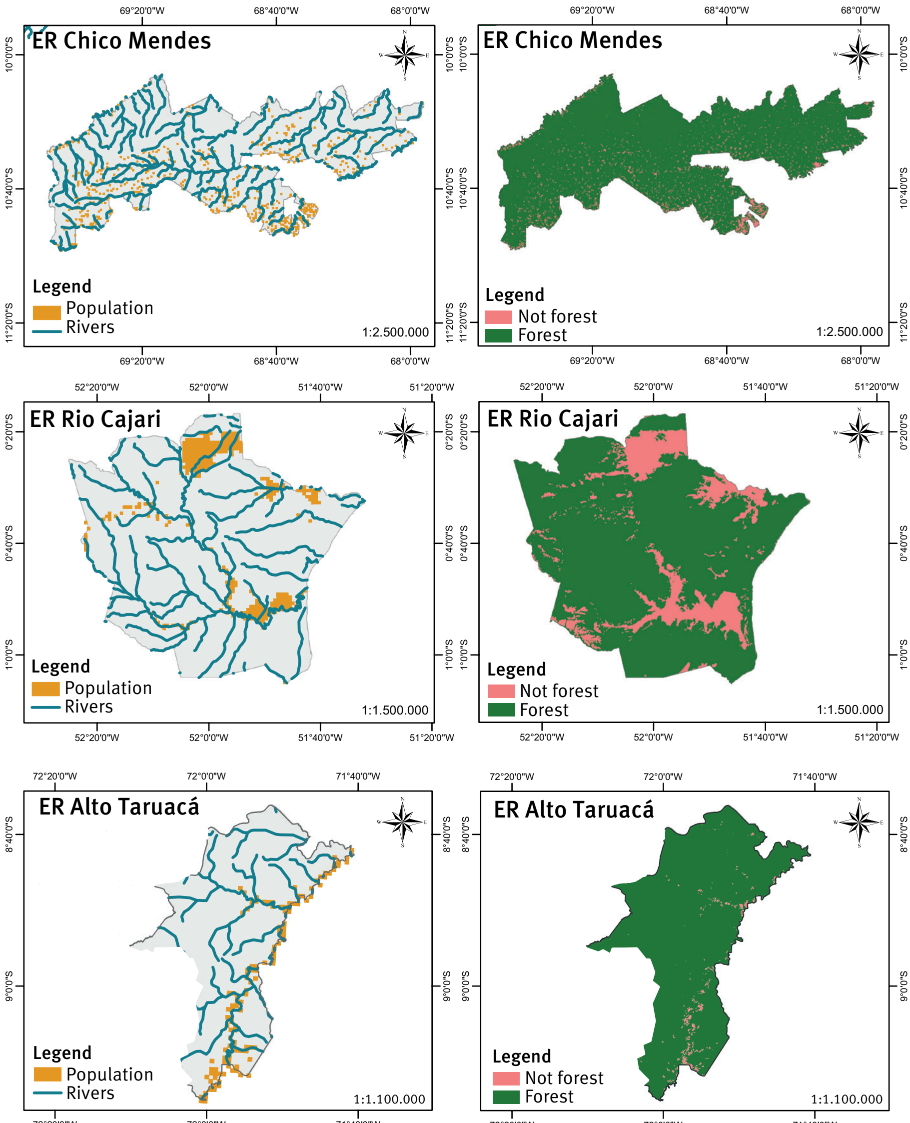
In which $|A|$ indicates the number of variables in subset A (similarly for $|M|$ that in this case is equal to 18). One of the interesting aspects of the Shapley value is that the sum of all $\Phi_j = j \in \{v1, v2, ..., v18\}$, is equal to the total payoff of the game. In other words, the Shapley values indicate the importance or portion of contribution each predictor variable has in the achieved coefficient of determination R^2. In addition, the calculation of the Shapley value (3) is based on a weighted average of the marginal contribution of the predictor variable in the coefficients of determination. Thus, the negative effect of multicollinearity in the calculation of the importance of the predictor variable is mitigated. Therefore, to answer the questions of this study, the use of Shapley values leads to better interpretations of the contribution of each predictor variable regarding the quality of the linear regression model.

Results

Results indicated human presence combined with a significant percentage of forest cover in 2010. The 31 ERs encompass 120,521 cells of the statistical grid, with 91% of the total area having forest cover. The population living within the ERs was estimated at 83,669 inhabitants (44,654 men and 39,015 women) distributed along 15,774 households. The population living in the 10 km buffer zone (79,526 cells; 7,952,600 hectares) was estimated at 183,170 inhabitants distributed along 39,815 households – the damping areas around the ERs concentrated a population more than twice as large as the population estimated within the conservation units. This result is consistent with the literature (D'Antona *et al.*, 2013).

We found three general patterns of population distribution, as illustrated in Figure 2: dispersed, in clusters of cells, and along an axis. In the Chico Mendes ER, the dispersed distribution corresponded to a predominant solid ground organization. In the Cajari River, occupation along watercourses (to the west) combined with density in blocks to the north and south. In Alto Tarauacá, occupation occurred along watercourses. Visually, the distribution of cells with resident population tended to correspond to the distribution of non-forest areas, not necessarily to the same shape or area extent. The population's settlement pattern generally follows the main rivers within the Reserves, shaping Amazonian history (Neves, 2022).

FIGURE 2
Three patterns of the spatial distribution of population and forest cover in the ERs



Source: INPE (2022); IBGE (2016); ICMBIO (2017). Prepared by the authors.

Table 4 lists the correlations among variables of groups 1 and 2 (in rows) with variables of group 3 (in columns), as well as the associated P-values. Note that high standard deviations, combined with the low number of ERs, explain the low significances (measured by the P-values) of part of the correlations. However, all ERs of the Amazon Biome were used in the analyses; therefore, the samples used were equivalent to the entire study population. For result analysis, we considered correlations with a statistical significance level (P-value) lower than 0.10 or lower than 0.05.

TABLE 4
Correlations

	Variables	Pearson correlation coefficient (P-value)					
		19	20	21	22	23	24
		Number of forest patches	Density of forest patches	Forest largest patch	Forest patch area mean	Forest (%)	Deforestation (%)
1	Cells	0.485 (0.006**)	-0.334 (0.066*)	0.229 (0.216)	0.318 (0.082*)	0.323 (0.077*)	-0.190 (0.307)
2	Resident population	0.769 (0.000**)	0.098 (0.600)	-0.079 (0.671)	-0.252 (0.171)	-0.055 (0.768)	0.108 (0.565)
3	Occupied cells	0.653 (0.000**)	-0.053 (0.778)	-0.076 (0.684)	-0.210 (0.256)	-0.119 (0.524)	0.157 (0.400)
4	Proportion of occupied cells	-0.027 (0.886)	0.886 (0.000**)	-0.544 (0.002**)	-0.262 (0.155)	-0.705 (0.000**)	0.396 (0.027**)
5	Gini index – all cells	0.028 (0.881)	-0.641 (0.000**)	0.477 (0.007**)	0.267 (0.147)	0.617 (0.000**)	-0.539 (0.002**)
6	Gini index – occupied cells	0.124 (0.507)	0.349 (0.054*)	-0.191 (0.305)	-0.118 (0.526)	-0.150 (0.421)	-0.111 (0.552)
7	Population density	-0.125 (0.504)	0.895 (0.000**)	-0.173 (0.353)	-0.149 (0.425)	-0.467 (0.008**)	-0.025 (0.893)
8	Patches of occupied cells	0.525 (0.002**)	-0.097 (0.603)	0.022 (0.909)	-0.129 (0.488)	0.156 (0.403)	-0.016 (0.932)
9	Median patch size of occupied cells	0.532 (0.002**)	0.477 (0.007**)	-0.391 (0.030**)	-0.259 (0.159)	-0.430 (0.016**)	0.142 (0.447)
10	Mean shape index of occupied cells	0.324 (0.075*)	0.351 (0.053*)	-0.369 (0.041**)	-0.356 (0.050**)	-0.364 (0.044**)	0.602 (0.000**)
11	SDE – perimeter	0.254 (0.169)	-0.345 (0.058*)	0.205 (0.270)	0.142 (0.446)	0.349 (0.055*)	-0.160 (0.392)
12	SDE – area	0.501 (0.004**)	-0.234 (0.205)	0.135 (0.468)	-0.021 (0.911)	0.176 (0.345)	-0.123 (0.510)
13	SDE – eccentricity	0,561 (0.001**)	0,080 (0,669)	-0,106 (0,572)	-0,353 (0,051*)	-0,223 (0,227)	0,235 (0,202)
14	Surrounding population	0.302 (0.099*)	0.436 (0.014**)	-0.084 (0.655)	-0.213 (0.251)	-0.347 (0.056*)	-0.009 (0.960)
15	Surrounding forest cover	-0.430 (0.016**)	-0.595 (0.000**)	0.407 (0.023**)	0.300 (0.102)	0.742 (0.000**)	-0.131 (0.482)
16	Surrounding protected areas	-0.301 (0.100)	-0.270 (0.142)	0.247 (0.181)	0.814 (0.000**)	0.324 (0.075*)	-0.235 (0.203)
17	Distance to nearest urban patch	-0.386 (0.032**)	-0.351 (0.053*)	0.280 (0.127)	0.506 (0.004**)	0.362 (0.045**)	-0.209 (0.258)
18	Distance of the five closest urban patches	-0.228 (0.217)	-0.354 (0.051*)	0.287 (0.118)	0.197 (0.289)	0.484 (0.006**)	-0.139 (0.456)

Source: INPE (2022); IBGE (2016); ICMBIO (2017). Prepared by the authors.
Note. *p<0.10, **p<0.05

Correlations served as the starting point to analyze the influence of the population on both the extent of forest cover and forest fragmentation. It was complemented by the use of linear regression models combined with a game theory framework to interpret the impact of selected predictor variables on the quality of the predicted number of forest patches (v19) and the percentage of ERs with forest (v23), based on the obtained Shapley values Φ_j, for all variables *j*.

Population and extension of the forest cover

The size of the ER (v1) had a weak positive correlation with the percentage of forest cover within it (v23). Resident population (v2) does not significantly correlate with forest cover (v23) and deforested area. The number of occupied cells (v3) also had no correlation with forest cover. Variables expressing occupation in absolute terms appear less relevant than those measuring population size and occupation relative to ER size: the proportion of occupied cells (v4) had strong negative correlation with forest (v23) and a weak positive with deforestation (v24). Population density (v7) had only a moderate negative correlation with forest cover (v23). The larger the occupied area – and the higher the density – in the ER, the lower the forest cover. These findings surpass earlier studies, demonstrating that population size and occupied area alone do not fully explain variations in forest cover or deforestation (Barbieri, 2024; Côrtes; D’Antona, 2014; Ferreira *et al.*, 2005; Ferretti-Gallon; Busch, 2914).

Greater inequality in population concentration appears to be linked to a higher forest cover and lower deforestation percentage. The Gini index for all cells (v5) demonstrated a moderate positive correlation with forest cover (v23) and a negative correlation with deforestation (v24); while the Gini index for occupied cells (v6) did not show any significant correlations. On the other hand, the number of patches of occupied cells (v8) did not have a significant correlation, while the median patch size of occupied cells (v9) exhibited a weak to moderate negative correlation with forest proportion (v24). In other words, and contrary to expectations, a larger number and size of occupied patches did not show a substantial relationship with lower forest covers. This suggests that the concentration of population across the entire territory is more significant than population size or the number of occupied patches.

The occupation shape variables did not show strong correlations either. The mean shape index (v10) had a weak negative correlation with forest cover (v23) and a moderate positive correlation with deforestation (v24). Greater geometry complexity was associated with lower forest proportion and higher deforestation. The complexity affects the perimeter of the patch with population occupation, increasing the zone of influence. Considering the indicators based on the standard deviation ellipse, the only significant correlation is that between the perimeter of the ellipse (v11) and the percentage of forest in the ER (v23 – weak, positive).

The correlations indicated that analyses focused solely on population and ER size may be insufficient, as the strongest correlations observed are from variables related to population concentration concerning v23. The importance of considering the context around reserves is also highlighted. The entire set of external condition variables showed a correlation with the proportion of forest conservation within the ER (v23), although none of them was associated with deforestation (v24). The isolation of an ER by protecting its surrounding areas is essential for forest conservation within these territories. The population in the buffer zone (v14) exhibited a weak negative correlation with the forest proportion (v23). The forest cover percentage in the surrounding area (v15) had a strong positive correlation, while the presence of a protected area in the buffer zone (v16) showed a weak positive correlation. Variables related to the effect of urban areas around the ER (v17 and v18) both showed positive correlations.

The results indicated that forest cover is influenced by the spatial arrangement of the population and, to a lesser extent, by population size (Table 5). This is a key finding and makes an important and novel contribution to literature. Among the predictive models of v23 (Percentage of Forest Cover), the inclusion of population volume (v2) in M3 negatively impacted the quality of the model based on M1 (R^2=0.600 decrease to R^2=0.268). The proportion of forest in the buffer zone (v15) had a strong significant contribution on R^2_{v23}. The R^2 increase to 0.681 in M4, highlighting the primary role of external drivers' forces. The replacement of population volume (v2) with Gini index – all cells (v5) in M2 again indicated the need to attempt more complex forms of population occupation in land use science. The R^2 increased to 0.747 in M2, the best model for forest landscape. In this model, the most relevant variable was the Gini index – all cells (v5) and the external variable (v15), with the higher coefficient.

TABLE 5
Regression models and Shapley values for forest cover percentage (v23)

Model (R^2_{v23})	**Measures**	**Predictor variables**					
		v2	**v5**	**v8**	**v9**	**v10**	**v15**
		Resident population	**Gini index – all cells**	**Patches of occupied cells**	**Median patch size of occupied cells**	**Mean shape index of occupied cells**	**Surrounding forest cover**
M1 (0.600)	Φ	-	0.340	0.022	0.155	0.083	-
	P-value	-	0.000**	0.196	0.002**	0.016**	-
M2 (0.747)	Φ	-	0.227	0.038	0.082	0.056	0.344
	P-value	-	0.002**	0.035**	0.174	0.077*	0.001**
M3 (0.268)	Φ	0.023	-	0.015	0.151	0.079	-
	P-value	0.266	-	0.967	0.048**	0.269	-
M4 (0.681)	Φ	0.040	-	0.022	0.086	0.059	0.474
	P-value	0.182	-	0.912	0.051*	0.522	0.198

Source: INPE (2022); IBGE (2016); ICMBIO (2017). Prepared by the authors
Note. *p<0.10, **p<0.05.

The Shapley value analysis proves useful in these results. While the correlation coefficient between v9 and v23 (-0.430, in Table 4) might suggest a high impact of v9 on predicting forest cover, multicollinearity reduces its marginal contribution (as shown by its Shapley value). This underscores the advantage of using a complex strategy to achieve interpretability in scenarios where data structure could lead to misleading conclusions.

These findings advance the literature on population's role in deforestation (Becker, 2001; De Filho; Metzger, 2006; Côrtes; Silva Júnior, 2021), showing that beyond population size, spatial organization significantly correlates with deforestation, enriching discussions on land use and cover. Demographic factors, often viewed as secondary to macrostructural influences like political and economic conditions (Lambin; Geist, 2006; Côrtes; D'Antona, 2014), gain new relevance here. While population size and growth – widely studied attributes (Bremner *et al.*, 2010; DeFries *et al.*, 2010; Geist; Lambin, 2001; Jorgenson; Burns, 2007; Maja; Ayano, 2021; Martin, 2023) – show limitations, spatial indicators emerge as more promising. Distribution across the territory, impacting variables such as the Gini index, population concentration, occupied cell proportion, and average occupied patch size, are critical for understanding forest cover and deforestation. These insights open fresh perspectives for existing research.

Population and forest fragmentation

The presented analyses on the relationship between population indicators and forest fragmentation are rare in the literature, offering a new perspective by proposing spatial parameters and emphasizing the need to examine demographic impacts on forest fragmentation beyond deforestation. The number of cells (v1) had a moderate positive correlation with the number of forest patches (v19), a weak positive correlation with the forest patch mean size (v22), and a weak negative correlation with the density of forest patches (v20): the larger the ER, the greater the forest fragmentation and the mean size of the fragments, and the lower the density of the fragments. The resident population (v2) and the number of occupied cells (v3) showed a significant strong positive correlation only with the number of forest fragments (v19): the larger the population size and occupation extent of the ER, the more fragmented the forest cover. This result is intriguing as it reveals, in a novel way, that although population volume does not directly affect the deforested area or remaining forest cover in these territories, it impacts the environment through the effects of forest fragmentation – including impacts on biodiversity and the ecological function of the forest (Haddad *et al.*, 2015; Laurance *et al.*, 1998; Martínez-Ramos *et al.*, 2016; Metzger, 2021).

The Proportion of occupied cells (v4) and Population density (v7) – relative measures of occupation and population size – showed a strong positive correlation with forest fragment density (v20), suggesting that relatively more extensive and dense occupation corresponded to lower forest connectivity. The v4 also exhibited a moderate negative correlation with the largest forest patch (v21): the greater the proportion of the ER with occupied cells, the smaller the size of the largest forest fragment relative to the size of the ER itself. This result goes beyond previous studies, showing that population density and the proportion of area occupied have a dual impact on forest, affecting not only forest extent but also the forest structure.

The Gini index – all cells (v5) had a moderate negative correlation with the density of the forest patches (v20) and a positive moderate correlation with the forest largest patch (v21), while the Gini index – occupied cells (v6) showed only a weak positive correlation with v20. The higher the inequality in the distribution of the population in the ER (higher concentration), the lower the number of fragments per 100 hectares and the larger the size of the largest forest fragment in relation to the size of the ER. Considering only the occupied cells, the higher the population concentration (a tendency toward clustering), the greater the density of forest patches. This means that more dispersed population patterns within the occupied area reduce the fragmentation process, a finding that expands upon previous studies and provides valuable insight into the effects of infrastructure on land cover change, in shaping population distribution patterns (Assunção; Chiavari, 2015; França *et al.*, 2021; Milien *et al.*, 2021; Perz *et al.*, 2013).

The number of patches of occupied cells (v8) had only a positive correlation with the number of forest patches (v19). The median patch size of occupied cells (v9) exhibited a moderate and positive correlation with the number (v19) and the density (v20) of forest patches, and a weak negative correlation with the largest forest patch (v21). The greater the number of patches of occupied cells – and the larger the patches – the higher the forest fragmentation and patch density, and the smaller the size of the largest forest fragment. This finding converges to the results on the proportion of occupied cells (v4) and Gini Index – all cells (v5).

Regarding the set of variables related to occupation shape, the mean shape index of occupied cells (v10) showed weak correlations with all forest fragmentation variables: the more complex the patches of occupied cells, the larger the number (v19) and density (v20) of forest patches, and the smaller the size of the largest forest fragment (v21) and the mean area of the fragments (v22). Geometry complexity associated with landscape connectivity increases forest fragmentation effects, as reductions in area, isolation and edge effect (Haddad *et al.*, 2015; Laurance; Vasconcelos, 2009). Considering indicators based on the standard deviation ellipse, the perimeter of the ellipse (v11) had a weak negative correlation with the density of forest patches (v20), the ellipse area (v12) showed a moderate positive correlation with the number of forest patches (v19), while eccentricity (v13) had a moderate positive correlation with v19: the more concentrated the occupied area along an axis, the higher the forest fragmentation; the larger the occupied area, the greater the number of forest fragments. This finding converges to the results on the Gini Index – occupied cells (v6), suggesting that population concentration and geometry in settlement areas increase the likelihood of forest fragmentation, offering new insights into previous studies about deforestation patterns and spatial population settlement, such as fishbone pattern or urbanization (Becker, 2001; Browder; Godfrey, 1997; Côrtes; Silva Júnior, 2021).

External conditions also yielded significant correlations, indicating that isolation positively impacts the contiguity of forest cover in the ER. The total population in the buffer zone (v14) had a weak positive correlation with both the number of forest patches (v19) and the density of forest patches in the ER (v20). Other aspects showed more pronounced correlations. The forest cover percentage in the surrounding area (v15) had a significant correlation with nearly all forest fragmentation variables in the ER. This variable presented a moderate negative correlation with the number (v19) and density (v20) of forest patches, and a weak positive correlation with the largest forest patch (v21); meanwhile, the existence of a protected area in the buffer zone (v16) had a strong positive correlation with the mean area of forest patches in the ER (v22). In relation to the proximity of urban areas, the distance to the nearest urban patch (v17) had a weak negative correlation with forest fragmentation – number (v19) and density (v20) – and a positive correlation with the mean area of forest patches (v22), while the distance of the five closest urban patches had a weak negative correlation only with the density of forest patches (v20). These findings align with previous research, confirming the effects of urban areas on land use and cover change, while enhancing our understanding of how the connectivity and geometry of extended urbanization impact forest structure (Browder; Godfrey, 1997; Côrtes; Silva Júnior, 2021).

The results indicate that the size and spatial distribution of the population are important for understanding forest fragmentation and the distribution of forest patches. In fact, for predicting the number of forest fragmentation, we found that population volume had a limited contribution, while the spatial configurations of population occupation offered more consistent effects – population dispersion, concentration, and geometry. This is a key finding that goes beyond previous studies and aligns with results obtained from forest cover proportion models.

The predictive models for the Number of Forest Fragments (Table 6), v2 (resident population) contributed significantly to R^2_{v19} when comparing M1 (R^2 0.660) with M3 (R^2 0.672). This suggests that the total population in the ER impacted on the quality of prediction of the number of forest fragmentation. The model M3 showed improvement when the variable of forest proportion on buffer zone (v15) in M4 was included, highlighting the significance of external forces. In this situation, population size ceased to be statistically significant. Despite the increase in R^2, both M3 and M4 presented predictor variables with weak significance values. When the population size (v2) was replaced with the Gini index – all cells (v5), presented in the M2, we achieved the best R^2 value (0.724) with strong significances. In this model, the most important variable was the patches of occupied cells (V8) and the variable with no significant effect was Mean Patch Size of occupied cells (V9).

As in the results for forest cover percentage, by comparing the correlation coefficients from Table 4 and the contributions of features from Table 6, one may confirm the benefit brought by the Shapley value analysis. The marginal contributions highlighted the impact of variables v8 and v15, even if v5 and v10 are the only ones highly correlated with the number of forest fragments.

The significant correlations between population variables (size, concentration, dispersion, and shape of occupation) and forest fragmentation variables indicate that as the occupation became larger and more complex, the forest cover in the ER became more fragmented. Beyond the use of absolute measures (population size; occupied area) and relative measures (population density; proportion of occupied area), our work proves the significance of including variables related to population spatial distribution in LUCC studies. Although space is a current topic in Population and Environment (Cortes; D'Antona, 2014), this study provided empirical evidence of the importance of incorporating this dimension into demographic parameters.

TABLE 6
Regression models and Shapley values for the number of forest fragments (v19)

Model R^2_{v19}	Measures	Predictor variables					
		v2	v5	v8	v9	v10	v15
		Resident population	Gini index – all cells	Patches of occupied cells	Median Patch Siz4e of occupied cells	Mean shape index of occupied cells	Surrounding forest cover
M1 (0.660)	Φ	-	0.051	0.293	0.210	0.106	-
	P-value	-	0.020**	0.000**	0.009**	0.021**	-
M2 (0.724)	Φ	-	0.080	0.268	0.156	0.110	0.110
	P-value	-	0.002**	0.000**	0.265	0.003**	0.023**
M3 (0.672)	Φ	0.322	-	0.170	0.139	0.041	-
	P-value	0.012**	-	0.034**	0.111	0.623	-
M4 (0.676)	Φ	0.301	-	0.163	0.117	0.035	0.060
	P-value	0.806	-	0.557	0.877	0.912	0.995

Source: INPE (2022); IBGE (2016); ICMBIO (2017). Prepared by the authors.
Note. *p‹0.10, **p‹0.05

Aligning the results obtained for fragmentation with those of forest cover extent reveals the set of concentration variables suggests a convergence between the Gini index – all cells (v5) with the proportion of occupied cells (v4) and population density (v7). Overall, this means that the larger the occupation area, the smaller the concentration, directly affecting land cover with more deforestation and less forest extent, beyond fragmentation (increases the forest patches density and reduces the forest largest patch). Dispersion metrics indicate that the spatial arrangements of the population also affect forest extent and fragmentation. The number and size of patches with population increased the likelihood of forest fragmentation and decreased forest extent. The shape of occupation also seemed relevant: greater complexity in the shape of the occupation may increase fragmentation and decrease the extent of forest cover, while a more scattered distribution of the population along an axis appeared to reduce forest cover change.

The results indicate the relevance of interdisciplinary collaboration between population and environmental studies as it addresses the role of population distribution and density in forest fragmentation, a model still scarce in the literature. On the other hand, forest fragmentation is an environmentally significant phenomenon for biodiversity studies (Laurance *et al.*, 1998; Martínez-Ramos *et al.*, 2016), yet its incorporation into population studies is still low. Besides, establishing connections between population spatial distribution and forest fragmentation brings valuable contributions to Environmental Sciences. Considering that, the use of landscape ecology metrics (Metzger *et al.*, 2021) has shown to be promising, as it enables the integration of population variables with environmental variables at multiple levels of analysis.

Conclusions

Population size and spatial distribution were related to land cover and forest fragmentation in ER. The concentration, dispersion and geometry of population distribution – as well as population size – contributed to understanding deforestation and forest conservation, as well as the landscape structure. The regression models and calculation of the Shapley values revealed the role of external forces but specifically indicated that forest fragmentation and forest cover extent are not necessarily related processes or defined by the same population aspects. The models suggest that forest cover change is demographically driven mostly by the population concentration on the Reserve, while forest fragmentation is highly shaped by population dispersion – and the geometry of population patches should be considered in both processes.

The case study highlights the importance of incorporating forest spatial distribution measures into the Population and Environment research, beyond the traditional focus on forest extent. From the same perspective, we assert the significance of working with spatial demographic variables, going beyond conventional approaches centered on population size. The contribution to Population and Environment and Land Use Sciences also involved emphasizing the significance of including external variables, particularly in studying demographic aspects of protected areas, such as population size and urban concentrations, counterbalance barriers to occupation (forests and protected areas in the buffer zone), resulting in different levels of protection of the natural cover within the reserves.

The proposed methodology based on the use of the IBGE Statistical Grid has proven promising to analyze the relationship between population and forest cover. However, it is important to highlight the analytical limitations resulting from the unavailability of information in the data sources, which vary in update frequency and seasonality. In future studies, we intend to expand the analysis to other categories of conservation units, not only broadening the theoretical perspective on the diversity of population occupations in the Amazon but also ensuring a larger sample volume for analysis. New investigative approaches will allow for further exploration of the findings of this study, incorporating fresh insights into the relationship between population and environment within the context of Amazonian sociobiodiversity conservation.

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Resumo

Distribuição espacial da população e cobertura florestal em reservas extrativistas no bioma amazônico, Brasil

Este estudo relaciona medidas espaciais de cobertura florestal com medidas de distribuição espacial da população nas 31 reservas extrativistas (REs) dentro do bioma amazônico, Brasil, em 2010. Integramos camadas de informações sobre as REs, cobertura florestal e distribuição espacial da população em um Sistema de Informação Geográfica. Produzimos 24 variáveis em três grupos: população; condições externas (ambas como variáveis preditoras); e cobertura da terra (variáveis previstas). Avaliamos se as variáveis preditoras estão correlacionadas com as variáveis de cobertura florestal e fragmentação florestal. Análises de regressão linear baseadas na teoria dos jogos cooperativos foram realizadas para entender a importância das variáveis preditoras na previsão do número de fragmentos florestais e do percentual de cobertura florestal nos modelos. Verificou-se que o tamanho, a concentração, a dispersão e a geometria da população contribuíram para a compreensão do desmatamento, bem como da estrutura da paisagem. No entanto, a fragmentação florestal e a extensão da cobertura florestal não são necessariamente definidas pelos mesmos aspectos populacionais. Os modelos sugerem que a mudança na cobertura florestal é principalmente impulsionada pela concentração da população na RE, enquanto a fragmentação florestal é altamente moldada pela dispersão populacional. O papel das condições externas (florestas circundantes e áreas protegidas) também foi relevante. Nosso estudo destaca a importância de incorporar medidas de distribuição espacial das florestas na pesquisa sobre população e meio ambiente, além do foco usual na extensão florestal. Também mostra a relevância de trabalhar com variáveis demográficas espaciais, indo além do enfoque convencional centrado no tamanho da população.

Palavras-chave: Distribuição espacial. Áreas protegidas. LUCC. Fragmentação florestal. Regressão linear. Valor de Shapley.

Resumen

Distribución espacial de la población y cobertura forestal en reservas extractivas en el bioma amazónico, Brasil

Este estudio relaciona las medidas espaciales de la cobertura forestal con las de la distribución espacial de la población en las 31 reservas extractivas (REs) dentro del bioma amazónico, Brasil, en 2010. Para ello, integramos capas de información sobre las REs, la cobertura forestal y la distribución espacial de la población en un sistema de información geográfica (SIG). Generamos 24 variables en tres grupos: población; condiciones externas (ambas como variables predictoras); y cobertura terrestre (variable predicha). Evaluamos si las variables predictoras están correlacionadas con las variables de cobertura y de fragmentación forestal. Se hicieron análisis de regresión lineal basados en la teoría de juegos cooperativos para comprender la importancia de las variables predictoras en la predicción del número de fragmentos forestales y del porcentaje de cobertura forestal en los modelos. Así. encontramos que el tamaño, la concentración, la dispersión y la geometría de la población contribuyeron a comprender la deforestación y la estructura del paisaje. Sin embargo, la fragmentación forestal y la extensión de la cobertura forestal no están necesariamente definidas por los mismos aspectos de la población. Los modelos sugieren que el cambio en la cobertura forestal está impulsado sobre todo por la concentración de la población en la RE, mientras que la fragmentación forestal está altamente influenciada por la dispersión de la población. El papel de las condiciones externas (bosques circundantes y áreas protegidas) también fue relevante. Nuestro estudio destaca la importancia de incorporar medidas de distribución espacial de los bosques en la investigación sobre población y medioambiente, más allá del enfoque habitual en la extensión forestal. También muestra la importancia de trabajar con variables demográficas espaciales, más allá del enfoque convencional centrado en el tamaño de la población.

Palabras clave: Distribución espacial. Áreas protegidas. LUCC. Fragmentación forestal. Regresión lineal. Valor de Shapley.

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