



Individual tree mortality: Risks of climate change in the eastern Brazilian Amazon region

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ABSTRACT

The mortality of trees in humid tropical forests plays a fundamental role in understanding forest development, particularly after disturbances such as those caused by logging and extreme weather events. The aim of this study was to evaluate estimates of individual tree mortality following Reduced Impact Logging (RIL) in the Eastern Brazilian Amazon at biennial intervals from 2005 to 2012. RIL is based on operations planning, personnel training, and investments in forest management, and harvesting through RIL must: (a) minimize environmental damage, (b) diminish operation cost by increasing work efficiency, and (c) reduce operational waste. A mortality model was constructed based on the estimation of three distance-independent competition-indices (*DII*) and five models for predicting the probability of individual tree mortality. The Kolmogorov-Smirnov statistical test was used to determine the most representative model, from which a Neural Network Autoregressive (NNAR) model was constructed to forecast mortality after RIL. Mortality data was correlated with the El Niño–Southern Oscillation (ENSO) and climate (Rainfall, Maximum, Minimum, and Average air temperature). The tested models showed similar and accurate estimates with R^2 exceeding 0.90, although underestimation and overestimation trends were observed. The NNAR satisfactorily represented species mortality over the simulated years. The period from 2012 to 2014 was characterized by a Neutral and Weak El Niño event, and exhibited the highest mortality value for a 25 cm DBH (diameter at breast height), the smallest DBH class measured in this study. In the correlation matrix analysis, maximum air temperature showed the highest positive correlation with trees mortality. Despite the challenges in estimating individual tree mortality in tropical forests after selective logging, accurate estimates were achieved using traditional regression techniques and NNAR. These results can support technical and silvicultural decisions regarding forest management in the Eastern Amazon region of Brazil.

1. Introduction

Climate change is a complex phenomenon that affects the planet in various ways, altering average conditions of temperature, rainfall, sea levels, and the frequency of extreme events (Fell et al., 2022; Gonçalves et al., 2024; Mano et al., 2023). These variations over the years can

stimulate species development, migration to locations with better conditions, or their extinction. Tree mortality is a fundamental ecological and demographic process for understanding forest ecosystem dynamics (Bayat et al., 2019a; Ruiz-Benito et al., 2013; Zhu et al., 2019). It directly affects species composition, modifies population and community structures, reduces annual net increments, and alters nutrient cycling

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(Archambeau et al., 2020; Bertini et al., 2019).

In the context of climate change, there is growing concern that tree mortality may lead to rapid and significant shifts in the diversity, structure, and functionality of tropical forests (Hill et al., 2017; Reategui-Betancourt et al., 2024). Studies have indicated that the likelihood of mortality tends to increase due to factors associated with individual species growth, wood density, and tree size (de Oliveira et al., 2023; Hill et al., 2017). Understanding these processes is therefore essential to grasp the impact of climate change on forests and to guide future conservation and restoration efforts for these ecosystems (Gonçalves et al., 2024).

Although predicting tree mortality in humid tropical forests represents a major challenge (Archambeau et al., 2020) given its complex (Adame et al., 2010), gradual, and highly variable (Arellano et al., 2019; Dietze and Moorcroft, 2011a) nature, as well as the different mortality behaviors among species (Castro et al., 2015; Rossi et al., 2007), it has significant implications for long-term tree growth estimates (Weiskittel et al., 2011). Therefore, an accurate representation of mortality in vegetation models is necessary (Fisher et al., 2018).

One of the challenges in modeling tree mortality is that various random factors can lead to their death. Regular mortality, also known as non-catastrophic mortality, is caused by factors such as competition, age, senescence, normal pest and disease presence, and genetic characteristics of species (Arellano et al., 2019; Esquivel-Muelbert et al., 2020). On the other hand, irregular or catastrophic mortality is generally associated with extreme or random events, such as insect attacks, pest and disease epidemics, and climate events related to the El Niño-Southern Oscillation (ENSO) (Aleixo et al., 2019; Das et al., 2016; Rossi et al., 2007; Ruiz-Benito et al., 2013).

Tree mortality can also occur due to damage caused by selective logging, which can damage roots and bark, favoring pest and disease attacks, or canopy disturbances which can disadvantage some tree species (de Oliveira et al., 2023). Therefore, understanding and predicting tree mortality after natural and anthropogenic disturbances is essential for understanding the dynamics and diversity of forest ecosystems (Purves and Pacala, 2008), particularly using individual tree models which constitute one of the alternatives for managing tropical forests in aiming for sustainability (Reis et al., 2016).

Modeling individual tree mortality can be primarily accomplished using regression models (Reis et al., 2018) or artificial intelligence tools such as Autoregressive Integrated Moving Average (ARIMA) (Arévalo et al., 2023; Delgado et al., 2022) and Network Autoregressive Model (NNAR) algorithms (Hasenauer et al., 2001; Reis et al., 2018). These models generally estimate the probability of a tree dying based on various factors. These factors may include: diameter at breast height (DBH), tree height, presence or absence of damage, vigor, competition for light, species, climatic conditions, biotic and abiotic disturbances, and management history.

Models for predicting the probability of individual tree mortality after natural or anthropogenic disturbances are one of the alternatives for managing tropical forests with the goal of sustainability (Reis et al., 2018). These models provide information about forest dynamics and are important for accurately forecasting tree numbers, basal area, diameter distribution, and forest production (Reis et al., 2016; Reis et al., 2018). Therefore, accurate estimates of tree mortality are crucial for developing effective forest management policies (Ma et al., 2013).

Few studies have modeled tree mortality or survival in the Amazon Rainforest. For example, Reis et al. (2018) used Artificial Neural Networks (ANNs) to predict the probability of mortality after selective logging, while Nascimento et al. (2009) evaluated different growth and yield models at the diameter class level to estimate tree survival and mortality.

In the specific context of the Amazon Rainforest, especially in areas subject to selective logging, such as forest management areas in the Amazon, which have different growth from unmanaged natural areas (Reis et al., 2016), there are still no studies that have modeled the

mortality of individual trees following disturbances, such as those caused by logging and associated with extreme climatic events. It is, therefore, essential to understand the vegetation dynamics and the factors influencing tree mortality after selective logging and climatic phenomena, such as the extremely dry years of the El Niño-Southern Oscillation (ENSO).

Given this gap, the objective of this study was to model and evaluate the estimates of individual tree mortality following selective logging, considering the dynamics of meteorological elements and the influence of climate change associated with ENSO years. Furthermore, this study proposes a Neural Network Autoregressive Model (NNAR) for the future prognosis of mortality, aiming to support technical and silvicultural decisions in forest management in the eastern region of the Brazilian Amazon.

2. Materials and methods

2.1. Study area

The study was conducted in the Forest Management Area (FMA) of the Rio Capim Farm (Fig. 1) belonging to the CKBV Florestal Ltda. company, located in the municipality of Paragominas in the state of Pará, Brazil (03°39'28.16"S and 48°49'59.73"W). The Rio Capim Farm has a total area of 140,000 ha, from which 121,000 ha are under forest management certified by the Forest Stewardship Council (FSC) since 2001 (de Oliveira et al., 2019). The region's climate is classified as "Aw1" according to the Koppen climate classification: wet tropical, with a mean annual rainfall around 1800 mm, annual mean temperature of 26.3 °C, and relative humidity of 81 % (Alvares et al., 2013). The characteristic vegetation of the region is Dense Ombrophilous Forest (Instituto Brasileiro de Geografia e Estatística (IBGE), 2012).

2.2. Data collection - Rio Capim farm

Data were collected at Work Unit No. 14 (WU 14), which occupies 100 ha and is located at Annual Production Unit No. 07 (APU 07) of the Rio Capim Farm's forestry management plan. In June 2004, before selective logging, two transects of 9 ha (100 m × 900 m) each were delimited in this WU (Fig. 2), subdivided into 9 permanent plots of 100 m × 100 m (1 ha), in which all trees with DBH ≥ 20.0 cm were measured (de Oliveira et al., 2019; de Oliveira et al., 2021).

In addition to the DBH (diameter measured at 1.30 m from the ground), the x and y coordinates of each tree were also determined in relation to its plot origin and all individual trees were identified to the species level by parobotanists from Embrapa Eastern Amazon and the CKBV Florestal Ltda. company. The procedures adopted for installing plots and collecting continuous forest inventory data in the respective study area followed the protocol adopted by the Brazilian Agricultural Research Corporation (Embrapa Eastern Amazon), available in Silva et al. (2005).

Next, the first selective cutting operation with was carried out in WU 14 in August 2004. The harvest resulted in extracting 21.3 m³ ha of commercial wood, equivalent to 7 trees ha (Sist and Ferreira, 2007a). Measurements in the permanent plots after selective logging were conducted on five occasions (2005, 2006, 2008, 2010, and 2012), totaling 8 years of monitoring.

2.3. Competition Indices (CI)

For each tree, in each measurement year, three distance-independent competition indices (DII) were calculated. In the calculation of the DII, all other trees within the same permanent plot were considered as competitors to the target tree (de Oliveira et al., 2021). The CI estimates were made considering the area of the plots (100 m × 100 m). The functional relationship of each CI (Eq. (1) to Eq. (3)) is presented in Table 1.

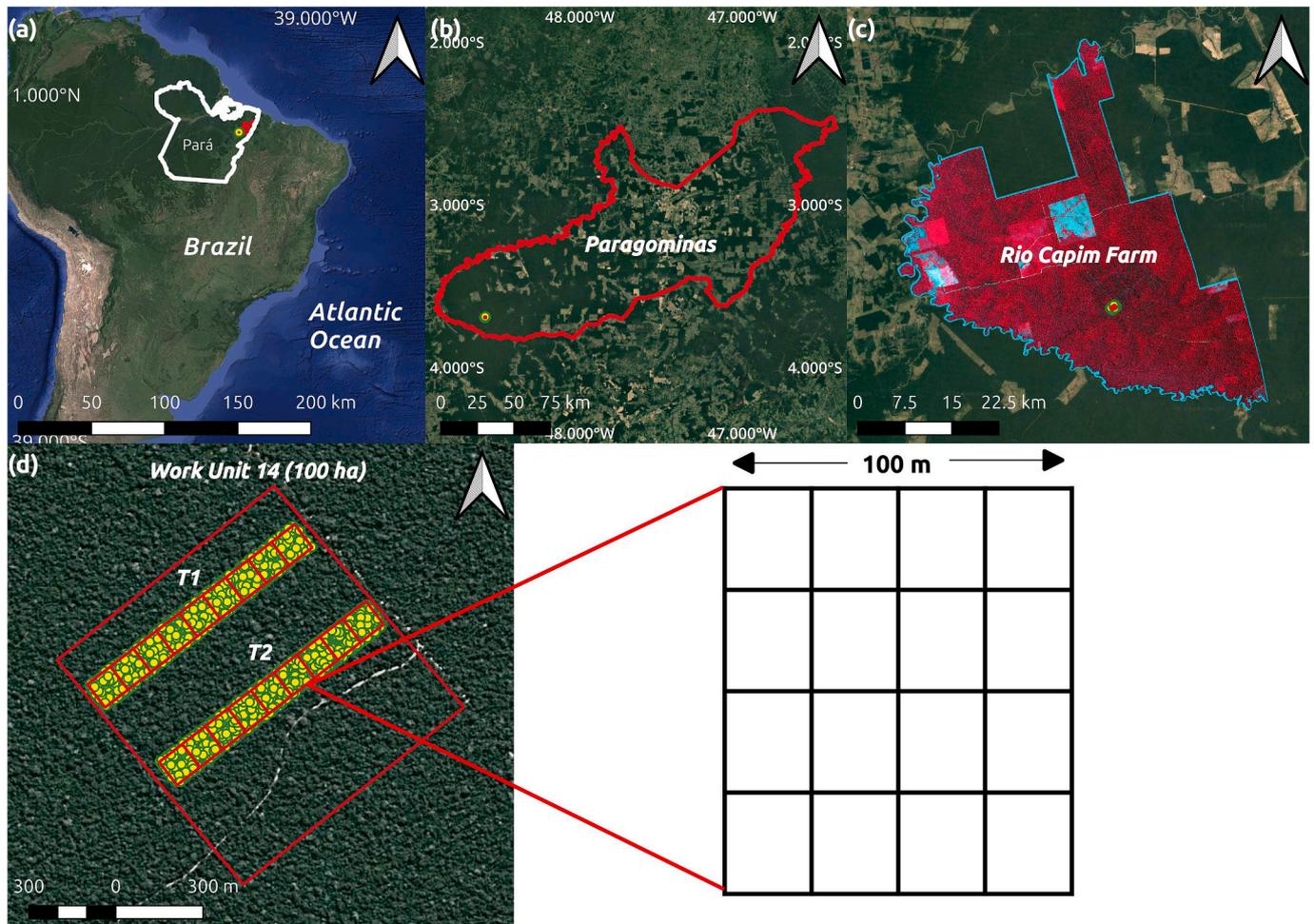


Fig. 1. Location of the study area and experimental design. (a) Map of Brazil (showing Pará state in white). (b) Map of Paragominas municipality. (c) Rio Capim Farm (Composition of bands 4, 3 and 2) and (d) Work Unit 14 harvested in 2004. T1 and T2: Transect 1 and 2 (black squares).

2.4. Mortality modeling

The mortality probability (P_m) was obtained from the proportion of dead trees by diameter class per permanent plot in four distinct measurement intervals (2005–2006, 2006–2008, 2008–2010, and 2010–2012), according to Eq. (4) (de Oliveira et al., 2021).

$$P(m) = \frac{(n_{j1} - n_{j2}) - I_{j1j2}}{\sum_{i=1}^j n_{j1}} \cdot 100 \quad (4)$$

In which: n_{j1} = number of living individuals in the j^{th} diameter class at the beginning of the period; n_{j2} = number of living individuals in the j^{th} diameter class at the end of the period, minus the individuals entering in the period (I_{j1j2}).

2.5. Probability of Mortality (P_m) models

Five models were tested to model mortality (Table 2). The evaluated models present non-linear relationships between P_m and their independent variables and were fitted using the Levenberg-Marquardt algorithm in the Statistica 10.0 software program (Statsoft, 2010).

2.6. Evaluation of models

The decision rule adopted for classifying trees as dead was the same as proposed by Pretzsch et al. (2002). First, the Mortality Probability (P_m) for each tree in each permanent plot was calculated (Eq. (4)). Subsequently, a random number (P_a) between 0 and 1 was generated for

each tree, which was then compared to the P_m values. The decision rule for mortality during the projection period was as follows: if $P_m > P_a$, the tree is considered dead and must be removed from the database; otherwise, the tree is deemed alive and its dimensions are projected to the next period (Castro et al., 2020; de Oliveira et al., 2023; Pretzsch et al., 2002). Given that this is a random process, this procedure was repeated 30 times to obtain an average trend of the estimated number of dead trees for each projection period. The sample that most closely approximated the mean value of the 30 repetitions for each period was selected to compose the list of dead trees.

Next, the best model for predicting forest mortality was determined through graphical analysis of the observed and estimated frequency diameter distribution and based on the result of the Kolmogorov-Smirnov test (Sokal and Rohlf, 1969) (Eq. (5)).

$$dn = \text{Max}|F_o(x) - F_e(x)| \quad (5)$$

In which: dn = calculated value of the K-S statistic; $F_o(x)$ = observed accumulated frequency; and $F_e(x)$ = estimated cumulative frequency.

The null hypothesis (H_0 : the estimates do not differ from the actual values) was rejected for the calculated value of dn greater than the critical value, at a significance level α equal to 5 %.

2.7. Neural network autoregression (mortality)

Neural Network Autoregressive Model (NNAR): We implemented an NNAR model to forecast future tree mortality rates based on historical data and projected climate scenarios associated with ENSO events. After

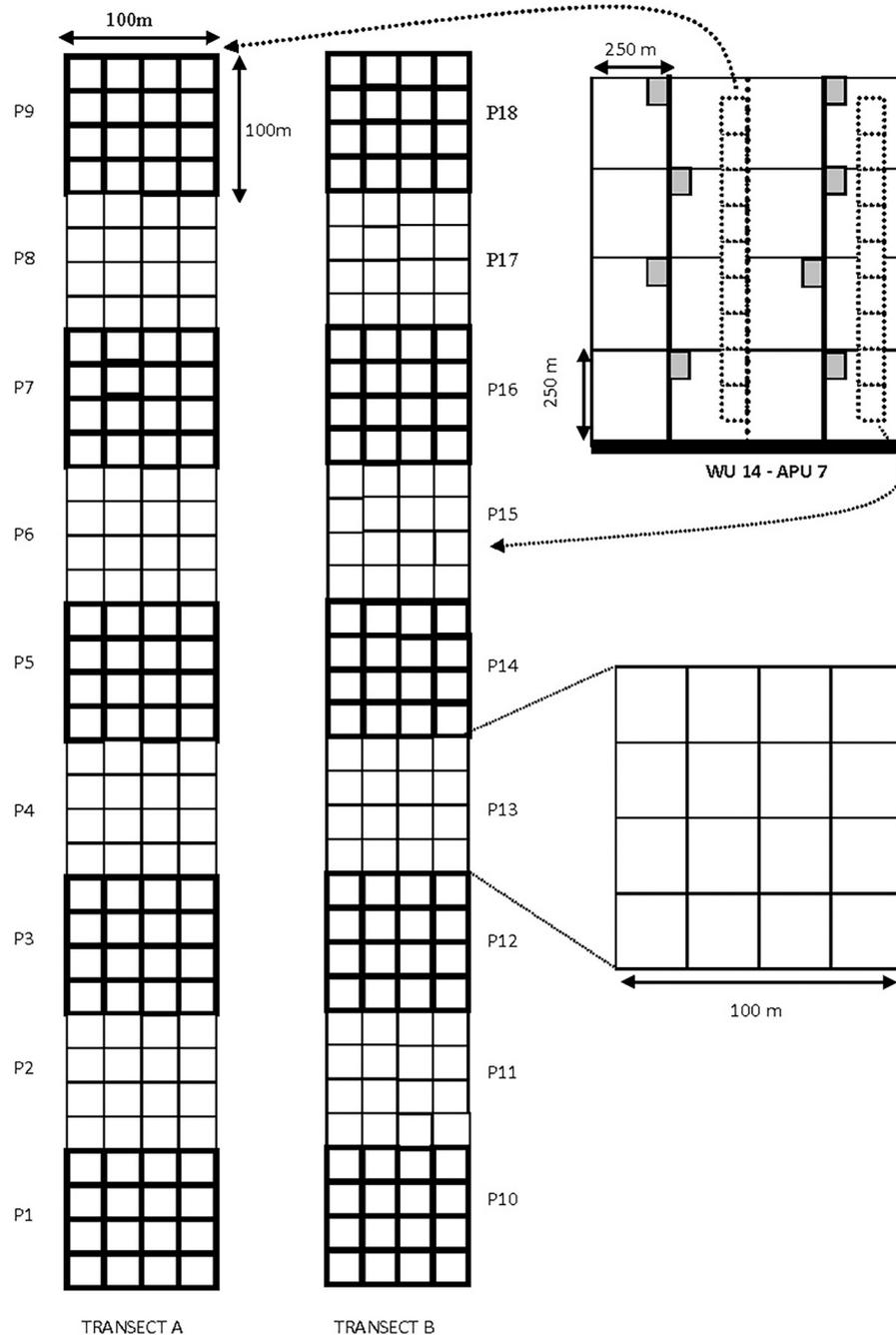


Fig. 2. Schematic drawing of transects A and B at Rio Capim Farm. The 18 plots measuring 1 ha (100 m × 100 m) are highlighted. Grey squares represent landings, bold lines inside the WU 14 - APU 7, secondary roads.

choosing the best model, NNAR (Venables and Ripley, 2002) was used to simulate tree mortality data from 2012 to 2024. The NNAR considers a feed-forward network architecture with an intermediate layer using the notation NNAR (p, k) for series without seasonality. For this work, the methodology described by As'ad et al. (2020) and Maleki et al. (2018) was adopted. NNAR followed the routine of the forecast (Hyndman et al., 2019; Hyndman and Khandakar, 2008) and ggplot2 (Wickham, 2016) packages in the R version 4.3.1 software program.

The mortality model was calibrated using historical data on observed tree mortality rates. Neural Networks were used to validate the mortality model by assessing its performance through comparisons between the predicted mortality rates and observational data collected in the field during the periods of 2005–2006, 2006–2008, 2008–2010, and

2010–2012. Starting from 2012, Neural Networks were implemented to simulate mortality rates up to the 2022–2024 interval. This approach allows for the capture of complex and nonlinear patterns in the data, enhancing the accuracy of mortality predictions over time.

2.8. Meteorological variables and ENSO phenomenon

Four meteorological variables obtained and validated by Xavier et al. (2016) were used. A point grid with the same resolution as the reanalysis data (~30 km) was assembled to characterize these elements during the period from 2005 to 2012. These data are available in NetCDF format at the University of Texas at Austin (<https://utexas.app.box.com/v/Xavier-et-al-IJOC-DATA>). The variables used were Rainfall (mm), maximum,

Table 1

Functional relationship of competition indices used to estimate the Pm after reduced impact logging in a Dense Ombrophilous Forest in the Eastern Amazon, Pará, Brazil.

Distance-independent indices	Author	Equation
$DII_1 = \frac{DBH_1^2}{DBH^2}$	Glover and Hool (1979)	(1)
$DII_2 = \frac{BA_1^2}{BA_q^2}$	Stage (1973)	(2)
$DII_{BAL} = \sum BA_m$	Stage (1973)	(3)

In which: DBH_1 = Diameter with bark of the object-tree, measured at 1.30 m height (cm); DBH = arithmetic mean of the tree diameters of the sample unit (cm); BA_1 = basal area of the object-tree, measured at 1.30 m height (m^2); BA_q = basal area corresponding to the mean diameter (q) of the neighboring trees in the sample unit (m^2); BAL = sum of the basal areas (BA_m) of the neighboring trees larger than the object-tree ($m^2 ha^{-1}$).

Table 2

Models tested to estimate the probability of mortality in a Dense Ombrophilous Forest in the Eastern Amazon, Pará, Brazil.

Number	Model	Author
1	$P(m) = \beta_0 \cdot IC^{\beta_1} \cdot \epsilon$	Allometric (West, 1981)
2	$P(m) = 1 - \left[\beta_0 - \left(\frac{1}{1 + \exp(\beta_1 + \beta_2 \cdot IC^{\beta_3})} \right) \right] \cdot \epsilon$	Buchman et al. (1983) modified
3	$P(m) = \left(\frac{\gamma}{\beta} \right) \cdot \left[\left(\frac{IC}{\beta} \right) \right]^{(\gamma-1)} \cdot \exp \left\{ - \left[\left(\frac{IC}{\beta} \right) \right]^\gamma \right\} \cdot \epsilon$	Weibull (Glover and Hool, 1979)
4	$P(m) = \beta_0 + \exp(\beta_1 + \beta_2 \cdot IC) \cdot \epsilon$	Exponential (Payandeh, 1983)
5	$P(m) = (1 + \exp(\beta_0 + \beta_1 \cdot IC))^{-1} \cdot \epsilon$	Logistic (Hamilton, 1986)

In which: Pm = probability of mortality of each tree; exp. = exponential; CI = competition index; β_i = model parameters, with i ranging from 1 to 3; β = scale parameter; γ = shape parameter; α = location parameter; ϵ = random error.

minimum and average air temperature (tmax, tmin and tavg respectively; °C).

Classified ENSO data was used for the observed tree mortality data. ENSO was used to investigate the relationship between species mortality during the collection interval from 2005 to 2012. The data were classified by ENSO events. The observed and simulated years were classified

Table 3

ENSO classification for observed (2005–2012) and forecast data (2012–2024).

Data collection and NNAR	Years	Acronym	Classification
Observed	2005–2006	WL	Weak La Niña
	2006–2008	WE/SL/ WL	Weak El Niño/Strong La Niña/ Weak La Niña
	2008–2010	WL/ME/ SL	Weak La Niña/Moderate El Niño/Strong La Niña
	2010–2012	SL/ML/NE	Strong La Niña/Moderate La Niña/Neutrality
	Forecast	2012–2014	NE/WE
2014–2016		WE/VSE	Weak El Niño/Very Strong El Niño
2016–2018		VSE/WL/ WE	Very Strong El Niño/Weak La Niña/Weak El Niño
2018–2020		WE/NE/ ML	Weak El Niño/Neutrality/ Moderate La Niña
2020–2022		ML/WL	Moderate La Niña/Weak La Niña
2022–2024		ML/WL/ WE	Moderate La Niña/Weak La Niña/Weak El Niño

according to Table 3, based on the classification available at: <<https://www.webbweather.com/ensemble-oceanic-nino-index.html/>>.

2.9. Correlation matrix between mortality and weather variables

A correlation matrix was used to verify the influence of climate on tree mortality. Data observed in the field from 2005 to 2012 and the meteorological variables maximum, minimum, average air temperature and rain were used for this analysis. The “spline” method for interpolation was used for matrix correlation and the libraries to run the package were ggplot2 and GGally.

3. Results

3.1. Mortality analysis

Considering a harvest intensity of 21.3 m^3 ha of commercial wood, equivalent to 7 trees ha, the average annual mortality rate observed (Pm % year⁻¹) after selective logging during the study period (2005 to 2012) was 2.06 % year⁻¹ (Fig. 3). The highest percentage of mortality occurred in the 125 cm diameter at breast height (DBH) class (6.25 %) due to the low density of these trees (0.83 ind ha), and it was caused by the death of a single tree during the study period.

3.2. Analysis of tree mortality applying the Pretzsch Rule

The average number of trees classified as dead after selective logging, based on the mean of 30 repetitions, was 435 with a standard deviation of 17 trees, out of a total of 436 observed dead trees (Fig. 4).

3.3. Estimation and evaluation of mortality probability models

The allometric and Weibull models fitted with the DII_{BAL} index and the exponential model fitted with the DII_2 index did not converge during fitting and are therefore not presented (Table 4).

The fitted models exhibited similar patterns among themselves; however, the mortality estimates did not follow a defined trend concerning the DBH (Diameter at Breast Height) of the trees (Fig. 5).

All five evaluated models overestimated the number of dead trees for the study period (2005 to 2012), with a smaller range for the DBH classes of 25, 45, and 55 cm and a larger range for the classes of 65, 85, 95, and 105 cm in diameter. The exception was model 3, fitted with the DII_2 index, which underestimated mortality in the 95 and 105 cm DBH classes. Models 1 and 2, fitted with the DII_1 index, showed the highest overestimation of mortality for these classes. Meanwhile, model 3 (using the DII_2 index) and model 5 (using the DII_{BAL} index) were similar to each other and also came closest to the observed values.

There was a slight tendency to underestimate observed mortality for DBH classes of 35, 75, and 125 cm in diameter. Model 5 (using the DII_{BAL} index) showed slight superiority over the others, demonstrating greater proximity between the estimates and the observed values, especially for the 75 and 125 cm DBH classes. On the other hand, model 3, fitted with the DII_2 index, resulted in the largest errors, mainly for the 125 cm diameter class. There was greater accuracy in the estimates generated by the five evaluated models in the DBH classes of 115, 135, and 155 cm in diameter, and although these estimates did not show a defined trend, they demonstrated similar behavior to the observations.

Overall, all models overestimated mortality in both the larger and smaller diameter classes. Despite this trend, the K-S test considered statistical equality among the estimates generated by the five equations ($p > 0.05$) (Table 5). However, the number of dead trees estimated by the Logistic Function model (Model 5) was closer to the respective observed values. Thus, logistic regression employing the DII_{BAL} competition index was the selected model to estimate mortality in the managed forest of Rio Capim Farm.

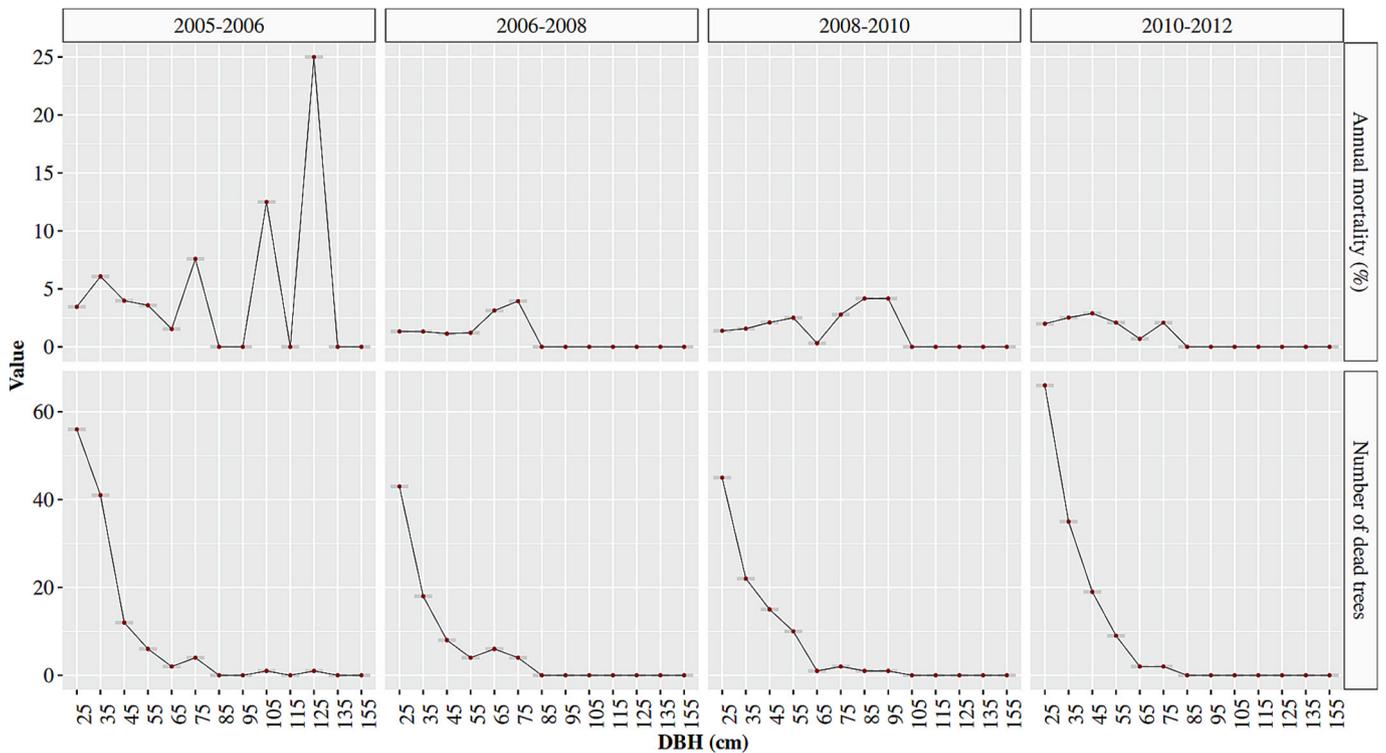


Fig. 3. Annual mortality (Pm % year⁻¹) and number of dead trees for the period from 2005 to 2012 after selective logging in the Eastern Amazon, Pará, Brazil.

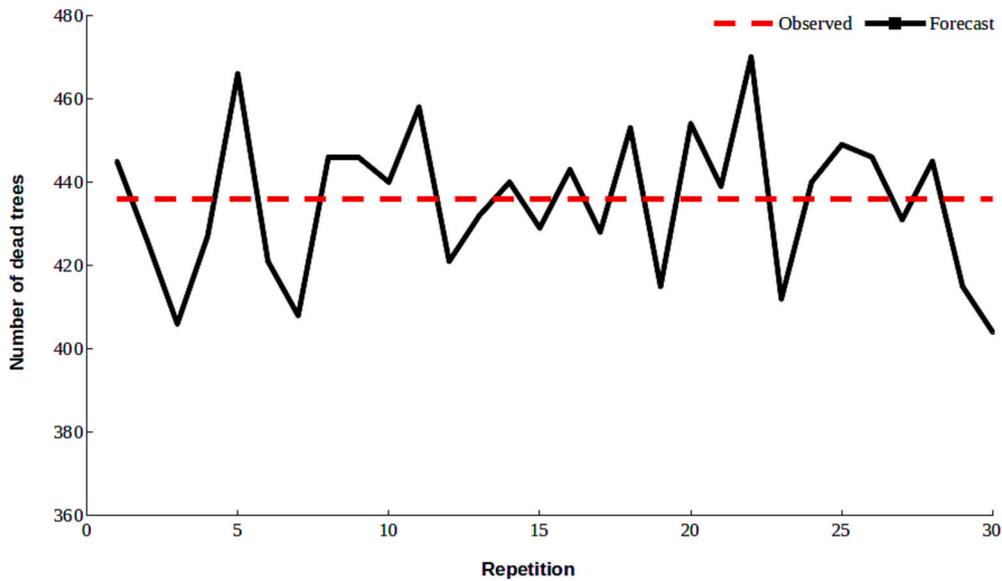


Fig. 4. Estimated number of dead trees from applying the Pretzsch rule to the observed data in a Dense Ombrophilous Forest in the Eastern Amazon, Pará, Brazil.

3.4. Estimated mortality by logistic function (Model 5)

The annual mortality rate over time after RIL was tracked by the selected model (Fig. 6). However, there was a tendency for underestimation between 2005 and 2006, transitioning to overestimation in the periods from 2006 to 2008 and 2008 to 2010. Mortality increased again between 2010 and 2012. During this period, the mortality values estimated by the Logistic Function model were the closest to the observed values, although there was still a slight underestimation of actual mortality.

3.5. Neural network autoregressive model (mortality)

Higher mortality values were observed between 2005 and 2006, followed by a slowdown in the two subsequent periods (2006 to 2008 and 2008 to 2010). Mortality increased again in the last period analyzed (2010 to 2012) about 8 years after Reduced Impact Logging. The forecasts generated by the NNAR model for the years 2012 to 2024 followed the trend of observed mortality values. The period from 2012 to 2014, characterized by Neutral and Weak El Niño events, exhibited the highest mortality value for trees with up to 25 cm DBH (Fig. 7).

Table 4

Estimated coefficients of the mortality probability models after Reduced Impact Logging in a Dense Ombrophilous Forest in the Eastern Amazon, Pará, Brazil.

CI	Models	$\beta_0\gamma$	$\beta_1\beta$	β_2	β_3
DII ₁	$P(m) = \beta_0 \cdot \text{DII}_{1^{\beta_1}} \cdot \varepsilon$	0.0236366	0.0855750	-	-
DII ₁	$P(m) = 1 - \left[\beta_0 - \left(\frac{1}{1 + \exp^{(\beta_1 + \beta_2 \cdot \text{DII}_{1^{\beta_3}})}} \right) \right] \cdot \varepsilon$	1.2954531	3.8446590	-3.0871276	0.0033716
DII ₁	$P(m) = \left(\frac{\gamma}{\beta} \right) \cdot \left[\left(\frac{\text{DII}_1}{\beta} \right)^{\gamma-1} \cdot \exp \left\{ - \left[\left(\frac{\text{DII}_1}{\beta} \right)^\gamma \right] \right\} \right] \cdot \varepsilon$	1.1397362	29.0136847	-	-
DII ₁	$P(m) = \beta_0 + \exp^{(\beta_1 + \beta_2 \cdot \text{DII}_1)} \cdot \varepsilon$	-0.0194321	-3.1600995	0.0077974	-
DII ₁	$P(m) = (1 + \exp^{\beta_0 + \beta_1 \cdot \text{DII}_1})^{-1} \cdot \varepsilon$	3.7481910	-0.0133423	-	-
DII ₂	$P(m) = \beta_0 \cdot \text{DII}_{2^{\beta_1}} \cdot \varepsilon$	0.0239855	0.0415002	-	-
DII ₂	$P(m) = 1 - \left[\beta_0 - \left(\frac{1}{1 + \exp^{(\beta_1 + \beta_2 \cdot \text{DII}_{2^{\beta_3}})}} \right) \right] \cdot \varepsilon$	1.0862765	0.8558459	1.2310335	-0.0091192
DII ₂	$P(m) = \left(\frac{\gamma}{\beta} \right) \cdot \left[\left(\frac{\text{DII}_2}{\beta} \right)^{\gamma-1} \cdot \exp \left\{ - \left[\left(\frac{\text{DII}_2}{\beta} \right)^\gamma \right] \right\} \right] \cdot \varepsilon$	1.0997858	30.1340931	-	-
DII ₂	$P(m) = (1 + \exp^{\beta_0 + \beta_1 \cdot \text{DII}_2})^{-1} + \varepsilon$	3.7313153	0.0003222	-	-
DII _{BAL}	$P(m) = 1 - \left[\beta_0 - \left(\frac{1}{1 + \exp^{(\beta_1 + \beta_2 \cdot \text{DII}_{\text{BAL}}^{\beta_3})}} \right) \right] \cdot \varepsilon$	1.2514283	0.9610706	0.0000005	3.6248846
DII _{BAL}	$P(m) = \beta_0 + \exp^{\beta_1 + \beta_2 \cdot \text{DII}_{\text{BAL}}} \cdot \varepsilon$	-0.0137742	-3.1918575	-0.0077243	-
DII _{BAL}	$P(m) = (1 + \exp^{\beta_0 + \beta_1 \cdot \text{DII}_{\text{BAL}}})^{-1} \cdot \varepsilon$	3.5715717	0.0123606	-	-

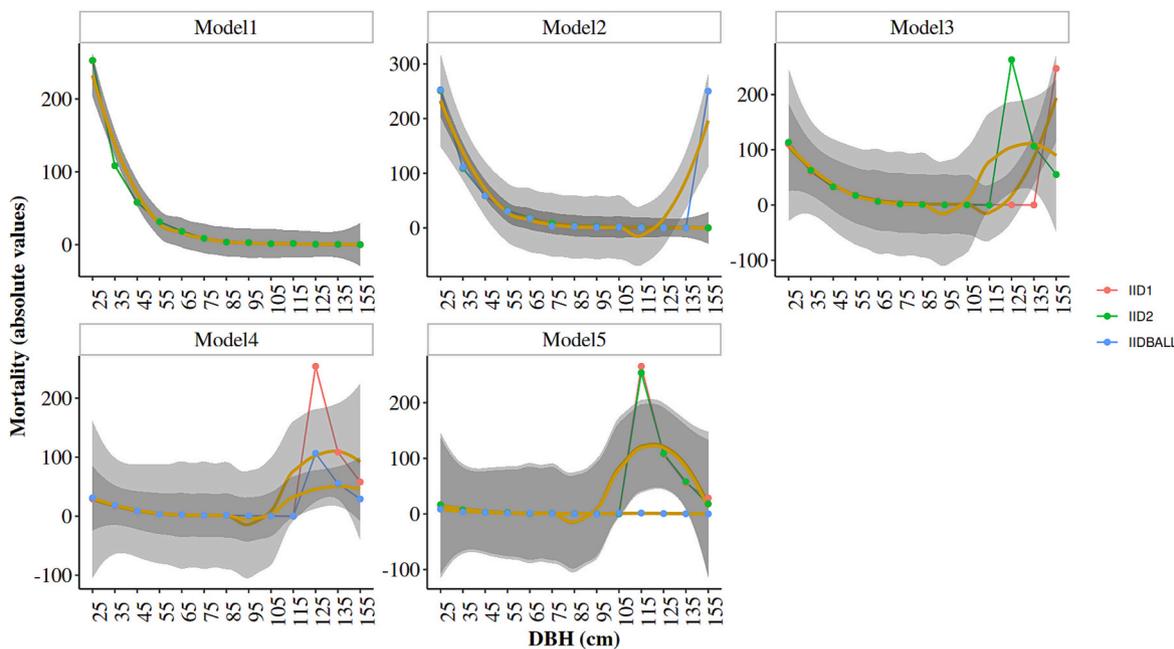


Fig. 5. Observed and estimated mortality for the period from 2005 to 2012 in a Dense Ombrophilous Forest in the Eastern Amazon, Pará, Brazil.

3.6. Meteorological variables - Reanalysis data

In the Boxplot analysis (Fig. 8), it is observed the years 2005 and 2010 showed the highest average air temperatures, with values exceeding 33 °C. The year 2008 presented the highest maximum air temperature with a value exceeding 34 °C in October, and the lowest minimum air temperature with a value below 21 °C in July. The average air temperatures followed the same seasonal pattern for the study area. Rainfall was mainly concentrated at maximum values in the year 2009, in which the total annual value was the highest with values exceeding 2500 mm. The highest monthly rainfall in the same year was found for the month of April with a value exceeding 550 mm. The lowest average rainfall values were concentrated in the years 2010 and 2012, with the year 2012 being the least rainy with monthly average values of the series below 120 mm.

The correlation analysis conducted for the period from 2005 to 2012

showed that the maximum air temperature (tmax) had the highest correlation (0.394) with species mortality, while the minimum temperature (tmin) was the least correlated variable, as illustrated in Fig. 9.

4. Discussion

4.1. Mortality analysis

Our study demonstrated that smaller trees (25 cm DBH) had a higher probability of mortality compared to those with larger diameters. Thus, the observed tree mortality probability was directly influenced by tree size. This coincides with the findings of de Oliveira et al. (2021), who also assessed mortality after selective logging in the Amazon and found that tree diameter classes had a significant effect on mortality rates. Similar behavior was found by Nascimento et al. (2009), who observed a higher probability of mortality in the smaller size classes (12.5 and 22.5

Table 5

Kolmogorov-Smirnov (KS) Goodness-of-Fit Test between observed and estimated diameter distributions in a Dense Ombrophilous Forest in the Eastern Amazon, Pará, Brazil.

Competition Index	Model	D _{max}	p-value
DII ₁	1	0.05866	0.08958 ^{ns}
DII ₁	2	0.05928	0.08957 ^{ns}
DII ₁	3	0.06060	0.08955 ^{ns}
DII ₁	4	0.05696	0.08961 ^{ns}
DII ₁	5	0.05725	0.08962 ^{ns}
DII ₂	1	0.05837	0.08959 ^{ns}
DII ₂	2	0.05834	0.08961 ^{ns}
DII ₂	3	0.06677	0.08984 ^{ns}
DII ₂	4	–	–
DII ₂	5	0.06243	0.08964 ^{ns}
DII _{BAL}	1	–	–
DII _{BAL}	2	0.05789	0.08961 ^{ns}
DII _{BAL}	3	–	–
DII _{BAL}	4	0.05774	0.08960 ^{ns}
DII _{BAL}	5	0.05739	0.08962 ^{ns}

In which: DII₁ = competition index by Glover and Hool (1979); DII₂ = competition index by Stage (1973); DII_{BAL} (Basal Area Larger Trees) = competition index by Stage (1973); ns: not significant at 5 % by the K-S test.

cm DBH) while studying the dynamics of a managed forest in south-western Amazon.

According to de Oliveira et al. (2023), smaller trees tend to show higher mortality after selective logging due to various ecological and environmental factors, which are amplified by the removal of larger trees. These changes include modifications in the microclimate, alterations in soil characteristics, physical damage, increased competition, and impacts on symbiotic relationships (de Oliveira et al., 2021; Reis et al., 2018).

Some research has shown that tree size is one of the important intrinsic attributes that strongly influences mortality rates (Wu et al., 2017), and this process does not occur randomly in relation to diameter classes (Ganey and Vojta, 2011). Mortality is inversely proportional to tree size (de Souza and Soares, 2013). However, other studies have noted no relationship between mortality and tree size. Therefore, there is still no consensus on the relationship between tree diameter and mortality after selective logging.

The unanimous finding among studies evaluating tree dynamics after selective logging is that the mortality of remaining trees tends to increase following logging activities, especially in the first years after management. In this context, adapting forest management to climate change is another significant challenge to ensure forest sustainability, timber production, and the provision of ecosystem services.

4.2. Analysis of tree mortality applying the Pretzsch Rule

This study showed that the decision rule proposed by Pretzsch (Pretzsch et al., 2002) is an efficient methodology for assessing the mortality of trees after RIL (see Fig. 4). Castro et al. (2020) also showed good performance of the methodology developed by Pretzsch et al. (2002) when validating an individual-tree model for a tropical forest in Southeastern Brazil. The same was reported by de Oliveira et al. (2023) in modeling the mortality of individual trees in a Dense Ombrophilous Forest in the Brazilian Amazon and Figueiredo et al. (2020) in modeling the mortality of individual trees in a Seasonal Semi-deciduous Forest in Brazil.

4.3. Probability of mortality (Pm) models

Estimates generated by the five mortality models tested were consistent with field-observed values (K-S test; $p > 0.05$), although they showed overestimation of observed data for both smaller trees (smaller DBH) and those with larger diameter. This observed bias likely occurred because mortality is an extremely variable event and, therefore, difficult to predict (de Oliveira et al., 2023; Reis et al., 2018; Rossi et al., 2007). According to de Carvalho (1997), mortality can be caused by various factors, such as attacks by pathogens, parasites, and herbivores, storms, rays, damage from heavy rains, particularly in emergent trees, damage during logging, and age-related death (Dionísio et al., 2027).

Reis et al. (2018) found higher errors associated with smaller diameter classes in modeling individual tree mortality in a managed forest in FLONA Tapajós, Pará State, which was also a pattern found by da Rocha et al. (2018) in modeling mortality and survival in an Atlantic Forest area in Brazil. The authors also noted the absence of a defined pattern in mortality estimates in relation to diameter classes.

Different studies have already reported the difficulty in estimating

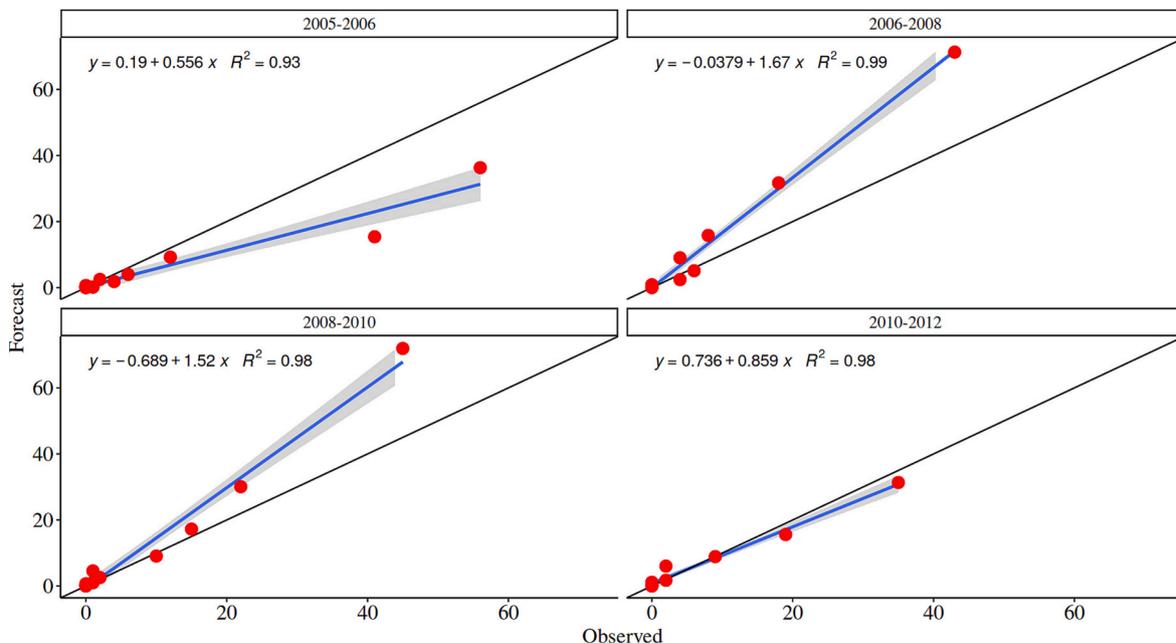


Fig. 6. Observed and estimated mortality by logistic function (Model 5) fitted with the DII_{BAL} competition index in a Dense Ombrophilous Forest in the Eastern Amazon, Pará, Brazil.

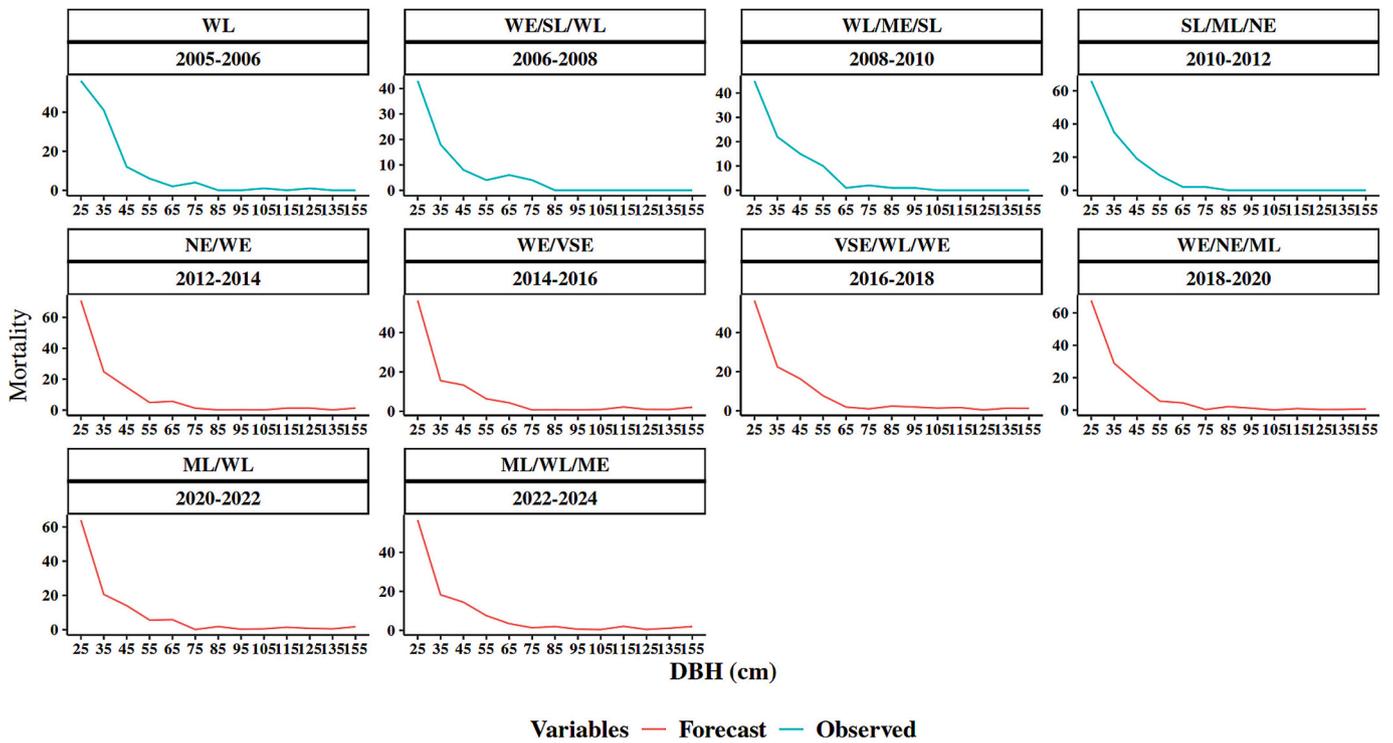


Fig. 7. Observed mortality (2005 to 2012) and forecast (2012 to 2024) with ENSO classifications for a tropical forest after Reduced Impact Logging in a Dense Ombrophilous Forest in the Eastern Amazon, Pará, Brazil.

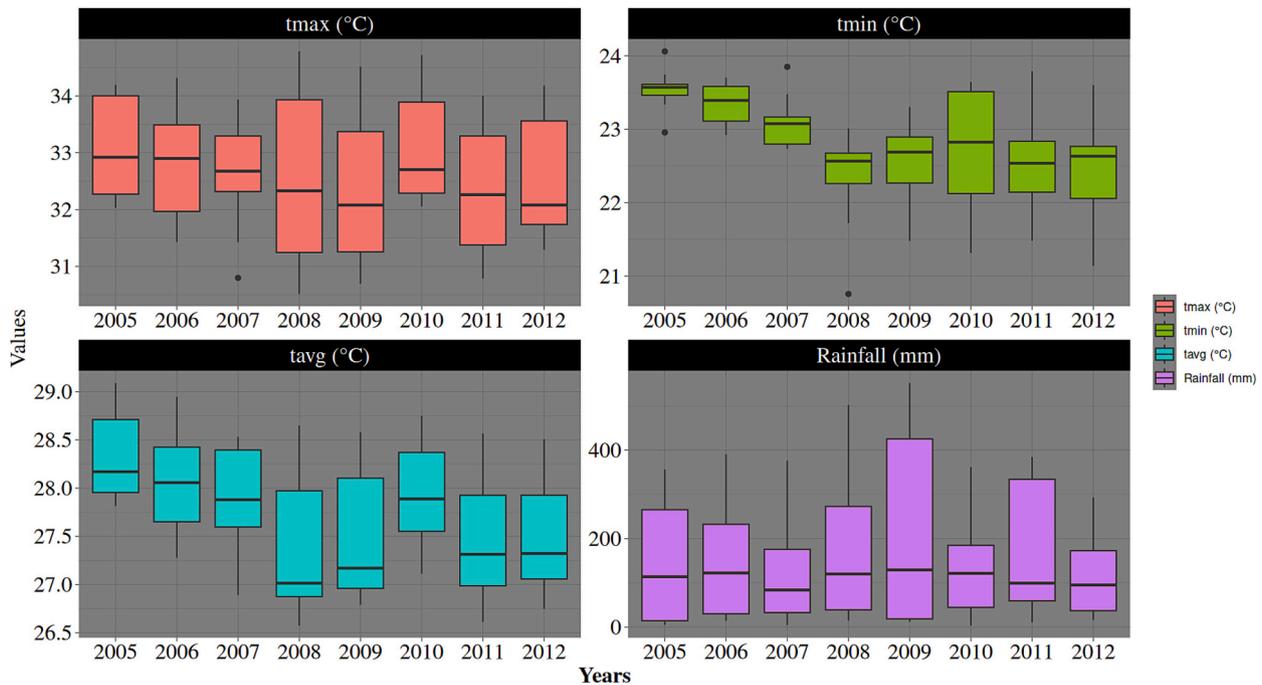


Fig. 8. Boxplot analysis during the years of observed collections for the meteorological variables Rainfall (mm), tmax, tmin, and tavg (maximum, minimum, and average air temperature; °C) after Reduced Impact Logging in a Dense Ombrophilous Forest in the Eastern Amazon, Pará, Brazil.

the mortality probability of individual trees (Bayat et al., 2019a; Bravo et al., 2019; Zhu et al., 2019), especially for natural and heterogeneous forests such as those in the Amazon region; these forests have great diversity of species and high structural complexity (de Solar et al., 2016), making tree mortality an even more complex phenomenon (Bugmann et al., 2019), and making it difficult for probability models to obtain accurate estimates (Monserud and Sterba, 1999).

Additionally, Eid and Tuhus (2001) highlight another significant challenge in modeling tree-level mortality in managed rainforests which is associated with alterations in the natural dynamics of the remaining forest after selective harvesting. These changes lead to higher mortality rates in the subsequent years and also contribute to shifts in species composition. Various studies have demonstrated that implementing RIL techniques can reduce the likelihood of forest degradation by up to 50 %

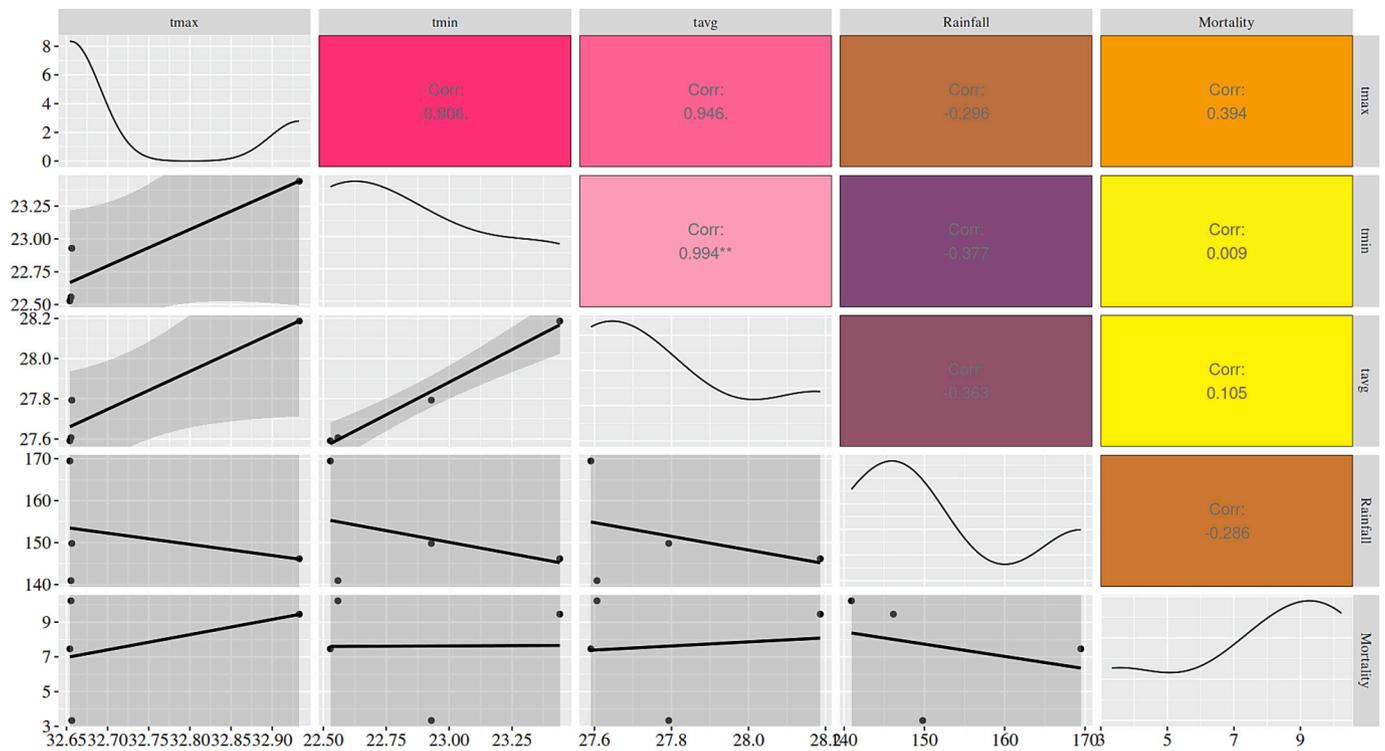


Fig. 9. Correlation between mortality and meteorological variables (rainfall, maximum (tmax), minimum (tmin), and average (tavg) air temperature) in tropical forest after Reduced Impact Logging in the Eastern Amazon Pará, Brazil.

(Sist and Ferreira, 2007b). Nevertheless, even in well-managed areas, an increase in tree mortality following logging is anticipated (D'Oliveira et al., 2017). The effects of RIL on mortality persist for a period ranging from seven to eleven years after the intervention (de Oliveira et al., 2023).

Among the tested models, the Logistic Function (Hamilton, 1986) fitted with the DII_{BAL} competition index (Stage, 1973) resulted in the most accurate estimates ($R^2 > 0.90$). de Oliveira et al. (2023) also employed the DII_{BAL} index in developing an individual tree model based on the Logistic Function for managed forests in the Brazilian Amazon.

The DII_{BAL} index has been widely used in various studies to evaluate competition in individual tree models (de Oliveira et al., 2021). This index is recognized for its simplicity in calculation and interpretation, as well as for providing individual metrics for each tree based on its basal area (Yang et al., 2009). Basal area is a population density parameter that indicates the degree of area occupation (Campos and Leite, 2017). This variable alone already highlights the competitive status of each tree, eliminating the need to incorporate other variables (Martins et al., 2011).

Yang and Huang (2013) used the Logistic Function model fitted with the DII_{BAL} index to model the mortality and survival of mixed stands in a boreal forest in Canada. These authors concluded that the model satisfactorily estimated stand mortality. Nguyen et al. (2012) obtained good statistical performance when using the Logistic Function model to build a growth and yield model for dipterocarp forests in Vietnam. Logistic regression was also successfully used by Hülsmann et al. (2016) to model the mortality of 18 tree species in forest reserves in Switzerland and Germany.

The Logistic Function model fitted to individual tree data may be the best way to model the probability of mortality in tropical forests (Crecente-Campo et al., 2009; Rossi et al., 2007). The superiority of this method over others lies in its relative ease of fitting and the quality of the results generated.

4.4. Neural network autoregressive model (mortality)

The forecasts generated by the NNAR model (from 2012 to 2024) followed the trend of observed mortality (from 2005 to 2012). The increase in mortality immediately following logging activities may occur as a result of the damage caused by logging and log skidding activities, as noted by de Oliveira et al. (2023) in their assessment of the dynamics of the Amazon tropical rainforest following selective extraction.

Selective logging typically damages approximately 24.5 % of the remaining trees (Martins et al., 1997), and these impacts can remain visible for decades. Trees located near logging clearings, log storage yards, and roads are at greater risk of dying. This behavior has also been corroborated by previous studies, such as those by Reis et al. (2015) in the Tapajós National Forest, in the state of Pará, Brazil; Locks and Matricardi (2019) in concession areas in the Jamari and Jacundá National Forests in Rondônia, southwestern Amazon, and in the Saracá-Taquera National Forest in Pará; as well as studies by de Oliveira et al. (2019) and Sist and Ferreira (2007a) in the same region as the present study. These studies suggest a direct association between logging practices and increased tree mortality.

On the other hand, the decrease in mortality rate in the periods from 2006 to 2008 and 2008 to 2010 can be explained by the forest canopy opening caused by logging, which provided greater light incidence on the remaining individuals, thus reducing competition, as observed by de Oliveira et al. (2023). However, as the forest canopy gradually closes, the light incidence inside the forest decreases, resulting in increased competition for increasingly limited resources. This may reduce tree growth (de Avila et al., 2017; Vatrax and Alder, 2018), which in turn may influence the increase in mortality rate, especially of species that require light for their growth (de Oliveira et al., 2019).

Another possible explanation for the increase in mortality about 8 years after management interventions (2010–2012), as recorded in this study, may be related to changes in precipitation regimes in the year 2010, characterized by strong, moderate, and neutral La Niña events. Studies such as those by D'Oliveira et al. (2017), Allen et al. (2015),

Shenkin et al. (2018), Aleixo et al. (2019), Fell et al. (2022), Bennett et al. (2023) and Leisenheimer et al. (2024), have shown that high temperatures and years of extreme drought increase tree mortality for at least two years after the climatic event.

The increase in post-harvest mortality rates found in this study is in line with observations in other managed tropical forests (Darrigo et al., 2016; Reis et al., 2015; Toyama et al., 2015; Van der Werf et al., 2019). Studies have shown that the effect of logging on mortality rates persists between 7 and 11 years after silvicultural interventions (Darrigo et al., 2016).

Tree mortality is an important component of forest dynamics processes, and at the same time, one of the least understood. However, consistent estimates have been observed with the use of mortality probability models, especially with Logistic Function using the DII_{BAL} competition index for a forest with a large diversity of species and tree sizes.

This information is relevant from the perspective of forest management, as understanding the factors governing post-harvest tree mortality can provide insights to increase survival and indicate possibilities for utilizing dead trees or those at high risk of death (Barros et al., 2024).

4.5. Climate influence on vegetation health

Although Reduced Impact Logging performed in 2004 may have played a significant role in tree mortality over the years assessed in this study (2005–2012), it is crucial to consider that drought and extreme rainfall events, along with temperature changes associated with the ENSO phenomenon occurring during the same period, may have influenced tree mortality patterns in this region (Aleixo et al., 2019; Bennett et al., 2023; Vilanova et al., 2020).

Studies on forest dynamics conducted in the Southwestern Amazon region have shown that extreme climatic events result in biomass losses greater than those estimated for Reduced Impact Logging (D'Oliveira et al., 2017). Furthermore, an increase in average tree mortality from 2 % to 5 % was observed over 20 years of research due to water deficit caused by these phenomena. For example, the severe drought recorded in 2005 (Jiménez-Muñoz et al., 2016; Vilanova et al., 2020; Vilanova et al., 2021), combined with high temperatures (exceeding 33 °C) in that same year (Fig. 8), may have contributed to the increased tree mortality between 2005 and 2006 (Fig. 6).

The rise in temperatures, coupled with severe drought anomalies caused by the El Niño phenomenon, results in decreased precipitation, making forests more susceptible to fires (Alencar et al., 2015; Delgado, 2024; Melo et al., 2024; Vilanova et al., 2020), promoting reduced carbon storage, sensitivity of younger tree yield, and plant mortality (Bennett et al., 2023; Giardina et al., 2018). These studies corroborate the results obtained herein, in which a correlation between maximum temperature and tree mortality was observed (Fig. 9).

5. Conclusions

The use of traditional regression models and the decision rule proposed by Pretzsch et al. (2002) enabled precise estimation of individual tree mortality following Reduced Impact Logging (RIL) and climate events related to the El Niño-Southern Oscillation (ENSO) in the Eastern Amazon.

The Logistic Function model proposed by Hamilton (1986) was demonstrated to be the most accurate in estimating the probability of individual tree mortality ($R^2 > 0.90$), based on a total of 436 observed dead trees from 2005 to 2012 in the studied forest.

The Neural Network Autoregressive (NNAR) model successfully predicted future species mortality over the simulated years (2012 to 2024).

Significant climate events with implications for atmospheric conditions were observed during the years 2005 and 2012. A severe drought alongside a Weak La Niña event occurred in 2005, while a Strong La

Niña event took place in 2010. The highest maximum temperatures (exceeding 33 °C) of the period from 2005 to 2012 were recorded during these times.

The correlation between maximum air temperature and tree mortality suggests the importance of adopting new management practices which favor the resilience of tropical forests versus climate change. Studies of this nature are essential for deepening understanding of the causes of tree mortality, especially following Reduced Impact Logging (RIL) and extreme climate events associated with ENSO in the Amazon.

CRedit authorship contribution statement

Erica Karolina Barros de Oliveira: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Alba Valéria Rezende:** Writing – original draft, Supervision, Methodology. **Leonidas Soares Murta Júnior:** Methodology, Formal analysis, Data curation. **Lucas Mazzei:** Writing – original draft, Supervision. **Renato Vinícius Oliveira Castro:** Supervision, Methodology, Formal analysis. **Marcus Vinício Neves D'Oliveira:** Writing – original draft. **Rafael Coll Delgado:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis.

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Data availability

The code is available on the professional data storage platform Figshare, with part of it developed based on the ARIMA model, as described in Delgado et al. (2022) (<https://doi.org/10.1016/j.eiar.2022.106815>). The specific script used can be accessed here: <https://github.com/Gelsleichter/Auto-Arima-for-multiple-time-series/blob/main/Auto%20Arima%20for%20multiple%20time%20series.R>.

Author's Experimental Environment:

OS: Ubuntu 24.04.1 LTS.

CPU: Dell Inc. Inspiron 155510, 11th Gen Intel® Core™ i7-11390H × 8.

RAM: 16.00 GB.

GPU: Intel® Xe Graphics (TGL GT2).

Due to the number of tables and scripts run in R software (version 4.3.3) and the file size exceeding 800 MB, all data has been uploaded to Figshare for improved accessibility: <https://doi.org/10.6084/m9.figshare.27390513>.

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