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Spatio-temporal Distribution of Aboveground Forest Biomass and Carbon in Tropical Dry Forest under Anthropogenic Pressure, Brazil

Distribuição espaço-temporal da biomassa e carbono florestal acima do solo em Floresta Tropical Seca sob pressão antrópica, Brasil

Distribución espacio-temporal de la biomasa y el carbono forestal sobre el suelo en Bosque Tropical Seco bajo presión antropogénica, Brasil

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Abstract: The present study aimed to characterize the spatiotemporal variability of aboveground biomass and carbon in two fragments of Dry Tropical Forest in the Brazilian semi-arid region using the kriging interpolation technique. One fragment experienced vegetation suppression for alternative land use, while the other had no history of use or wood extraction. The vertices of 80 plots (20 m x 20 m) were georeferenced, and biomass and carbon were estimated using allometric equations adjusted for Caatinga species. Spatial analyses and mapping of aboveground biomass and carbon were performed using GS+ software, with semivariograms fitted using spherical, exponential, and Gaussian models. The research aims to fill gaps regarding the impacts of inadequate forest exploitation in Dry Tropical Forests, specifically on the spatiotemporal distribution of biomass and carbon, as anthropogenic pressure can cause significant environmental degradation, resulting in reduced stocks. This investigation seeks to elucidate these dynamics and provide insights for management and conservation strategies based on robust empirical data, in addition to answering the following questions: Does the history of anthropogenic interventions in Dry Tropical Forest areas cause variations in the spatial distribution of biomass and carbon stocks that can be detected by the kriging method? Which attributes related to conservation and anthropogenic use reflect the spatial distribution of biomass and carbon stocks in Dry Tropical Forest areas? The results showed a strong spatial dependence of biomass and carbon stocks in both studied areas, indicating the influence of the areas' use history. The conserved fragment presented a more homogeneous spatial distribution, suggesting that the selective and unauthorized wood extraction was dispersed throughout the area.
Keywords: Geostatistics, Kriging, Semi-arid, Interpolation Techniques.

Resumo: O presente trabalho teve como objetivo caracterizar a variabilidade espaço-temporal da biomassa e do carbono acima do solo em dois fragmentos de Floresta Tropical Seca no semiárido brasileiro utilizando a técnica de interpolação por krigagem. Um fragmento sofreu supressão de vegetação para uso alternativo do solo, enquanto o outro não possui histórico de uso e extração de madeira. Foram georreferenciados os vértices de 80 parcelas (20 m x 20 m), e a biomassa e o carbono foram estimados utilizando equações alométricas ajustadas para espécies da caatinga. As análises espaciais e o mapeamento da biomassa aérea e do carbono foram realizados no software GS+, com semivariogramas ajustados usando os modelos esférico, exponencial e gaussiano. A pesquisa visa preencher lacunas sobre os impactos da exploração florestal inadequada na Floresta Tropical Seca, especificamente na distribuição espaço-temporal de biomassa e carbono, uma vez que a pressão antrópica pode causar degradação ambiental significativa, resultando na redução dos seus estoques. Esta investigação busca elucidar essas dinâmicas e fornecer subsídios para estratégias de manejo e conservação baseadas em dados empíricos robustos, além de responder às seguintes questões: O histórico de intervenções antrópicas em áreas de Floresta Tropical Seca provoca variações na distribuição espacial dos estoques de biomassa e carbono que possam ser constatados pelo método de krigagem? Quais atributos relacionados à conservação e ao uso antrópico refletem na distribuição espacial dos estoques de biomassa e carbono em áreas de Floresta Tropical Seca? Os resultados mostraram uma forte dependência espacial dos estoques de biomassa e carbono nas duas áreas estudadas, indicando a influência do histórico de uso das áreas. O fragmento considerado conservado apresentou uma distribuição espacial mais homogênea, sugerindo que a extração pontual e não autorizada de madeira foi seletiva e dispersa.
Palavras-chave: Geoestatística, Krigagem, Semiárido, Técnicas de interpolação.

Resumen: El presente estudio tuvo como objetivo caracterizar la variabilidad espacio-temporal de la biomasa y el carbono por encima del suelo en dos fragmentos de Bosque

Tropical Seco en la región semiárida de Brasil utilizando la técnica de interpolación por krigaje. Un fragmento experimentó la supresión de la vegetación para uso alternativo del suelo, mientras que el otro no tenía historial de uso o extracción de madera. Se georreferenciaron los vértices de 80 parcelas (20 m x 20 m) y la biomasa y el carbono se estimaron utilizando ecuaciones alométricas ajustadas para especies de la Caatinga. Los análisis espaciales y el mapeo de la biomasa aérea y el carbono se realizaron utilizando el software GS+, ajustando los semivariogramas con modelos esféricos, exponenciales y gaussianos. La investigación tiene como objetivo llenar los vacíos en cuanto a los impactos de la explotación forestal inadecuada en los Bosques Tropicales Secos, específicamente en la distribución espacio-temporal de la biomasa y el carbono, ya que la presión antropogénica puede causar una degradación ambiental significativa, resultando en una reducción de los stocks. Esta investigación busca dilucidar estas dinámicas y proporcionar información para estrategias de manejo y conservación basadas en datos empíricos robustos, además de responder a las siguientes preguntas: ¿El historial de intervenciones antropogénicas en áreas de Bosque Tropical Seco provoca variaciones en la distribución espacial de los stocks de biomasa y carbono que pueden ser detectadas por el método de krigaje? ¿Qué atributos relacionados con la conservación y el uso antropogénico reflejan la distribución espacial de los stocks de biomasa y carbono en áreas de Bosque Tropical Seco? Los resultados mostraron una fuerte dependencia espacial de los stocks de biomasa y carbono en ambas as áreas estudiadas, lo que indica la influencia del historial de uso de las áreas. El fragmento conservado presentó una distribución espacial más homogénea, lo que sugiere que la extracción selectiva y no autorizada de madera se dispersó por toda el área.
Palabras clave: Geoestadística, Kriging, Semiárido, Técnicas de interpolación.

INTRODUCTION

Half of the earth's surface is covered by forests, with half dominated by Tropical Dry Forests (TDFs). The true original extent of these forests will likely never be known due to many being classified as disturbed areas (Murphy & Lugo, 1986). Despite their significance, dry forests are among the most threatened and least studied forest ecosystems globally (Blackie et al., 2014).

The United Nations General Assembly proclaimed the period until 2030 as the United Nations Decade on Ecosystem Restoration (UN, 2019). Resolution 73/284 identified six main areas of investment, several of which are directly related to tropical dry forest restoration, including resource mobilization, capacity building, scientific research and cooperation for ecosystem restoration at multiple scales. Integration of ecosystem restoration into policies and plans to address current national development is also emphasized. In response to this UN resolution, attention is drawn to the imperative of restoring a geographically, ecologically, and socioculturally significant biome - the Brazilian Caatinga, considered a tropical dry forest (Campo et al., 2023).

In Brazil, two important vegetation formations are classified as TDF: the Caatinga and part of the Cerrado biome vegetation. Together, they constitute nearly 33.80% of the Brazilian territory (IBGE, 2004). The Caatinga, located in the semi-arid region of Brazil, is the largest and one of the most diverse nuclei of the TDF in Latin America (Dexter et al., 2018; Sunderland et. al., 2015). This neotropical biome exhibits a disjunct distribution and is strongly marked by climatic seasonality, characterized by low annual rainfall, an ephemeral herbaceous stratum and high diversity and endemism of Leguminosae (Costa et al., 2015). The species are morphophysiologically adapted to withstand long periods of drought, through deciduous and high regrowth capacity by stumps and roots (Gariglio et al., 2010). Although many are still native, they exist in different stages of regeneration due to anthropization actions (Araújo Filho et al., 2018).

Forests play a crucial role in the global carbon cycle (Anderegg et al., 2013; Bonan, 2008; Lin et al., 2022). In terrestrial ecosystems, plants contain 90% of biomass carbon and 80% of soil carbon (Landsberg & Gower, 1997; Lin et al., 2022). Consequently, forested areas are considered vital carbon sinks in terrestrial ecosystems, which can absorb carbon dioxide from the atmosphere, convert it into organic carbon, store it in plants, and contribute to clean air (Chen et al., 2017; Lin et al., 2022).

Forests also play a role in regulating microclimates and mitigating the greenhouse effect, underscoring their importance in the context of climate change. Through long-term research, it has been determined that global forests can absorb approximately 2.4 billion tons of carbon from the atmosphere annually (Pan et al., 2011; Lin et al., 2022). Consequently, sustainable forest management is currently recognized as one of the most effective methods to address global warming (FAO, 2015).

Traditionally, plant productivity has been directly estimated by measuring biomass and aboveground cover, a process demanding significant human, financial and time resources. To address this challenge, the use of biomass estimates from remote sensing products is emerging as a valuable tool applicable to large-scale studies (Pessi et al., 2023; Yu et al., 2018).

Within the realm of forest dynamics studies, a technique gaining popularity is spatio-temporal interpolation, associated with geostatistics. This approach has the potential to elucidate the spatial performance of dendrometric variables (Pelissari et al., 2014), tree spacing, sampling configuration in forest inventories (Rufino et al., 2006; Oda-Souza et al., 2008; Mello et al., 2009), and the spatio-temporal dynamics of vegetation cover over the years (Pessi et al., 2023, Pessi et al., 2022). There is mounting evidence that spatial structure is a characteristic inherent in these variables and cannot be adequately identified using classical statistics alone, leading to a loss of information (Pereira et al., 2011; Rosa Filho et al., 2011; Pelissari et al., 2013).

Native forests result from the co-evolution of various factor over time and space. The spatial dependence of forest variables mirrors the occupation and utilization of available spaces in the environment. This is influenced by different levels of competition, the form and type of architecture, location quality, distance between trees and openings in the forest, among other factors (Amaral et al., 2013).

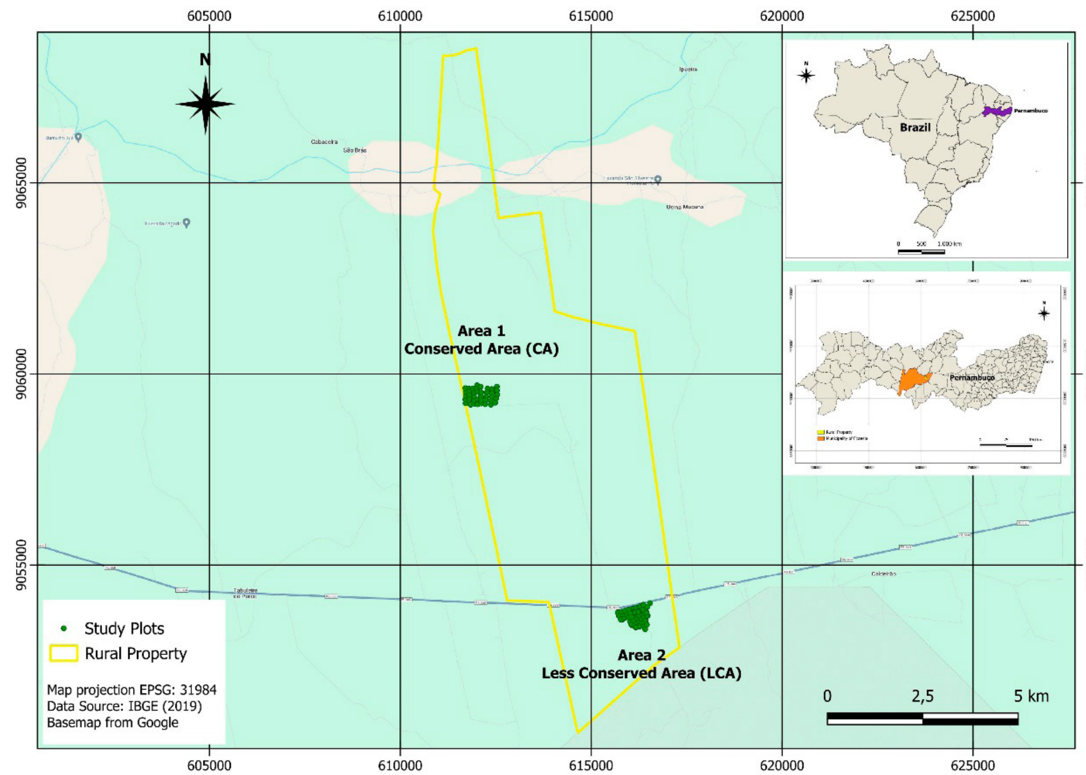
The aim of this study was to examine and represent the spatio-temporal distribution of individuals of species within a remnant of Tropical Dry Forest of the Caatinga biome that has experienced anthropogenic pressure, utilizing geostatistics and kriging interpolation. Therefore, to assess the state of the forest altered by anthropogenic pressures, we hypothesized that inadequate forest exploitation contributes to the reduction of biomass and carbon stocks, directly influencing the spatio-temporal distribution of forest species.

MATERIAL AND METHODS

Field of study

The study area is situated in the municipality of Floresta-PE, Brazil (Figure 1). The investigation was conducted in two sampling units with different conservation histories, each totaling 1.6 ha: Area 1 - The most recent clear-cutting in the area occurred in 1987 (34 years without intervention), referred to as less conserved area (LCA); and Area 2 – With no recent major interventions on record, it is classified as conserved vegetation and referred to as the conserved area (CA).

Figure 1: Image of the location of the study area (Itapemirim Farm) in the municipality of Floresta, State of Pernambuco, Brazil.



According to the Köppen climate classification, the region experiences a BS'h type climate, indicating a hot semi-arid climate with total annual rainfall ranging between 100 and 600 mm (Alvares et al., 2013). The average annual air temperature in the hinterland can exceed 26 °C (Embrapa, 2000). Rainfall is concentrated from January to May, with March and April being the wettest months, and many years have recorded below-average rainfall (Apac, 2017). The vegetation is classified as shrubby steppe savanna - Caatinga

(Ibge, 2012) and the soil of the region is characterized as chromic luvisol, being shallow and typically abrupt in texture (Embrapa, 2011).

The study's history outlines the establishment and monitoring of 80 plots since 2008 in two areas with distinct land use histories. Each plot measures 20 m by 20 m (400 m²), spaced 80 m apart during installation, with 50 m at the edges. Forty (40) plots were allocated to each area, totaling 3.2 ha of the sampled area.

The first area, named LCA (Figure 2A), is located near a state highway and has a history of land use involving the complete clearing of vegetation with the help of chains until 1987, followed by total abandonment. The second area, CA (Figure 2B), is considered conserved as there are no records of vegetation exploitation in the area, reinforcing its state of conservation. In CA, only the removal of forest by-products (stakes, posts, beams, among others) for occasional fence maintenance occurs, which does not interfere with the area's patterns and dynamics, as these activities are sporadic and occasional. Each area covers approximately 50 hectares and is predominantly grazed by animals, mainly goats.

Figure 2: Aerial image of the two study areas, LCA in letter A and CA in letter B, located at Fazenda Itapemirim, in the municipality of Floresta, State of Pernambuco, Brazil.

Sampling and data collection

At the installation of the plots in 2008, all individuals with a circumference of 1.30 m from the ground (CAP) and ≥ 6 cm were identified and marked. Throughout the study years (2008, 2013, and 2018), height and CAP measurements were conducted for all individuals meeting the inclusion criteria. Both newly recruited individuals, reaching the minimum CAP stipulated in the remediation years, and deceased individuals were recorded and added to the database.

The selection of these specific intervals (2008, 2013 and 2018) was influenced by the Caatinga's response time to extreme drought event that occurred between 2012 and 2015 (Marengo et al., 2016). By choosing a previous period (2008-2013), a subsequent interval (2013-2018) and a total of ten years, we aimed to comprehensively assess the vegetation's response in each area based on its history of use in the face of the effects of drought.

Biomass and carbon stock and balance in vegetation

In the Caatinga, species exhibit the characteristic of emitting multiple stems. Therefore, in this study, bifurcations below 0.30 m in height were considered as a single individual. To estimate the biomass stock of the study area, the allometric equations adjusted by Dalla Lana et al. (2018) for eight species of the Caatinga were used. Additionally, a general equation, based on a forest inventory conducted in the conserved area (CA) in 2013, was employed. The selected species and equations are presented in Table 1. The selected species, by the authors, due to their representativeness, collectively accounting for over 90% of the total density in the area. Carbon stock was estimated using the conversion factors described by Dalla Lana et al. (2019).

Table 1: Equations for estimating the dry biomass stock for eight tropical dry forest species.

Species	Equations	
Anadenanthera colubrina var. cebil (Griseb.) Altschul	$\widehat{Bio}$=48.7255*[1-exp(-0.1435*DAP)]$^{2.4096}$	(1)
Aspidosperma pyrifolium Mart.	$\widehat{Bio}$=0.7858*(DAP^2*H)$^{0.4550}$	(2)
Bauhinia cheilantha (Bong.) Steud.	$\widehat{Bio}$=0.0669*(DAP2.^{2115})*(H$^{0.8155}$)	(3)
Cnidoscolus quercifolius Pohl	$\widehat{Bio}$=0.6064*(DAP1.4216)	(4)
Croton heliotropiifolius Kunth	$\widehat{Bio}$=0.1868*(DAP1.^{2764})*(H$^{0.9401}$)	(5)
Mimosa Ophthalmocenters Mart. ex Benth.	ln =1.1118+1.7371*lnDAP-0.9536*lnH$\widehat{Bio}$	(6)
Mimosa tenuiflora (Willd.) Poir.	$\widehat{Bio}$=0.5084*(DAP1.7121)	(7)
Poincianella bracteosa (Tul.) L.P.Queiroz	$\widehat{Bio}$=6.6205+0.0341*(DAP^2*H)	(8)
General Equation	**ln $\widehat{Bio}$ = −1.2884+1.6102* ln(DAP)+0.4343*ln(H)**	**(9)**

$\widehat{Bio}$ = estimated total dry biomass aboveground (kg); DBH* = diameter at 1.30 m aboveground (cm) and H = total height (m). *DAP=CAP/π.
Source: Dalla Lana et al. (2018).

Spatio-temporal distribution of biomass and carbon stock

To survey the 80 plots, a Trimble Catalyst Digital Antenna connected to a smartphone device was used, capable of tracking L1/GPS L2C signals. Coordinates were collected with submetric precision (0.3 to 0.75 m).

Using the field-collected coordinates, tables were generated for each sampling unit, incorporating data on forest variables (Number of individuals, Number of stems, DBH, height [H], biomass and carbon). These tables were organized into a Microsoft Excel 2016 spreadsheet (Microsoft® Corporation, 2016). Descriptive statistics (mean, median, mode, variance, standard deviation, coefficient of variation) were calculated for the data and imported into GS + software version 7.0. The software was utilized for variographic analysis, cross-validation and data interpolation (GS+, 2000).

A preliminary trend analysis was conducted to assess the influence of external factors on the dataset of the study area in all directions, considering potential edge effects on the forest fragment. To configure this analysis, a scatter plot was created with X (longitude) and Y (latitude) against Z (dry biomass and carbon) attributes. Semivariograms were constructed in the 0°, 45º, 90º and 135º directions with an angular tolerance of 45º to evaluate anisotropy and select the experimental semivariogram with the longest range or isotropy for each variable. The theoretical semivariogram models tested in the GS+ Geostatistics software (GS+, 2000) are listed in Table 2.

Table 2: Geostatistical models used in the selection of experimental semivariograms.

Models		
Spherical	$\gamma(h) = \beta0 + \beta1 * + \varepsilon i$ for $h < A\left[1{,}5\left(\frac{h}{\beta_2}\right) - 0{,}5\left(\frac{h}{\beta_2}\right)^3\right]$ $\gamma(h) = [\beta0 + \beta1] + \varepsilon i$ for $h \geq A$	(10)
Exponential	$\gamma(h) = \beta0 + \beta1 * + \varepsilon i\left[1 - exp\left(-\frac{h}{\beta_2}\right)\right]$	(11)
Gaussian	$\gamma(h) = \beta0 + \beta1 * + \varepsilon i\left[1 - exp\left(-3 * \frac{h}{\beta_2}\right)^3\right]$	(12)

Where: γ(h) = semivariance, β0 = nugget effect, β1 = plateau, β2 = range, h = distance between two sampling points, ei = sampling error.

In this analysis, it was assumed that the data exhibit spatial dependence (Krempi, 2004). Following the adjustment of theoretical models, the nugget coefficients (C0) were obtained. This coefficient represents the variability, randomness and probabilistic error of the theoretical semivariogram models adjusted to the experimental semivariogram of the analyzed attribute. The level (C0 + C1) and the spatial dependence range (A) were submitted to spatial dependency analysis using the Spatial Dependency Advisor (Zimback, 2001). To visualize the distribution of the variable in the graph, IDW (Inverse Distance Weighting) interpolation was applied, generating heat plots via interpolation.

Once the theoretical semivariogram models were adjusted, the kriging step was performed using its estimator, represented by the following expression (Equation 13):

$$\hat{Z}x_0 = \sum_{i=1}^{n} \lambda_{1i} Z_{1i}(x_i) \qquad \text{Equation 13}$$

Where: Ẑx0 is the estimate of the value at position X0; n is the number of neighboring sampling points used to predict the unsampled value (kriging neighborhood); λ_{1i} are the i-th weights assigned to each i-th observation of the variables Z_{1i} (observed variable).

Cross-validation was conducted for all sampling points. To determine the optimal semivariogram model, we considered the sum of the residual squares (SQR), the standard deviation (SD) and the alignment between the actual and estimated data lines in the cross-validation. It's crucial to emphasize that the user sensitivity is more significant than the values obtained during the adjustment process. Attempts at adjustment should be made, even if they result in a change in the R^2 value (Coefficient of Determination) and an increase in the SQR value (Guimarães, 2004). It's important to note that the model with the lowest nugget effect may not always be the one that best fits the data through cross-validation (Ortiz, 2002).

The selection of the best-fitted model for the semivariogram was guided by considerations of the lowest SQR, the R^2 and the cross-validation parameters derived from the regression adjustment between observed values and those predicted by the model. Once the model was adjusted, data interpolation was performed using the Kriging method. This method assigns weights to unsampled points based on the data from neighboring points, considering the spatial variability expressed in the semivariograms.

The classification of the degree of spatial dependence (PD) was based on the ratio between the contribution (C) and the level (C0 + C). It was categorized as strong for PD greater than 75%, moderate for values between 25 and 75% and weak for PD less than 25%. This classification scheme was proposed by Cambardella et al. (1994) in their studies on soil attributes.

RESULTS AND DISCUSSION

The values obtained for the mode, representing the highest observed frequency, were higher in the CA for the years 2008 and 2013. However, in the year 2018, the mode value remained similar only for the number of stems (Table 3).

Position measures, which serve as central tendency indicators, are subject to the influence of extreme values (maximum value - V. Max and minimum value - V. Min.), directly impacting the values of the mean, median and mode.

Table 3: Descriptive statistics of the number of individuals and stems per hectare, and carbon stock, based on the different land use histories of the area (LCA - Less Conserved Area and CA - Conserved Area) for the three years of evaluation in a fragment of tropical dry forest in the semi-arid region, Floresta municipality, State of Pernambuco, Brazil.

Nind.ha^{-1}											
Area	**Year**	**Avg.**	**With.**	**Mode**	**V.Max**	**V.Min**	**S2**	**SD**	**Asy.**	**Kurt.**	**CV**
CA	2008	55.28	54.00	54.00	99.00	27.00	350.26	18.72	0.20	-0.15	0.34
	2013	49.93	48.00	46.00	84.00	20.00	247.71	15.74	0.37	-0.03	0.32
	2018	34.03	13.00	29.00	60.00	13.00	152.38	12.34	0.49	-0.60	0.36
LCA	2008	26.13	22.50	3.00	106.00	1.00	480.67	21.92	0.50	2.86	0.84
	2013	29.65	21.00	3.00	148.00	2.00	831.93	28.84	0.90	6.02	0.97
	2018	23.55	16.00	8.00	84.00	3.00	394.51	19.86	1.14	0.46	0.84
Nstem.ha^{-1}											
Area	**Year**	**Avg.**	**With.**	**Mode**	**V.Max**	**V.Min**	**S2**	**SD**	**Asy.**	**Kurt.**	**CV**
CA	2008	152.15	148.50	116.00	283.00	76.00	2026.90	45.02	0.24	1.22	0.30
	2013	138.78	134.50	143.00	231.00	53.00	1486.59	38.56	0.33	0.14	0.28
	2018	85.03	82.50	62.00	173.00	35.00	1306.38	36.14	0.21	0.67	0.43
LCA	2008	70.53	61.50	82.00	217.00	3.00	2411.44	49.11	0.55	1.02	0.70
	2013	80.83	66.50	17.00	249.00	3.00	3959.38	62.52	0.68	0.80	0.78
	2018	65.43	61.00	68.00	241.00	8.00	2188.05	46.78	0.28	3.56	0.71

continue

conclusion

Biomass (Kg)											
Area	**Year**	**Avg.**	**With.**	**Mode**	**V.Max**	**V.Min**	**S2**	**SD**	**Asy.**	**Kurt.**	**CV**
CA	2008	1144.63	1071.09	-	2082.65	403.59	112852.82	335.94	0.66	1.61	0.29
	2013	1110.65	1075.47	-	1745.47	260.25	90713.59	301.19	0.35	0.54	0.27
	2018	762.96	749.10	-	1380.53	195.99	89503.56	299.17	0.14	-0.42	0.39
LCA	2008	350.00	304.95	-	1522.23	19.02	69001.99	262.68	0.51	9.22	0.75
	2013	457.15	402.44	-	1819.57	21.88	100114.21	316.41	0.52	7.64	0.69
	2018	527.26	474.75	-	2011.37	33.29	124670.71	353.08	0.45	6.76	0.67
Carbon (Kg)											
Area	**Year**	**Avg.**	**With.**	**Mode**	**V.Max**	**V.Min**	**S2**	**SD**	**Asy.**	**Kurt.**	**CV**
CA	2008	520.96	491.38	-	954.36	185.40	23239.26	152.44	0.58	1.67	0.29
	2013	504.19	487.54	-	789.12	119.81	18356.26	135.49	0.37	0.57	0.27
	2018	345.90	339.53	-	623.84	89.92	18191.89	134.88	0.14	-0.42	0.39
LCA	2008	158.05	138.58	-	685.40	8.82	14025.11	118.43	0.49	9.12	0.75
	2013	206.56	182.32	-	819.26	10.15	20380.18	142.76	0.51	7.51	0.69
	2018	238.39	214.68	-	905.89	14.97	25413.15	159.42	0.45	6.62	0.67

Where: Avg. = average; Med. = median; V. Max. = Maximum value; V. min. = Minimum value; S^2 - Variance; SD = standard deviation; Asy. = Asymmetry; kurt. = kurtosis; CV - Coefficient of Variation; $Nind.ha^{-1}$ = number of individuals per hectare; $Nstem.ha^{-1}$ = number of stems per hectare.

For the variables $Nind.ha^{-1}$ and $Nstem.ha^{-1}$, the mean and median values closely aligned for the years 2008 and 2013, suggesting that the central point of the analyzed values is like the arithmetic mean of the variables studied, with no marked discrepancies. This indicates a normal distribution of the data, a pattern not observed for the year 2018. In 2018, the mean and median exhibited distant values, and this observation is also applying to carbon and biomass stocks.

As for asymmetry and kurtosis, both areas displayed negative and positive values, some significantly deviating from the central value of zero, as observed in the mean and median. According to Guimarães et al. (2010), these values do not signify a significant departure from normality; rather, they illustrate that natural distributions often deviate from a perfect normal distribution.

The results revealed that the variables exhibit a moderate to high coefficient of variation (CV) based on parameters established in numerous studies with various types of forest crops (Fu et al., 2015; Benítez et al., 2016), resulting in values surpassing 30%. Among these, the highest values were observed in the LCA for all the variables, regardless of the evaluation year. This is likely attributed to the historical exploitation of the area, coupled with the forest's current state characterized by disturbance and anthropization. These factors contribute to structural variation, with individuals of different sizes reflecting the regeneration rate and irregular disposition in the sampled area, thus presenting heterogeneity in the sampling.

The emergence of high coefficients of variation in the spatial distribution analysis may also be attributed to a low sampling effort, leading to less accurate estimates. The heterogeneity of an environment, influenced by location variations, determines the development of individuals. Less variability is expected within small plots, while between plots this variability can increase, consequently elevating the values of the coefficient of variation (Péllico Netto, 1997). This observation is consistent with the findings of Kershaw et al. (2017), who indicated that small sample plots in small homogeneous forests can result in high coefficients of variation.

Regarding the number of individuals per hectare (Table 4), spatial dependence ranged from moderate to strong, except for the years 2008 and 2013 in the CA where the spatial dependence was weak. Conversely, for the number of stems per hectare, strong spatial dependence was observed for all years, except for 2013 in the LCA. Biomass and carbon stocks exhibited strong spatial dependence for all evaluated years, regardless of the area's history of use. Since the condition for the use of kriging is that the data exhibit moderate to strong spatial dependence (Yamamoto & Landim, 2015), the results are deemed satisfactory.

Table 4: Semivariographic parameters for the number of individuals and stems per hectare based on different degrees of anthropic disturbance (LCA - Less Conserved Area and CA - Conserved Area) in a fragment of tropical dry forest in the semi-arid region, Floresta municipality, State of Pernambuco, Brazil.

Variable	Year	Model	C0	C0+C	R (m)	R^2	SRS	C/C0+C	SD
Less Conserved Area – LCA									
$Nind.ha^{-1}$	2008	Gaussian	248.00	496.10	578.33	0.95	777.00	0.50	M
	2013	Gaussian	1.00	636.00	254.44	0.88	37597.00	0.99	S
	2018	Gaussian	250.65	337.37	344.96	0.23	10434.00	0.26	M
$Nstem.ha^{-1}$	2008	Gaussian	1.00	2370.00	199.01	0.80	777.00	1.00	S
	2013	Gaussian	3610.39	3610.39	344.96	0.08	918734.00	0.00	In
	2018	Gaussian	1.00	1952.00	212.69	0.84	491585.00	0.99	S
Biomass (kg)	2008	Exponential	100.00	57700.00	94.80	0.05	1.85E+08	0.99	S
	2013	Gaussian	100.00	88160.00	170.08	0.89	2.30E+08	0.99	S
	2018	Gaussian	100.00	111600.00	172.34	0.90	3.37E+08	0.99	S
C (kg)	2008	Exponential	10.00	11740.00	94.20	0.05	7708500.0	0.99	S
	2013	Gaussian	10.00	17990.00	170.95	0.90	9589618.0	0.99	S
	2018	Gaussian	10.00	22810.00	173.21	0.91	1.41E+07	1.00	S
Conserved Area – CA									
$Nind.ha^{-1}$	2008	Linear	327.99	392.72	401.16	0.12	17689.00	0.16	In
	2013	Linear	216.57	284.01	401.16	0.20	9348.00	0.24	In
	2018	Gaussian	0.10	154.40	154.33	0.79	2284.00	0.99	S
$Nstem.ha^{-1}$	2008	Spherical	1.00	1954.00	86.60	0.14	236704.00	0.99	S
	2013	Gaussian	1.00	1486.00	108.95	0.83	61734.00	0.99	S
	2018	Gaussian	1.00	1219.00	173.72	0.88	125430.00	0.99	S
Biomass (kg)	2008	Spherical	100.00	105100.0	61.90	0.00	3.67E+08	0.99	S
	2013	Exponential	7400.00	88420.00	69.00	0.05	3.67E+08	0.92	S
	2018	Exponential	2100.00	96490.00	437.70	0.75	6.48E+08	0.98	S
C (kg)	2008	Exponential	690.00	21760.00	62.10	0.05	1.49E+07	0.97	S
	2013	Exponential	1279.00	17950.00	80.40	0.11	1.49E+07	0.93	S
	2018	Exponential	290.00	19530.00	431.70	0.75	2.67E+07	0.98	S

Where: C0 = nugget effect; C0+C = level; C/(C0+C) = structure or spatial proportion; R = range; R^2 = coefficient of determination e SRS = sum residual squares; SD = spacial dependence; W = weak; M = moderate; S = strong; $Nind.ha^{-1}$ = number of individuals per hectare; $Nstem.ha^{-1}$ = number of stems per hectare; Bio = Aerial biomass; C = Carbon.

As proposed by Kravchenko et al. (2006), higher values of spatial dependence indicate a more robust spatial structure and greater precision in mapping properties using geostatistical techniques like kriging. The observed spatial dependencies underscore the need to move beyond classical statistics, where observations are considered random and spatially independent, and adopt spatial analyses that take account for relationships with neighboring observations (Correia et al., 2014).

The mean spatial range (R) for all variables consistently exceeded the distance between the plots, except for biomass in 2008 and 2013 (61.90 and 69.00 m, respectively) and carbon stock in 2008 in CA (62.10 m). When the spatial range falls between plots (80.00 m), the use of geostatistical models for these variables is precluded. This is because samples taken at distance greater than the intervals are not correlated, indicating a lack of spatial variability (Zimmermann et al., 2008). The highest range was observed in 2008 in the LCA for Nind.ha^{-1} (578.33 m), demonstrating that this attribute has the lowest variability and the greatest spatial continuity, ensuring greater precision in the estimates at unsampled locations.

Alternatively, an exceptionally long range exhibits linear behavior, indicating the presence of the infinite dispersibility. This suggests that the size of the sampled field was insufficient to capture the entire variance (Vieira et al., 2008). A longer range implies a greater dependence among neighboring points, potentially leading to more accurate estimates for geostatistics with fewer samples. Lundgren et al. (2016) emphasize the significance of the range as it assists other studies of the same attribute in determining the spacing between samples.

The CA exhibited lower variation in the variables compared to the LCA, with the exception of biomass and carbon stock in 2018 and Nind.ha^{-1} in 2013. This indicates that the LCA has larger patches of variability between sample points, a finding consistent with the results of Guedes et al. (2015) who studied the spatial continuity of dendrometric characteristics in eucalyptus stands over time.

Concerning the nugget effect (C0), Chiles and Delfiner (1999) report that high values may be attributed to structures with a shorter range than the minimum distance between two surveyed points. As show in Table 4, for the Gaussian model of Nind.ha^{-1} in 2008 (LCA), the nugget effect corresponds to 50.00% of the threshold, indicating that half of the variability was explained by the spatial correlation, while the rest was considered random. This analysis is important because a higher proportion of nugget effect can negatively impact Kriging estimates. The assumption is that lower similarity between neighbors and less continuity of the phenomenon lead to impaired Kriging estimation. For most of the models evaluated, the proportion was high, showing that the Kriging estimation was compromised.

The precise factors influencing this result cannot be definitively determined due to the research design and sampling approach. It is believed that factors such as the age of the areas, anthropic disturbance and preservation time may contribute to an increased nugget effect. According to Kanegae Júnior et al. (2007), competition between plants can affect the spatial relationship between sampled units.

Despite most variables exhibiting strong SD, many encountered interpolation challenges. The semivariograms displayed few points in the ascending region of the adjustment line (Figures 3 and 4), or did not exhibit an ascending line at all, indicating a significant nugget effect. In cross-validation, substantial discrepancies were observed at the extremes of the data amplitude between the interpolated and actual values (Figures 5 and 6).

Figure 3: Semivariograms of Biomass (kg) – Bio and Carbon (kg) – C stocks, in a less conserved area of Tropical Dry Forest (Caatinga) (LCA) for the years 2008, 2013 and 2018.

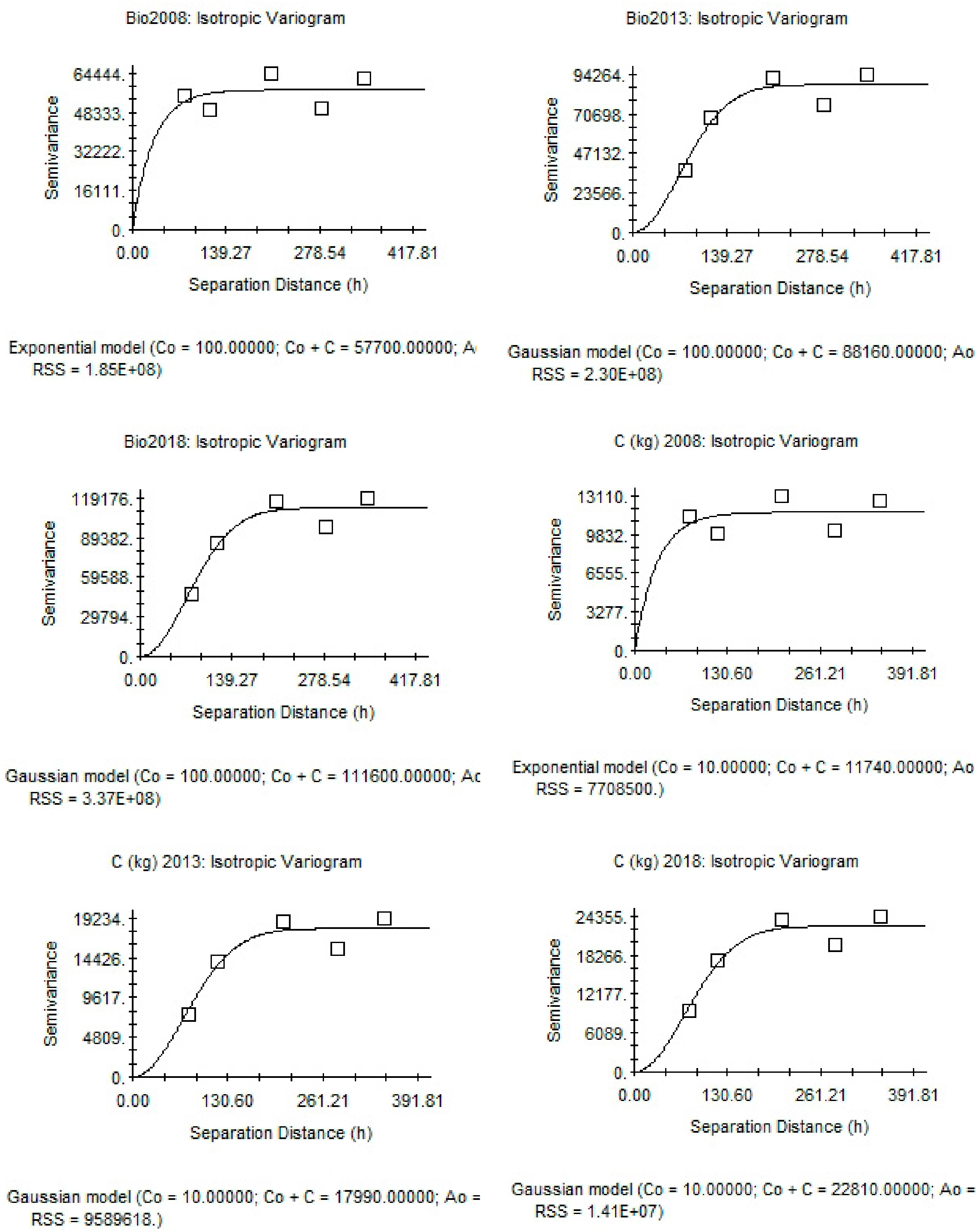


Figure 4: Semivariograms of Biomass (kg) – Bio and Carbon stock (kg) – C, in a conserved area of Tropical Dry Forest (Caatinga) (CA) for the years 2008, 2013 and 2018.

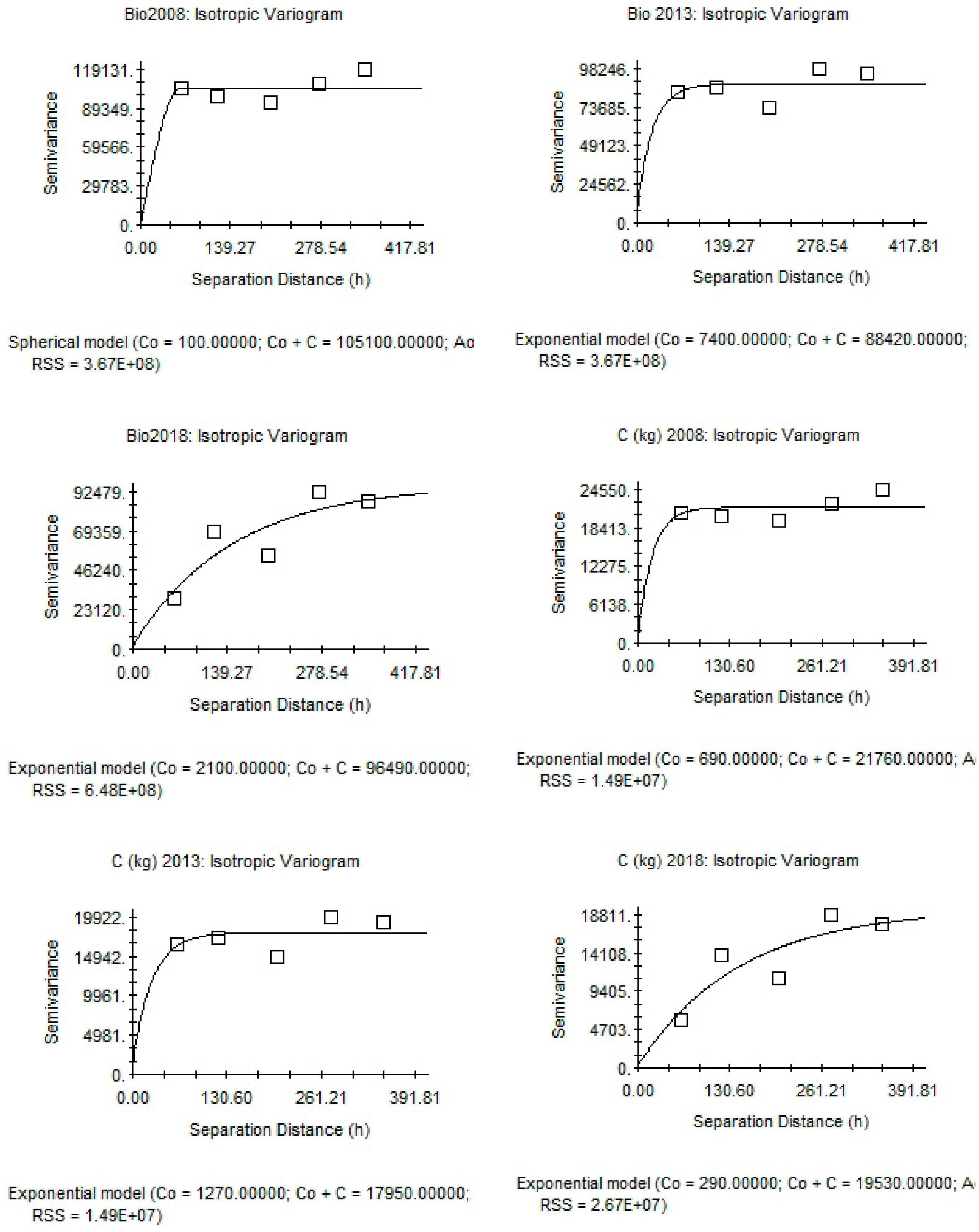
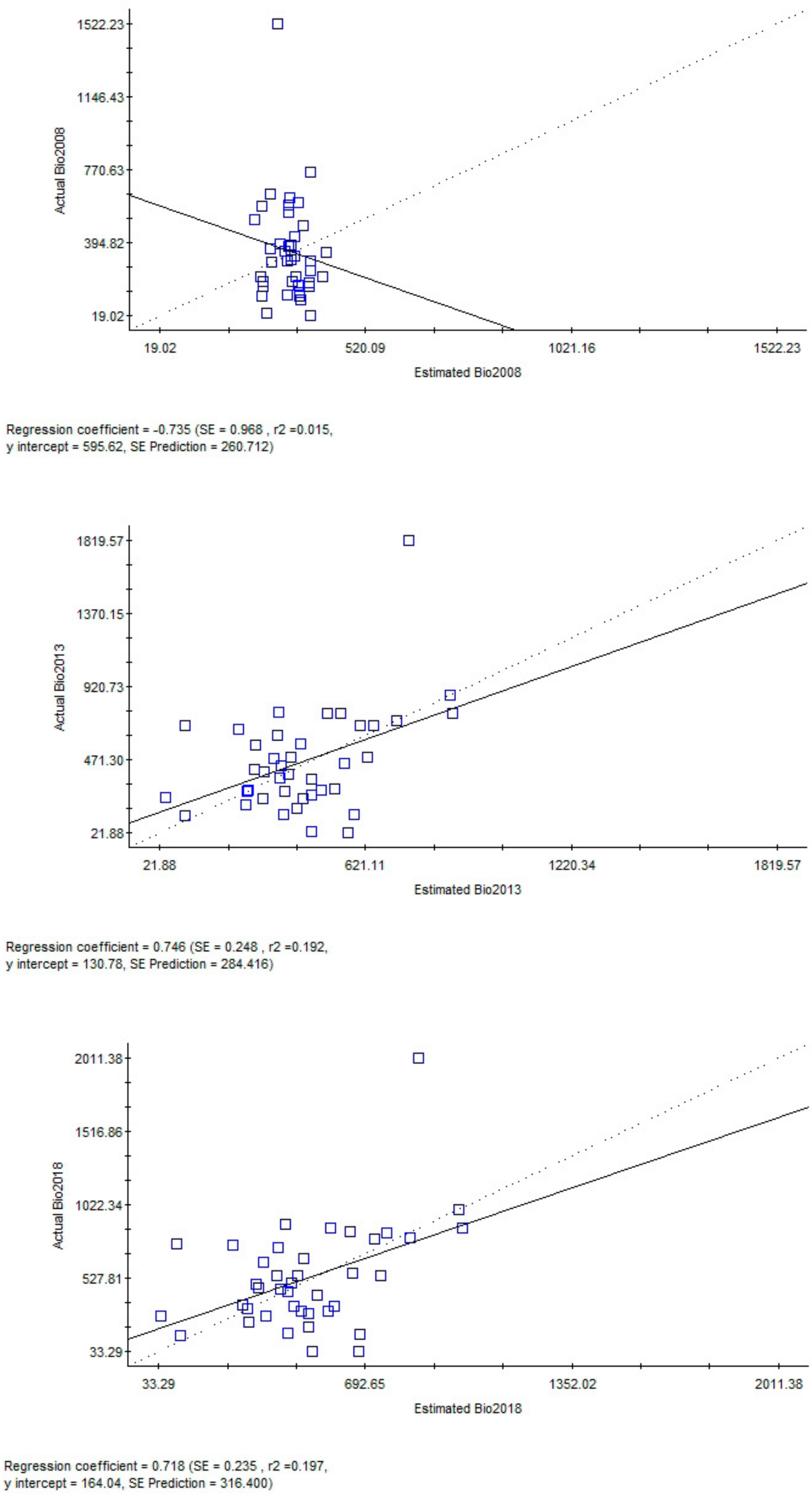
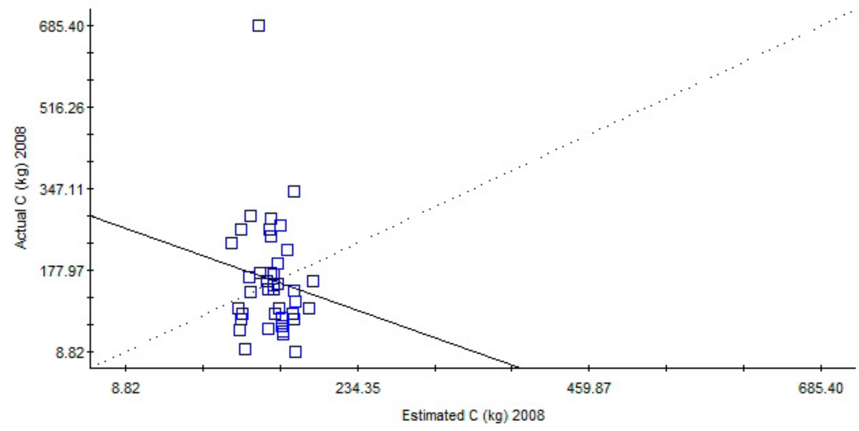
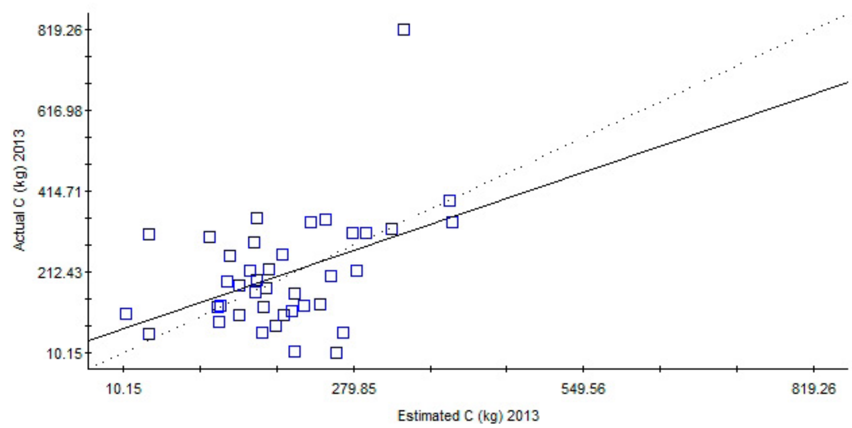


Figure 5: Cross-validation of Biomass (kg) – Bio and Carbon stock (kg) – C, in a less conserved area of Tropical Dry Forest (Caatinga) (LCA) for the years 2008, 2013 and 2018.

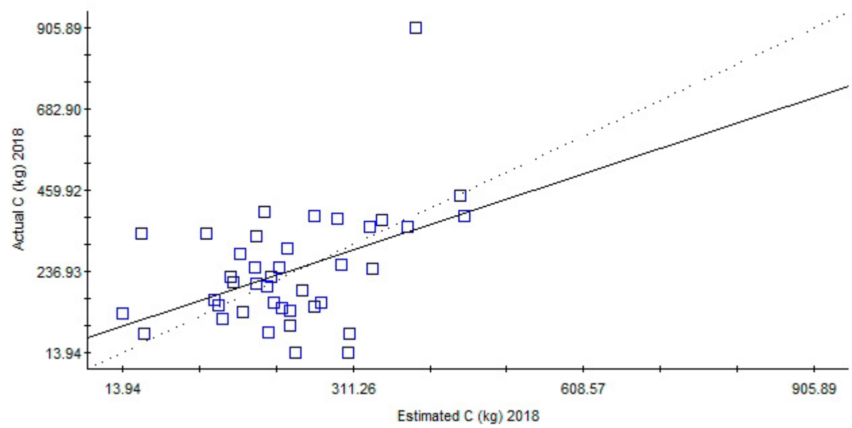




Regression coefficient = -0.756 (SE = 0.971 , r2 =0.016,
y intercept = 272.06, SE Prediction = 117.494)

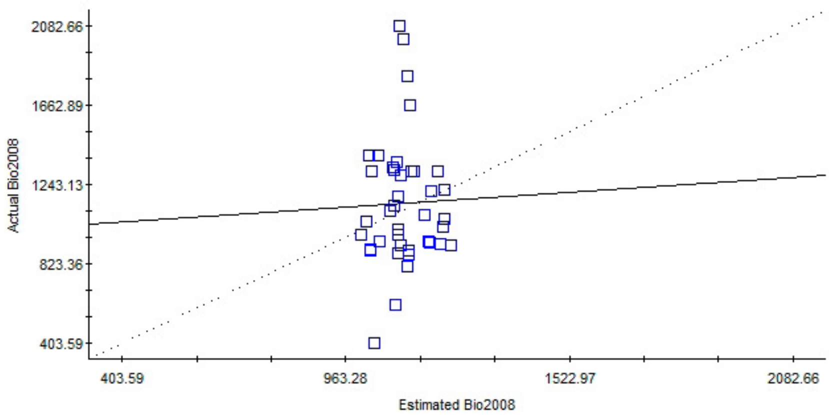


Regression coefficient = 0.729 (SE = 0.245 , r2 =0.189,
y intercept = 62.38, SE Prediction = 128.527)

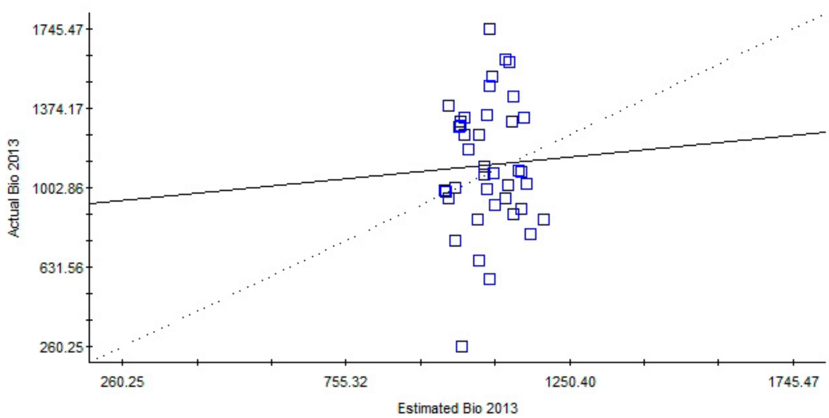


Regression coefficient = 0.701 (SE = 0.232 , r2 =0.194,
y intercept = 78.03, SE Prediction = 143.126)

Figure 6: Cross-validation of the stock of Biomass (kg) – Bio and Carbon stock (kg) – C, in a conserved area of Tropical Dry Forest (Caatinga) (CA) for the years 2008, 2013 and 2018. (a) biomass; (b) carbon.

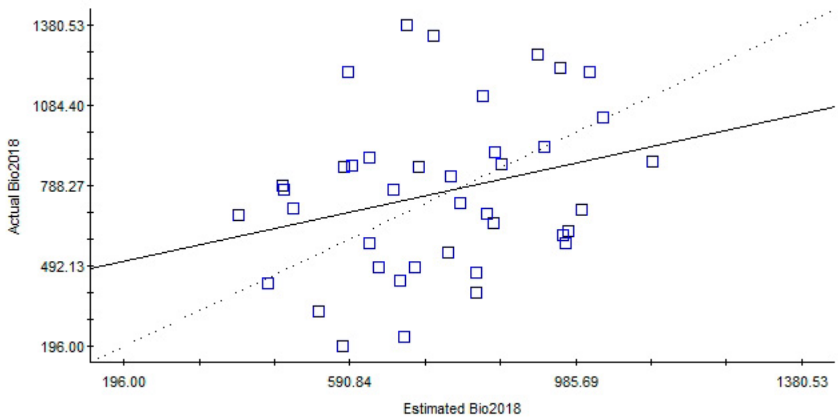


Regression coefficient = 0.140 (SE = 0.900 , r2 =0.001,
y intercept = 989.29, SE Prediction = 335.829)

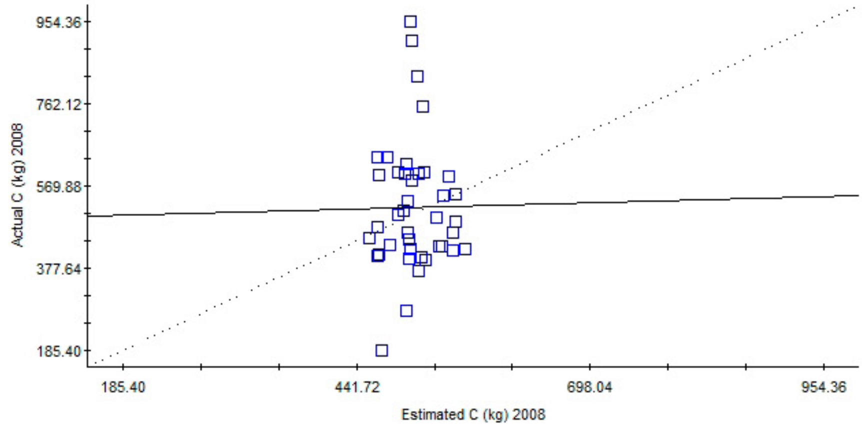


Regression coefficient = 0.206 (SE = 0.822 , r2 =0.002,
y intercept = 889.84, SE Prediction = 300.938)

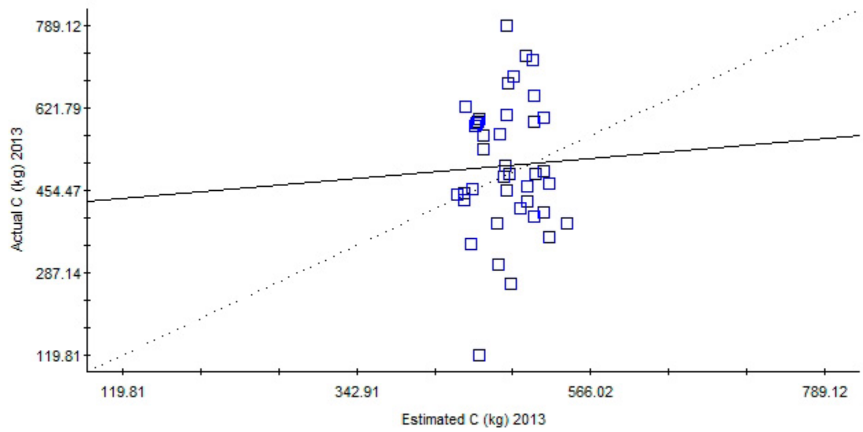
,



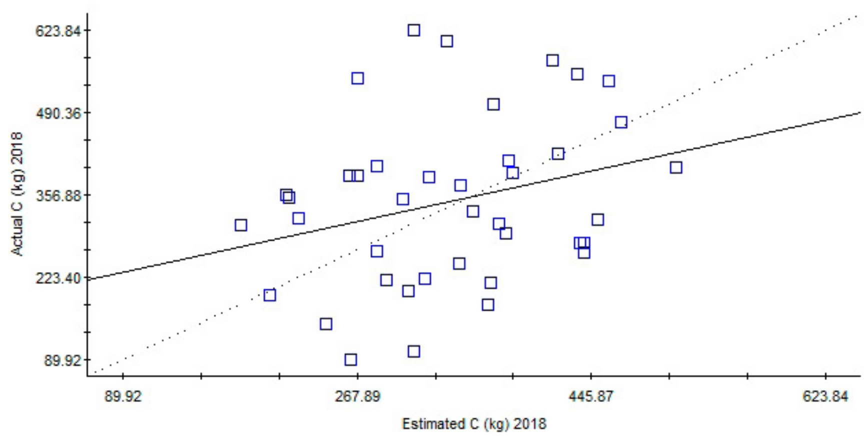
Regression coefficient = 0.460 (SE = 0.255 , r2 =0.079,
y intercept = 418.59, SE Prediction = 287.149)



Regression coefficient = 0.056 (SE = 0.883 , r2 =0.000,
y intercept = 492.74, SE Prediction = 152.437)



Regression coefficient = 0.184 (SE = 0.803 , r2 =0.001,
y intercept = 414.97, SE Prediction = 135.392)

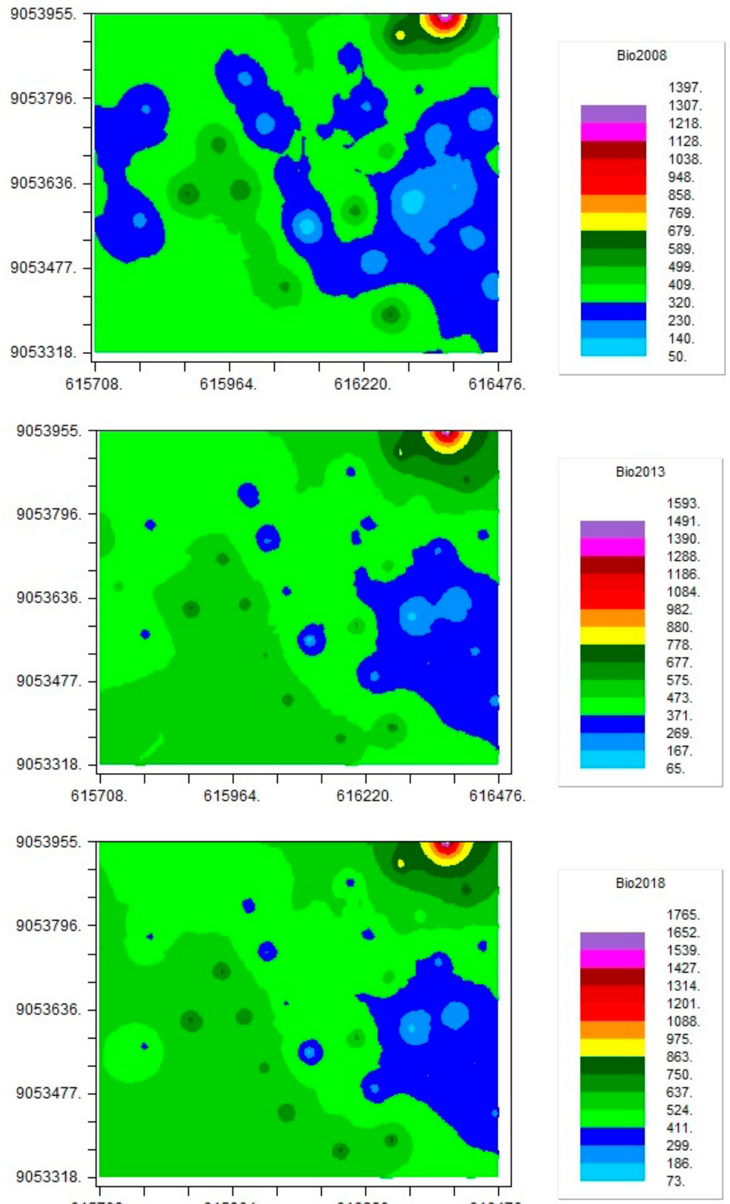


Regression coefficient = 0.462 (SE = 0.254 , r2 =0.080,
y intercept = 189.07, SE Prediction = 129.346)

Disturbed forest areas may pose challenges to the use of geostatistics. While they present a strong SD, continuity issues may arise due to clearings within the area (Amaral, 2010). This phenomenon is evident in the LCA, where patches of vegetation-free areas are observed. These patches result from intense exploitation before 1987, extensive grazing by goats and sheep, and climatic events such as persistent droughts and high temperatures, which hinder the natural regeneration of the area.

In the thematic maps obtained for the LCA (Figures 7 and 8), the color gradient varies from light blue to light purple, representing lower and higher concentrations, respectively. These maps clearly illustrate regions with the highest concentrations of biomass and carbon stocks in kilograms within the two study areas for each assessment year.

Figure 7: Thematic maps of the stock of Biomass (kg) - Bio and Carbon stock (kg) - C, in a less conserved area of Tropical Dry Forest (Caatinga) (LCA) for the years 2008, 2013 and 2018.



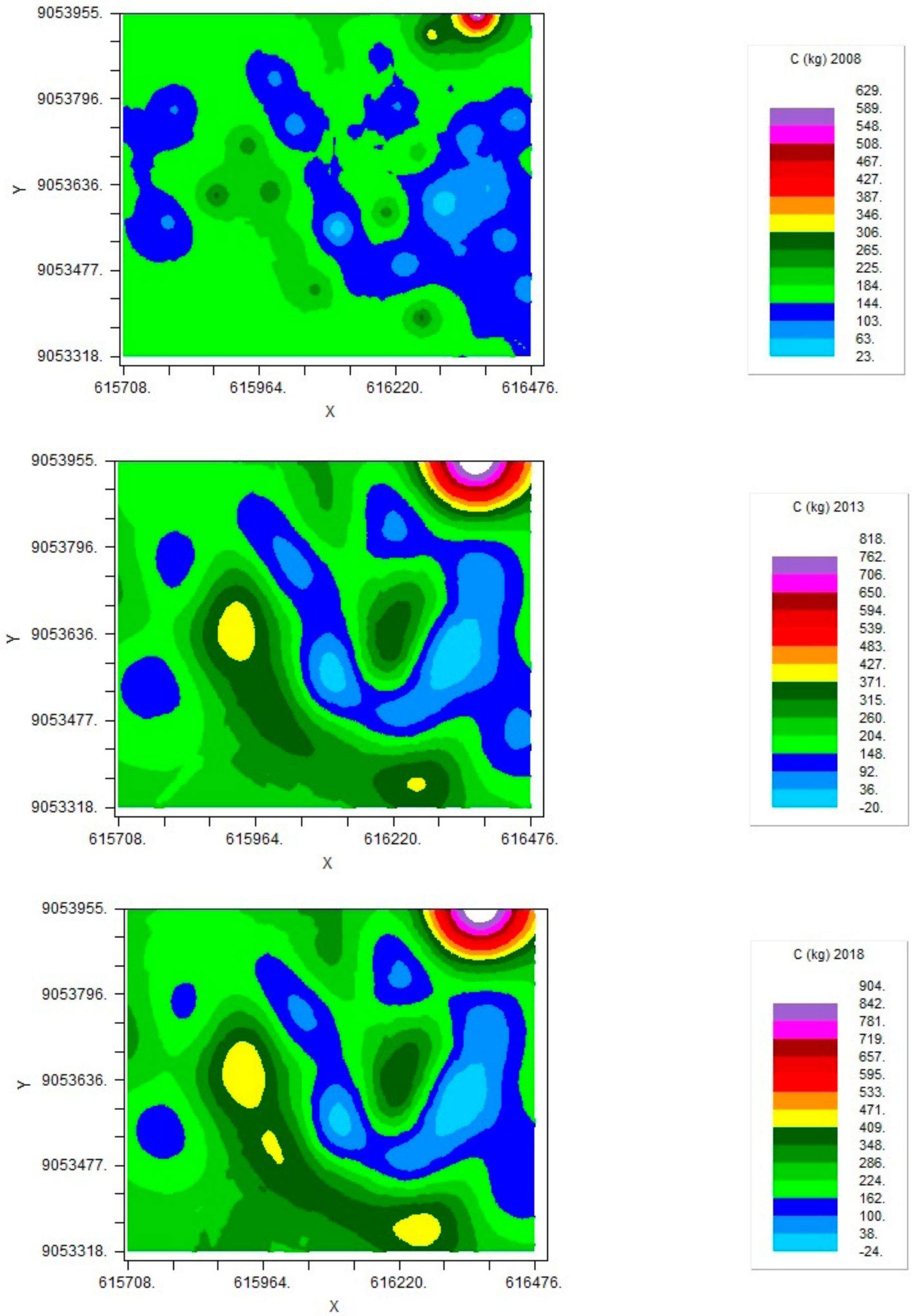
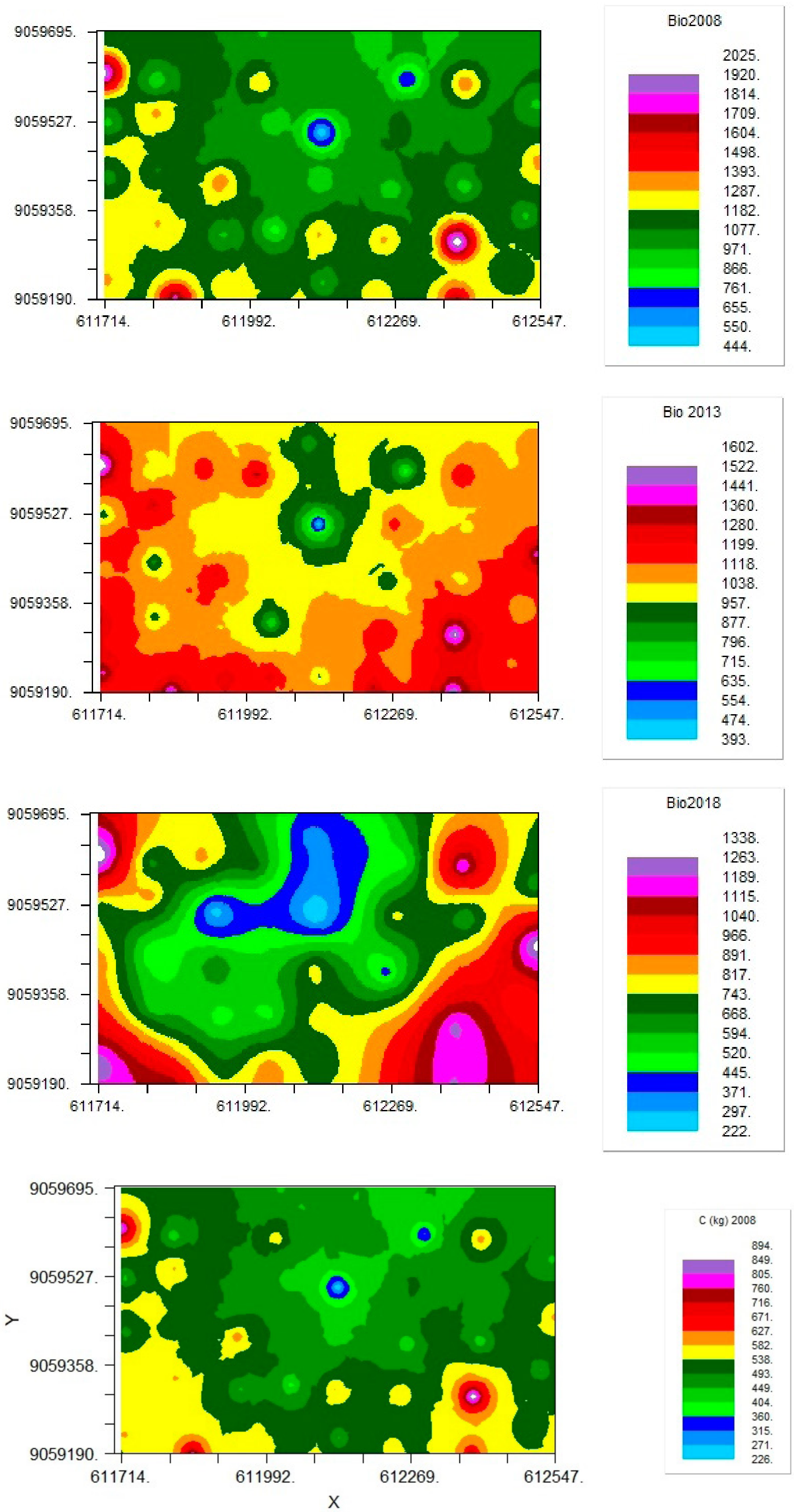
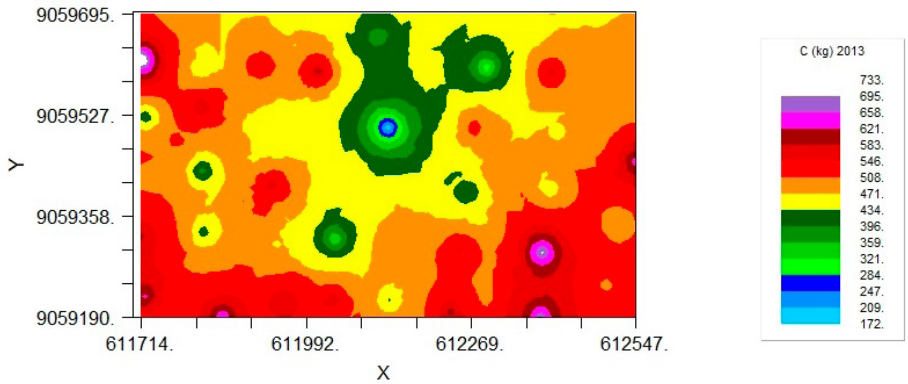
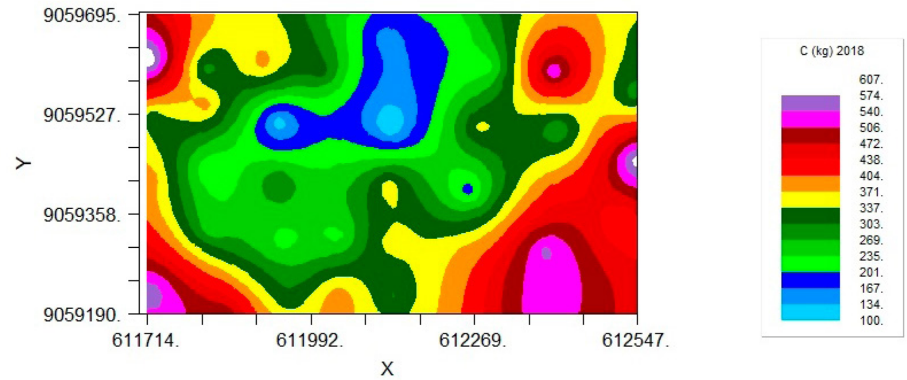

9053955.
9053796.
9053636.
9053477.
9053318.
Y
615708.
615964.
616220.
616476.
X
C (kg) 2008
629.
589.
548.
508.
467.
427.
387.
346.
306.
265.
225.
184.
144.
103.
63.
23.
C (kg) 2013
818.
762.
706.
650.
594.
539.
483.
427.
371.
315.
260.
204.
148.
92.
36.
-20.
C (kg) 2018
904.
842.
781.
719.
657.
595.
533.
471.
409.
348.
286.
224.
162.
100.
38.
-24.

Figure 8: Thematic maps of Biomass (kg) – Bio and Carbon stock (kg) – C, in a conserved area of Tropical Dry Forest (Caatinga) (CA) for the years 2008, 2013 and 2018.







For the LCA, there was an increase in the number of individuals, as depicted in the blue-shaded area in Figure 7. This increase is likely associated with the interior of the plot, where the removal of wood may have been less intense due to accessibility challenges in cutting and transporting wood. The most significant change was observed between 2008 and 2013, reveling a more homogeneous distribution in the blue-shaded area. The spatial distribution of the number of stems is more homogeneous, with higher values in 2008. However, in 2013 and 2018, there was a higher concentration of stems in the study area. This observation underscores that the increase in the number of individuals in a more uniform manner resulted in a higher number of stems. Regarding biomass and carbon stocks, the maps clearly delineate regions with the highest stock in the study area, predominantly located further inland. The spatial distribution mirrors that of the number of stems.

For the CA, the distribution of individuals and stems is more homogeneous, giving the challenging and remote access to this site, making illegal logging difficult, though not impossible. There was a reduction in the number of individuals and stems in the area, with this reduction showing a homogeneous distribution between the years 2008 and 2013 and becoming more pronounced between 2013 and 2018, as depicted in the green-shaded area in Figure 8. This map illustrates a greater prevalence of blue spots in the area during the latter period. Although there was also a reduction in the number of stems over the evaluated period, their spatial distribution exhibited greater homogeneity between 2008 and 2013. However, in 2018, a higher number of stems (blue spots) were spatially concentrated in specific points.

The maps depicting the spatial distribution of biomass and carbon stocks clearly indicate that, despite the decrease in values, there has been a greater homogenization over the years, with values consistently higher than the average. Their spatial distributions follow in a pattern like the number of stems.

When comparing the data for Nind**-1**, Nstems**-1** (Table 4) in relation to carbon stocks, it becomes evident that these stocks are primarily influenced by the number of stems rather than the number of individuals. This fact can be attributed to the distinctive characteristic of Caatinga species, where some may not necessarily have the highest number of stems. This is in line with the greater number of individuals in the areas, indicating that certain species exhibit a greater capacity to produce stems, whether new or resprouted.

Tropical Dry Forests serve as crucial repositories of forest carbon, contributing significantly to the Earth's carbon sink and as a key indicator of ecosystem stability (Franklin et al., 2002; Yang et al., 2017). As a representative of the tropical dry forest of the Caatinga, the observed changes in forest carbon stocks within the study areas reflect, to a certain extent, the variability in carbon stock influenced by factors such as mismanagement (LCA) resulting from human interventions. Such mismanagement can lead to significant reductions in carbon stocks. Therefore, gaining insights into and predicting the spatial and temporal distribution of carbon stocks in tropical dry forest, while implementing proper management practices to avoid drastic decreases, are essential steps for optimizing forest resource management. This approach can enhance the carbon sequestration potential in this arid region, contributing to the mitigation the adverse effects of climate change and associated impacts.

CONCLUSION

- Despite the reduction in the number of individuals and stems, biomass and carbon stocks showed smaller variations, highlighting the impact of the area's historical use on its resilience and maintenance.
- Over the evaluated period, there was an increase in carbon and biomass stocks in the less conserved area. This increase can be attributed to higher cellular activity in younger forests compared to mature ones. Conversely, the reduction in conversed area is linked to the maturity of individuals, leading to a decrease in increment and the elimination of smaller diameter stems.
- In the less conserved area, over the 10-year period, aerial biomass is functioning as a carbon fixer, effectively increasing its stocks within this timeframe.
- In the area considered conserved, over the same 10-year period, it cannot be definitively stated that it acts as a carbon source based solely on the reduction in aerial biomass stocks, as the carbon content in the soil has not been studied.
- The biomass and carbon stocks exhibit strong adjustments in the semivariograms, meeting the requirements for a satisfactory estimate. This enables the creation of thematic

maps due to the spatial dependence of their stocks, which are influenced by the area's history of use and preservation time.

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REFERENCES

Alvares, C.A., Stape, J.L., Sentelhas, P.C. et al. (2013). Köppen's climate classification map for Brazil. *Meteorologische Zeitschrift*. 22(6), 711-728. https://doi.org/10.1127/0941-2948/2013/0507

Amaral, L.P. (2010). *Geostatistics in the characterization of soil and vegetation in Mixed Ombrophilous Forest.* Master's Thesis. Guarapuava, Paraná: Universidade Estadual do Centro-Oeste. http://tede.unicentro.br:8080/jspui/handle/jspui/921

Amaral, L.P., Ferreira, R.A., Watzlawick, L.F. et al. (2013). Influence of the altered forest on the spatial distribution of three species of the Mixed Ombrophilous Forest evaluated by geostatistics. *Tree Magazine*. 37(3), 491-501.

Anderegg, W.R.L., Kane, J.M., Anderegg, L.D.L. (2013). Consequences of widespread tree mortality triggered by drought and temperature stress. *Nat. Clim. Chang.* 3(1), 30-36. https://doi.org/10.1038/nclimate1635.

APAC. Pernambuco Water and Climate Agency. (2017). *Pernambuco Hydrometeorological Geoinformation System*. Recovered: http://www.apac.pe.gov.br/sighpe/.

Araújo Filho, R.N., Freire, M.B.G.S., Wilcox, B.P. et al. (2018). Recovery of carbon stocks in deforested caatinga dry forest soils requires at least 60 years. *Forest Ecology and Management*, 407(1), 210-220. https://doi.org/10.1016/j.foreco.2017.10.002

Benítez, F.L., Anderson, L.O., Formaggio, A.R. (2016). Evaluation of geostatistical techniques to estimate the spatial distribution of aboveground biomass in the Amazon rainforest using high-resolution remote sensing data. *Acta Amazonica*, 46(2), 151-160. https://doi.org/10.1590/1809-4392201501254.

Blackie, R., Gautier, D. et al. (2014). Tropical dry forests: The state of global knowledge and recommendations for future research. In: CIFOR Discussion Paper pp. 1-30. Bogor: Center for International Forestry Research (CIFOR). Recovered: https://doi.org/10.17528/cifor/004408

Bonan, G.B. (2008). Forests and climate change: forcings, feedbacks, and the climate benefits of forests. *Science,* 320(5882), 1444–1449. https://doi.org/10.1126/science.1155121

Cambardella, C.A. et al. Field-Scale Variability of Soil Properties in Central Iowa Soils. *Soil Science Society of America Journal.* 1994. 58(5), 1501-1511. https://doi.org/10.2136/sssaj1994.03615995005800050033x

Campo, J., Giardina, C.P., Dirzo, R. (2023). Tropical Dry Forest Restoration in an Era of Global Change: Ecological and Social Dimensions. *Sustainability*, 15(4), 3052. https://doi.org/10.3390/su15043052

Chen, C.I., Lin, H.H., Wang, C.W., Wang, Y.N. (2017). What is carbon sequestration in forests? Nat. Conserv. Q. 99, 4–15.

Chiles, J.P., Delfiner, P. *Geostatistics: modeling spatial uncertainty*. New York (NY): Wiley, 1999.

Correia, M.D., Menezes, R.S.C., Olinda, R.A. (2014). Geostatistical modeling of the distribution of soil carbon and biomass of herbaceous plants in a silvopastoral system in the northeastern region of Brazil. *Brazilian Journal of Biometrics*. 31(2), 116-129.

Costa, G.M., Cardoso, D., Queiroz, L.P. et al. (2015). Local changes in floristic richness in two ecorregions of the caatinga. *Rodriguésia*, 66(3), 685-709. https://doi.org/10.1590/2175-7860201566303

Dalla Lana, M., Ferreira, R.L.C., Silva, J.A.A. et al. (2018). Biomass equations for Caatinga species. *Nativa*. 6(5), 517-525. https://doi.org/10.31413/nativa.v6i5.5361

Dalla Lana, M., Ferreira, R.L.C., Silva, J.A.A. et al. (2019). Carbon Content in Shrub-tree Species of the Caatinga. Forest and Environment. 26(2), e20170617. https://doi.org/10.1590/2179-8087.061717

Dexter, K.G., Pennington, T.D., Oliveira-Filho, A.T. (2018). *The Caatinga: a neglected tropical dry forest*. In Pennington, R.T., Ratter, J.A., Lewis, G.P. (Eds.), Neotropical Savannas and Dry Forests: Diversity, Biogeography, and Conservation (pp. 381-399). CRC Press.

EMBRAPA. Brazilian Agricultural Research Corporation. (2000). *Survey of low and medium intensity reconnaissance of soils in the State of Pernambuco*. Recovered: https://www.embrapa.br

EMBRAPA. Brazilian Agricultural Research Corporation. (2011). *Brazilian soil classification system*. Recoverd: https://www.embrapa.br

FAO. Food and Agriculture Organization. (2015). *Emerging approaches to Forest Reference Emission Levels and/ or Forest Reference Levels for REDD+*. Recovered: 2_82_redd_20141113_unredd_frel.pdf (unfccc.int)

Franklin, J.F., Spies, T.A., Pelt, R.V. et al. (2002). Disturbances and Structural Development of Natural Forest Ecosystems with Silvicultural Implications, Using Douglas-Fir Forests as an Example. *For. Ecol. Manag*., 155(1-3), 399-423. https://doi.org/10.1016/S0378-1127(01)00575-8

Fu, W., Fu, Z., Ge, H. et al. (2015). Spatial variation of biomass carbon density in a subtropical region of southeastern China. *Forests*, 6(6), 1966-1981. http://dx.doi.org/10.3390/f6061966.

Gariglio, M.A. et al. (Org.). (2010). Sustainable use and conservation of Caatinga forest resources. Brasília, Serviço Florestal Brasileiro, 368p.

GS+. *Geostatistical for environmental science*. Version 5.0, Michigan: Gamma Design Software, 2000.

Guedes, I.C.L., Mello, J.M., Silveira E.M.O., et al. (2015). Spatial continuity of dendrometric features in clonal stands of Eucalyptus sp. evaluated over time. *Heartwood*. 21(4), 527-534. https://doi.org/10.1590/0 1047760201521041824

Guimarães, E.C. Basic and applied geostatistics. Uberlândia (MG): UFU/FAMAT, 2004.

Guimarães, R.M.L., Gonçalves, A.C., Tormena, C.A. et al. (2010). Spatial variability of physico-hydric properties of an Oxisol under irrigated common bean crop. *Agricultural Engineering*. 30(4), 657-669. https://doi.org/10.1590/S0100-69162010000400010

IBGE. Brazilian Institute of Geography and Statistics. (2004). *Map of Biomes of Brazil, first approximation*. Recovered: https://biblioteca.ibge.gov.br/

IBGE. Brazilian Institute of Geography and Statistics. (2012). *Technical Manual of Brazilian Vegetation*. Recovered: https://biblioteca.ibge.gov.br/

Kanegae Júnior, H., Mello, J.M., Scolforo, J.R.S. et al. (2007). Evaluation of the spatial continuity of dendrometric traits in different 70 ages of clonal stands of Eucalyptus sp. *Tree Magazine*. 31(5), 859-866. https://doi.org/10.1590/S0100-67622007000500010

Kershaw, J.A., Ducey, M.K., Beers, T.W. et al. (2017). Forest Mensuration. Hoboken (NJ): WileyBlackwell - John Wiley & Sons.

Kravchenko, A.N., Robertson, G.P., Snap, S.S. et al. (2006). Using information about spatial variability to improve estimates of total soil carbon. *Agronomy Journal*. 98(3), 823-829. https://doi.org/10.2134/agronj2005.0305

Krempi, A.P. (2004). Exploring spatial statistics resources for the analysis of accessibility in the city of Bauru. Master's Thesis. São Carlos, São Paulo: Universidade de São Paulo. https://doi.org/10.11606/D.18.2004.tde-10032005-064613

Landsberg, J.J., Gower, S.T. (1997). *Applications of Physiological Ecology to Forest Management.* Academic Press. https://doi.org/10.1016/B978-012435955-0/50010-8

Lin, C.Y. Wang, S.M., Wu, S.W. et al. (2022). Environmental indicators combined with conceptual models to assess the spatial distribution of carbon storages in the Liukui Experimental Forest in southern Taiwan. *Ecological Indicators.* 137, 108724. https://doi.org/10.1016/j.ecolind.2022.108724

Lundgren, W.J.C., Silva, J.A.A.D., Ferreira, R.L.C. (2016). Sampling Type Influence in the Estimation of Eucalyptus Wood Volume by Kriging. *Floram*. 23(4), 511-523. https://doi.org/10.1590/2179-8087.136315

Marengo, J.A., Torres, R.R., Alves, L.M. (2016). Drought in Northeast Brazil-Past, present, and future. *Theor Appl Climatol*. 129, 1189-1200. https://doi.org/10.1007/s00704-016-1840-8

Mello, J.M., Diniz, F.S., Oliveira, A.D. et al. (2009). Sampling methods and geostatistics for estimating the number of stems and volume in Eucalyptus grandis plantations. *Floresta*. 39(1), 157-166. http://dx.doi.org/10.5380/rf.v39i1.13735

Microsoft Corporation. (2016). *Microsoft Excel.* Retrieved from https://office.microsoft.com/excel.

Murphy, P., Lugo, A. (1986). Ecology of tropical dry forest. *Annual Review of Ecology and Systematics*. 17, 67-88. https://doi.org/10.1146/annurev.es.17.110186.000435

Oda-Souza, M., Barbin, D., Júnior, P.J.R. et al. (2008). Application of geostatistical methods to identify spatial dependence in the data analysis of a forest spacing experiment with a fan systematic design. *Tree Magazine*. 32(3), 499-509. https://doi.org/10.1590/S0100-67622008000300011

Ortiz, G.C. (2002). Application of geoestatistical methods to identify the magnitude and structure of spatial variability of physical variable of the soil. Master's Thesis. Piracicaba, São Paulo: Escola Superior de Agricultura Luiz de Queiroz. https://doi.org/10.11606/D.11.2002.tde-21082002-135604

Pan, Y., Birdsey, R.A., Fang, J. et al. (2011). A large and persistent carbon sink in the world's forests. *Science*, 333(6045), 988-993. https://doi.org/10.1126/science.1201609

Pelissari, A.L., Caldeira, S.F., Drescher, R. (2013). Quantitative and qualitative development of Tectona grandis L.f. in Mato Grosso. *Floram*. 20(3), 371-383. https://doi.org/10.4322/floram.2013.027

Pelissari, A.L., Filho, F.A., Caldeira, S.F. et al. (2014). Geostatistics applied to the management of teak forest stands, on days before selective thinning, in the state of Mato Grosso. *Brazilian Journal of Biometrics.* 32(3), 430-444.

Péllico Netto, S., Brena, D.A. *Forest Inventory*. Curitiba (PR): 1997.

Pereira, J.C., Mourão, D.A.C., Scalet, V. et al. (2011). Comparison between hypsometric relationship models with and without spatial component for Pinus sp. at FLONA Ipanema – SP. *Scientia Forestalis*. 39(89), 43-52.

Pessi, D.D., Diodato, M.A., Guerra, A. et al. (2022). Loss of Natural Habitats: High-Altitude Vegetation, Pantanal. *Research, Society and Development.* 11(3), e2911326242. https://doi.org/10.33448/rsd-v11i3.26242

Pessi, D.D., Silva, N.M., Mioto, C.L. et al. (2023). Application of Remote Sensing in the analysis of vegetation changes in high-altitude grasslands in the Pantanal using Landsat multitemporal data. *Terr@Plural*. 17, e2321497. https://doi.org/10.5212/TerraPlural.v.17.2321497.003

Rosa Filho, G., Carvalho, M.P., Montanari, R. et al. (2011). Spatial variability of dendrometric properties of eucalyptus and physical attributes of a Rhodic Eutrudox. *Bragantia*. 70(2), 439-446. https://doi.org/10.1590/S0006-87052011000200027

Rufino, T.M.C., Thiersch, C.R., Ferreira, S.O. et al. (2006). Geostatistics applied to the study of the relationship between dendometric variables of Eucalyptus sp. populations and soil attributes. *Ambiencia*. 2(1), 83-93.

Sunderland, T.C., Vasconcelos, M.F., Carvalho, F.A. (2015). *Human impacts on the Caatinga*. In Silva, J.M.C., Leal, I.R. (Eds.), The Caatinga: Towards Sustainable Management of the Brazilian Semi-Arid (pp. 195-217). Springer.

United Nations Organization - ONU. (2019). United Nations Resolution 73/284: United Nations Decade on Ecosystem Restoration (2021–2030). Recovered: https://undocs.org/A/RES/73/284

Vieira, S.R., Xavier, M.A., Greek, C.R. (2008). *Applications of geostatistics in sugarcane research.* In: Dinardo-Miranda LL, Vasconcelos ACM, Landell MGA. (Eds). Sugar cane. Ribeirão Preto (SP): Agronomic Institute.

Yamamoto, J.K., Landim, P.M.B. Geostatistics: concepts and applications. São Paulo (SP): Text workshop. 2015.

Yang, J., Ji, X., Deane, D. et al. (2017). Spatiotemporal Distribution and Driving Factors of Forest Biomass Carbon Storage in China: 1977–2013. *Forests*, 8(7), 263. https://doi.org/10.3390/f8070263

Yu, T. Sun, R., Xiao, Z. et al. (2018). Estimation of global vegetation productivity from global land surface satellite data. *Remote Sensing*, 10(2), 327. https://doi.org/10.3390/rs10020327

Zimback, C.R.L. Spatial analysis of soil chemical attributes for soil fertility mapping. Master's Thesis. Botucatu, São Paulo: Universidade Estadual Paulista, 2001.

Zimmermann, B., Zehe, E., Hartmann, N.K. et al. (2008). Analyzing spatial data: An assessment of assumptions, new methods, and uncertainty using soil hydraulic data. *Water Resources Research*. 44(10), 1-18. https://doi.org/10.1029/2007WR006604

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