UNIVERSIDADE FEDERAL DE VIÇOSA

Monitoramento nutricional e de produção de espécies florestais utilizando equações alométricas, índices espectrais e machine learning

César Oswaldo Arévalo Hernández
Doctor Scientiae

VIÇOSA - MINAS GERAIS
2025

CÉSAR OSWALDO ARÉVALO HERNÁNDEZ

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Tese apresentada à Universidade Federal de Viçosa, como parte das exigências do Programa de Pós-Graduação em Solos e Nutrição de Plantas, para obtenção do título de *Doctor Scientiae*.

Orientador: Julio Cesar Lima Neves

Coorientador: Elpidio I. Fernandes Filho

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César Oswaldo Arévalo Hernández
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Julio Cesar Lima Neves
Orientador

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RESUMO

HERNÁNDEZ, César Oswaldo Arévalo, D.Sc., Universidade Federal de Viçosa, maio de 2025. **Monitoramento nutricional e de produção de espécies florestais utilizando equações alométricas, índices espectrais e machine learning**. Orientador: Julio Cesar Lima Neves. Coorientador: Elpidio Inacio Fernandes Filho.

Monitorar o crescimento e a nutrição de espécies florestais sempre foi desafiador, principalmente devido às limitações na coleta de dados dessas espécies. Nesse contexto, surgiram outros métodos, como o uso de modelos com equações alométricas e, mais recentemente, o uso de aprendizado de máquina. Além disso, métodos de monitoramento da nutrição além do intervalo de suficiência têm sido implementados com sucesso. No entanto, as espécies florestais mais estudadas são Eucalipto e Pinus, havendo poucas pesquisas realizadas em espécies nativas ou de alta qualidade, como a Teca. Portanto, este trabalho teve como objetivo explorar essa necessidade de pesquisa em quatro capítulos: I) Uso do método da linha de fronteira e CND para determinar valores de referência de nutrientes para teca (Tectona grandis). II) Modelagem da produtividade da Teca (Tectona grandis) no Brasil com variáveis ambientais, imagens de satélite e aprendizado de máquina. III) Modelagem da produtividade da Teca (Tectona grandis) com variáveis ambientais, imagens de satélite e aprendizado de máquina no Brasil. IV) Características do solo e modelos alométricos para características biométricas e quantidades de nutrientes em árvores de alto rendimento de “Bolaina” (Guazuma crinita). No primeiro capítulo, o uso do Método da Linha de Fronteira como nova abordagem mostrou-se eficiente para selecionar uma população de alto rendimento. Além disso, o uso das normas CND foi prático para realizar o estabelecimento de valores de referência de equilíbrio e pode servir como guia para interpretação e diagnóstico nutricional em Teca, além de outras espécies vegetais. No segundo capítulo, foram explorados seis algoritmos de aprendizado de máquina para a modelagem da produtividade e características dendrométricas. Os algoritmos Cubist e Random Forest apresentaram melhor desempenho, sendo que o modelo Cubist selecionou variáveis relacionadas à topografia, enquanto o Random Forest resultou em um modelo mais equilibrado. Além disso, este é o primeiro estudo a utilizar uma abordagem holística para previsão de crescimento em Teca. No terceiro capítulo, foi explorada uma abordagem semelhante à do capítulo dois, mas com foco nas concentrações de macronutrientes (N, P, K, Ca, Mg, S) e micronutrientes (B, Cu, Fe, Mn e Zn) nas plantas. O Random Forest apresentou melhor desempenho e selecionou as variáveis de S disponível, idade, dias sem chuva e déficit hídrico como as mais importantes. Este também é o primeiro estudo publicado em Teca (Tectona grandis) que utiliza estes algoritmos para predizer concentrações de nutrientes, mas são necessárias mais pesquisas para aprimorar os modelos atuais e tornar o manejo nutricional florestal mais eficiente. Por fim, no quarto capítulo, o trabalho foi realizado com uma espécie nativa da Amazônia no Peru e o uso de equações alométricas para predizer o crescimento e o acúmulo de nutrientes. Este estudo foi o primeiro a avaliar e modelar o crescimento, as quantidades de macro e micronutrientes no ciclo produtivo dessa espécie. Também demonstrou que a espécie seguiu o padrão Ca>N>K>P>S>Mg para macronutrientes e Fe>B>Mn>Zn>Cu para micronutrientes, sendo os melhores modelos de predição o modelo de raiz quadrada e o modelo logístico.

Palavras-chave: Teca – Análise de folhas; Teca – Reflectância espectral; Teca – Aprendizado de máquina; Teca – CND; Teca - Modelagem; Guazuma crinita – Equações alométricas; Guazuma crinita – Nutrição

ABSTRACT

HERNÁNDEZ, César Oswaldo Arévalo, D.Sc., Universidade Federal de Viçosa, May, 2025. **Nutritional and production monitoring of forest species using allometric equations, spectral indices and machine learning**. Adviser: Julio Cesar Lima Neves. Co-adviser: Elpidio Inacio Fernandes Filho.

Monitoring forest species growth and nutrition has always been a challenging topic, mainly because of the limitations for collecting data in these species. In this matter, other methods have arisen such as the use of models with allometric equations and, lately, the use of machine learning. Also, nutrition monitoring methods besides the sufficiency range have been implemented successfully. However, the most studied forest species are Eucalyptus and Pine but very few research has been performed in native species or high-quality wood such as Teak. Therefore, this work aimed to explore this research gap in 04 chapters: I) Use of borderline method and CND to determine nutrient reference values for teak (Tectona grandis). II) Modelling of Teak (Tectona grandis) productivity in Brazil with environmental variables, satellite imagery and machine learning. III) Modelling of Teak (Tectona grandis) productivity with environmental variables, satellite imagery and machine learning in Brazil. IV) Soil characteristics and allometric models for biometric characteristics and nutrient amounts for high yielding “Bolaina” (Guazuma crinita) trees. In the first chapter, the use of the Border Line Method as a new approach proved to be efficient for selecting a high-yield population in Teak. Also, the use of the CND norms was practical to report the first study in establishing equilibrium reference values and can serve as a practical guide for interpretation and nutrition diagnostics in Teak and a baseline for other plant species. In the second chapter, the use of 06 machine learning algorithms was explored for the modelling of yield and dendrometric characteristics. Cubist and Random Forest algorithms performed better. Where Cubist model selected topographic related variables while Random Forest a more equilibrated model. Also, to our knowledge is the first study to use a holistic approach using machine learning for growth prediction in Teak. In the third chapter, we explored a similar approach as chapter two but focused on plant macro- (N, P, K, Ca, Mg, S) and micronutrients (B, Cu, Fe, Mn and Zn) concentrations. Where random forest performed better and selected the variables of Available S, Age, Days without rain and Water Deficit as the most important for most nutrients. Also, this is the first published study in Teak (Tectona grandis) that uses machine learning algorithms for nutrition prediction, but further research is needed to improve the current models and make forest nutrition management more efficient. Finally, in the fourth chapter, the work was performed around a native species from the amazon in Peru and the use of allometric equations for the prediction of its growth and nutrient accumulation. This study was the first to assess and model growth, macro- and micronutrient amounts in the productive cycle in this species. Also, it showed that this species followed a pattern of Ca>N>K>P>S>Mg for macronutrients and Fe>B>Mn>Zn>Cu for micronutrients, and the best prediction models were the square root and logistic models.

Keywords: Teak – Leaf analysis; Teak – Spectral reflectance; Teak – Machine learning; Teak – CND; Teak - Modelling; Guazuma crinita – Allometric equations; Guazuma crinita – Nutrition

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SUMARIO

CAPÍTULO 1. USE OF BORDERLINE METHOD AND CND TO DETERMINE NUTRIENT REFERENCE VALUES FOR TEAK (*TECTONA GRANDIS*) IN FERTILIZED SOILS IN BRAZIL

CAPÍTULO 1. USE OF BORDERLINE METHOD AND CND TO DETERMINE NUTRIENT REFERENCE VALUES FOR TEAK (*TECTONA GRANDIS*)

ABSTRACT

Teak (*Tectona grandis*) is an important forest tree planted in tropical regions worldwide. However, nutritional mineral diagnostics are normally performed using the critical limit method, without considering nutritional balance that could lead to biases in the diagnostics. Therefore, this work had the objective of Propose an alternative method to determine the high-yield population, Compositional Nutrient Diagnosis (CND) and equilibrium norms in Teak. The study was performed in clonal teak plantations (n=594) of different ages in Mato Grosso, Brazil. Volume and MAI were calculated from field measurements. Also, chemical analysis of leaf for macronutrients (N, P, K, Ca, S) and micronutrients (B, Cu, Fe, Mn and Zn) were used. The Boundary Line Method (BLM) was used to determine the high-yield population. After, CND norms were calculated for each nutrient and equilibrium norms from this data. Nutrients in teak were in the order of Ca>N>K>Mg>P>S for macronutrients and Fe>Mn>B>Zn>Cu for micronutrients. The use of BLM as a new approach has proven to be an efficient technique for selecting a high-yield population in Teak. The CND method has proven its importance in this species and can be used as an important technique that evaluates not only equilibrium but contents in Teak. The CND norms and Equilibrium reference values determined in this study will serve as a practical guide for interpretation and nutrition diagnostics in Teak and can serve as a baseline for other works in other plant species.

Keywords: Nutrition Diagnostics, Equilibrium nutrition, Critical limit, Forest nutrition

INTRODUCTION

Plant nutrition is one of the main topics in forestry management in Brazil. Higher temperatures induce to a higher uptake of nutrients in comparison to other latitudes making the monitoring of both soil fertility and forestry nutrition fundamental for high productivity in the Tropics (Alvarado, 2015). The most planted species in the Tropics corresponds to Eucalyptus and Pinus genera. Especially, the first is the most planted species in South America with Brazil leading the statistics in planted area (IBA, 2024). Nevertheless, the demand for different species with higher quality of wood has promoted increasing areas of Teak (*Tectona grandis*) or African Mahogany (*Khaya ivorensis*). Especially the first one, is the third most planted species in Brazil. Even though it is still far from the planted area of eucalyptus or pine in this country.

Teak (*Tectona grandis*) as other forestry species, needs soil with good drainage and good precipitation regimes. However, it is characterized as being a high nutrient demanding species in contrast to other forest species such as Eucalyptus (Fernández-Moya et al., 2014). Especially its high requirements in Ca, makes it not suitable for acidic soils. In general, Teak has nutrient demand as follows N>Ca>K>Mg>P>S>Fe>Mn>B>Zn>Cu (da Favare et al., 2012), being Ca the second most demanded nutrient. Considering the nutrient demands for this species, monitoring nutrient status is an important activity to achieve higher productivity. However, to perform this practice the use of reference values is necessary to avoid errors that could lead to a super or sub estimation of nutrient status in teak stands.

There are different approaches for estimating reference values in cultivated trees, some of the early methods were the definition of critical concentrations (Macy, 1936). Which is normally calculated based on regression or graphic methods between yield and nutrient concentration (Munson & Nelson, 1990). While other approach is using probabilistic methods with the aid of frequency tables to determine sufficiency ranges (Wadt et al., 1998).

Newer approaches such as the Boundary Line Method follows the same logic but working with the highest values and can reduce the environmental effects often observed in commercial plantations (Lima Neto et al., 2020; Walworth et al., 1986; Webb, 1972). Also, To explore nutrient balance methods such as the Compositional Nutrient Diagnosis (CND) and Kenworthy Indexes are commonly used (Bahia et al., 2021; Kenworthy, 1961). However, in terms of equilibrium of nutrients Diagnosis and Recommendation Integrated System (DRIS) norms have been widely adopted in different species from the initial work of Beaufilis, E.R. (1973) (Filho & Alves, 2004).

Even though different methods may be used to determine reference values it is important that both balance and equilibrium are determined to have efficient nutrient diagnosis. However, these values can be greatly affected by environmental, soil and topographic conditions, especially in fertilized soils, where high nutrient availability modifies root absorption capacities (Marschner, 2011).

In the case of Teak (*Tectona grandis*) even though information is not as abundant as for other species (i.e. *Eucalyptus* sp.) several works have been carried out over the years to establish reference values. The first published norms is the work of Drechsel, (1992) and Drechsel & Zech, (1994), establishing the first reference values and DRIS norms in teak, respectively. Other recent works have also determined these norms for Costa Rica (Fernández-Moya et al., 2014) and Brasil (Carvalho, 2016). However, other works have focused only on DRIS norms, in China (Zhou et al., 2017), Indonesia (Chanan et al., 2019) and the Brazilian Amazon (Neto et al., 2022). Even though, DRIS method has the most used for nutrient diagnostics. The CND method is an alternative method that uses a multivariate approach (Silva et al., 2004). The use of CND has been successfully demonstrated in Citrus (Bendaly Labaied et al., 2018), Banana (de Lima Neto et al., 2022), Cotton (Serra et al., 2010), bean (Partelli et al., 2014) and Eucalyptus (Silva et al., 2004; Squizani et al., 2023). However, little to work has been done in Teak (*Tectona grandis*), with the only published publication using this tool carried out by Neto et al., (2022) in the Brazilian amazon.

Diagnostics of Teak (*Tectona grandis*) nutrition is a critical area of study that must be revised and updated due to the high dynamics of nutrients over time. However, without adequate and robust reference values both for nutrient balance and equilibrium, the diagnosis becomes constrained. This issue may increase the probability of a misdiagnosis but may also lead to suboptimal strategies that can affect overall productivity on the farms. Therefore, this work had the objective of i) Propose an alternative method to determine the reference population in Teak ii) Generate norms for CND to be used for Teak nutrition diagnostics. iii) Determine the sufficiency ranges for each nutrient for Teak nutrition diagnostics based in equilibrium.

MATERIAL AND METHODS

Localization

The research was performed in 10 farms of clonal teak located in São José dos Quatro Marcos –Mato Grosso, Brazil located at UTM 365203 E 8268930 S and 211 m (Figure 1). The area is characterized by a tropical humid Climate (Am) (Köppen, 1931), with mean annual precipitation of 1500 mm and mean annual temperature of 24°C, with minimum means of 18°C and maximum of 33°C.

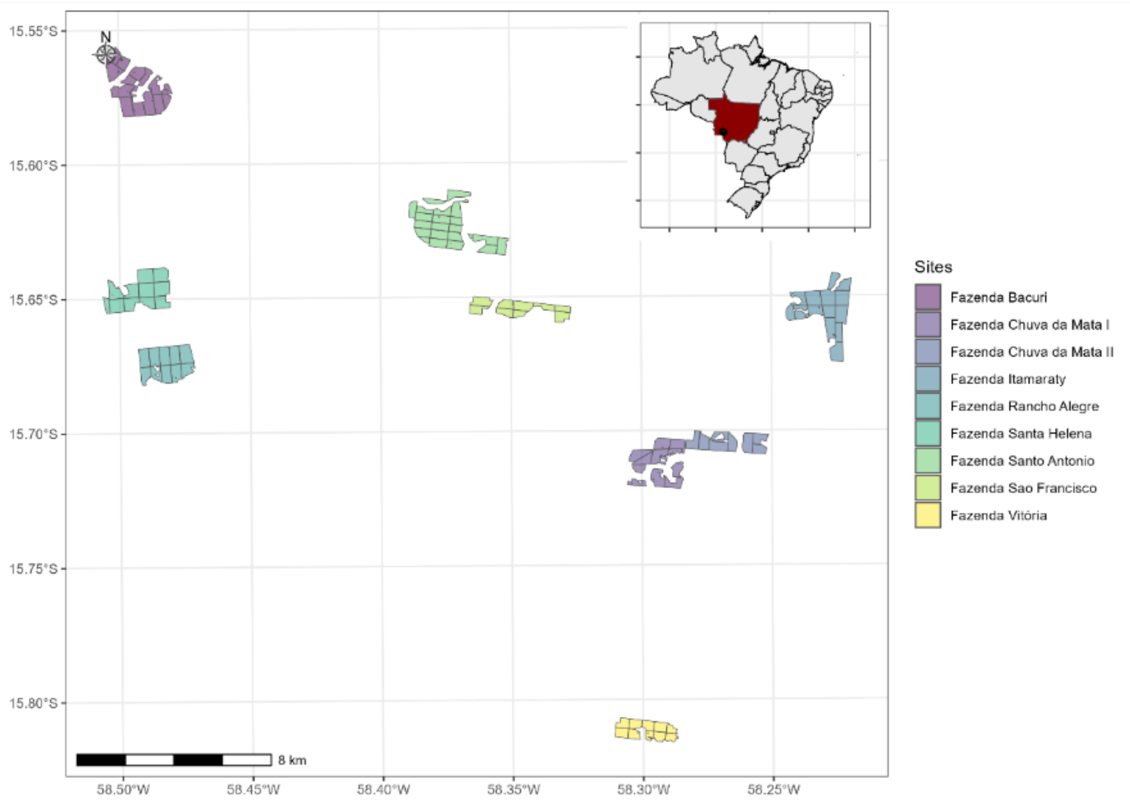

Figure 1. Location of Teak stands used for the research in Mato Grosso, Brazil

Teak Plots Characteristics

Selected farms for the study were 07: “Bacuri”, “Chuva da Mata”, “Itamaraty”, “Rancho Alegre”, “Santa Helena”, “Santo Antonio” and “Vitoria”. These farms are characterized by plantations of different years and different precipitation regimes that are summarized in table 1.

The management of the teak stands were typically with control of weeds each month, with pruning when necessary. Soil acidity correction was executed, when necessary, with the use of Dolomite. Soil fertilization was performed by an initial P fertilization with subsoiling operation, with Simple Superphosphate (12% P2O5) at 40 kg of P_2O_5/ha and at planting with MAP (Monoammonium Phosphate – 48% P_2O_5) at 70 kg of P_2O_5/ha. After, Potash (KCl – 60% K_2O) at 60 kg of K_2O/ha was used. Nitrogen source was derived from MAP.

Table 1. Teak farms characteristics used for reference nutrition values estimation in Mato Grosso, Brazil

Characteristics	**Bacuri**	**Chuva da Mata**	**Itamaraty**	**Rancho Alegre**	**Santa Helena**	**Santo Antonio**	**Vitória**
Year of initial planting	2018	2016	2013-2014	2014	2012-2013	2017	2015
Stand age*	4 years	6 years	8-9 years	8 years	9-10 years	5 years	7 years
Genetic material	Clonal	Clonal	Clonal	Clonal	Clonal	Clonal	Clonal
Area (ha)	366	249.24	258.77	276.71	320.17	194.99	168.67
Mean Annual precipitation (mm)	1,176	1,401	1,358	1,421	1,517	1,352	1,378
Mean Days with rain	318	292	300	300	300	293	306
Mean Days without rain	47	73	65	65	65	72	59
Precipitation deficit** (mm)	125	-101	-59	-121	-217	-53	-78

*Age at present work conditions (2022) ** Considering 1300 mm as average minimum conditions for teak growth (Medeiros et al., 2019).

Volume and Relative Volume determination

Volume determination was estimated based on the following allometric equation, using DBH (Diameter at Breast Height) at 1.3 m and Height, both in cm and m, respectively:

$$V\ \left(\frac{m3}{ha}\right) = 0.25\ x\ \pi\ x\ DBH\ (m)^2\ x\ Height\ (m)\ x\ 0.55 \quad (1)$$

The field measurements were carried out in subplots equally distributed in each plot. For the purposes of this study, only volume values from plots that were sampled for plant analysis were used. After, the MAI (Mean Average Increase) per tree was calculated according to the following formulae:

$$MAI\ \left(\frac{m3}{ha}\right) = \frac{V\ (m3)}{Age*n} \quad (2)$$

Where Age = Age of Tree and n= number of trees per hectare.

Also, the relative volume (R_MAI) was calculated considering the highest value as the 100% and then it was calculated for the other observations with the following formulae:

$$R\_MAI\ (\%) = \frac{Observation\ MAI\ \left(\frac{m3}{ha}\right)}{Maximum\ MAI\ (\frac{m3}{ha})}\ x\ 100 \quad (3)$$

Plant sampling and chemical analyses

For Teak leaves, the sampling was performed in July-August of each year, and 10 plants were selected using the middle lower leaves. They were cleaned with distilled water and then dried at 60°C in an air stove until reaching constant weight. The dried samples of plant tissues were weighted (500 mg each) and digested with H_2SO_4 (95%) for N and, HNO_3 (65%) and $HClO_4$ (70 %) for P, K, Ca, Mg, K, Cu, Fe, Mn and Zn. Chemical procedures for determination of concentration of nutrients are detailed elsewhere (EMBRAPA, 2009). They are summarized as follows; Nitrogen was determined by MicroKjeldah method. In the case of K, Ca, Mg, Cu, Fe, Mn and Zn the determination of the nutrients in the filtrate were determined using ICP-OES. B was determined by colorimetric method using azomethine-H at 550 nm. P using molibdate-ascorbate method at 420 nm. Finally, S was determined by turbidimetric method at 420 nm.

Determination of reference values and CND

The methodology to estimate the reference values was based in previous work with other species (Bahia et al., 2021; Galdino, 2015; Lima Neto et al., 2020; Santos et al., 2022) but can be summarized as follows:

First data from the different plots of Teak (n=594) were grouped based on their age and MAI, since plants had different ages, the Boundary Line Method (BLM) (Galdino, 2015; Santos et al., 2022) was used to determine the reference population for each age. After, the Relative MAI (R_MAI) was performed considering the values estimated by the curve (MAI vs Age) as the maximum value. From this data, the superior quartile (Q3) was selected as the reference population for all teak plantations.

Afterwards, determination of CND was performed according to Parent & Dafir, (1992) & Silva et al., (2004). This calculation was performed in two steps: First, the determination of the multi-nutrient variable (zi), using the following formulae:

$$zi \ = \ Ln \ [(\frac{xi}{g(x)}] \tag{4}$$

Where xi = nutrient concentration in g/kg; g (x) = geometric mean of the nutritional composition. The latter is calculated with formula:

$$\mathrm{g(x)} = (\mathrm{N\ x\ P\ x\ K\ x\ ....\ x\ Zn\ x\ R})^{1/D} \tag{5}$$

Where N x P x K….x Zn= Multiplication of nutrient concentration (g kg^{-1}); D = Number of elements multiplied. R = value of the complement to 1000 g/kg. The latter is calculated with formula:

$$\mathrm{R} = 1000 - \sum Nut \tag{6}$$

where R = value of the complement to 1000 g kg^{-1}; Nut = Nutrient concentration in g/kg.

Although this step of the algorithm has received an update by the author, the results have been similar (Parent et al., 2013). For this reason, the original approach was used (L. E. Parent & Dafir, 1992; Silva et al., 2004), as calculations are simpler.

The second step consisted in determining the CND indexes for each nutrient and were calculated considering data from the reference population, as expressed in the following formula [4]:

$$Inut = \frac{(zi - \bar{x}R\_p)}{sR\_p} \quad (7)$$

Where Inut = CND index for nutrient, x̄R_p = Mean of Nutrient in reference population, sR_p = standard deviation of reference population.

With CND indexes and R_MAI, values were plotted and then BLM was used to determine the Upper population reference for each nutrient (N, P, K, Ca, Mg, S, B, Cu, Fe, Mn and Zn). Then, a non-linear regression function was used to fit these populations, taking into consideration the values of R^2 and AIC.

With the estimated formulae from the curve, the reference norms were determined. For each nutrient, the sufficiency ranges were classified as follows: deficient (R_Vol < 70%, to the left of the maximum), tendency to sufficient (70% ≤ R_Vol < 90%, to the left of the maximum), sufficient (90%, to the left of the maximum ≤ R_Vol ≤ 100%), high (100% > R_Vol ≥ 90% to the right of the maximum), tendency to excess (90 > R_Vol ≥ 70%, to the right of the maximum) and excess (R_Vol < 70%, to the right of the maximum).

Finally, for the determination of the reference values in equilibrium a linear regression was performed between the multinutrient variable (Inut) for each nutrient vs the nutrient content (xi). With the results of the formulae, values were determined and the reference values in equilibrium were constructed.

Statistical Analysis

Descriptive statistics (mean and sd) were performed for all nutrients (N, P, K, Ca, Mg, S, B, Cu, Fe, Mn and Zn). Determination of points of lower and upper boundary line was performed with "Boundary fit". Also, nonlinear regression analysis was performed to fit the best model to the selected points. All statistical analysis were performed in R (R Core Team, 2021).

RESULTS

Characteristics of Teak (*Tectona grandis*) High-Yield population

Teak High-Yield selection was performed using all available data from different ages and is presented in figure 2. This population was successfully selected by BLM method (Figure 2, left), these observations diminished from the initial data (n=594) in 75% (n=149). The final selection of the teak observations for establishing diagnostics norms had a Relative MAI (%) above 60% that represented the Q3 and a total of n=37 observations (6.25%).

The reference population of teak plants was composed of 149 observations (25%) with their main characteristics (descriptive statistics) in terms of nutrients (N, P, K, Ca, Mg, S, B, Cu, Fe, Mn and Zn) are presented in table 2.

In the case of macronutrients, Nitrogen had a minimum, maximum and mean value of 15.0 g/kg, 24.0 g/kg and 18.6 g/kg, respectively, being the second highest content and the least variable nutrient (CV=11.6%). Phosphorus had a minimum, maximum and mean value of 0.7 g/kg, 2.0 g/kg and 1.3 g/kg, respectively. Potassium had a minimum, maximum and mean value of 2.4 g/kg, 13.0 g/kg and 7.5 g/kg, respectively.

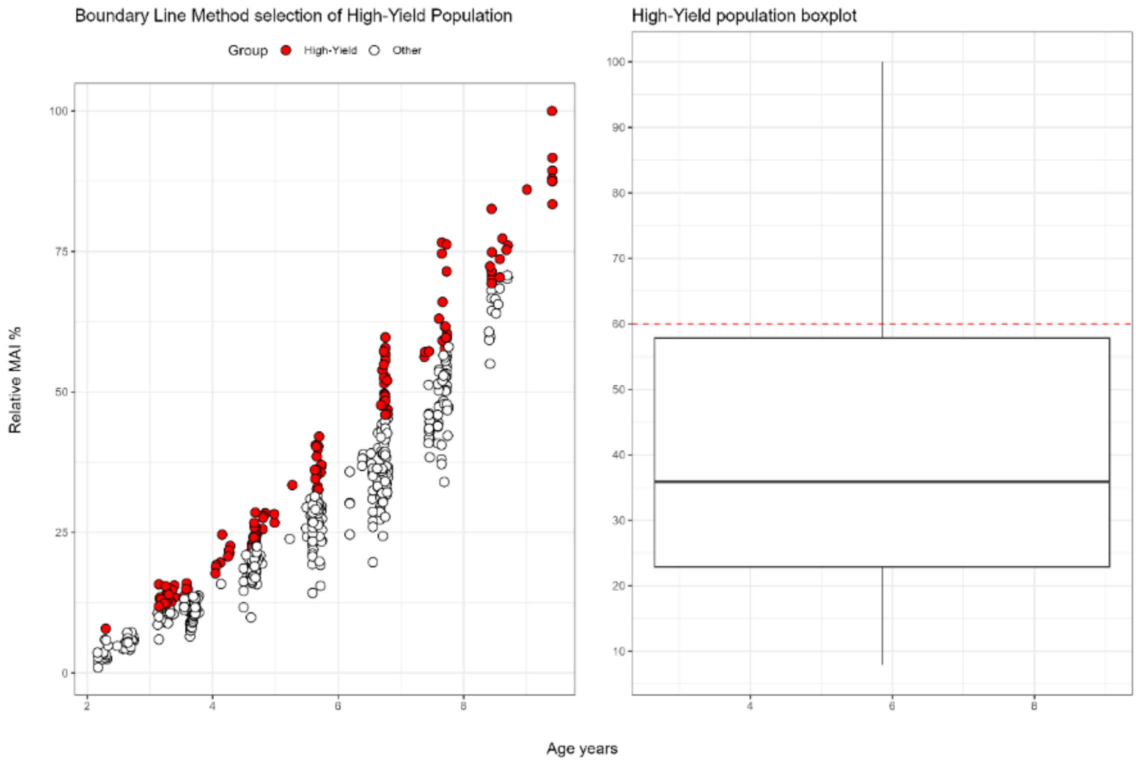

Figure 2. Selection of High-Yield population in Teak (Tectona grandis) by the BLM method (left) and boxplot (right) of the high-yield population for selection of Q3 (red dotted line) for nutrient norms estimation in Mato Grosso, Brazil

Calcium had the highest concentration value, it had a minimum, maximum and mean value of 16.1 g/kg, 54.9 g/kg and 26.9 g/kg, respectively. Magnesium had a minimum, maximum and mean value of 2.3 g/kg, 8.4 g/kg and 3.8 g/kg, respectively. Sulfur had a minimum value of 0.3 g/kg, maximum of 1.5 g/kg and mean value of 0.7 g/kg. In the case of micronutrients, Boron had a minimum value of 10.2 mg/kg, mean value of 31.4 mg/kg and maximum value of 53.8 mg/kg. Copper had a minimum value of 5.1 mg/kg, mean value of 11.5 mg/kg and maximum value of 22.6 mg/kg. Iron had a minimum value of 29.8 mg/kg, mean value of 162.9 mg/kg and maximum value of 570.2, this was the nutrient with highest variability in the teak plantations (CV = 70.1 %). Manganese had a minimum value of 32.5 mg/kg, mean value of 99.1 mg/kg and maximum value of 200.5 mg/kg, being the second most variable nutrient (CV = 35.2 %). Finally, Zinc had a minimum value of 6.9 mg/kg, mean value of 12.5 mg/kg and maximum value of 27.4 mg/kg. In general, apart from Fe, most mean values for all nutrients were like median values, indicating that they follow a normal distribution. Also, except for Fe, most nutrients had a CV according to expected under field conditions.

Table 2. Reference values for nutrients (N, P, K, Ca, Mg, S, B, Cu, Fe, Mn and Zn) for Teak (Tectona Grandis) of the population of reference

Nutrient	Minimum	Mean	Median	Maximum	SD*	CV %
N g/kg	15.0	18.6	18.5	24.0	2.2	11.6
P g/kg	0.7	1.3	1.3	2.0	0.3	23.7
K g/kg	2.4	7.5	7.4	13.0	1.9	25.9
Ca g/kg	16.1	26.9	24.9	54.9	6.9	25.8
Mg g/kg	2.3	3.8	3.6	8.4	0.9	25.1
S g/kg	0.3	0.7	0.7	1.5	0.2	32.1
B mg/kg	10.2	31.4	31.6	53.8	10.5	33.3
Cu mg/kg	5.1	11.5	10.6	22.6	3.6	30.8
Fe mg/kg	29.8	162.9	95.6	570.2	114.3	70.1
Mn mg/kg	32.5	99.1	94.3	200.5	34.8	35.2
Zn mg/kg	6.9	12.5	11.9	27.4	3.4	26.8

SD = Standard deviation, CV = Coefficient of variation

Reference Values for Teak (*Tectona grandis*)

The reference values for macronutrients (N, P, K, Ca, Mg, S) and micronutrients (B, Cu, Fe, Mn and Zn) are presented in table 2 and 3, respectively. The macronutrient contents were in the order of magnitude of Ca>N>K>Mg>P>S. For N, it presented an amplitude from 11.56 g/kg to 25.56 g/kg, while the sufficiency range was determined from 14.53 g/kg to 18.47 g/kg. P presented an amplitude from 0.72 g/kg to 2.08 g/kg and the sufficiency range was from 1.02 g/kg to 1.39 g/kg. K presented an amplitude from 2.24 g/kg to 13.24 g/kg and the sufficiency range was from 4.58 g/kg to 7.67 g/kg. Ca presented an amplitude from 14.43 g/kg to 64.06 g/kg and the sufficiency range was from 18.54 g/kg to 26.38 g/kg. Mg presented an amplitude from 1.38 g/kg to 8.55 g/kg and the sufficiency range was from 1.02 g/kg to 1.39 g/kg. Finally, S presented an amplitude from 0.31 g/kg to 1.53 g/kg and the sufficiency range was from 0.57 g/kg to 0.92 g/kg.

Table 3. Reference values for macronutrients (N, P, K, Ca, Mg, S) for Teak (Tectona Grandis)

Range	N	P	K	Ca	Mg	S
	g/kg					
Present Work						
Deficient*	<11.56	<0.72	<2.24	<14.43	<1.38	<0.31
Tendency to sufficiency	11.56-14.52	0.72-1.01	2.24-4.57	14.43-18.54	1.38-2.23	0.31-0.57
Sufficient	14.52-18.47	1.01-1.39	4.57-7.67	18.54-26.38	2.23-3.31	0.57-0.92
High	18.47-22.60	1.39-1.79	7.67-10.92	26.38-41.2	3.31-5.36	0.92-1.27
Tendency to excessive	22.60-25.56	1.79-2.08	10.92-13.24	41.20-64.06	5.36-8.55	1.27-1.53
Excessive	≥25.56	≥2.08	≥13.24	≥64.06	≥8.55	≥1.53
Carvalho (2016)						
Low	<15.9	<1.3	<6.6	<11.8	<1.3	<0.7
Sufficient	15.9-20.5	1.3-1.9	6.6-10.2	11.8-31.6	1.3-3.5	0.7-1.1
High	>20.5	>1.9	>10.2	>31.6	>3.5	>1.1
Fernandez-Moya et al. (2014)						
Low	<18.3	<1.2	<7.3	<11.3	<2.2	<1.1
Sufficient	18.3-21.5	1.2-2.0	7.3-10.2	11.3-15.4	2.2-3.4	1.1-1.3
High	≥21.5	≥2.0	≥10.2	≥15.4	≥3.4	≥1.3
Dreschel (1992)						
Low	<15.0	<1.7	<9.0	<6.0	<2.0	<1.3
Sufficient	15.0-26.0	1.7-2.3	9.0-19.0	6.0-10.0	2.0-3.3	1.3-1.8
High	≥26.0	≥2.3	≥19.0	≥10.0	≥3.3	≥1.8

* Deficient (R_Vol < 70%, to the left of the maximum), Tendency to sufficient (70% ≤ R_Vol < 90%, to the left of the maximum), Sufficient (90%, to the left of the maximum ≤ R_Vol ≤ 100%), High (100% > R_Vol ≥ 90% to the right of the maximum), Tendency to excess (90 > R_Vol ≥ 70%, to the right of the maximum) and Excess (R_Vol < 70%, to the right of the maximum)

The micronutrient contents were in the order of magnitude of Fe>Mn>B>Zn>Cu. For B, it presented an amplitude from 10.7 mg/kg to 60.2 mg/kg, while the sufficiency range was determined from 16.3 mg/kg to 26.9 mg/kg. Cu presented an amplitude from 4.9 mg/kg to 24.7 mg/kg and the sufficiency range was from

1.02 mg/kg to 1.39 mg/kg. Fe presented an amplitude from 6.0 g/kg to 602.8 g/kg and the sufficiency range was from 78.7 mg/kg to 212.1 mg/kg. Mn presented an amplitude from 12.0 g/kg to 197.4 g/kg and the sufficiency range was from 65.2 mg/kg to 128.4 mg/kg. Zn presented an amplitude from 6.2 mg/kg to 28.5 mg/kg and the sufficiency range was from 8.6 mg/kg to 13.3 mg/kg.

Table 4. Reference values for micronutrients (B, Cu, Fe, Mn and Zn) for Teak (Tectona Grandis)

Range	B	Cu	Fe	Mn	Zn
	mg/kg				
Present Work					
Deficient*	<10.7	<4.9	<6.0	<12.0	<6.2
Tendency to sufficiency	10.7-16.3	4.9-7.1	6.0-78.7	12.0-29.2	6.2-8.6
Sufficient	16.3-26.9	7.1-11.0	78.7-212.1	29.2-65.2	8.6-13.3
High	26.9-43.5	11.0-17.9	212.1-410.1	65.2-128.4	13.3-20.8
Tendency to excessive	43.5-60.2	17.9-24.7	410.1-602.8	128.4-197.4	20.8-28.5
Excessive	≥60.2	≥24.7	≥602.8	≥197.4	≥28.5
Carvalho (2016)					
Low	<12.42	<7.36	<41.97	<27.69	<12.42
Sufficient	12.42-27.32	7.36-13.96	41.97-280.73	27.69-95.75	12.42-27.32
High	≥27.32	≥13.96	≥280.73	≥95.75	≥27.32
Fernandez-Moya et al. (2014)					
Low	<18.32	<10.22	<84.63	<39.03	<24.73
Sufficient	18.32-20.91	10.22-11.93	84.63-174.59	39.03-46.07	24.73-39.26
High	≥20.91	≥11.93	≥174.59	≥46.07	≥39.26
Dreschel (1992)					
Low	---	<7.0	<50.0	<33.0	<14.0
Sufficient	---	7.0-17.0	50.0-100.0	33.0-49.0	14.0-23.0

High	---	≥17.0	≥100.0	≥49.0	≥23.0

* Deficient (R_Vol < 70%, to the left of the maximum), Tendency to sufficient (70% ≤ R_Vol < 90%, to the left of the maximum), Sufficient (90%, to the left of the maximum ≤ R_Vol ≤ 100%), High (100% > R_Vol ≥ 90% to the right of the maximum), Tendency to excess (90 > R_Vol ≥ 70%, to the right of the maximum) and Excess (R_Vol < 70%, to the right of the maximum)

CND Indexes for Teak (*Tectona grandis*)

The CND indexes for macronutrients (N, P, K, Ca, Mg, S) and micronutrients (B, Cu, Fe, Mn and Zn) are presented in table 5 and 6, respectively. For this method, values in positive indicate excess and values in negative indicate deficiency. Therefore, considering "0" as the optimum value. In the case of macronutrients, the variation of the sufficiency range in relation to the optimum was in the following order of magnitude: P>K>N>S>Mg>Ca. Also, for most macronutrients, except for Ca, values in the sufficiency range were in negative values, indicating that the use of the general norms applied for this method may not be efficient for nutrition diagnostics.

Table 5. Reference values for CND for macronutrients (N, P, K, Ca, Mg, S) for Teak (Tectona Grandis)

Range	N	P	K	Ca	Mg	S
Deficient*	<-2.35	<-2.47	<-3.4	<-2.85	<-2.82	<-2.48
Tendency to sufficiency	-2.35 to -1.85	-2.47 to -2.1	-3.4 to -2.17	-2.85 to -1.35	-2.82 to -1.92	-2.48 to -1.92
Sufficient	-1.85 to -0.74	-2.10 to -1.20	-2.17 to -0.51	-1.35 to 0.21	-1.92 to -0.47	-1.92 to -0.66
High	-0.74 to 1.79	-1.20 to 1.02	-0.51 to 1.21	0.21 to 1.75	-0.47 to 1.46	-0.66 to 2.09
Tendency to excessive	1.79 to 6.04	1.02 to 4.87	1.21 to 2.45	1.75 to 3.25	1.46 to 3.14	2.09 to 6.70
Excessive	≥6.04	≥4.87	≥2.45	≥3.25	≥3.14	≥6.70

* Deficient (R_Vol < 70%, to the left of the maximum), Tendency to sufficient (70% ≤ R_Vol < 90%, to the left of the maximum), Sufficient (90%, to the left of the maximum ≤ R_Vol ≤ 100%), High (100% > R_Vol ≥ 90% to the right of the maximum), Tendency to excess (90 > R_Vol ≥ 70%, to the right of the maximum) and Excess (R_Vol < 70%, to the right of the maximum)

In the case of micronutrients, the variation of the sufficiency range in relation to the optimum was in the following order of magnitude: Zn>Mn>B>Cu>Fe. For most micronutrients, except for Fe, as in the case of micronutrients, values in the sufficiency range were in negative values. This confirms that the use of general norms from the original method may not be optimal in different conditions, being more efficient to estimate the values for each condition and nutritional diagnostics.

Table 6. Reference values for CND for micronutrients (B, Cu, Fe, Mn and Zn) for Teak (Tectona Grandis)

Range	B	Cu	Fe	Mn	Zn
Deficient*	<-2.52	<-2.33	<-2.93	<-2.28	<-2.96
Tendency to sufficiency	-2.52 to -1.61	-2.33 to -1.51	-2.93 to -1.22	-2.28 to -1.71	-2.96 to -2.00
Sufficient	-1.61 to -0.40	-1.51 to -0.19	-1.22 to 0.22	-1.71 to -0.80	-2.00 to -0.42
High	-0.40 to 0.87	-0.19 to 1.49	0.22 to 1.48	-0.80 to 0.68	-0.42 to 1.77
Tendency to excessive	0.87 to 1.78	1.49 to 2.91	1.48 to 2.45	0.68 to 2.73	1.77 to 3.70
Excessive	≥1.78	≥2.91	≥2.45	≥2.73	≥3.70

* Deficient (R_Vol < 70%, to the left of the maximum), Tendency to sufficient (70% ≤ R_Vol < 90%, to the left of the maximum), Sufficient (90%, to the left of the maximum ≤ R_Vol ≤ 100%), High (100% > R_Vol ≥ 90% to the right of the maximum), Tendency to excess (90 > R_Vol ≥ 70%, to the right of the maximum) and Excess (R_Vol < 70%, to the right of the maximum)

Equilibrium norms for Teak

The construction of the equilibrium norms for teak, followed two steps. First, adjust the curves from the CND index for each nutrient to their concentration in leaves. After, the estimation of norms from these curves in terms of the CND values.

The results of the adjusted regression formulas and equations are presented in figure 3 and 4, for macronutrients (N, P, K, Ca, Mg, S) and micronutrients (B, Cu, Fe, Mn and Zn), respectively.

For macronutrients, they presented a good fit with the quadratic curve ($y=a+bx+cx^2$) with R^2 values above 0.8. However, Nitrogen presented a lower performance ($R^2<0.4$) in comparison to the other nutrients.

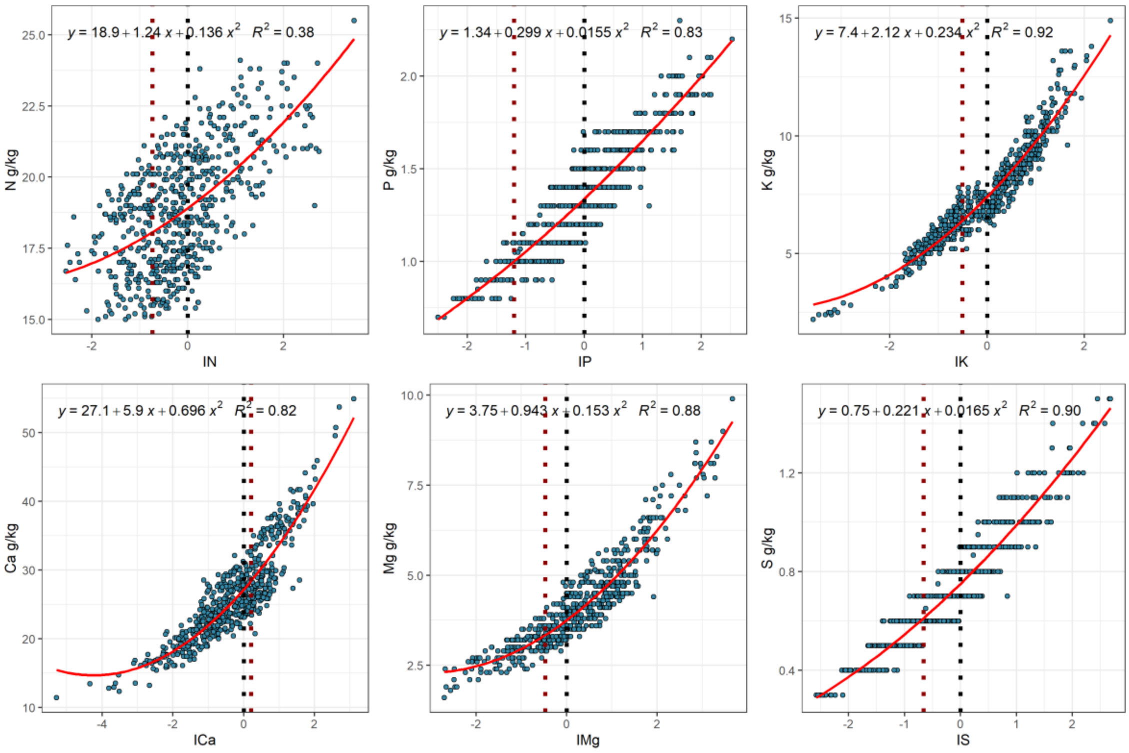

Figure 3. Regression graphs of CND indexes vs contents for macronutrients (N, P, K, Ca, Mg and S) with their respective equation and R^2 for Teak (*Tectona grandis*) in Brazil. Black and red dotted lines represent the theoretical and the determined critical limit, respectively

For micronutrients, they presented also a good fit with the quadratic curve ($y = ax + bx^2 + c$) with R^2 values above 0.8. However, Fe was adjusted to a cubic curve ($y = ax + bx^2 + cx^3 + d$) and presented the highest fit (R^2=0.98) from all the micronutrients.

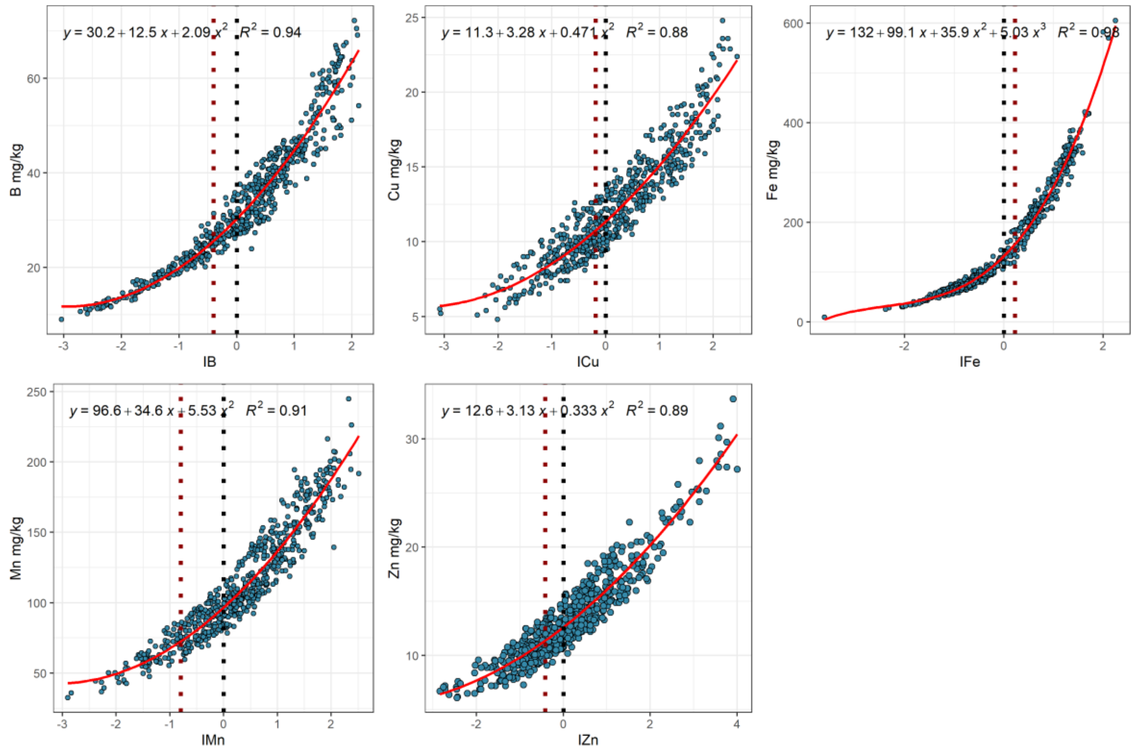

Figure 4. Regression graphs of CND indexes vs contents for macronutrients (B, Cu, Fe, Mn and Zn) with their respective equation and R^2 for Teak (*Tectona grandis*) in Brazil. Black and red dotted lines represent the theoretical and the determined critical limit, respectively

The reference values in Equilibrium for macronutrients (N, P, K, Ca, Mg, S) and micronutrients (B, Cu, Fe, Mn and Zn) are presented in table 7 and 8, respectively. For macronutrients, the sufficiency range was higher for N, P, K, Ca and S; similar for Mg in comparison to the regular norms. While the deficiency range was also higher for N, K, Ca, Mg and similar for P and K.

Table 7. Reference values in "Equilibrium" for macronutrients (N, P, K, Ca, Mg and S) for Teak (Tectona Grandis)

Range	N	P	K	Ca	Mg	S
Deficient*	<16.74	<0.70	<2.90	<15.94	<2.31	<0.30
Tendency to sufficiency	16.74-17.07	0.70-0.78	2.90-3.90	15.94-20.40	2.31-2.50	0.30-0.39
Sufficient	17.07-18.06	0.78-1.0	3.90-6.38	20.40-28.37	2.50-3.34	0.39-0.65
High	18.06-21.56	1.0-1.66	6.38-10.31	28.37-39.56	3.34-5.45	0.65-1.11
Tendency to excessive	21.56-31.35	1.66-3.16	10.31-14.00	39.56-53.62	5.45-8.22	1.11-1.61

Excessive	>=31.35	>=3.16	>=14.00	>=53.62	>=8.22	>=1.61

* Deficient (R_Vol < 70%, to the left of the maximum), Tendency to sufficient (70% ≤ R_Vol < 90%, to the left of the maximum), Sufficient (90%, to the left of the maximum ≤ R_Vol ≤ 100%), High (100% > R_Vol ≥ 90% to the right of the maximum), Tendency to excess (90 > R_Vol ≥ 70%, to the right of the maximum) and Excess (R_Vol < 70%, to the right of the maximum)

For micronutrients the sufficiency range was lower for B, Fe and Zn; similar to Cu and higher for Mn in comparison to the previously determined norms. While the deficiency range was higher for all micronutrients.

Table 8. Reference values in "Equilibrium" for micronutrients (B, Cu, Fe, Mn and Zn) for Teak (Tectona Grandis)

Range	B	Cu	Fe	Mn	Zn
Deficient*	<11.97	<6.21	<23.31	<46.46	<6.25
Tendency to sufficiency	11.97-15.49	6.21-7.42	23.31-55.40	46.46-53.60	6.25-7.67
Sufficient	15.49-25.53	7.42-10.69	55.40-155.6	53.60-72.46	7.67-11.34
High	25.53-42.66	10.69-17.23	155.6-373.6	72.46-122.7	11.34-19.18
Tendency to excessive	42.66-59.07	17.23-24.83	373.6-664.3	122.7-232.3	19.18-28.74
Excessive	>=59.07	>=24.83	>=664.3	>=232.3	>=28.74

* Deficient (R_Vol < 70%, to the left of the maximum), Tendency to sufficient (70% ≤ R_Vol < 90%, to the left of the maximum), Sufficient (90%, to the left of the maximum ≤ R_Vol ≤ 100%), High (100% > R_Vol ≥ 90% to the right of the maximum), Tendency to excess (90 > R_Vol ≥ 70%, to the right of the maximum) and Excess (R_Vol < 70%, to the right of the maximum)

DISCUSSION

Reference values in Teak

The research worked with data from field plantations in teak from different years, plots and production with the aim to establish reference values for nutrient diagnostics in teak. Nutrition diagnostics is important for the management of planted species, especially for commercial purposes, it helps to improve fertilizer use and productivity (Alvarado, 2015). In the case of the values obtained, only the sufficiency range will be addressed, since it is considered the optimum value for Teak plants. For macronutrients, N, values were lower, for the work in Costa Rica (Fernández-Moya et al., 2014), and similar to the developed in seminal plants (Carvalho, 2016; Drechsel, 1992). The values obtained in the present work for P, K and S, were lower than the previously described (Table 3). While for Mg were similar and for Ca were higher. These differences may be attributed to different factors such as soil different characteristics, climate, geology, genetics among others (Zhang & Wang, 2021). Even though geographical distances of the regions studied in the referred literature are vast. Differences were also observed in studies in the same region (Mato Grosso), with seminal plants. These differences may also be attributed to the methodology of selection of the High-Yield population that is key for establishing norms. In general, all the published data in most species, starts with the selection of high productivity stands and then derives on the norms assuming optimum growth conditions and maximum phenological expression (Chanan et al., 2019; Fernández-Moya et al., 2014; Neto et al., 2022). Even though this presumption may be correct, variability in high productivity stands is still high. This can lead to a sub- or overestimation of reference values in plants depending on the methodology used. Especially, if norms are directly estimated directly from the descriptive statistics of the high-yield population without furth refinement. This issue was partially assessed by Carvalho (2016) that used the coefficient of variation in relation to the means to select plots with a higher productivity than the average within this high-yield population.

To solve this issue, this work used the Boundary Line Method (BLM) which selects the maximum expression of productivity for each age, making a better selection of the reference population in comparison to other methods. This methodology difference may explain the higher or lower values for some nutrients in comparison to the cited studies.

Another main difference is the selection of data after the high-yield population has been identified. Most works observed make the selection based only on DBH (Diameter at Breast Height – 1.3m), however this measurement just focusses on growth and not growth rate, being the latter more important because is more sensitive to environmental, topographic and soil factors (Tian et al., 2024). This makes MAI (Mean Annual Increase m3/year/tree) a more interesting variable to be used. Therefore, to identify the reference values, this variable was used to select as the final high-yield population.

CND indexes and Equilibrium reference values in Teak

Teak (*Tectona grandis*) is generally monitored in terms of nutrition using reference values, which focus on nutrients contents without considering nutrient equilibrium. For this assessment, the DRIS method has been used as an important tool in nutrition diagnostics in many works from different plant species (Villamil-Carvajal et al., 2021). Also, this technique has been used in teak worldwide, as in Africa (Drechsel & Zech, 1994), China (Zhou et al., 2017), Indonesia (Chanan et al., 2019) and the Brazilian Amazon (Neto et al., 2022). Nevertheless, CND method is also an interesting tool for assessing nutrient diagnostics and has been reported in many species but is not as popular as DRIS. The only work published in Teak using CND is in the Brazilian Amazon (Neto et al., 2022), a radically different area in terms of climate, soil and even topography. However, the latter used reference values from Costa Rica (Fernández-Moya et al., 2014), to estimate the CND values in the teak plantation. The use of this data, which reflects a completely different teak population in terms of soil, climate and topography, could have affected nutrient diagnostics. As the results of reference values in this work varies greatly in comparison to the values reported in Costa Rica. Also, in the original paper, it implies that the norms for high-yield population must be calculated for proper diagnostics, otherwise may be biased (L. E. Parent & Dafir, 1992).

The CND method has many advantages as it considers not only equilibrium but also contents as compared to DRIS. Also, the multivariate approach permits to relate each nutrient to the whole plant and delivers an easier method for calculating nutritional indexes (Rozane et al., 2016; Silva et al., 2004). Also, many studies have shown that both DRIS and CND have similar performances (Bendaly Labaied et al., 2018; Partelli et al., 2014), and, in some cases, CND is superior in terms of nutrient diagnostics (Agbangba et al., 2024).

However, even though CND interpretation is straightforward, since positive values indicate “excess” at some extent and negative values “deficiency” (Parent & Dafir, 1992; Rozane et al., 2016). The most widely used approach is still the critical nutrient approach, based on the optimum law. This responds to the easy adoption and the interpretation based directly on the leaf analysis without further calculations.

Equilibrium ranges, consider concentrations in terms of quantity and equilibrium, making it a practical guide to interpret leaf analysis directly taking both parameters that are important to assess in nutrition mineral diagnostics. The differences between the equilibrium values (Table 7 and 8) in comparison to the initial reference values (Table 3 and 4), express the bias that can occur when using the critical limit method. The direct use of this method may lead to expressing deficiencies or sufficiency making a false positive or negative when using this method.

CONCLUSIONS

The use of the boundary line method has been used successfully for determining the high yield population for Teak. The CND method has proven its importance in this species and can be used as an important technique for nutritional diagnostics in Teak. For this work the sufficiency ranges in “Equilibrium” were as follows: N (17.07-18.06), P (0.78-1.00), K (3.90-6.38), Ca (20.40-28.37), Mg (2.50-3.34), S (0.39-0.65), B (15.49-25.53), Cu (7.42-10.69), Fe (55.40-155.6), Mn (53.60-72.46) and Zn (7.67-11.34) The CND norms and Equilibrium reference values determined in this study will serve as a practical guide for interpretation and nutrition diagnostics in Teak and can serve as a baseline for other works in other plant species.

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CAPITULO 2. MODELLING OF TEAK (*TECTONA GRANDIS*) PRODUCTIVITY IN BRAZIL WITH ENVIRONMENTAL VARIABLES, SATELLITE IMAGERY AND MACHINE LEARNING

ABSTRACT

Teak (*Tectona grandis*) is an important forest species worldwide, however the costs of monitoring and assessing growth are expensive. Remote sensing techniques aligned with machine learning algorithms may offer a better alternative to current monitoring methods. Therefore, the main objective of this study was to model teak growth parameters using current field data and satellite multispectral images using machine learning algorithms. The research was performed in Mato Grosso, Brazil, with teak stands from different ages and different climate, soil and topography conditions. Data of climate (precipitation variables), soil variables (pH, O.M., P, K, Ca, Mg, K, S, B, Cu, Fe, Mn, Zn) and topography were used. Also, biometric measurements of DBH, total height, commercial height, basal diameter, MAI and total volume were used. Modelling was performed using Cubist, Random Forest, ANN, KKNN, SVM and GLM. The best model was selected using RMSE, R2 and MAE statistics. In general, good predictions were obtained using the machine learning methods, where cubist and random forest performed better in relation to all variables with low RMSE and MAE and high R2 (>0.9). Cubist model selected topographic related variables while Random Forest a more equilibrated model. The latter selected Age, available S, Days without rain and Water Deficit as the most important. Finally, this study highlights the importance of utilizing machine learning algorithms to predict the growth of forest species. Also, to our knowledge is the first study to use a holistic approach using machine learning for growth prediction in Teak.

KeyWords: Forestry species, Random Forest, Cubist, Forest growth, Sentinel-2

INTRODUCTION

Original from dry mix deciduous forests from India, Myanmar, Thailand and Laos, the Tectona genera forms part of the Verbenaceae family and comprises four species: *T. abludens*, *T. hamiltoniana* Wall., *T. philippinensis* Benth & Hook. f. and *T. grandis* Linn. f. The latter, commonly known as Teak (*Tectona grandis*), is a deciduous tree that is widely distributed in subtropical and tropical regions. This species is considered a high value hardwood and represents nearly 2% of the global cover of planted trees globally (Kollert & Kleine, 2017). Among, Latin America producing countries, Brazil has the highest planted area, with nearly 84,466 ha representing 1% of planted trees. Around 90% of planted trees in the Mato Grosso state are from Teak (IBA, 2024). This species has become highly valuable, especially for the fabrication of furniture, ships, cabinets, floors, panels, and agricultural implements due its durability, workability and finishing quality (Balakrishnan et al., 2024).

Teak, like other forest species, is highly dependent on the quality of site (climate, topography and soil factors) as well as on ecosystem interactions between abiotic and biotics factors (Kusbach et al., 2021). In general, high production stands have precipitation in the order of 1300 mm to 2200 mm, mean wind speed lower than 7.9 m s^{-1}, mean temperatures of 25 °C to 28 °C, and a dry season duration of 2 to 4 months (Medeiros et al., 2019). Regarding topography, low terrain slope (<9%) and topographic humidity index – THI below 6% (Medeiros et al., 2019) are preferred. This species prefers deep, well drained fertile soils with high Ca and low acidity (Arevalo-Hernández et al., 2023; Fernández-Moya et al., 2014; Vaides-López et al., 2019).

The productivity of forest stands, and the quality of their products depend on silvicultural practices defined by forest management. In general, most plantations are measured each year to evaluate their growth performance (Diameter of Breast Height - *dbh* and Total Height - *ht*) which is an indirect assessment of the management practices. However, to obtain adequate information, constant monitoring of plants and soil is required which leads to high investment in time and costs. Measurements take place in specified plots inside the plantations where a small sample is used to estimate field values ignoring spatial variation in the field. Consequently, the data reported is highly variable (Hyyppä et al., 2020).

In this context, remote sensing in forestry areas has nearly 30 years of research focused on spectral reflectance characteristics with development of sensors and platforms and has been recognized as a feasible low-cost alternative (Ustin, 2013; Watt et al., 2019). Remote data provides means of predicting biometric measurements and growth in forestry stands even in low biomass sites (Rodríguez-Veiga et al., 2017). Therefore, some alternatives have been used over the years to reduce costs and improve overall forest plantations. Some examples are the use of images from airborne vehicles -AV (Wing et al., 2012), unmanned airborne vehicles- UAV (Hyyppä et al., 2020), satellite imagery (Adiningrat et al., 2024), aerial (Melo et al., 2020), terrestrial laser scanner (Newnham et al., 2015), and Lidar (Leite et al., 2020).

The use of satellite imagery, specifically multispectral images, has gained interest due their low cost and the use of spectral indices (Vegetation index) related to different plant growth stages and productivity (Farias et al., 2023; Frampton et al., 2013). From these systems, the Sentinel 2 multispectral system has a high potential of use given its availability, revisit time of 5 days, and high spatial resolution. Also, the spectral data captured from this satellite allows to capture information related to forest conditions which can be helpful in estimating overall growth and stressed areas (Schiller et al., 2024).

Nevertheless, the generation of high volume of data has demanded new techniques to analyze the relationship between different stand and plant conditions and overall satellite spectral images. In this context, the use of machine learning algorithms have gained importance in different research fields, such as agriculture, forestry and soil science given their ability to work with a large amount of information and to adjust predictions with high reliability (Oliveira Teixeira, 2022; Siqueira et al., 2023; Wadoux et al., 2020).

The use of machine learning algorithms with the use of spectral imagery can be useful in estimating teak growth characteristics. Therefore, the main objectives were to: (i) explore the main variables responsible for growth parameters in teak; (ii) relate the feasibility to use multispectral satellite imagery to predict growth parameters in teak; and (iii) predict teak growth parameters using current field data and satellite multispectral images using machine learning algorithms.

MATERIAL AND METHODS

Localization

The research was performed in 10 stands of clonal teak in São José dos Quatro Marcos –Mato Grosso, Brazil located at UTM 365203 E 8268930 S and 211 m (Figure 5). The area is characterized by a tropical humid climate (Am) (Köppen, 1931), with mean annual precipitation of 1500 mm and mean annual temperature of 24°C, with minimum means of 18°C and maximum of 33°C.

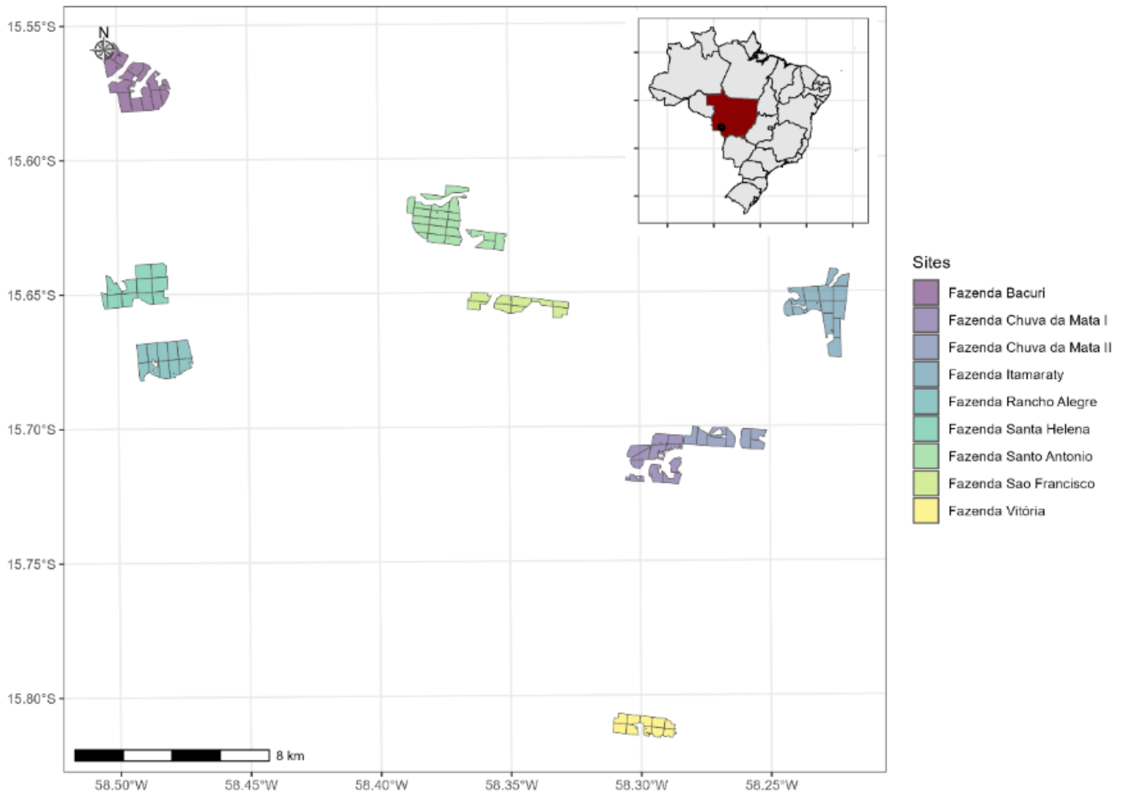

Figure 1. Location of Teak stands used for the research in Mato Grosso, Brazil

Imaging processing

Images were obtained for free from the Copernicus Browser in the Copernicus Data Space Ecosystem, considering the date of sampling of plants from the clonal teak stands in different years. Images from satellite Sentinel-2 were selected taking into consideration the cartographic base available from the "4M Agroflorestal" company that was visualized in Google Earth. Sentinel-2 has a regular multispectral camera with 13 bands in the visible, near infrared and short-wave infrared part of the spectrum with main applications such as in agriculture, land ecosystems and forest management. To improve values obtained from the satellite, only previous atmospherically corrected images (L2A product) were used.

Vegetation indexes (VI)

Proposed vegetation indexes (VI) are presented in Table 9 and were based on previous work executed for oil palm (Oliveira Teixeira, 2022). These 58 VI were calculated to predict their relationship with biometric variables related to growth in teak clones.

Table 1. Proposed vegetation indexes for predicting nutrition and growth in teak clones in Mato Grosso

N	Index	Equation
1	Anthocyanin Reflectance Index 1 (ARI 1) (Gitelson et al., 2001)	$\frac{1}{G}-\frac{1}{RedEdge1}$
2	Anthocyanin Reflectance Index 2 (ARI 2) (Gitelson et al., 2001)	$\frac{NIR}{G}-\frac{1}{RedEdge1}$
3	Atmospherically Resistant Vegetation Index (ARVI) (Kaufman & Tanré, 1992)	$\frac{NIR-(2*R-B)}{NIR+(2*R-B)}$
4	Burn Area Index (BAI) (Chuvieco et al., 2002)	$\frac{1}{(0.1-R)^2+(0.06-NIR)^2}$
5	Blue Normalized Difference Vegetation Index (BNDVI) (Wang et al., 2007)	$\frac{NIR-B}{NIR+B}$
6	Chlorophyll Red-edge (ChRE) (Gitelson et al., 2003)	$\frac{RedEdge1}{NIR}$
7	Canopy Index (CI) (Vescovo & Gianelle, 2008)	$SWIR-G$
8	Color index of Vegetation Extraction (CIVE) (Kataoka et al., 2003)	$0.441*R-0.811*G+0.385*B+18.78745$
9	Carotenoid Reflectance Index 1 (CRI 1) (Gitelson et al., 2002)	$\frac{1}{B}-\frac{1}{G}$
10	Carotenoid Reflectance Index 2 (CRI 2) (Gitelson et al., 2002)	$\frac{1}{B}-\frac{1}{Rededge1}$
11	Difference Vegetation Index (DVI) (Tucker, 1980)	$NIR-R$

12	Enhanced Red-Green-Blue Vegetation Index (ERGBVE) (Themistocleous, 2019)	$\pi * \frac{G^2 - R * B}{G^2 + R * B}$
13	Enhanced Vegetation Index 1(EVI 1) (Jiang et al., 2008)	$2.5 * \frac{NIR - R}{NIR + 6 * R - 7.5 * B + 1}$
14	Enhanced Vegetation Index 2 (EVI 2) (Jiang et al., 2008)	$2.5 * \frac{NIR - R}{NIR + 2.4 * R + 1}$
15	Excess of Green (ExG) (Woebbecke et al., 1995)	$2 * G - R - B$
16	Excess of Green minus Excess Red (ExGexR) (Meyer & Neto, 2008)	$2 * G - R - B - 1.4 * R - G$
17	General Difference Vegetation Index (GDVI, n=2) (Wu, 2014)	$\frac{NIR^2 - R^2}{NIR^2 + R^2}$
18	Green Blue Normalized Difference Vegetation Index (GBNDVI) (Wang et al., 2007)	$\frac{NIR - G - B}{NIR + G + B}$
19	Green Chlorophyll Index (GCI) (Gitelson et al., 2003)	$\frac{NIR}{G} - 1$
20	Green Difference Vegetation Index (GDVI) (Sripada et al., 2006)	$NIR - G$
21	Green Leaf Index (GLI) (Louhaichi et al., 2001)	$\frac{2 * G - R - B}{2 * G + R + B}$
22	Green Normalized Vegetation Index (GNVI) (Gitelson et al., 1996)	$\frac{NIR - G}{NIR + G}$
23	Green optimized Soil Adjusted Vegetation Index (GOSAVI) (Rondeaux et al., 1996)	$\frac{NIR - G}{NIR + G + 0.16}$
24	Green and Red Normalized Vegetation Index (GRNDVI) (Wang et al., 2007)	$\frac{NIR - G - R}{NIR + G + R}$
25	Green-Red Vegetation Index (GRVI) (Falkowski et al., 2005)	$\frac{G - R}{G + R}$
26	InfraRed Porcentage Vegetation Index (IPVI) (Crippen, 1990)	$\frac{NIR}{R + NIR}$
27	Inverted Red-Edge Chlorophyll Index (IRECI) (Guyot & Baret, 1988)	$(RedEdge3 - R) * \frac{RedEdge2}{RedEdge1}$
28	Leaf Area Index (LAI) (Boegh et al., 2002)	$3.618 * \frac{2.5 * (NIR - R)}{NIR + 6 * R - 7.5 * B + 1} - 0.118$
29	Moisture Adjusted Vegetation Index (MAVI) (Zhu et al., 2014)	$\frac{NIR - R}{R + NIR + SWIR}$
30	Modified Chlorophyll Absorption in Reflectance Index 1 (MCARI 1) (Haboudane et al., 2004)	$1.2 * (2.5 * (NIR - R) - 1.3 * (NIR - G))$
31	Modified Chlorophyll Absorption in Reflectance Index 2 (MCARI 2) (Zarco-Tejada et al., 2001)	$1.5 * \frac{2.5 * (NIR - R) - 1.3 * (NIR - G)}{((2 * NIR + 1)^2 - (6 * NIR - 5 * \sqrt{R}) - 0.5)^{0.5}}$
32	Modified Green Red Vegetation Index (MGRVI) (Bendig et al., 2015)	$\frac{G^2 - R^2}{G^2 + R^2}$

33	Modified Soil Adjusted Vegetation Index 1 (MSAVI 1) (Qi et al., 1994)	$\frac{NIR - R}{NIR + R + 0.5} * 1.5$
34	Modified Soil Adjusted Vegetation Index 2 (MSAVI 2) (Qi et al., 1994)	$\frac{(2 * NIR + 1) - \sqrt{(2 * NIR + 1)^2 - 8 * (NIR - R)}}{2}$
35	Modified Simple Ratio (MSR) (Chen, 1996)	$\frac{\frac{NIR}{R} - 1}{\sqrt{\frac{NIR}{R} + 1}}$
36	MERIS Terrestrial Chrolophyll Index (MTCI) (Dash & Curran, 2007)	$\frac{RedEdge2 - RedEdge1}{RedEdge1 - R}$
37	Normalized Burn Ratio (NBR) (Roy et al., 2006)	$\frac{NIR - SWIR}{NIR + SWIR}$
38	Normalized Canopy Index (NCI) (Vescovo & Gianelle, 2008)	$\frac{SWIR - G}{SWIR + G}$
39	Normalized Difference Index (Band 4 e 5 –Sentinel Satellite) (NDI 45) (Frampton et al., 2013)	$\frac{RedEdge1 - R}{RedEdge1 + R}$
40	Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974)	$\frac{NIR - R}{NIR + R}$
41	Normalized Green-Red Difference Index (NGRDI) (Tucker, 1980)	$\frac{G - R}{G + R}$
42	Non-linear Vegetation Index (NLI) (Goel & Qin, 1994)	$\frac{NIR^2 - R}{NIR^2 + R}$
43	Optimized Soil Adjusted Vegetation Index (OSAVI) (Rondeaux et al., 1996)	$\frac{NIR - R}{NIR + R + 0.5}$
44	Plant Senescence Reflectance Index (PSRI) (Merzlyak et al., 1999)	$\frac{R - B}{RedEdge2}$
45	Perpendicular Vegetation Index (PVI) (Richardson & Wiegand, 1977)	$\sqrt{(0.355 * NIR - 0.149 * R)^2 + (0.355 * R - 0.852 * NIR)^2}$
46	Red-Blue Normalized Vegetation Index (RBNDVI) (Wang et al., 2007)	$\frac{NIR - R - B}{NIR + R + B}$
47	Renormalized Difference Vegetation Index (RDVI) (Roujean & Breon, 1995)	$\frac{\sqrt{NIR - R}}{NIR + R}$
48	Red Edge Normalized Difference Vegetation Index/Normalized Difference Red Edge (RENDRE) (Fernández-Manso et al., 2016)	$\frac{NIR - RedEdge1}{NIR + RedEdge1}$
49	Red-Green Index (RGI) (Gamon & Surfus, 1999)	$\frac{R}{G}$
50	Red Green Blue Vegetation Index (RGBVI) (Bendig et al., 2015)	$\frac{G^2 - B * R}{G^2 + B * R}$
51	Rice Growth Vegetation Index (RGVI) (Nuarsa et al., 2011)	$1 - \frac{(R + G)}{NIR + SWIR1 + SWIR2}$
52	Sentinel-2 Red-Edge Position (S2REP) (Frampton et al., 2013)	$705 - \frac{35 * (0.5 * (RedEdge3 + R) - RedEdge1)}{RedEdge2 - RedEdge1}$
53	Soil Adjusted Vegetation Index (SAVI) (Huete, 1988)	$1.5 * \frac{NIR - R}{NIR + R + 0.5}$

54	Specific Leaf Area Vegetation Index (SLAVI) (Lymburner et al., 2000)	$\frac{NIR}{R + SWIR}$
55	Simple Ratio or Ration Vegetation Index (SR) (Jordan, 1969)	$\frac{NIR}{R}$
56	Triangular Vegetation Index (TVI) (Broge & Leblanc, 2001)	$0.5 * (120 * (NIR - G) - 200 * (R - G))$
57	Visible Atmospherically Resistant Index (VARI) (Gitelson et al., 2003)	$\frac{G - R}{G + R - B}$
58	Vegetativen (VEG)	$\frac{G}{R^{0.667} * B^{0.333}}$

In field sampling and measurements

The biometric variables were obtained from the databank from "4M Agroflorestal". Variables such as *dbh* (measured at 1.3 m), Total Height (h_t), Commercial height (h_c) and Basal area (*g*), were measured in subplots adequately distributed in every plot. Volume (m^3) was estimated using hypsometric equations with *dbh* and Height. Mean Annual Increase (MAI – m^3 $year^{-1}$ $tree^{-1}$) was estimated by the relation between Volume and the age of the stands. Also, the number of plants were recorded each year (2017 to 2022) to observe changes in survival and adjustments to MAI when partial cuttings were performed. Measurements were performed each year, however only data corresponding to soil available data were used to observe soil variables impact on predictions.

For soil sampling, soil was collected from each plot at 0.0-0.2 m depth in 2016, 2018, 2020 and 2021 to evaluate soil fertility, texture and micronutrients according to the methods described in (EMBRAPA, 2009). Briefly, pH was determined in a solution of soil:water of 1:2.5. Organic matter was determined using the Walkey and Black method. Phosphorus was determined using the Melich-1 and an UV-VIS spectrophotometer at 880 nm. Calcium, Magnesium and Potassium were also determined using Mehlich-1 and Atomic Absorption Spectrophotometry (AAS). Aluminum was determined using KCl 1M while Potential acidity (H.Al) with Calcium acetate and both were titrated with NaOH 0.1 M. CEC was determined by the sum of potential acidity and bases. For S, extraction was carried with $Ca(H_2PO_4)$ 500 mg/L and determined in UV-VIS at 420 nM. For B, it was extracted in hot water and determined in UV-VIS at 420 nm. The available content of Fe, Mn, Cu, and Zn in the soil samples was extracted with Mehlich-1 and determined in AAS.

Topographic and environmental characteristics

In the case of climatic characteristics, only precipitation (mm) was measured using a pluviometer. From this measurement, other variables were estimated such as days without rain, rain deficit (considering an annual precipitation of 1200 mm as adequate), monthly and annual precipitation (mm).

For topographic variables, elevation data was obtained using “elevatr” package (Hollister, 2023). With this information and the use of “MultiscaleDTM” package (Ilich et al., 2024), the following geomorphometric terrain attributes were calculated: Aspect, Difference from Mean Value - DMV, Eastness, Elevation, Features, Mean curvature, Maximum curvature, Minimum curvature, Northness, Profile curvature, Planar curvature, Relative Position of a focal cell, Roughness Index Elevation - RIE, Slope, Ruggedness measure, Standard deviation of bathymetry adjusted for slope, Surface area, Surface area to planar area rugosity -SAPA, Twist curvature and Topographic Position Index - TPI.

Modelling and statistical analyses

Procedures and inputs for modelling scheme are summarized in Figure 2. For modelling, the procedures described in Fernandes-Filho et al., (2024) were used. The following procedures were repeated 50 times for each machine learning algorithm. First, data was divided into training and testing data. For the training phase, 75% of data from stands were used while the remaining 25% for prediction assessment (testing data). Descriptive statistics (minimum, quartil-1, mean, median, quartil-3, standard deviation, maximum, interquartile range and coefficient of variation) were performed for all biometric variables (*dbh*, h_t, h_c, Volumen and MAI) and number of plants. In the case of covariables used for modelling, soil variables, topographic variables obtained from DEM and Vegetation indexes (VI) were used.

The data obtained from descriptive statistics was used for modelling procedures. Then, a correlation matrix was constructed using Spearman correlation (5%

confidence), between each pair of highly correlated variables (r > |0.90|), and the variable with the highest global correlation was eliminated using “findcorrelation” function in the caret package (Kuhn, 2024). With the selected variables, the Recursive Feature Elimination algorithm (RFE) was performed to select the best subset of predictors and their relative importance (Kuhn & Johnson, 2013). Consequently, the selected predictors were used to train each selected model and their relative importance (0-100%) were calculated using the “VarImp” function in caret package.

The six machine learning algorithms used were: Cubist model (C), General Linear Model (GLM), Random Forest (RF), Weighted K-Nearest Neighbor Classifier (KKNN), Support Vector Machine (SVM) and Neural Network (NN). The Cubist model is a rule-based ensemble regression model based on the work of Quinlan (1992), which creates a basic model tree that has a separate linear regression model corresponding to each terminal node. The General Lineal model is a flexible statistical framework used to model the relationship between two variables (independent and dependent). This is a generalization of multiple regression where its simplicity, interpretability and ease of implementation make it a powerful statistical tool. The Random Forest model can be used for both classification and regression. It operates by constructing multiple decision trees during training and combines its output to improve prediction and control overfitting. The KKNN model can also be used both for classification and regression, it predicts the target values based on the values of their nearest neighbors, with closer neighbors having a greater influence on the prediction. The SVM model is effective in high dimensional spaces, it predicts continuous target variables by finding a function that approximates the relationship between input features and the output, while maintaining a margin of tolerance. The NN models are designed to predict continuous target variables by learning complex, nonlinear relationships between input features and output values. Inspired by the structure and function of biological neural networks, they are highly flexible and capable of modeling intricate patterns in data.

Models were trained and tuned using a repeated cross-validation with 10 folds and 3 repeats. The tuning was made testing 3 different values for each hyperparameter. The optimization criterium was selecting the model configuration which achieved the biggest F1-Score value. Finally, the trained model was validated by comparing predicted data with the test set. To select the algorithm with the best performance, Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and the coefficient of determination (R^2) were used and calculated as follows:

$$MAE = \frac{\sum_{i=1}^{n} |Y_i - X_i|}{n} \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (X_i - Y_i)^2} \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (X_i - Y_i)^2}{\sum_{i=1}^{n} (\bar{Y} - Y_i)^2} \quad (3)$$

where n is the number of observations, yi is response variable, y is response variable approximation (estimated or predicted value of yi), and y is the mean of response variable. These statistics were calculated for the prediction of each model to compare and select the best algorithm with the higher R^2 and lower MAE and RMSE. All modelling procedures and statistical analyses were performed in R, version 4.1.2 (R Core Team, 2021).

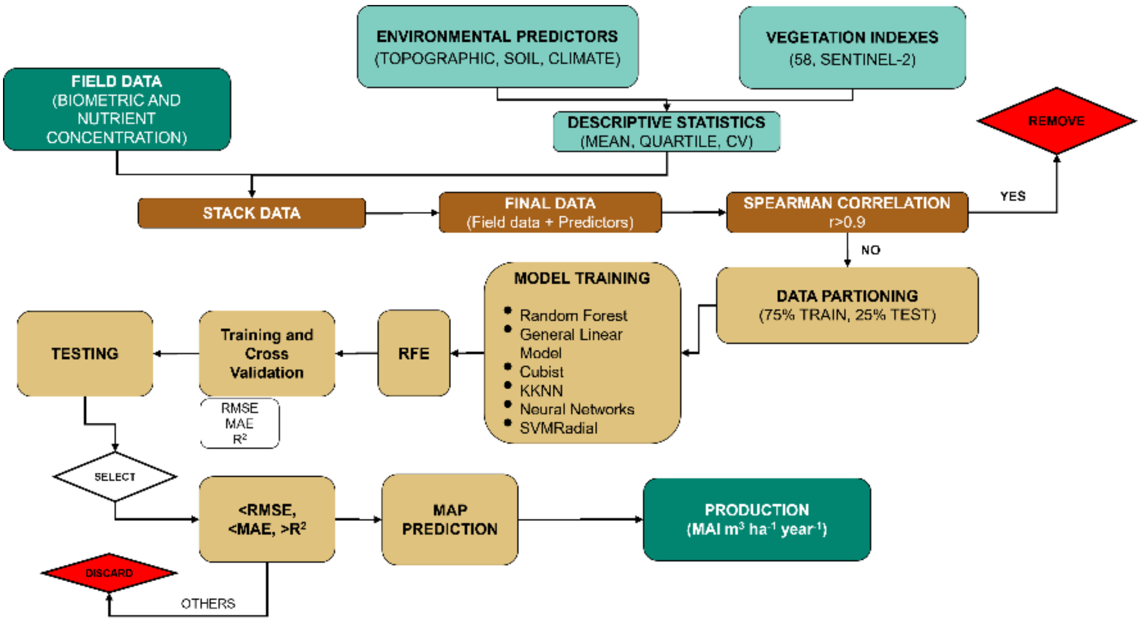

Figure 2. Modelling scheme of research for predicting plant growth in teak clones

RESULTS

Biometric characteristics

Biometric characteristics (*dbh, ht, hc*, Basal area – *g*, Volume, Number of trees and MAI_{tree}) of each stand are summarized in Figure 3. In general, all biometric characteristics increased with age with little variation depending on site. Therefore, only the final year of evaluation (2022) was selected for comparison. For *dbh*, h_t, h_c, g and Volume, Fazenda "Santa Helena" performed better with a mean (sd) value of 29.8 (1.9) cm, 19.87 (0.92) m, 19.6 (2.5) cm and 158 (23) m^3. By contrast, the other sites had significantly lower values, especially "Vitoria" that had the lowest value for dbh (22.2 cm), *g* (17.7 cm) and Volume (121 m^3/ha); while "Chuva da Mata" the lowest for h_t (15.67 m). Finally, in the case of the MAI_{tree}, "Santa Helena" had the highest value with 0.064 m^3 per tree whereas Bacuri and Santo Antonio had the lowest record with mean MAI_{tree} (sd) of 0.029 (0.005) and 0.035 (0.005), respectively.

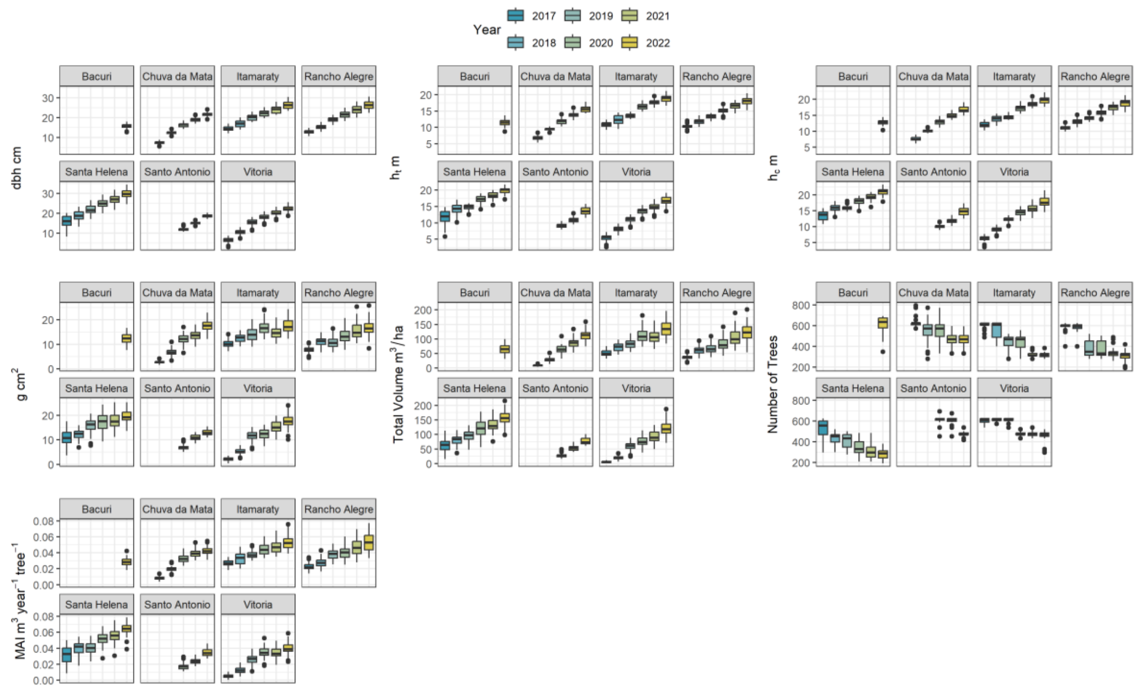

Figure 3. Dendrometric characteristics (*dbh*, h_t, h_c, *g*, Volume, Number of trees and MAI_{tree}) of Teak stands in different stands in Matto Grosso-Brazil from 2017 to 2022

Environmental variables

Topographic and precipitation variables are presented in table 2. In general, for all variables non-significant differences were observed between the fields (p-value > 0.05), except for Aspect, Eastness, Northness, RPS, DMV, TPI, Elevation and the Mean curvature. No major variation in slope % between plots was observed; however, mean aspect and elevation were significantly different between stands. "Chuva de Mata", "Itamaraty" and "Santo Antonio" presented the highest Aspect °, while "Bacuri" and "Itamaraty" the highest elevation %. In the case of Eastness, "Bacuri" and "Vitoria" presented the highest values while "Itamaraty" the lowest. For Northness, RPS, DMV and TPI, "Bacuri" represented the highest value while "Vitoria" and "Chuva da Mata" the lowest.

Annual precipitation was higher in "Santa Helena" (1517 mm) and the lowest value was observed in "Bacuri" (1176 mm). For days with rain, the farm with the highest value was "Bacuri" (318 days), and the lowest were observed in "Chuva da Mata" (292 days) and "San Antonio" (293 days). In the case of annual precipitation deficit, "Bacuri" was the only farm that presented a precipitation deficit of 25 mm. All precipitation variables presented significant differences (p-value < 0.01).

Table 2. Environmental variables (Topographic and precipitation) mean (SD) values in seven different Teak stands in Mato Grosso, Brazil from 2017-2022

Variables	**Bacuri**	**Chuva da Mata**	**Itamaraty**	**Rancho Alegre**	**Santa Helena**	**Santo Antonio**	**Vitória**	**p-value[1]**
Topographic variables								
Slope %	3.44 (0.64)	2.91 (0.39)	2.92 (0.52)	2.79 (0.44)	3.06 (0.42)	2.95 (0.59)	3.03 (0.69)	0.14
Aspect °	157 (31)	194 (17)	198 (28)	166 (13)	163 (18)	197 (26)	149 (26)	<0.001
Eastness °	0.22 (0.24)	-0.14 (0.14)	-0.17 (0.26)	0.15 (0.12)	0.14 (0.16)	-0.14 (0.23)	0.28 (0.16)	<0.001
Northness °	0.23 (0.22)	-0.07 (0.33)	-0.12 (0.27)	-0.10 (0.20)	0.01 (0.22)	-0.03 (0.31)	-0.21 (0.28)	<0.001
Surface	84.41 (0.08)	84.35 (0.04)	84.35 (0.05)	84.34 (0.04)	84.38 (0.05)	84.36 (0.06)	84.37 (0.08)	0.085
SAPA*	1.0003 (0.0001)	1.0003 (0.0000)	1.0002 (0.0000)	1.0002 (0.0000)	1.0003 (0.0000)	1.0002 (0.0000)	1.0002 (0.0000)	0.6
RIE	0.089 (0.007)	0.089 (0.004)	0.088 (0.005)	0.086 (0.005)	0.086 (0.004)	0.086 (0.006)	0.085 (0.005)	0.4
RPS	0.007 (0.008)	-0.001 (0.005)	0.001 (0.003)	0.002 (0.004)	0.003 (0.006)	0.005 (0.010)	0.002 (0.004)	0.03
Adsd	0.111 (0.012)	0.110 (0.008)	0.107 (0.006)	0.106 (0.008)	0.107 (0.005)	0.106 (0.007)	0.105 (0.009)	0.7

DMV	0.007 (0.008)	-0.001 (0.005)	0.001 (0.003)	0.002 (0.004)	0.003 (0.006)	0.005 (0.010)	0.002 (0.004)	0.03
TPI	0.008 (0.009)	-0.001 (0.006)	0.001 (0.004)	0.002 (0.005)	0.003 (0.006)	0.005 (0.012)	0.002 (0.005)	0.03
Elevation %	217 (8)	199 (12)	218 (11)	209 (8)	213 (6)	197 (6)	189 (12)	<0.001
Profile Curvature	0.0001 (0.0002)	0.0000 (0.0002)	0.0000 (0.0001)	0.0000 (0.0002)	0.0000 (0.0001)	0.0001 (0.0003)	0.0001 (0.0001)	0.3
Planar Curvature	0.0002 (0.0003)	0.0000 (0.0002)	0.0000 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0000 (0.0001)	0.2
Twist curvature	0.0000 (0.0000)	0.0000 (0.0001)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0001)	0.0000 (0.0000)	>0.9
Mean Curvature	0.0001 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)	0.0001 (0.0001)	0.0001 (0.0002)	0.0000 (0.0001)	0.031
Maximum curvature	0.0020 (0.0003)	0.0018 (0.0001)	0.0018 (0.0001)	0.0018 (0.0001)	0.0018 (0.0002)	0.0018 (0.0003)	0.0018 (0.0001)	0.4
Minimum Curvatre	-0.0017 (0.0002)	-0.0018 (0.0002)	-0.0017 (0.0001)	-0.0017 (0.0001)	-0.0017 (0.0001)	-0.0017 (0.0001)	-0.0017 (0.0001)	0.3
Features	4.93 (0.07)	4.88 (0.06)	4.90 (0.02)	4.90 (0.03)	4.91 (0.04)	4.91 (0.06)	4.89 (0.06)	0.5
Precipitation variables								
Annual precipitation	1,176 (0)	1,401 (225)	1,358 (240)	1,421 (259)	1,517 (295)	1,352 (272)	1,378 (297)	<0.001
Days with rain	318 (0)	292 (16)	300 (10)	300 (13)	300 (13)	293 (11)	306 (12)	<0.001
Days without rain	47 (0)	73 (16)	65 (10)	65 (13)	65 (13)	72 (11)	59 (12)	<0.001
Precipitation deficit	25 (0)	-201 (225)	-159 (241)	-221 (259)	-317 (295)	-153 (272)	-178 (297)	<0.001

*SAPA=Surface area to planar area rugosity, RIE: Roughness Index Elevation, RPS: Ruggedness measure, Adsd: Standard deviation of bathymetry adjusted for slope, DMV: Difference from mean value, TPI: Topographic Position Index
[1]Kruskal-Wallis rank sum test

Soil variables

Soil variables are presented in Figure 4 (pH, Organic Matter, P, K, Ca and Mg), Figure 5 (S, B, Cu, Fe, Mn and Zn). For pH in water (pHw), no significant differences were observed between sites and years (p-value > 0.05). “Chuva da Mata” had the lowest mean value (6.36) while “Santa Helena” had the highest (6.51). In general, significant differences of organic matter (g/kg) between sites were observed, with values that reached the highest values in 2020 and then decreased. The minimum OM value was presented in “Itamaraty” and the maximum in “Vitoria”, with 29.19 g/kg and 36.23 g/kg, respectively. In the case of macro-nutrients, P contents were similar across all the evaluated years with exception of 2022. Where concentrations decreased and significant differences were observed between sites (p-value < 0.05). In the case of K, significant differences were observed between sites and values decreased over the years. Both P and K presented the lowest mean values in “Vitoria” with 2.64 mg/dm^3 and 68.78 mg/dm^3, respectively, while “Bacuri” the highest values of P with 5.19 mg/dm^3 and K with 101.6 mg/dm^3.

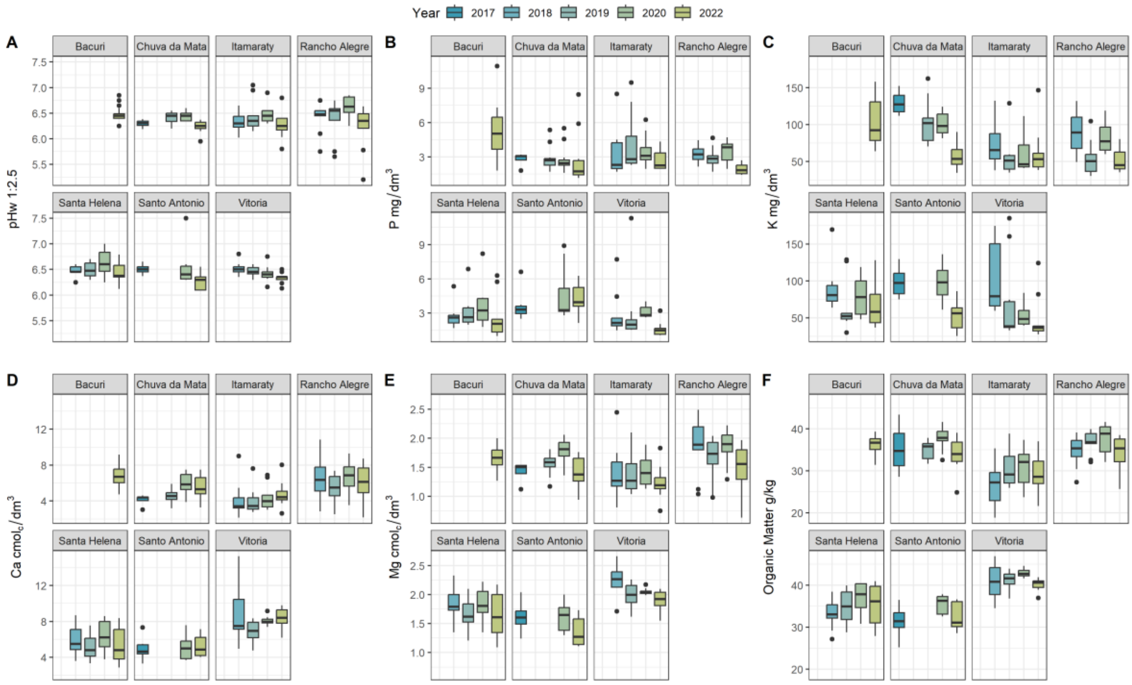

Figure 4. Soil Attributes (pH, Organic Matter, P, K, Ca and Mg) at 0.0-0.2 m depth of Teak (Tectona grandis) in seven stands in Matto Grosso-Brazil from 2017 to 2022.

In the case of Ca and Mg, significant differences were observed between sites (p-value < 0.05). Mg concentrations varied across years reaching a maximum in 2020 while Ca concentrations had similar values in different years. “Santo Antonio” had the lowest value for Ca (5.04 cmol$_c$/dm^3) and Itamaraty for Mg (1.38 cmol$_c$/dm^3). “Vitoria” had the maximum value for Ca (8.03 cmol$_c$/dm^3) and Mg (2.05 cmol$_c$/dm^3).

For Sulfur, it presented significant differences between sites and a peak in 2020 (p-value < 0.05). “Bacuri” presented the lowest mean with 6.13 mg/dm^3 while “Santo Antonio” the highest with 11.81 mg/dm^3.

For micronutrients, Boron presented similar results between sites and the highest value between years was observed in 2020. However, the lowest mean value was obtained in “Bacuri” with 0.31 mg/dm^3 while the highest in “Rancho alegre” with 0.35 mg/dm^3. For Cu, similar results between years were observed and the general lowest mean in “Bacuri” and highest was obtained in “Vitoria” with 1.92 mg/dm^3 and 5.54 mg/dm^3, respectively. For Fe, no major differences were observed between sites, with exception of “Vitoria” and, only in 2022, values were higher in comparison to other years. The lowest observed mean value was in “Vitoria” with 67.31 mg/dm^3 and the highest in “Itamaraty” with 166.75 mg/dm^3. For Mn, significative differences between the sites were observed (p-value < 0.05). The year with the highest value was 2020 with exception of “Itamaraty” that had it in 2022. The lowest observed mean was observed in “Bacuri” with 68.07 mg/dm^3 and the highest mean in “Vitoria” with 132.7 mg/dm^3.

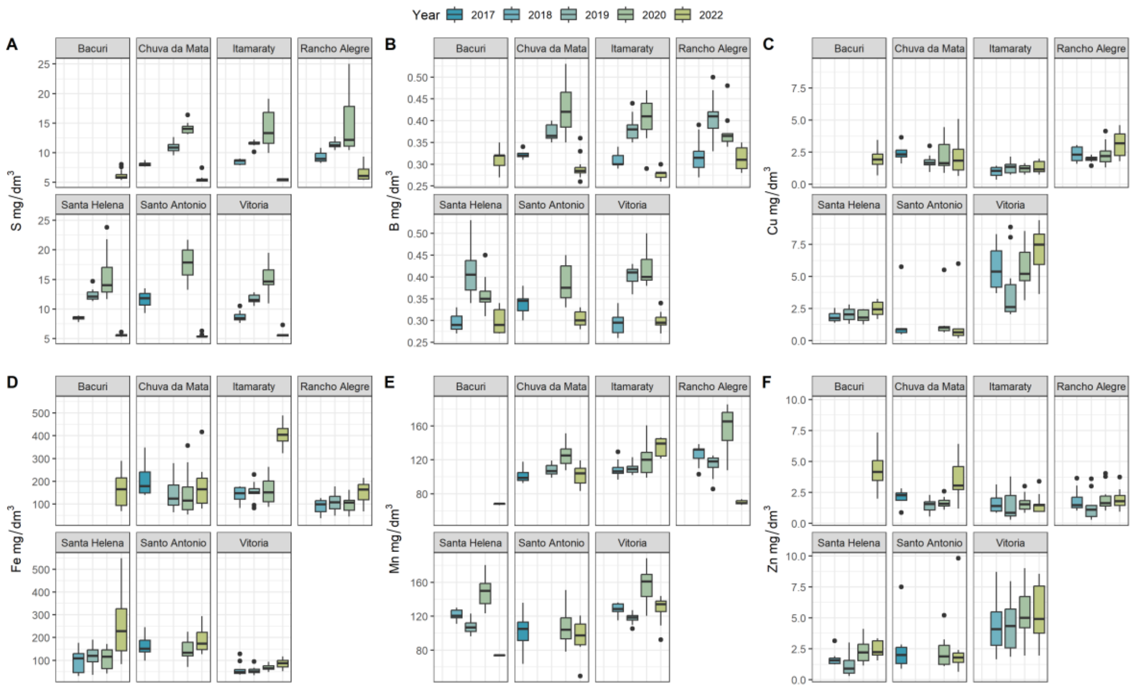

Figure 5. Soil Attributes (S, B, Cu, Fe, Mn and Zn) at 0.0-0.2 m depth of Teak (Tectona grandis) in seven stands in Matto Grosso-Brazil from 2017 to 2022.

Finally for Zn (Figure 5), significant differences were observed between sites (p-value < 0.05), but no major differences were observed between years, except for “Chuva da Mata” and “Santa Helena” which presented the higher mean in 2022. The lowest mean with 1.79 mg/dm^3 was observed in “Rancho Alegre”, while the highest mean in “Vitoria” with 4.89 mg/dm^3.

In general, most soil variables were above the range considered as “medium”, while in the case of K and B were in some years below 60 mg/dm^3 and 0.35 mg/dm^3, respectively, which are considered as sufficient. However, P in all stands and years was below the sufficiency range (10 mg/dm^3).

Teak growth modelling

Prediction metrics for all assessed biometric variables are shown in Figure 6, Figure 7, Figure 8 and Figure 9. In general, both Cubist and Random Forest algorithms performed better than the others (Figure 6, Figure 7 and Figure 8). By contrast, neural networks had the lowest performance for all metrics used for prediction assessment. In the case of RMSE (Figure 6), Cubist algorithm performed slightly better than random forest with mean values of 0.91; 0.82; 0.74 and 4.25 for *dbh, h_t, h_c*, and *MAI_{tree}* respectively. In the case of Basal area (*g*), Number of plants and Volume, Random Forest algorithm performed better than Cubist with mean values of 1.81, 52.6 and 13.5, respectively.

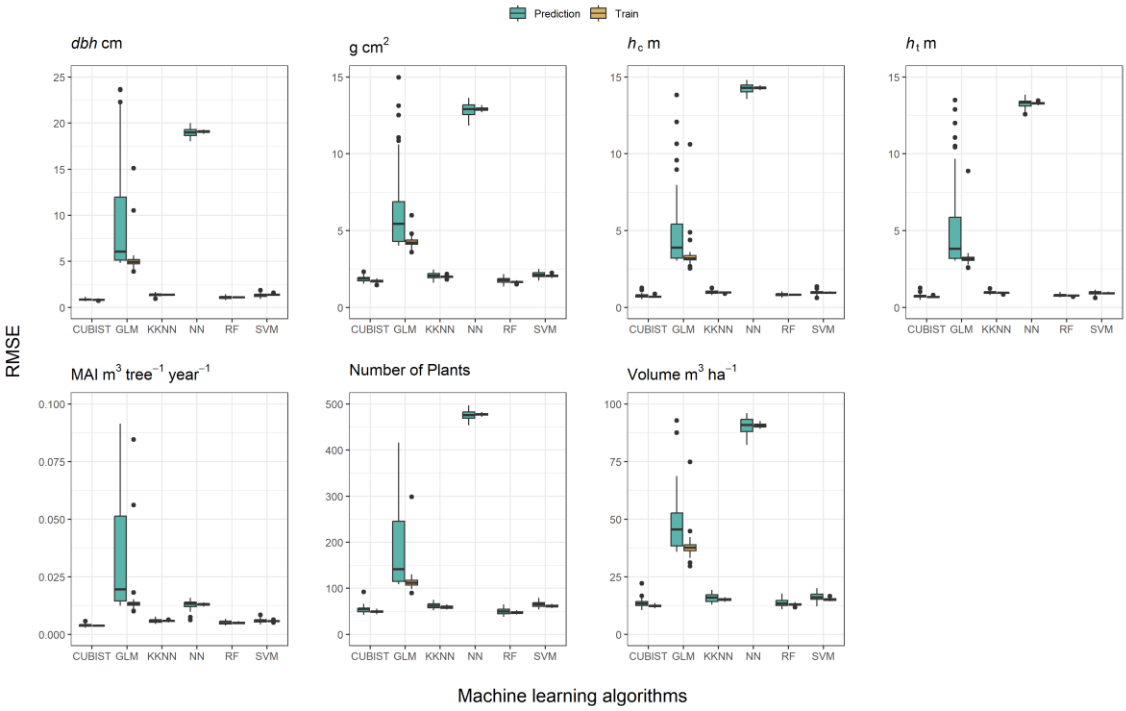

Figure 6. RMSE (Root Mean Square Deviation) of machine learning agorithms for biometric variables of Diameter at breast height - *dbh*, Basal Diameter – *g*, Commercial Height – *hc*, Total Height – *ht*, Mean Annual Increase per tree – *MAI_{tree}*, Number of plants and Volume in different Teak stands in Matto Grosso-Brazil. from 2017 to 2022

In the case of MAE (Figure 7), for *dbh, ht, hc* and MAI_{tree}, Cubist algorithm performed slightly better than random forest with mean values of 0.69; 0.60; 0.58 and 3.25, respectively. In the case of Basal area (*g*), Number of plants and Volume, Random Forest algorithm performed better than Cubist with mean values of 1.40, 38.8 and 10.4, respectively.

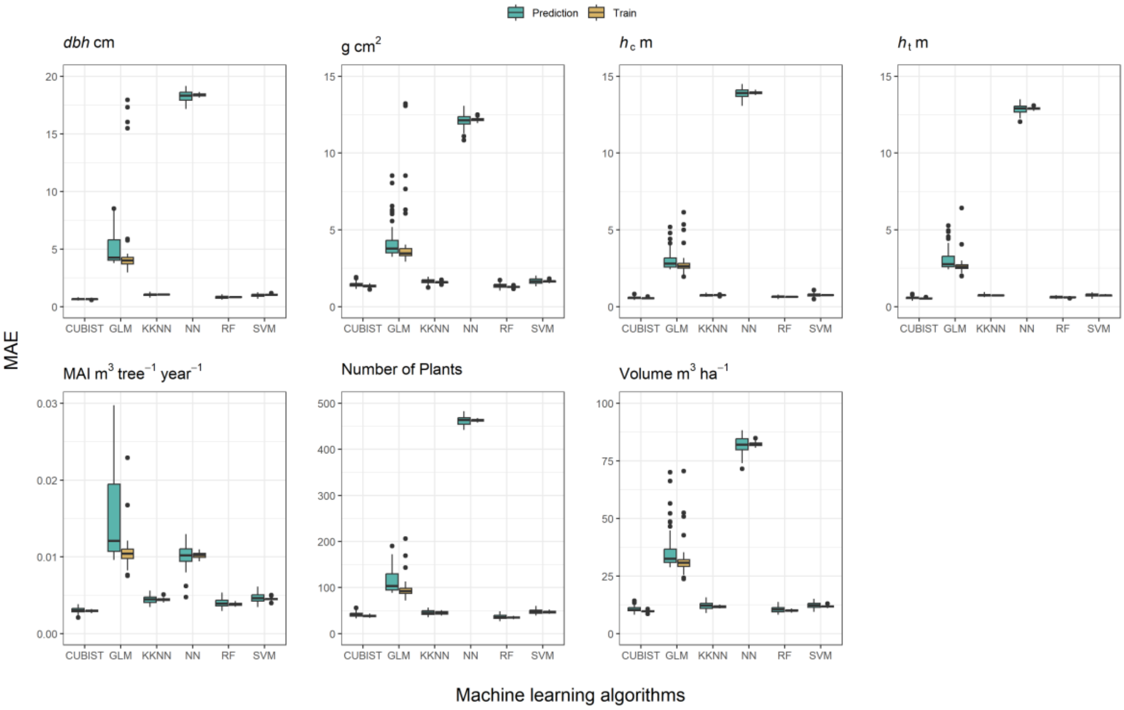

Figure 7. MAE (Mean Absolute Error) of machine learning agorithms for biometric variables of Diameter at breast height - *dbh*, Basal Diameter – *g*, Commercial Height – *hc*, Total Height – *ht*, Mean Annual Increase per tree – MAI_{tree}, Number of plants and Volume in different Teak stands in Matto Grosso-Brazil. from 2017 to 2022

In the case of R^2 (Figure 8), for *dbh*, h_t, h_c, and MAI_{tree}, Cubist algorithm performed slightly better than random forest with mean values of 0.97; 0.93; 0.95 and 0.90, respectively. In the case of Basal area (*g*), Number of plants and Volume, Random Forest algorithm performed better than Cubist with mean values of 0.83, 0.80 and 0.87, respectively

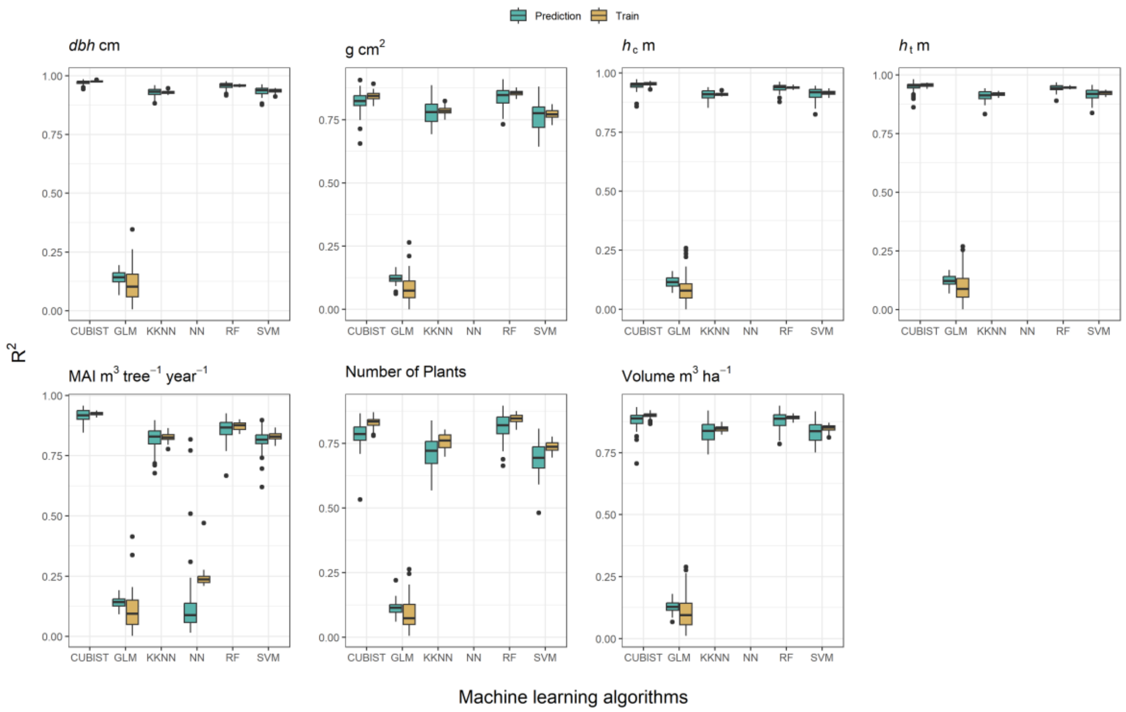

Figure 8. R^2 (Coefficient of Determination) of machine learning agorithms for biometric variables of Diameter at breast height - *dbh*, Basal Diameter – *g*, Commercial Height – *hc*, Total Height – *ht*, Mean Annual Increase per tree – MAI_{tree}, Number of plants and Volume in different Teak stands in Matto Grosso-Brazil. from 2017 to 2022

Overall predicted values agree with observed values (figure 13), except for *g* (basal area) and number of plants which presented fair predictions.

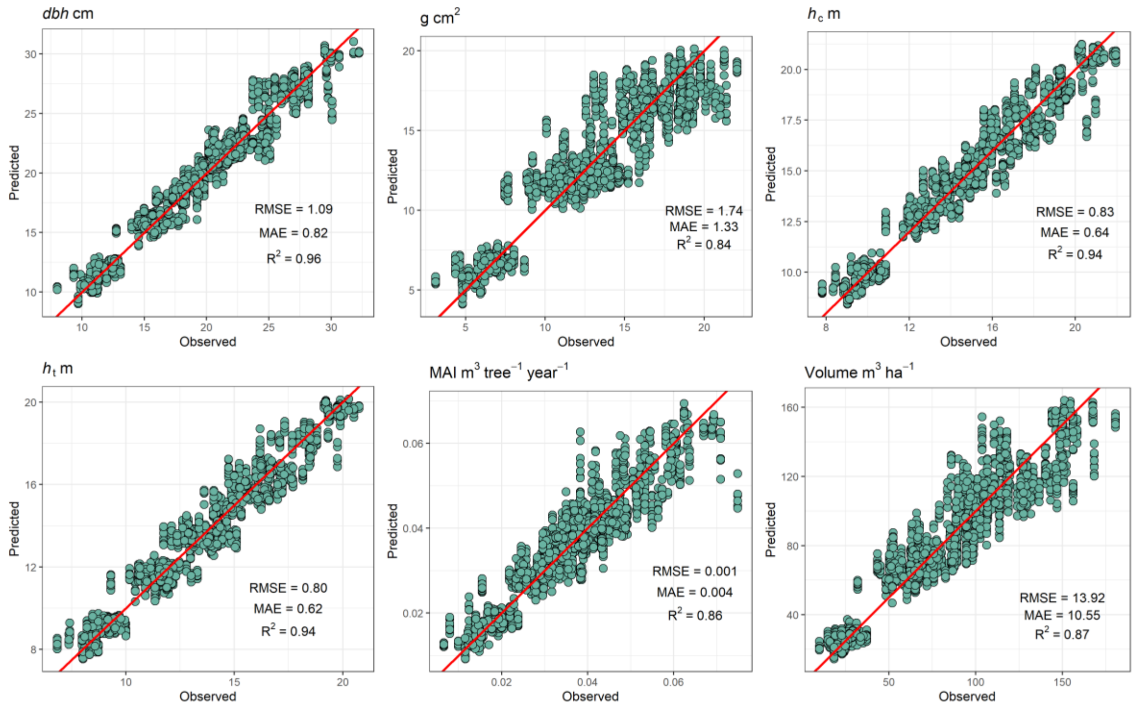

Figure 9. Predicted vs Observed values of 50 runs of the best machine learning algorithms (Cubist and Random Forest) for biometric variables of Diameter at breast height - *dbh*, Basal Diameter – *g*, Commercial Height – *hc*, Total Height – *ht*, Mean Annual Increase per tree – MAI_{tree}, and Volume in different Teak stands in Matto Grosso-Brazil. from 2017 to 2022

Variable importance

To model Teak, stand biometric variables, several covariables were used. Given that differences between cubist and random forest model were minimal, variable importance ranking after 50 runs for each algorithm is presented in Figure 10 and Figure 11. In this case, the 10 most important predictors were selected for each biometric parameter. The only exception was Number of plants, since its variation depended mostly on the stand management and may lead to a biased model. In the case of Random Forest, the age of stand (Id_Inv), available sulfur in the soil (S) and Days without rain (DIA_SEMCH) were the three most important variables. For all variables and algorithms (Cubist and Random Forest), the age of the stand was the most important predictor. However, in the case of *dbh* besides this predictor, Cubist selected 3 soil predictors (pH in water, Cu and S), 5 topographic predictors (minimum elevation, minimum slope, maximum profile curvature, minimum Adsd and first quartile of slope) and 1 vegetation index. For Basal area, Random Forest used 3 soil variables (Available Zn, Exchangeable K and Clay), 4 topographic variables (coefficient of variation of aspect, coefficient of variation of aspect of dmv, first quartil of aspect and coefficient of variation of maximum curvature) and 2 vegetation indexes (NDI45 and PSRI). In h_c, Cubist used 4 soil variables (Clay, Sand, Ca and Organic Matter), 3 topographic variables (Minimum elevation, Coefficient of variation of elevation and minimum aspect), 1 vegetation index (S2.REP) and 1 for climate data (Water deficit). In h_t, Cubist used 4 soil variables (Clay, exchangeable K and Ca and Available Fe), 4 topographic variables (Coefficient of Variation of aspect, Minimum and maximum aspect and first quartile of eastness) and 1 vegetation index (S2REP).

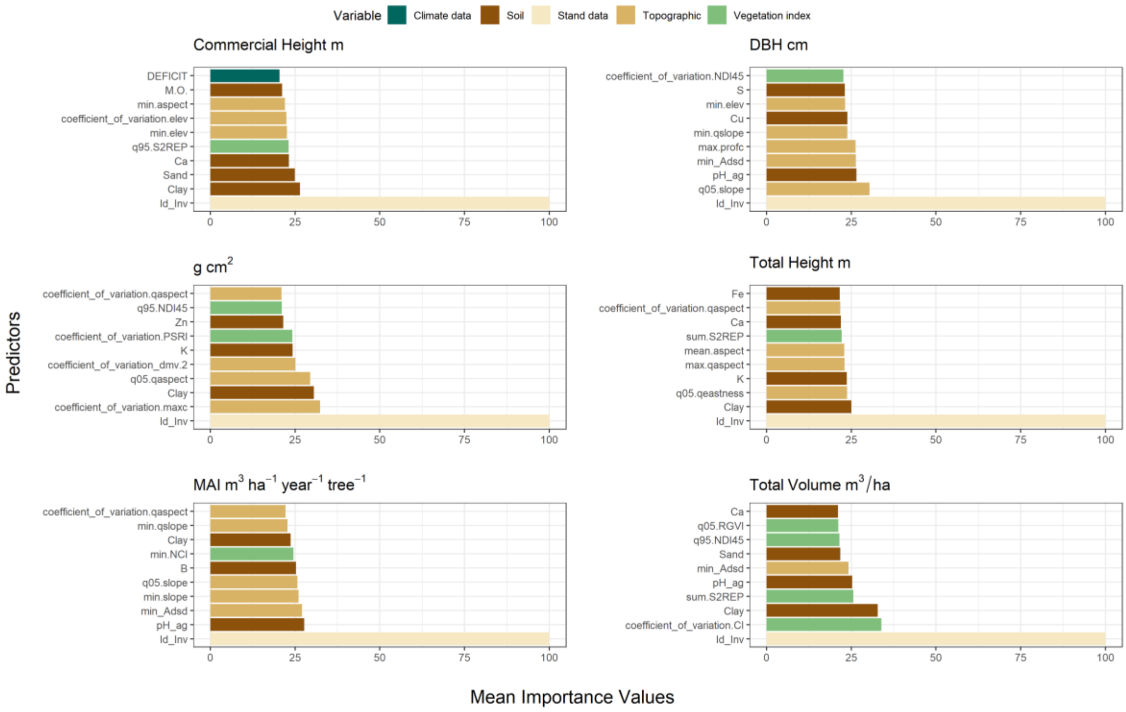

Figure 10. Variable importance ranking selected by Cubist for biometric variables of Diameter at breast height - *dbh*, Basal Diameter – g, Commercial Height – *hc*, Total Height – *ht*, Mean Annual Increase per tree – MAI_{tree}, Number of plants and Volume in different Teak stands in Matto Grosso-Brazil. from 2017 to 2022

For MAI_{tree}, Cubist presented 3 soil variables (pH in water, available B and Clay), 5 topographic variables (minimum and first quartile of slope and minimum q-slope, coefficient of variation of aspect and minimum Adsd) and 1 vegetation index (NCI). Finally for Volume, Random Forest, selected 3 soil variables (available S and B and Clay), 1 topographic variable (minimum elevation), 3 vegetation index (PSRI, NCI and CRI2) and 2 climate data (Days without rain and Water deficit).

In summary, for all variables, Cubist model used 41% of topographic variables, 39% of soil variables, 10% of vegetation index variables and only 2% of climate variables. By contrast, Random Forest, used 44% of soil variables, 24% of vegetation index, 22 % of climate variables and 9% of topographic variables, being a relatively more equilibrated result, in accordance to overall historical precedents. Of the 57 Vegetation indexes used for the study, only 6 were selected: NCl, S2Rep, ARI1, CRI2, PSRI and LAI. From these, the sum of S2REP was important for predicting dbh and ht. The minimum value of NCl was important for predicting hc. For MAItree, the sum of PSRI and the maximum value of LAI and the first quantile of ARI1 proved the most important VI. Finally, Volume predictors showed that the sum of S2REP and the coefficient of variation of CRI2 and PSRI were important. These general results indicate the importance of site election in forest plantations given that the main selected variables were mostly related to soil and topography followed by climate conditions.

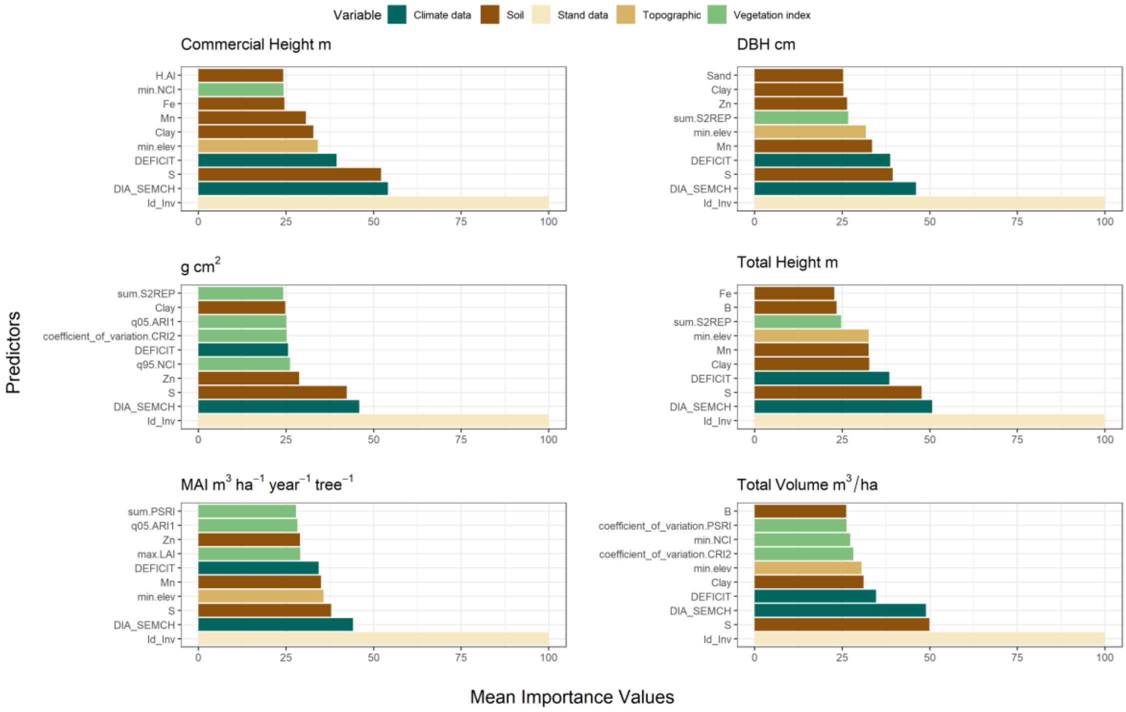

Figure 11. Variable importance ranking selected by "Random Forest" for biometric variables of Diameter at breast height - *dbh* -, Basal Diameter – *g*, Commercial Height – *hc*, Total Height – *ht*, Mean Annual Increase per tree – MAI_{tree}, Number of plants and Volume in different Teak stands in Matto Grosso-Brazil. from 2017 to 2022

DISCUSSION

Stand characteristics

In general, stand Teak characteristics showed an increase in most biometric variables except for the number of trees and MAItree. In most cases, the least productive plots were "Vitoria" and "Santo Antonio". However, this lower productivity in comparison to other stands cannot be explained by differences between climate and topographic characteristics as these were not significant. The "Santo Antonio" farm had the second highest number of days without rain after "Chuva da Mata" but with less annual precipitation. It is important to take in consideration that precipitation, especially precipitation timing, and water availability in the soil are the main drivers in net primary productivity and can alter overall stand conditions, survival and growth (Griffin-Nolan et al., 2021). These characteristics of the stands indicate that soil variables could be more important in explaining productivity rather than climate or topography.

In the case of soil variables in the stands (Figure 3 and 4), the most limiting factors were P, K, B and partially Cu and Zn. Phosphorous is an important nutrient in terms of root development and overall growth in plants and could also have a direct impact in abiotic stress such as drought (Khan et al., 2023; Soong et al., 2020), especially in areas with precipitation deficit as shown in "Bacuri". K is the highest nutrient required by Teak after Ca and N. Its supply in the soil is also important for tolerance to abiotic stress (Sardans & Peñuelas, 2021), which can compromise higher productivities since K concentrations in the last year (2022) were below the sufficient range, (Fernández-Moya et al., 2014; Neto et al., 2020). Finally, among micronutrients, B has shown the most limiting values even though Teak has a low requirement for this element. Boron is important for plant growth, cell wall formation, photosynthesis and the transport of sugars (Long & Peng, 2023). Despite Boron importance, Teak growth may not be affected even in soils with low available B. Therefore, the application of this element may not show any response in this species (Combatt Caballero et al., 2016).

Teak growth Modelling

Prediction of growth is not new for plants; however, the use of machine learning algorithms for forestry species is not so common as in commercial crops such as maize (Zea mays L.), cotton (Gossypium hirsutum L.), rice (Oryza sativa), sugarcane (Saccharum officinarum), among others (Choudhary et al., 2022; Everingham et al., 2016; Prasad et al., 2021; Zhang et al., 2023). However, research aiming to predict growth parameters such as Volume, dbh or height has been performed mainly on eucalyptus (Eucalyptus sp.) and pine (Pinus sp.), which are the most commercial species in the sector and they have used Cubist, KKNN, SVM, neural networks, random forest or deep neural networks as algorithms (Azevedo et al., 2020; de Oliveira et al., 2021; Ercanlı, 2020; Ou & Quiñónez-Barraza, 2023; Santana et al., 2023; Vinícius Oliveira Castro et al., 2013). The random forest, cubist and deep neural networks are the most successful algorithms, these results being similar to our study.

In the case of Teak (Tectona grandis), the construction of growth models has been typically performed by the use of allometric equations, which are obtained by the use of linear or non-linear regression models, being the latter the preferred in several works (Bermejo et al., 2004; Huy et al., 2022; Kenzo et al., 2020; Mahanta & Borah, 2017; Torres et al., 2020). In other studies, the 3PG model was used to improve the equations by including climatic variables (Gupta & Sharma, 2021). For machine learning algorithms in Teak, very few research has been performed. However, Tavares Júnior et al., (2021) used Regression, Artificial Neural Networks (ANN) and Support Vector Regression (SVR) for predicting wood stock, where ANN outperformed the other algorithms for tree volume prediction. Also, Fernández-Carrillo et al., (2022), aiming to predict stem diameter compared different models such as Genetic Programming (PG), Gaussian Regression Process (PGR), Category Boosting (CatBoost) and ANN, indicating that the latter had the highest accuracy. Finally, a recent work from Soraya et al., (2025) used aerial imagery and UAV-Lidar for aerial carbon stocks, where Multi-Linear Regression (MLR), Random Forest (RF), SVR, and XGBoost Regression were compared. The work concluded that MLR and RF performed better with lower MAE values. Therefore, the past use of machine learning algorithms in Teak has shown a good performance in relation to the common use of allometric equations, even though in those works they used different algorithms, except for ANN and RF.

Overall, for all biometric variables assessed in the present work, Cubist and RF algorithms performed better in comparison to the general linear model (GLM), artificial neural networks (ANN), Support Vector Machine (SVM) and Weighted K-Nearest Neighbor (KKNN). However, the published work (Fernández-Carrillo et al., 2022; Soraya et al., 2025; Tavares Júnior et al., 2021) performed in Teak indicated that both ANN and MLR performed better, contrary to our results, especially where ANN had the lowest accuracy from all the assessed algorithms. The work conducted in Eucalyptus and Pine had similar results to our study (de Oliveira et al., 2021; Ou & Quiñónez-Barraza, 2023). In the case of ANN, the low accuracy may be due to limitations on data. This was scarce and variables from soil, climate, and topography were used with different scales that could affect performance of this algorithm (Livingstone et al., 1997). Both RF and Cubist have a high performance for capturing non-linear relationships, robustness to noise in data, high accuracy in small datasets and can handle heterogenous data easily, minimizing noise and outliers (Breiman, 2001; Hastie et al., 2009; Siqueira et al., 2023). This may explain the high accuracy presented in this study, where limited data and high noise are often present. Finally, it’s important to mention that to our knowledge in the case of teak, this is the first modelling work using machine learning and variables from climate, soil, topography and vegetation indexes derived from satellite images.

Teak Growth main predictors

Growth is a multifactor variable that can be affected by several parameters, making its prediction in many aspects challenging. In general, site characteristics determined by climate, soil and topography and its interactions with biological agents affect the growth rate of Teak (Kusbach et al., 2021). Models have differences in predictors selection depending on their algorithms, which can be observed in the results from Cubist and Random Forest algorithms. However, in all biometric variables and, for both algorithms, the age of the stand was selected as the most important predictor, which is an expected outcome since age and growth parameters follow the same trend in time (Bermejo et al., 2004; Gupta & Sharma, 2021). Nevertheless, since different conditions are met in the assessed teak stands, other variables arise in terms of importance, as described in the results section. In the case of the models, Cubist seems to prefer topographic and soil variables rather than vegetation index or climate variables. This may be due its algorithm that has preference for more stable variables to reduce overfitting, noise and have stability on the prediction (Kuhn & Johnson, 2013), since the selected topographic or soil variables did not present any significant differences between sites in the initial descriptive statistics. However, this predictor election is contradictory to overall knowledge where climate variables tend to prevail as the most important for growth in forest species (Toledo et al., 2011).

In the case of the Random Forest algorithm, it reported a more equilibrated subset of variables. Where climate variables were always present and, it pointed out that soil variables were the most important. In the case of tropical climates, nutrient demands are generally greater in a less period due to higher temperatures and growth rates in comparison to northern latitudes (Ali et al., 2020; Toledo et al., 2011). This model reported that for all growth parameters, the most important predictors were available S, Days without rain and Precipitation deficit. Climate tends to be especially important for plant species. Within this parameter and in tropical forests, precipitation rather than temperature seems to play a major role, as has been reported in eucalyptus, pine, teak and some native forest species (Ali et al., 2020). However, the role of S, has been widely described for crop plants and limitations may reduce growth due to its essential function in the formation of aminoacids (ie: cysyteine and methionine), proteins and coenzymes and the tolerance to abiotic and biotic stress (Hawkesford et al., 2012). Nevertheless, in terms of forest species, studies have focused mainly on S cycling, where the deposition of atmospheric S is common; however, little amounts of S are needed in overall forest species to achieve sufficiency (Mitchell & Lindberg, 1992). Teak is not the exception, with only 50 kg of S needed for a 19 years old stand (Fernández-Moya et al., 2015)., Sulfur has a direct relation to C cycle and its transformations in soils are mainly related to microorganisms (Wilhelm Scherer, 2009) but S has a higher spatial variability in relation to organic carbon (Piotrowska-Długosz et al., 2017). Therefore, since variations of both S and C tend to have a similar path, S may reflect better the effect of C nutrition on the growth of Teak stands in this study.

Also, this algorithm selected more vegetation index derived variables which can express stress tolerance and health among other conditions which can reflect plant status in the field (Zhao et al., 2018). For instance, NCI and LAI are vegetation indexes related to plant quantity and distribution in a specific area (Fernández-Manso et al., 2016) and in this case; diverging values such as minimum or maximum tend to be more useful for estimation. However, in the case of ARI1, CRI2, PSRI and S2REP, they are VI designed to estimate pigment contents such as chlorophyll and carotenoids. This may reflect physiological and stress responses of the plants (J. K. Zhu, 2016), which can be the reason that the sum and the coefficient of variation measures were better.

CONCLUSION

The use of multispectral satellite imagery with field data performed well, with good predictions being obtained using machine learning methods. Cubist and random forest performed better in relation to all variables with low RMSE and MAE and high R2 (>0.9). In terms of variable importance, age was the most important variable for growth. Cubist model aimed for a selection of more topography-related variables. By contrast Random Forest reported a more equilibrated model with available S, Days without rain and Water Deficit were the most important variables. Finally, this study highlights the importance of utilizing machine learning algorithms to predict the growth of forest species and could furthermore reduce the costs for monitoring.

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CAPITULO 3. MODELLING OF TEAK (*TECTONA GRANDIS*) NUTRITION WITH ENVIRONMENTAL VARIABLES, SATELLITE IMAGERY AND MACHINE LEARNING IN BRAZIL

Abstract

Teak (Tectona grandis) is an important species that relies on good nutrition. However, the costs of monitoring are expensive, and remote sensing techniques aligned with machine learning algorithms may offer a better alternative to current monitoring methods. The main objective of this study was to model teak nutrition using field data and satellite multispectral images using machine learning algorithms. The research was performed in Mato Grosso, Brazil, with teak stands from different ages and different climate, soil and topography conditions. Data of climate (Precipitation variables), soil variables (pH, O.M., P, K, Ca, Mg, K, S, B, Cu, Fe, Mn, Zn) and topography were used. Also, concentration of nutrients (N, P, K, Ca, Mg, S, B, Cu, Fe, Mn and Zn) was used for modelling. Finally, modelling was performed using Cubist, Random Forest, KKNN, SVM and GLM and the best model was selected using RMSE, R^2 and MAE statistics. For Teak nutrition, random forest performed better in relation to other models in all variables with low RMSE and MAE and high R^2. In terms of variable importance, Available S, Age, Days without rain and Water Deficit were the most important variables for most nutrients. Also, map prediction indicates an overall increase in macronutrients concentration while a decrease in micronutrients contents. This is the first published study in Teak (Tectona grandis) and highlights the importance of the use of machine learning algorithms for nutrition prediction, but further research is needed to improve the current models and make forest nutrition management more efficient.

INTRODUCTION

Teak (*Tectona grandis*) is an important species worldwide for wood production with high quality, mainly used for furniture, ships and agricultural implements. This tree from subtropical origin is mainly planted in tropical areas (Kusbach et al., 2021). In the Americas, many countries plant this tree such as Colombia, Costa Rica and Brazil, being the latter with the highest planted area (84,466 ha), representing the third most planted species after Eucalyptus and Pine in Brazil (IBA, 2024).

Teak growth depends on the quality of site, that holds the interaction of the characteristics of climate, topography and soil that can optimize or decrease growth (Kenzo et al., 2020). In general, teak nutrition and the management of soil fertility are key factors for productivity and success in forest plantations, especially in high nutrient demanding species (Behling et al., 2014). According to Da Favare et al. (2012), teak nutrient requirement in shoots are related as follows: N>Ca>K>Mg>P>S>Fe>Mn>B>Zn>Cu, while in roots Behling et al., (2014), indicates that requirements in roots are in the order of K > Ca > N > Mg > P > S, in both cases Ca is the second most demanded nutrient, showing that teak is Ca sensitive species, and, liming is a key step on its establishment and growth, especially in acid soils. Despite liming importance, other nutrients are required for optimal productivity since this species could response positively to the application of nitrogen, phosphorus and potassium, promoting growth and diameter (Abod & Siddiqui, 2001; Siddiqui et al., 2009; Zhou et al., 2012). So adequate nutrition monitoring is required to achieve high growth and quality in teak stands.

Plant nutrition has generally been based on plant analysis by traditional chemical procedures, which in represent high costs related to sampling, testing, data analysis and especially time investment (Feng et al., 2020; Watt et al., 2019). Also, as monitoring is related to a critical nutrient level and a relatively little sample that represents the stand, it can lead to inaccuracies that can detriment nutrient equilibrium and productivity (Watt et al., 2019). Nowadays, with increasing costs for forestry production, new alternatives are being searched to achieve an effective procedure for monitoring equilibrium and quality of forestry nutrition at the lower cost and in large areas.

In this context, new methods have been searched for reducing costs but without compromising overall data quality, being remote sensing a series of techniques that can aid in the monitoring of the nutrition of different forest and crop fields (Ahamed, 2022). Remote sensing techniques such as the use of multispectral images from both satellites and drones are recognized as a feasible alternative where they can be used to predict different nutrients in plants (Adiningrat et al., 2024; Damasceno et al., 2023). From these images, the normal procedure is to use the vegetation indexes that have a relation with the objective nutrient, being more than 90 indexes to date (Giovos et al., 2021; Zhao et al., 2018).

However, most research carried over the years, related to remote sensing has been focused on N, while other nutrients have received little or no research at all (Stein et al., 2014; Watt et al., 2019). However, evidence has shown that prediction is possible, even though prediction is not as strong as for N. Therefore, nutrient prediction with vegetation indexes, in general, are ordered as follows: N> P, Ca, K> Mg, Zn, Fe, B and Mn (Masaitis et al., 2014). Some recent work performed in Oil palm (Oliveira Teixeira, 2022; Oliveira Texeira, 2018) and Coffee (Souza, 2022) have shown strong correlations (R^2>0.70) between vegetation indexes and macro and micronutrients, especially in coffee. However, correlations were not as strong for iron in Oil palm. Nevertheless, other work has shown that these indexes are not only related to plant nutrition but to plant biotic and abiotic stress such as prediction of occurrence of plant diseases or drought (Galieni et al., 2021; Monis Faria, 2022).

In general, studies using remote data relating to nutrition and growth are scarce in tropical forest trees such as teak, being important the development of these models for monitoring nutrition and predicting growth with the help of vegetation indexes, that may be a low-cost alternative to traditional method and improve nutrient use efficiency in these plantations. Considering the limitations of current monitoring practices and nutrition predictions performed in the field, and the potential use of different stand characteristics and their integration into satellite imagery and machine learning algorithms. The main objectives were to: (i) Explore the main variables responsible for nutrition parameters in teak; (ii) Relate the feasibility to use multispectral satellite imagery to predict nutrition in teak; and (iii) Predict teak nutrition using current field data and satellite multispectral images using machine learning algorithms.

MATERIAL AND METHODS

Localization

The research was performed in 10 farms of clonal teak located in São José dos Quatro Marcos –Mato Grosso, Brazil located at UTM 365203 E 8268930 S and 211 m (Figure 1). The area is characterized by a tropical humid Climate (Am) (Köppen, 1931), with mean annual precipitation of 1500 mm and mean annual temperature of 24°C, with minimum means of 18°C and maximum of 33°C.

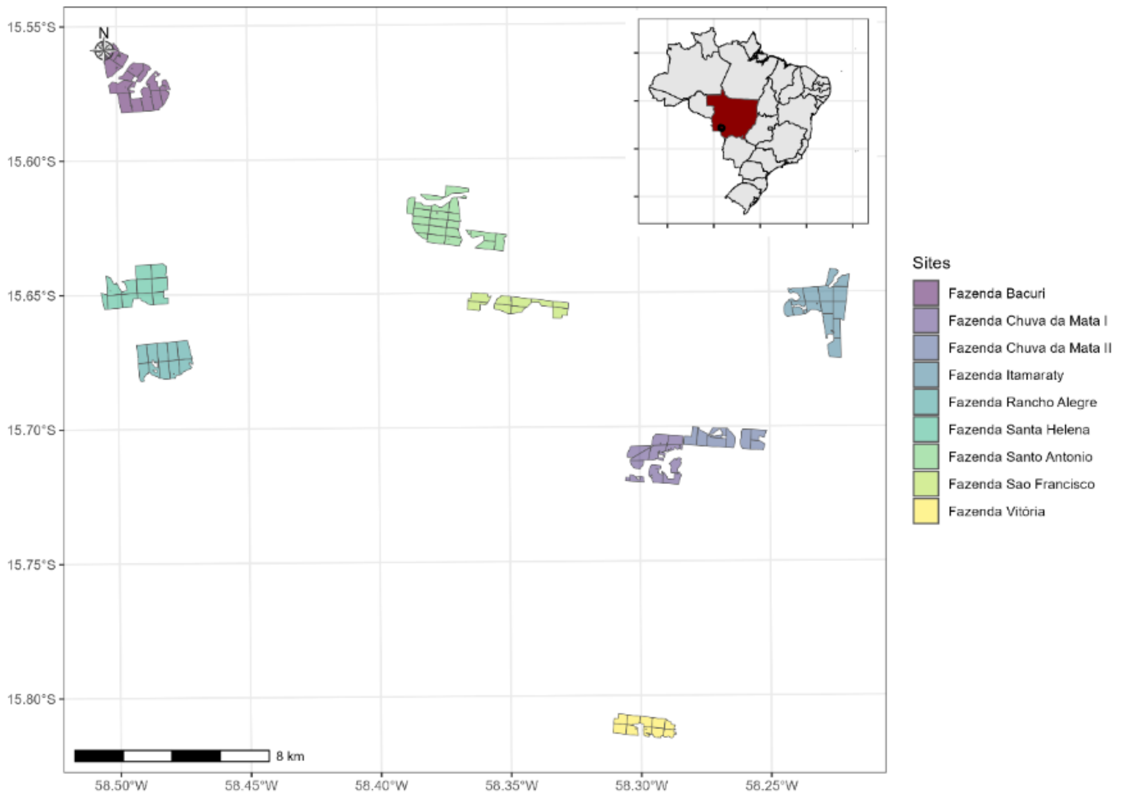

Figure 1. Location of Teak stands used for the research in Mato Grosso, Brazil

Images were obtained freely from the Copernicus Browser in the Copernicus Data Space Ecosystem, considering date of collection of plant samples from the clonal teak farms in different years. Images from satellite Sentinel-2 were selected taking into consideration the cartographic base available from the "4M Agroflorestal" company that was visualized in Google Earth. Sentinel-2 has a regular multispectral camera with 13 bands in the visible, near infrared and short-wave infrared part of the spectrum with main applications such as in agriculture, land ecosystems and forest management. To improve values obtained from the satellite, only previous atmospherically corrected images (L2A product) were used.

Vegetation indexes (VI)

Proposed vegetation indexes (VI) are presented in table 9 and were based on previous work executed for oil palm (Oliveira Teixeira, 2022). These 58 VI were calculated to predict their relationship with the biometric variables related to growth in teak clones.

Table 1. Proposed vegetation indexes for predicting nutrition and growth in teak clones in Mato Grosso

N	Index	Equation
1	Anthocyanin Reflectance Index 1 (ARI 1) (Gitelson et al., 2001)	$\frac{1}{G} - \frac{1}{RedEdge1}$
2	Anthocyanin Reflectance Index 2 (ARI 2) (Gitelson et al., 2001)	$\frac{NIR}{G} - \frac{1}{RedEdge1}$
3	Atmospherically Resistant Vegetation Index (ARVI) (Kaufman & Tanré, 1992)	$\frac{NIR - (2 * R - B)}{NIR + (2 * R - B)}$
4	Burn Area Index (BAI) (Chuvieco et al., 2002)	$\frac{1}{(0.1 - R)^2 + (0.06 - NIR)^2}$
5	Blue Normalized Difference Vegetation Index (BNDVI) (Wang et al., 2007)	$\frac{NIR - B}{NIR + B}$
6	Chlorophyll Red-edge (ChRE) (Gitelson et al., 2003)	$\frac{RedEdge1}{NIR}$
7	Canopy Index (CI) (Vescovo & Gianelle, 2008)	$SWIR - G$
8	Color index of Vegetation Extraction (CIVE) (Kataoka et al., 2003)	$0.441 * R - 0.811 * G + 0.385 * B + 18.78745$
9	Carotenoid Reflectance Index 1 (CRI 1) (Gitelson et al., 2002)	$\frac{1}{B} - \frac{1}{G}$
10	Carotenoid Reflectance Index 2 (CRI 2) (Gitelson et al., 2002)	$\frac{1}{B} - \frac{1}{Rededge1}$
11	Difference Vegetation Index (DVI) (Tucker, 1980)	$NIR - R$
12	Enhanced Red-Green-Blue Vegetation Index (ERGBVE) (Themistocleous, 2019)	$\pi * \frac{G^2 - R * B}{G^2 + R * B}$
13	Enhanced Vegetation Index 1(EVI 1) (Jiang et al., 2008)	$2.5 * \frac{NIR - R}{NIR + 6 * R - 7.5 * B + 1}$
14	Enhanced Vegetation Index 2 (EVI 2) (Jiang et al., 2008)	$2.5 * \frac{NIR - R}{NIR + 2.4 * R + 1}$
15	Excess of Green (ExG) (Woebbecke et al., 1995)	$2 * G - R - B$
16	Excess of Green minus Excess Red (ExGexR) (Meyer & Neto, 2008)	$2 * G - R - B - 1.4 * R - G$

17	General Difference Vegetation Index (GDVI, n=2) (Wu, 2014)	$\frac{NIR^2 - R^2}{NIR^2 + R^2}$
18	Green Blue Normalized Difference Vegetation Index (GBNDVI) (Wang et al., 2007)	$\frac{NIR - G - B}{NIR + G + B}$
19	Green Chlorophyll Index (GCI) (Gitelson et al., 2003)	$\frac{NIR}{G} - 1$
20	Green Difference Vegetation Index (GDVI) (Sripada et al., 2006)	$NIR - G$
21	Green Leaf Index (GLI) (Louhaichi et al., 2001)	$\frac{2 * G - R - B}{2 * G + R + B}$
22	Green Normalized Vegetation Index (GNVI) (Gitelson et al., 1996)	$\frac{NIR - G}{NIR + G}$
23	Green optimized Soil Adjusted Vegetation Index (GOSAVI) (Rondeaux et al., 1996)	$\frac{NIR - G}{NIR + G + 0.16}$
24	Green and Red Normalized Vegetation Index (GRNDVI) (Wang et al., 2007)	$\frac{NIR - G - R}{NIR + G + R}$
25	Green-Red Vegetation Index (GRVI) (Falkowski et al., 2005)	$\frac{G - R}{G + R}$
26	InfraRed Porcentage Vegetation Index (IPVI) (Crippen, 1990)	$\frac{NIR}{R + NIR}$
27	Inverted Red-Edge Chlorophyll Index (IRECI) (Guyot & Baret, 1988)	$(RedEdge3 - R) * \frac{RedEdge2}{RedEdge1}$
28	Leaf Area Index (LAI) (Boegh et al., 2002)	$3.618 * \frac{2.5 * (NIR - R)}{NIR + 6 * R - 7.5 * B + 1} - 0.118$
29	Moisture Adjusted Vegetation Index (MAVI) (Zhu et al., 2014)	$\frac{NIR - R}{R + NIR + SWIR}$
30	Modified Chlorophyll Absorption in Reflectance Index 1 (MCARI 1) (Haboudane et al., 2004)	$1.2 * (2.5 * (NIR - R) - 1.3 * (NIR - G))$
31	Modified Chlorophyll Absorption in Reflectance Index 2 (MCARI 2) (Zarco-Tejada et al., 2001)	$1.5 * \frac{2.5 * (NIR - R) - 1.3 * (NIR - G)}{((2 * NIR + 1)^2 - (6 * NIR - 5 * \sqrt{R}) - 0.5)^{0.5}}$
32	Modified Green Red Vegetation Index (MGRVI) (Bendig et al., 2015)	$\frac{G^2 - R^2}{G^2 + R^2}$
33	Modified Soil Adjusted Vegetation Index 1 (MSAVI 1) (Qi et al., 1994)	$\frac{NIR - R}{NIR + R + 0.5} * 1.5$
34	Modified Soil Adjusted Vegetation Index 2 (MSAVI 2) (Qi et al., 1994)	$\frac{(2 * NIR + 1) - \sqrt{(2 * NIR + 1)^2 - 8 * (NIR - R)}}{2}$
35	Modified Simple Ratio (MSR) (Chen, 1996)	$\frac{\frac{NIR}{R} - 1}{\sqrt{\frac{NIR}{R} + 1}}$
36	MERIS Terrestrial Chrolophyll Index (MTCI) (Dash & Curran, 2007)	$\frac{RedEdge2 - RedEdge1}{RedEdge1 - R}$
37	Normalized Burn Ratio (NBR) (Roy et al., 2006)	$\frac{NIR - SWIR}{NIR + SWIR}$

38	Normalized Canopy Index (NCI) (Vescovo & Gianelle, 2008)	$\frac{SWIR - G}{SWIR + G}$
39	Normalized Difference Index (Band 4 e 5 –Sentinel Satellite) (NDI 45) (Frampton et al., 2013)	$\frac{RedEdge1 - R}{RedEdge1 + R}$
40	Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974)	$\frac{NIR - R}{NIR + R}$
41	Normalized Green-Red Difference Index (NGRDI) (Tucker, 1980)	$\frac{G - R}{G + R}$
42	Non-linear Vegetation Index (NLI) (Goel & Qin, 1994)	$\frac{NIR^2 - R}{NIR^2 + R}$
43	Optimized Soil Adjusted Vegetation Index (OSAVI) (Rondeaux et al., 1996)	$\frac{NIR - R}{NIR + R + 0.5}$
44	Plant Senescence Reflectance Index (PSRI) (Merzlyak et al., 1999)	$\frac{R - B}{RedEdge2}$
45	Perpendicular Vegetation Index (PVI) (Richardson & Wiegand, 1977)	$\sqrt{(0.355 * NIR - 0.149 * R)^2 + (0.355 * R - 0.852 * NIR)^2}$
46	Red-Blue Normalized Vegetation Index (RBNDVI) (Wang et al., 2007)	$\frac{NIR - R - B}{NIR + R + B}$
47	Renormalized Difference Vegetation Index (RDVI) (Roujean & Breon, 1995)	$\frac{\sqrt{NIR - R}}{NIR + R}$
48	Red Edge Normalized Difference Vegetation Index/Normalized Difference Red Edge (RENDRE) (Fernández-Manso et al., 2016)	$\frac{NIR - RedEdge1}{NIR + RedEdge1}$
49	Red-Green Index (RGI) (Gamon & Surfus, 1999)	$\frac{R}{G}$
50	Red Green Blue Vegetation Index (RGBVI) (Bendig et al., 2015)	$\frac{G^2 - B * R}{G^2 + B * R}$
51	Rice Growth Vegetation Index (RGVI) (Nuarsa et al., 2011)	$1 - \frac{(R + G)}{NIR + SWIR1 + SWIR2}$
52	Sentinel-2 Red-Edge Position (S2REP) (Frampton et al., 2013)	$705 - \frac{35 * (0.5 * (RedEdge3 + R) - RedEdge1)}{RedEdge2 - RedEdge1}$
53	Soil Adjusted Vegetation Index (SAVI) (Huete, 1988)	$1.5 * \frac{NIR - R}{NIR + R + 0.5}$
54	Specific Leaf Area Vegetation Index (SLAVI) (Lymburner et al., 2000)	$\frac{NIR}{R + SWIR}$
55	Simple Ratio or Ration Vegetation Index (SR) (Jordan, 1969)	$\frac{NIR}{R}$
56	Triangular Vegetation Index (TVI) (Broge & Leblanc, 2001)	$0.5 * (120 * (NIR - G) - 200 * (R - G))$
57	Visible Atmospherically Resistant Index (VARI) (Gitelson et al., 2003)	$\frac{G - R}{G + R - B}$
58	Vegetativen (VEG)	$\frac{G}{R^{0.667} * B^{0.333}}$

Plant and Soil sampling and chemical analyses

For soil sampling, soil was collected from each plot at 0.0-0.2 m depth in 2016, 2018, 2020 and 2021 to evaluate soil fertility, texture and micronutrients according to the methods described in (EMBRAPA, 2009) and can be summarized as follows: pH was determined in a solution of soil:water of 1:2.5. Organic matter was determined using the Walkey and Black method. Phosphorus was determined using the Melich-1 and an UV-VIS spectrophotometer at 880 nm. Calcium, Magnesium and Potassium were also determined using Mehlich-1 and Atomic Absorption Spectrophotometry (AAS). Aluminum was determined using KCl 1M while Potential acidity (H.Al) with Calcium acetate and both were titrated with NaOH 0.1 M. CEC was determined by the sum of potential acidity and bases. For S, extraction was carried with $Ca(H_2PO_4)$ 500 mg/L and determined in UV-VIS at 420 nM. For B, it was extracted in hot water and determined in UV-VIS at 420 nm. The available content of Fe, Mn, Cu, and Zn in the soil samples was extracted with Mehlich-1 and determined in AAS.
For Teak leaves, the sampling was performed in 10 plants using the middle lower leaves. They were cleaned with distilled watter and then dried at 60°C in an air stove until reaching constant weight. The dried samples of plant tissues were weighted (500 mg each) and digested with H2SO4 (95%) for N and, HNO3 (65%) and $HClO_4$ (70 %) for P, K, Ca, Mg, K, Cu, Fe, Mn and Zn. Chemical procedures for determination of concentration of nutrients are detailed elsewhere (EMBRAPA, 2009). They are summarized as follows; Nitrogen was determined by MicroKjeldah method. In the case of K, Ca, Mg, Cu, Fe, Mn and Zn the determination of the nutrients in the filtrate were determined using ICP-OES. B was determined by colorimetric method using azomethine-H at 550 nm. P using molibdate-ascorbate method at 420 nm. Finally, S was determined by turbidmetric method at 420 nm.
Topographic and environmental characteristics
In the case of climatic characteristics, only precipitation (mm) was measured using a pluviometer. From this measurement, other variables were estimated such as days without rain, rain deficit (considering an annual precipitation of 1200 mm as adequate), monthly and annual precipitation (mm).

For topographic variables elevation data was obtained using “elevatr” package (Hollister, 2023). With this information and the use of “MultiscaleDTM” package (Ilich et al., 2024), the following geomorphometric terrain attributes were calculated: Aspect, Difference from Mean Value - DMV, Eastness, Elevation, Features, Mean curvature, Maximum curvature, Minimum curvature, Northness, Profile curvature, Planar curvature, Relative Position of a focal cell, Roughness Index Elevation - RIE, Slope, Ruggedness measure, Standard deviation of bathymetry adjusted for slope, Surface area, Surface area to planar area rugosity -SAPA, Twist curvature and Topographic Position Index - TPI.

Modelling and statistical analyses

Procedures and inputs for modelling scheme are summarized in figure 2. For modelling, the procedures described in Fernandes-Filho et al., (2024) were. All the following procedures were repeated 50 times for each machine learning algorithm. First, data was divided into training and testing data. For training phase, 75% of data from farms were used while the remaining 25% for prediction assessment (testing data). Descriptive statistics (minimum, quartil-1, mean, median, quartil-3, standard deviation, maximum, interquartile range and coefficient of variation) were performed for all biometric variables (DBH, Height, G, Commercial Height, Volume and IMA) and number of plants. In the case of covariables used for modelling, soil variables, topographic variables obtained from DEM and Vegetation indexes (VI) were used.

The data obtained from descriptive statistics was used for modelling procedures. After, a correlation matrix was constructed using Spearman correlation (5% confidence), between each pair of highly correlated variables ($r > |0.90|$), and the variable with the highest global correlation was eliminated using “findcorrelation” function in the caret package (Kuhn, 2024). After, with the selected variables, the Recursive Feature Elimination algorithm (RFE) was performed to select the best subset of predictors and their relative importance (Kuhn & Johnson, 2013). Consequently, the selected predictors were used to train each selected model and their relative importance (0-100%) were calculated using the “VarImp” function in caret package.

The 06 machine learning models used were: Cubist (C), General Linear Model (GLM), Random Forest (RF), Weighted K-Nearest Neighbor Classifier (KKNN), Support Vector Machine (SVM) and Neural Network (NN). The Cubist model is a rule-based ensemble regression model based on the work of Quinlan (1992), that creates a basic model tree that has a separate linear regression model corresponding to each terminal node. The General Lineal model is a flexible statistical framework used to model the relationship between two variables (independent and dependent), being a generalization of multiple regression where its simplicity, interpretability and ease of implementation make it a powerful statistical tool. The Random Forest model can be used for both classification and regression. It operates by constructing multiple decision trees during training and combines its output to improve prediction and control overfitting. The KKNN model can also be used both for classification and regression, it predicts the target values based on the values of their nearest neighbors, with closer neighbors having a greater influence on the prediction. The SVM model is effective in high dimensional spaces, it predicts continuous target variables by finding a function that approximates the relationship between input features and the output, while maintaining a margin of tolerance. The NN models are designed to predict continuous target variables by learning complex, nonlinear relationships between input features and output values. Inspired by the structure and function of biological neural networks, they are highly flexible and capable of modeling intricate patterns in data.

Models were trained and tuned using a repeated cross-validation with 10 folds and 3 repeats. The tuning was made testing 3 different values for each hyperparameter. The optimization criterium was selecting the model configuration which achieved the biggest F1-Score value. Finally, the trained model was validated by comparing predicted data with the test set. To select the algorithm with the best performance, Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and the coefficient of determination (R^2) were used and calculated as follows:

$$MAE = \frac{\sum_{i=1}^{n} |Y_i - X_i|}{n} \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (X_i - Y_i)^2} \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(X_i - Y_i)^2}{\sum_{i=1}^{n}(\bar{Y} - Y_i)^2} \quad (3)$$

Where n is the number of observations Xi are the predicted values, Yi are the observed values and Ȳ is the mean observed value. These error metrics were calculated for the prediction of each model to compare and select the best algorithm with the higher R^2 and lower MAE and RMSE. All modelling procedures and statistical analyses were performed in R, version 4.1.2 (R Core Team, 2021).

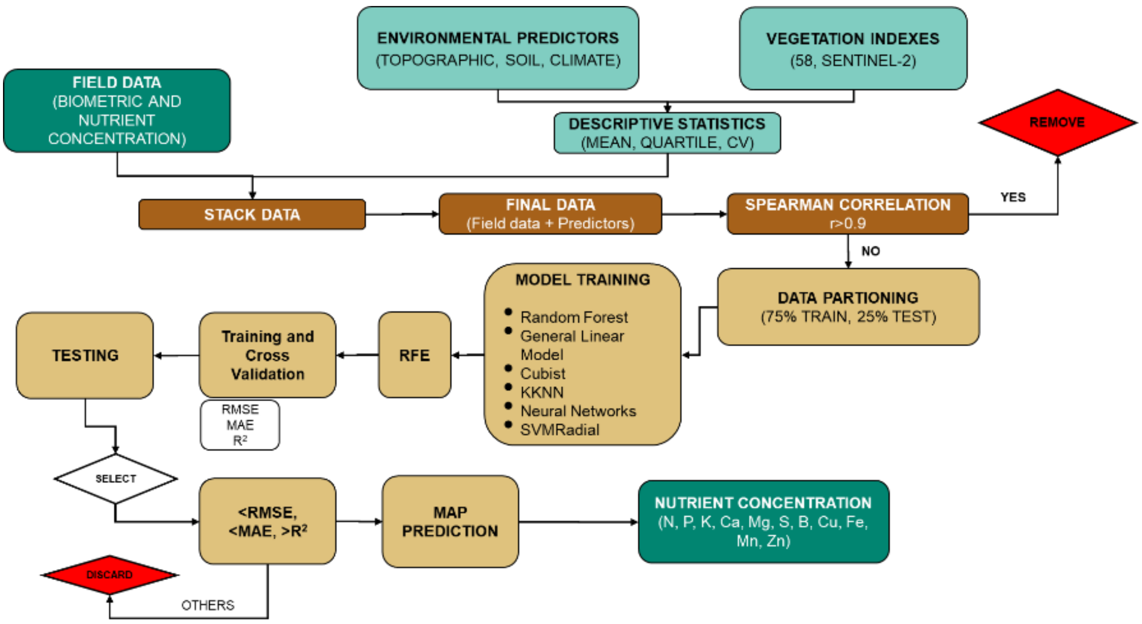

Figure 2. Modelling scheme of research for predicting plant nutrients concentration and growth in teak clones

RESULTS AND DISCUSSION

Nutrient concentration of Teak (*Tectona grandis*) plants

Nutrient concentrations are presented in figure 3 for macronutrients (N, P, K, Ca, Mg and S) in g/kg and figure 4 for micronutrients (B, Cu, Fe, Mn and Zn) in mg/kg in the different teak plots in Mato Grosso Brazil. In the case of macronutrients, N highest concentrations are observed in 2022, where “Santo Antonio” has the highest mean with 21.29 g/kg while “Itamaraty 2” the lowest with 20.42 g/kg.

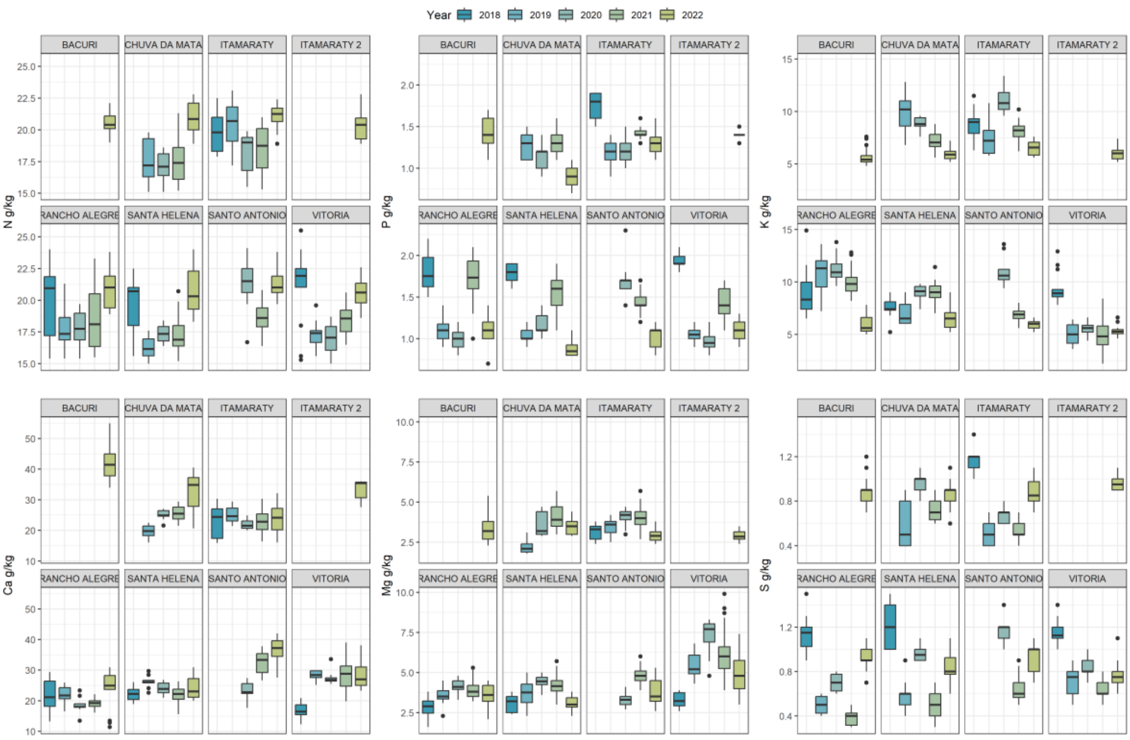

Figure 3. Macronutrients (N, P, K, Ca, Mg and S) concentration in teak (Tectona grandis) stands from 2018 to 2022 in Mato grosso, Brazil

For P, all the highest concentrations are presented in the first year of sampling (2018), and have been decreasing over the years, with the lowest values observed in “Santa Helena” and the Highest in “Bacuri” with 0.89 g/kg and 1.42 g/kg, respectively. For K, a similar trend is observed as in P, with the lowest mean observed in “Vitoria” with 5.33 g/kg and the highest in “Santa Helena” with 6.59 g/kg. Ca and Mg have similar values over the years in most plots, however, in the case of Ca, Santo Antonio” had an increasing trend over the years. The highest mean is observed in “Bacuri” for Ca with 42.2 g/kg and in “Vitoria” for Mg with 4.90 g/kg, while the lowest mean in “Itamaraty” with 23.6 g/kg and “Itamaraty” with 2.92 g/kg for Ca and Mg, respectively. For S, the concentrations were highly variable among the years, with the highest mean presented in 2018. The “Itamaraty 2” and “Vitoria”, presented the highest and lowest mean values with 0.97 g/kg and 0.76 g/kg, respectively.

For micronutrients, B concentrations evolved with an increasing trend over the years. For plots, “Rancho Alegre” presented the highest mean, while “Santa Helena” the lowest with 40.42 mg/kg and 36.07 mg/kg. For Cu, an increasing trend was observed with the highest means in the final year. “Rancho Alegre” had the highest mean with 19.37 mg/kg while “Santa Helena” the lowest with 10.85 mg/kg. Fe presented the highest mean concentration in 2022, with similar values between sites. “Bacuri” presented the highest mean with 344.4 mg/kg, while “Santa Helena” the lowest with 275.93 mg/kg. For Mn, values varied over the years, with “Itamaraty 2” having the highest value with 139.7 mg/kg while “Vitoria” the lowest with 81.6 mg/kg. Finally, for Zn similar values were observed between year from most sites, with the highest value observed in “Itamaraty 2” and the lowest in “Chuva da Mata” with 14.97 mg/kg and 10.32 mg/kg, respectively.

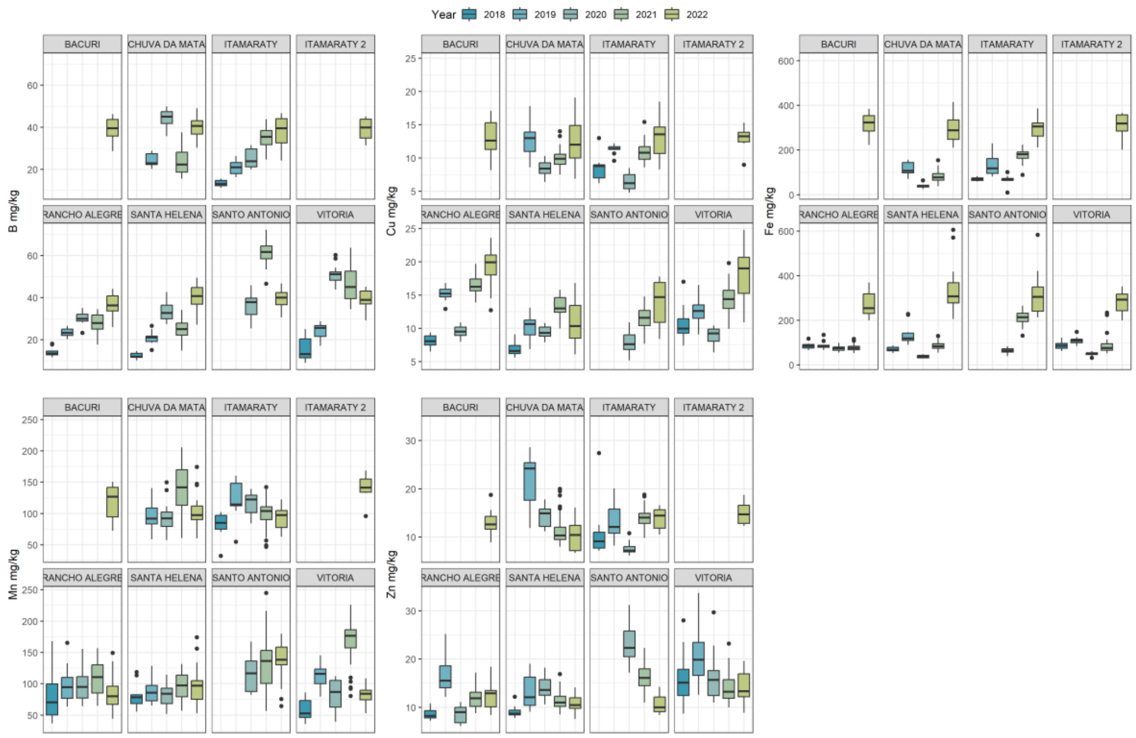

Figure 4. Micronutrients (B, Cu, Fe, Mn and Zn) concentration in teak (Tectona grandis) stands from 2018 to 2022 in Mato grosso, Brazil

Topographic and environmental variables

Topographic and precipitation variables are presented in table 2. In general, for all variables non-significant differences were observed between the fields (p-value > 0.05), except for Aspect, Eastness, Northness, RPS, DMV, TPI, Elevation and the Mean curvature. No major variation in slope % between plots was observed; however, mean aspect and elevation were significantly different between stands. “Chuva de Mata”, “Itamaraty” and “Santo Antonio” presented the highest Aspect °, while “Bacuri” and “Itamaraty" the highest elevation %. In the case of Eastness, “Bacuri” and “Vitoria” presented the highest values while “Itamaraty” the lowest. For Northness, RPS, DMV and TPI, “Bacuri” represented the highest value while “Vitoria” and “Chuva da Mata” the lowest.

Annual precipitation was higher in “Santa Helena” (1517 mm) and the lowest value was observed in “Bacuri” (1176 mm). For days with rain, the farm with the highest value was “Bacuri” (318 days), and the lowest were observed in “Chuva da Mata” (292 days) and “San Antonio” (293 days). In the case of annual precipitation deficit, “Bacuri” was the only farm that presented a precipitation deficit of 25 mm. All precipitation variables presented significant differences (p-value < 0.01).

Table 2. Environmental variables (Topographic and precipitation) mean (SD) values in seven different Teak stands in Mato Grosso, Brazil from 2017-2022

Variables	Bacuri	Chuva da Mata	Itamaraty	Rancho Alegre	Santa Helena	Santo Antonio	Vitória	p-value[1]
Topographic variables								
Slope %	3.44 (0.64)	2.91 (0.39)	2.92 (0.52)	2.79 (0.44)	3.06 (0.42)	2.95 (0.59)	3.03 (0.69)	0.14
Aspect °	157 (31)	194 (17)	198 (28)	166 (13)	163 (18)	197 (26)	149 (26)	<0.001
Eastness °	0.22 (0.24)	-0.14 (0.14)	-0.17 (0.26)	0.15 (0.12)	0.14 (0.16)	-0.14 (0.23)	0.28 (0.16)	<0.001
Northness °	0.23 (0.22)	-0.07 (0.33)	-0.12 (0.27)	-0.10 (0.20)	0.01 (0.22)	-0.03 (0.31)	-0.21 (0.28)	<0.001
Surface	84.41 (0.08)	84.35 (0.04)	84.35 (0.05)	84.34 (0.04)	84.38 (0.05)	84.36 (0.06)	84.37 (0.08)	0.085
SAPA*	1.0003 (0.0001)	1.0003 (0.0000)	1.0002 (0.0000)	1.0002 (0.0000)	1.0003 (0.0000)	1.0002 (0.0000)	1.0002 (0.0000)	0.6
RIE	0.089 (0.007)	0.089 (0.004)	0.088 (0.005)	0.086 (0.005)	0.086 (0.004)	0.086 (0.006)	0.085 (0.005)	0.4
RPS	0.007 (0.008)	-0.001 (0.005)	0.001 (0.003)	0.002 (0.004)	0.003 (0.006)	0.005 (0.010)	0.002 (0.004)	0.03
Adsd	0.111 (0.012)	0.110 (0.008)	0.107 (0.006)	0.106 (0.008)	0.107 (0.005)	0.106 (0.007)	0.105 (0.009)	0.7
DMV	0.007 (0.008)	-0.001 (0.005)	0.001 (0.003)	0.002 (0.004)	0.003 (0.006)	0.005 (0.010)	0.002 (0.004)	0.03
TPI	0.008 (0.009)	-0.001 (0.006)	0.001 (0.004)	0.002 (0.005)	0.003 (0.006)	0.005 (0.012)	0.002 (0.005)	0.03
Elevation %	217 (8)	199 (12)	218 (11)	209 (8)	213 (6)	197 (6)	189 (12)	<0.001
Profile Curvature	0.0001 (0.0002)	0.0000 (0.0002)	0.0000 (0.0001)	0.0000 (0.0002)	0.0000 (0.0001)	0.0001 (0.0003)	0.0001 (0.0001)	0.3

Planar Curvature	0.0002 (0.0003)	0.0000 (0.0002)	0.0000 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0000 (0.0001)	0.2
Twist curvature	0.0000 (0.0000)	0.0000 (0.0001)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0001)	0.0000 (0.0000)	>0.9
Mean Curvature	0.0001 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)	0.0001 (0.0001)	0.0001 (0.0002)	0.0000 (0.0001)	0.031
Maximum curvature	0.0020 (0.0003)	0.0018 (0.0001)	0.0018 (0.0001)	0.0018 (0.0001)	0.0018 (0.0002)	0.0018 (0.0003)	0.0018 (0.0001)	0.4
Minimum Curvatre	-0.0017 (0.0002)	-0.0018 (0.0002)	-0.0017 (0.0001)	-0.0017 (0.0001)	-0.0017 (0.0001)	-0.0017 (0.0001)	-0.0017 (0.0001)	0.3
Features	4.93 (0.07)	4.88 (0.06)	4.90 (0.02)	4.90 (0.03)	4.91 (0.04)	4.91 (0.06)	4.89 (0.06)	0.5
Precipitation variables								
Annual precipitation	1,176 (0)	1,401 (225)	1,358 (240)	1,421 (259)	1,517 (295)	1,352 (272)	1,378 (297)	<0.001
Days with rain	318 (0)	292 (16)	300 (10)	300 (13)	300 (13)	293 (11)	306 (12)	<0.001
Days without rain	47 (0)	73 (16)	65 (10)	65 (13)	65 (13)	72 (11)	59 (12)	<0.001
Precipitation deficit	25 (0)	-201 (225)	-159 (241)	-221 (259)	-317 (295)	-153 (272)	-178 (297)	<0.001

*SAPA=Surface area to planar area rugosity, RIE: Roughness Index Elevation, RPS: Ruggedness measure, Adsd: Standard deviation of bathymetry adjusted for slope, DMV: Difference from mean value, TPI: Topographic Position Index
[1]Kruskal-Wallis rank sum test

Variable exploration

Variable exploration was carried out with the use of Principal Component Analysis (PCA) divided into 04 subsets: Soil, Vegetation Indexes, Topographic and Climatic and Foliar variables. The PCAs are presented in figure 5. For the first PCA (Soil variables) the first two dimensions explained 59.3% of data variance. The first dimension (39.6 % variance) had a higher correlation (r>0.7) with Ca, Mg, OM, CEC and Clay. While the second dimension (19.6% variance) with pH and potential acidity. Also, Clay, Silt, available Zn and Cu seem to be the most important variable for distinction from “Vitoria” site in relation to the other farms. The same perspective can be observed in the case of Sand for “Itamaraty” and “Chuva da Mata” areas. For the second PCA (Vegetation indexes), the first two dimensions explained 87.8% of the variance for this subset, being most of the Vegetation indexes highly correlated, with the majority being highly correlated (r>0.7) with the first dimension (73.3% variance), with the exception of LAI, NCI, ARI1, CRI1 and CRI2 while the second dimension (14.5% of variance) is more correlated with ARI1, CI, CRI1, CRI2, EVI1, LAI, NCI, PSRI and RGVI. These vegetation indexes are probably more sensitive to variations in the field in comparison to the other selected VI in this work. For the third PCA (Topographic variables), the first two dimensions explained 55.3% of total variance. The first dimension (33.3 % of variance) was highly correlated (r>0.7) with the slope, standard deviation of bathymetry (a measure of rugosity) adjusted for slope (Adsd), Difference from Mean Value (dmv), and maximum curvature (maxc). The second dimension (22% of variance) was more correlated with the minimum curvature (minc).

Finally, for the last PCA, the first two dimensions accounted for 51.8% of total variance. The first dimension (33.8 %) was highly correlated (r>0.7) with Foliar P, Boron, Precipitation, Days with and without rain and annual precipitation deficit. The second dimension (18%) of variance with foliar K and Fe. In the case of "Chuva da Mata", Age (Id_Inv) and foliar Ca, have a higher relation with this farm, making it distinctive from other areas. For "Santo Antonio", Fe and K in leaves had also a major impact on distinction of this area.

The soil and foliar variables were the most important in terms of distinction of areas in comparison to the other variables.

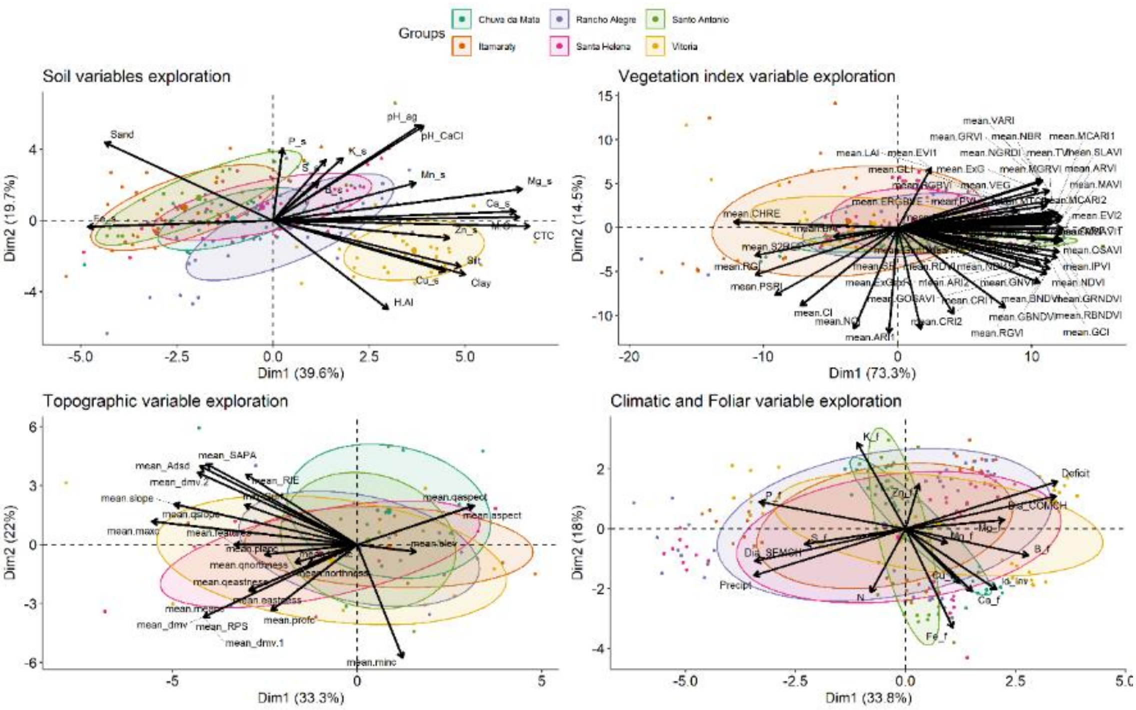

Figure 5. Variable exploration of soil, vegetation indexes, topographic and climatic and foliar variables in stands from 2018 to 2022 in Mato grosso, Brazil

Teak macronutrients modelling

Results from teak macronutrients (N, P, K, Ca, Mg and S) modelling using machine learning algorithms are presented in Figure 6 (RMSE), Figure 7 (MAE), Figure 8 (R^2) and Figure 9 (Predicted vs observed values). For all macronutrients, the lowest RMSE and MAE values and the highest R^2 were achieved with the use of Random Forest (RF) algorithm. Nevertheless, cubist performed with more error but with no significative differences with RF. In general, for all variables, prediction mean values of RMSE, MAE and R2 were more variable and lower than the training model.

In the case of macronutrients, mean values of RMSE (RF) for N, were 1.77 g/kg (train) and 1.86 g/kg (prediction), with similar values in cubist with 1.80 g/kg (train) and 1.87 g/kg (prediction). For P, 0.146 g/kg (train) and 0.150 g/kg (prediction). For K, 1.40 g/kg (train) and 1.49 g/kg (prediction). For Ca, 3.81 g/kg (train) and 4.01 g/kg (prediction). For Mg, 0.602 g/kg (train) and 0.617 g/kg (prediction). Finally, for S, 0.138 g/kg (train) and 0.143 g/kg (prediction). For all nutrients, GLM obtained the higher RMSE.

For the Mean Absolute Error (MAE), mean values in RF for N, were 1.39 g/kg (train) and 1.45 g/kg (prediction), with similar values in cubist with 1.41 g/kg (train) and 1.46 g/kg (prediction). For P, 0.116 g/kg (train) and 0.119 g/kg (prediction). For K, 1.03 g/kg (train) and 1.09 g/kg (prediction). For Ca, 2.93 g/kg (train) and 3.06 g/kg (prediction). For Mg, 0.479 g/kg (train) and 0.487 g/kg (prediction). Finally, for S, 0.112 g/kg (train) and 0.113 g/kg (prediction). For all nutrients, GLM obtained the higher MAE.

For the Coefficient of determination (R^2), mean values in RF for N, were 0.46 (train) and 0.39 (prediction), with similar values in cubist with 1.80 g/kg (train) and 1.87 g/kg (prediction). For P, 0.82 (train) and 0.80 (prediction). For K, 0.66 (train) and 0.63 (prediction). For Ca, 0.58 (train) and 0.51 (prediction). For Mg, 0.74 (train) and 0.72 (prediction). Finally, for S, 0.71 (train) and 0.69 (prediction). For all nutrients, GLM obtained the lowest R^2.

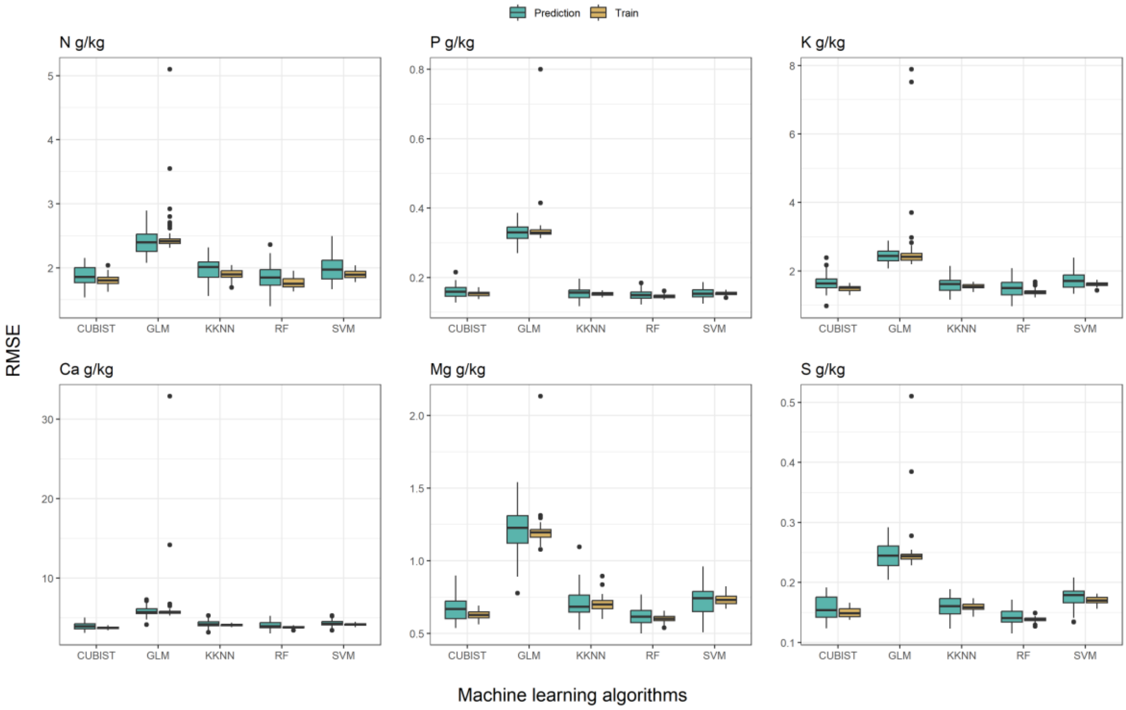

Figure 6. RMSE (Root Mean Square Deviation) of machine learning algorithms for nutrient concentration of N, P, K, Ca, Mg and S in g/kg in teaks stands in different farms from 2017 to 2022 in Matto Grosso-Brazil.

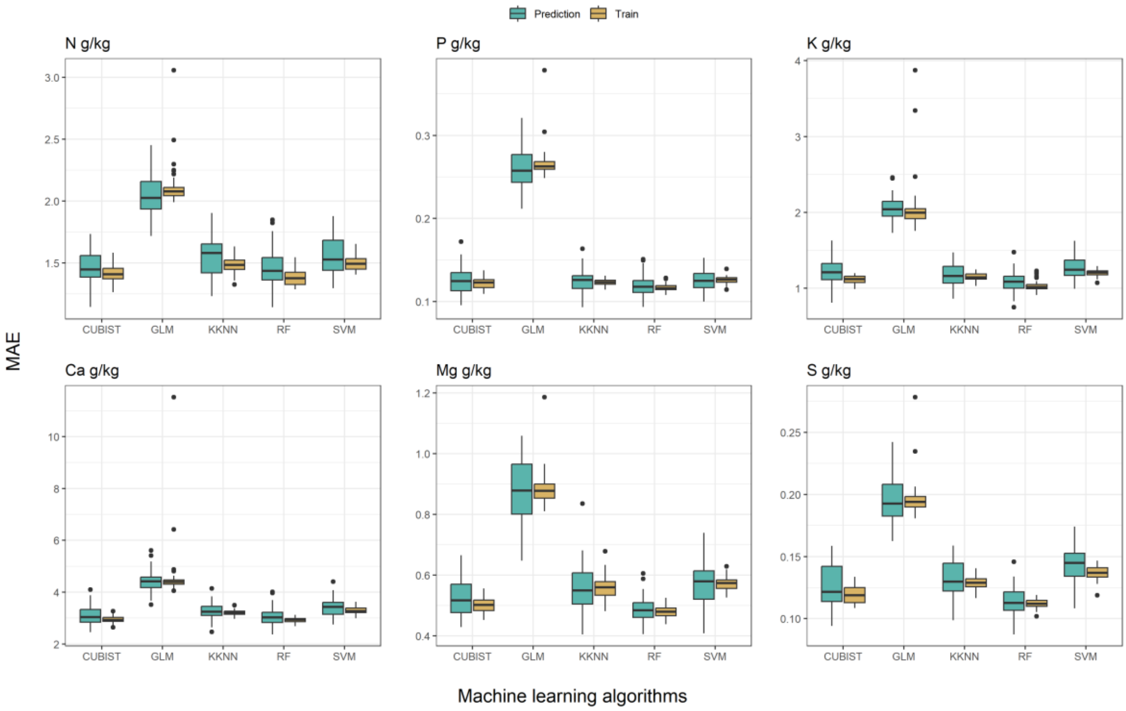

Figure 7. MAE (Mean Average Error) of machine learning algorithms for nutrient concentration of N, P, K, Ca, Mg and S in g/kg in teaks stands in different farms from 2017 to 2022 in Matto Grosso-Brazil.

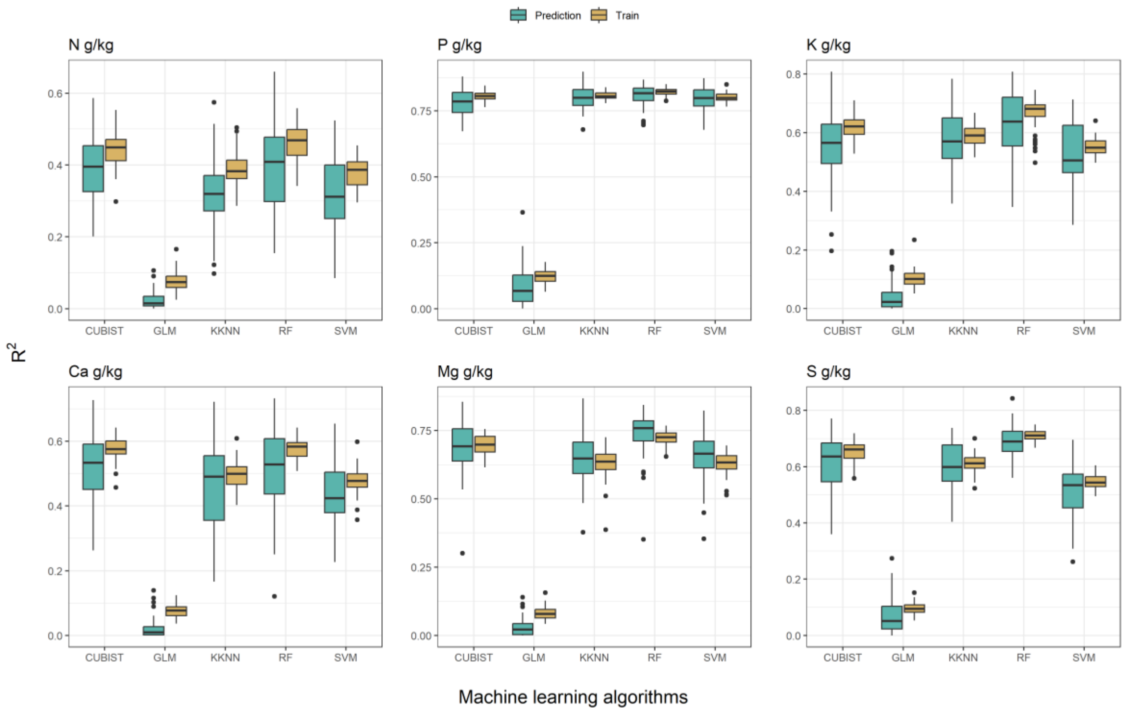

Figure 8. R^2 (Determination Coefficient) of machine learning algorithms for nutrient concentration of N, P, K, Ca, Mg and S in g/kg in teaks stands in different farms from 2017 to 2022 in Matto Grosso-Brazil.

Finally, the results of the observed macronutrients (N, P, K, Ca, Mg and S) in comparison to the predicted values using random forest algorithm are presented in Figure 9. In general, as expressed in the past metrics (RMSE, MAE and R^2) a good prediction was accomplished with most macronutrients, with exception of N and Ca, with lower prediction accuracy. However, as interpretation of foliar analysis is normally carried out in ranges, this error could be acceptable in the practical management of teak nutrition on the fields.

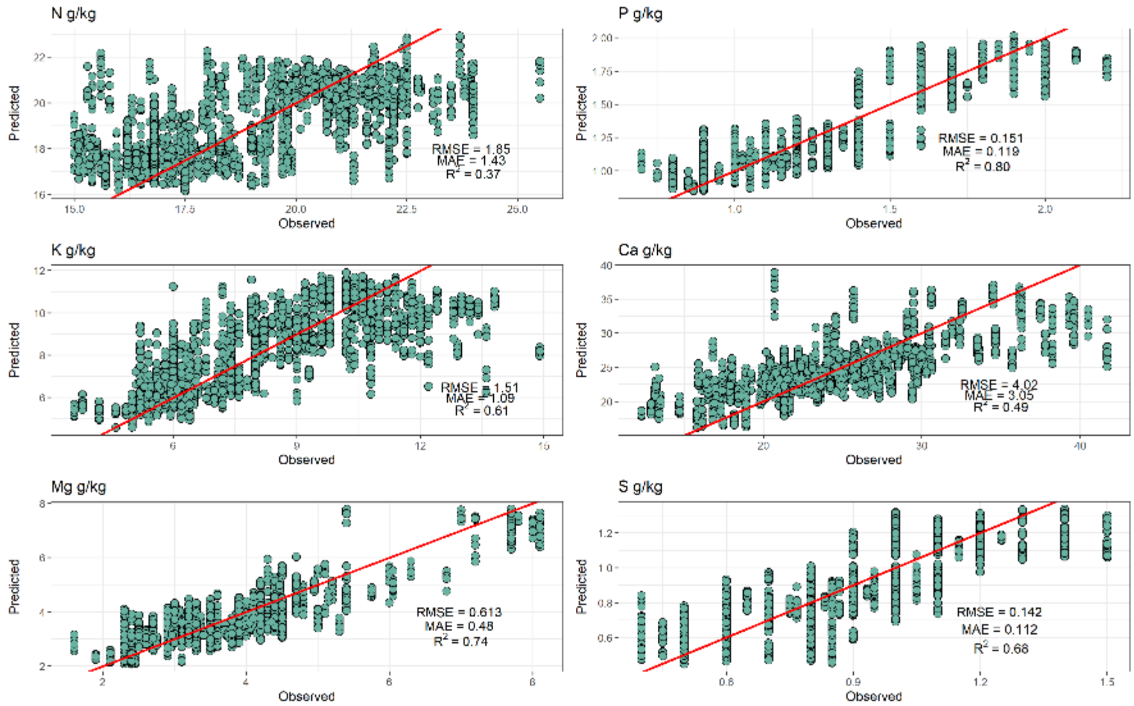

Figure 9. Predicted vs observed values of Random Forest machine learning algorithms for nutrient concentration of N, P, K, Ca, Mg and S in g/kg in teaks stands in different farms from 2017 to 2022 in Matto Grosso-Brazil.

Teak micronutrients modelling

Results from teak micronutrients (B, Cu, Fe, Mn and Zn) modelling using machine learning algorithms are presented in Figure 10 (RMSE), Figure 11 (MAE), Figure 12 (R^2) and Figure 13 (Predicted vs observed values). For all micronutrients, the lowest RMSE and MAE values and the highest R^2 were achieved with the use of Random Forest (RF) algorithm. Nevertheless, cubist performed with more error but with no significative differences with RF. In general, for all variables, prediction mean values of RMSE, MAE and R^2 were more variable and lower than the training model.

In the case of micronutrients, mean values of RMSE (RF) for B, were 4.54 mg/kg (train) and 4.61 mg/kg (prediction). For Cu, 2.58 mg/kg (train) and 2.75 mg/kg (prediction). For Fe, 50.9 mg/kg (train) and 53.9 mg/kg (prediction). For Mn, 21.8 mg/kg (train) and 23.5 mg/kg (prediction). Finally, for Zn, 3.51 mg/kg (train) and 3.58 mg/kg (prediction). For all nutrients, GLM obtained the higher RMSE.

For the Mean Absolute Error (MAE), mean values in RF for B, were 3.57 mg/kg (train) and 3.58 mg/kg (prediction). For Cu, 1.99 mg/kg (train) and 2.12 mg/kg (prediction). For Fe, 33.3 mg/kg (train) and 33.9 mg/kg (prediction). For Mn, 17.7 mg/kg (train) and 18.9 mg/kg (prediction). For Zn, 2.68 mg/kg (train) and 2.90 mg/kg (prediction). For all nutrients, GLM obtained the higher MAE.

For the Coefficient of determination (R^2), mean values in RF for B, were 0.85 (train) and 0.84 (prediction). For Cu, 0.57 (train) and 0.49 (prediction). For Fe, 0.82 (train) and 0.78 (prediction). For Mn, 0.49 (train) and 0.41 (prediction). For Zn, 0.58 (train) and 0.52 (prediction). For all nutrients, GLM obtained the lowest R2.

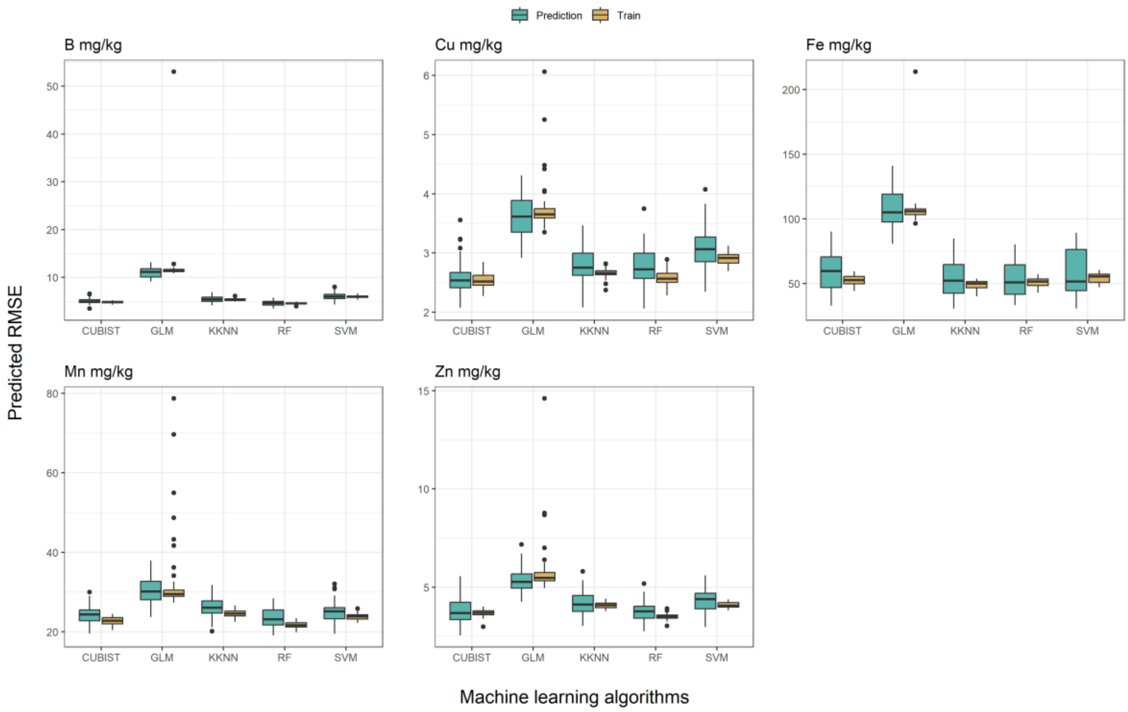

Figure 10. RMSE (Root Mean Square Deviation) of machine learning algorithms for nutrient concentration of B, Cu, Fe, Mn and Zn in mg/kg in teaks stands in different farms from 2017 to 2022 in Matto Grosso-Brazil.

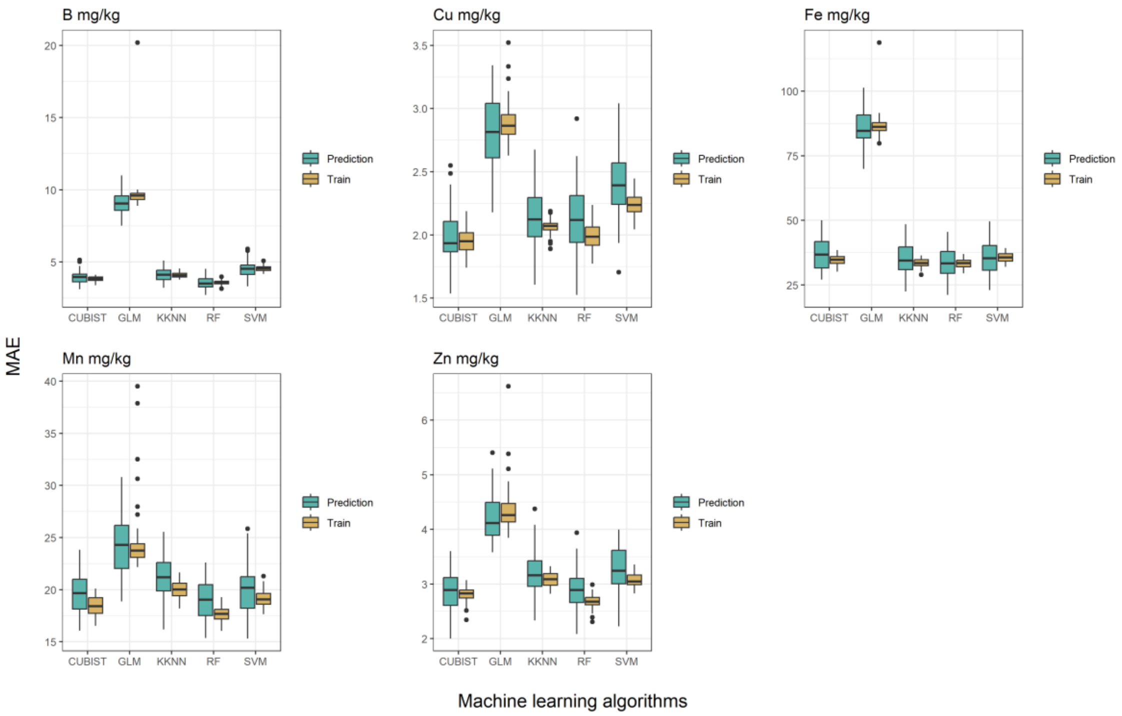

Figure 11. MAE (Mean Average Error) of machine learning algorithms for nutrient concentration of B, Cu, Fe, Mn and Zn in mg/kg in teaks stands in different farms from 2017 to 2022 in Matto Grosso-Brazil.

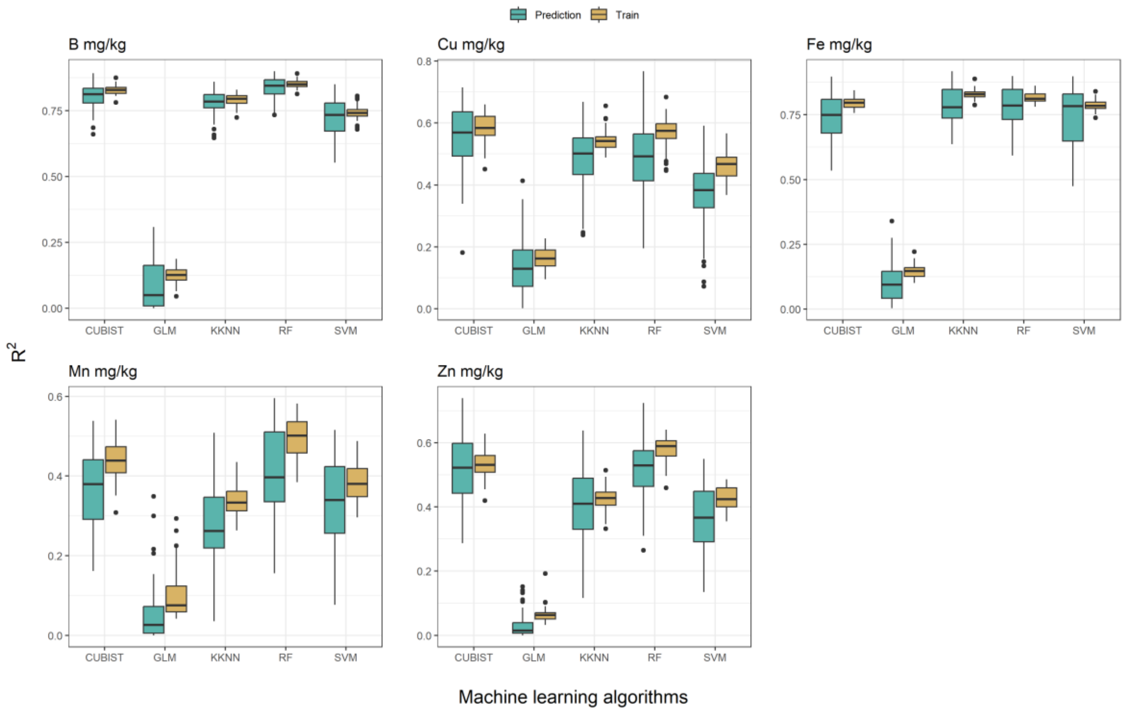

Figure 12. R^2 (Determination Coefficient) of machine learning algorithms for nutrient concentration of B, Cu, Fe, Mn and Zn in mg/kg in teaks stands in different farms from 2017 to 2022 in Matto Grosso-Brazil.

Finally, the results of the observed macronutrients (B, Cu, Fe, Mn and Zn) in comparison to the predicted values using random forest algorithm are presented in Figure 13. In general, as expressed in past metrics (RMSE, MAE and R^2) a good prediction was accomplished with most macronutrients, with exception of Cu and Mn, with lower prediction accuracy. However, as stated in the macronutrients modelling section, this error could be acceptable.

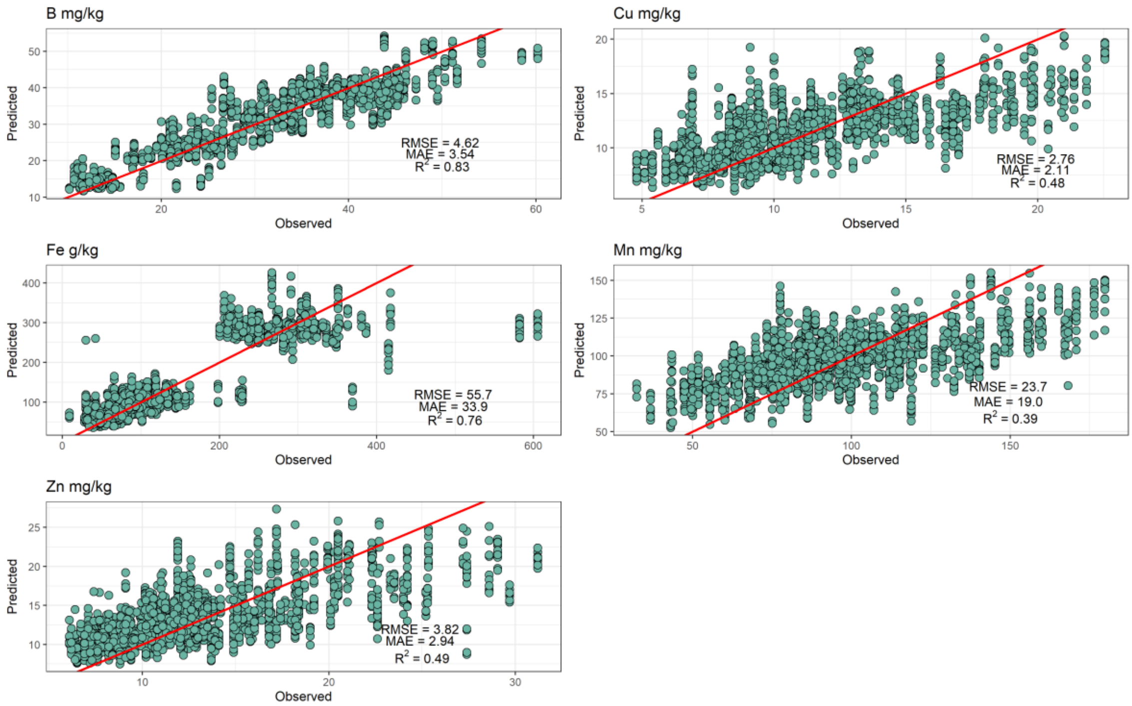

Figure 13. Predicted vs Observed values of Random Forest machine learning algorithms for nutrient concentration of B, Cu, Fe, Mn and Zn in mg/kg in teaks stands in different farms from 2017 to 2022 in Matto Grosso-Brazil.

Variable importance for nutrition modelling

Importance of selected variables for modelling for "Random Forest" algorithm for each nutrient is presented in figure 14. This algorithm was selected based on better performance in comparison to the others studied. In general, for all nutrients (N, P, K, Ca, Mg, S , B, Cu, Fe, Mn and Zn) studied, soil variables represented 39.3% of selected variables, vegetation indexes represented 32.7%, climate variables 17.7%, 8.5% the age of teak and topographic variables only 1.8%, indicating a low impact of topography in nutrient absorption in the studied area and the high representation of vegetation indexes and soil variables (72 %). For soil variables, the most repeatedly were available S (10 times), Clay (6 times) and Mn (5 times). In the case of vegetation indexes, the most repeatedly selected were MERIS Terrestrial Chlorophyll Index - MTCI (6 times), Normalized Burn Ratio - NBR (4 times) and Sentinel-2 Red-Edge Position - S2REP (3 times). For climate variables, days without rain (DIA_SEMCH) and the precipitation deficit (deficit) were the most important, being the latter selected for all nutrients.

In the case of each nutrient, only the 3 most important variables are mentioned. For N, Available B, S and Days without rain were indicated. For P and Mg, precipitation deficit, age and days without rain performed better. For K, S and Zn; precipitation deficit, age and available sulfur were selected. For Ca, the age, clay and available sulfur were observed. For B, precipitation deficit, available sulfur and days without rain. For Cu and Fe, available sulfur, age and available manganese. Finally, for Mn, Organic matter, the minimum of RGVI (Rice Growth Vegetation Index) and the precipitation deficit.

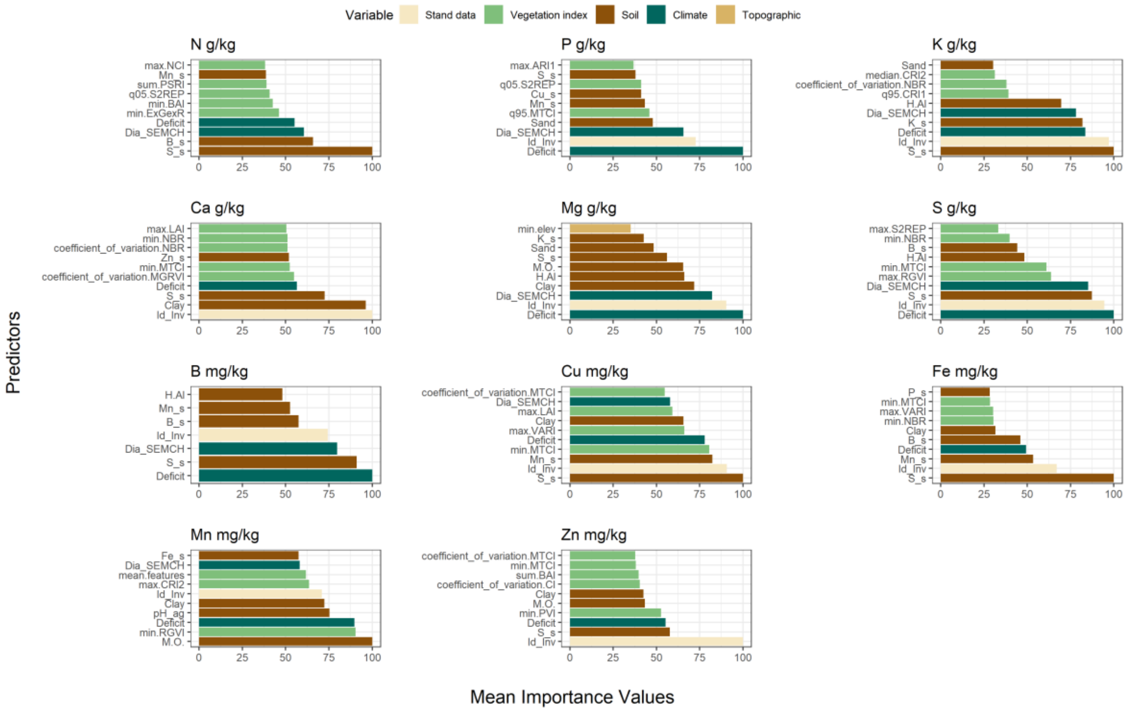

Figure 14. Predictors importance ranking selected by “Random Forest” for nutrient concentration of N, P, K, Ca, Mg and S in g/kg and B, Cu, Fe, Mn and Zn in mg/kg in teaks stands in different farms from 2017 to 2022 in Matto Grosso-Brazil.

Predicted maps for in Teak (Tectona grandis) plantations in Mato Grosso

Maps were constructed using a single model using all observations, considering that the errors and variance in these maps are related to the metrics presented in the models in the macro- and micronutrients modelling section.

Maps for macronutrients are presented in figures 15 to 20 while micronutrients in figures 21 to 26. In general, concentrations of macronutrients have increased or maintained at the same levels while micronutrients in most cases have decreased their levels in comparison to the initial year of monitoring. In the case of macronutrients, all values are in sufficiency or high nutrient range, with some exceptions arising to excessive levels such as K. For micronutrients, a continuous decrease in nutrient concentration has been observed in most farms. This can be a result of the lack of supply of these elements in the management of Teak. Care must be taken to avoid nutrient concentration reaching a low level, that can reduce the overall productivity of Teak plants.

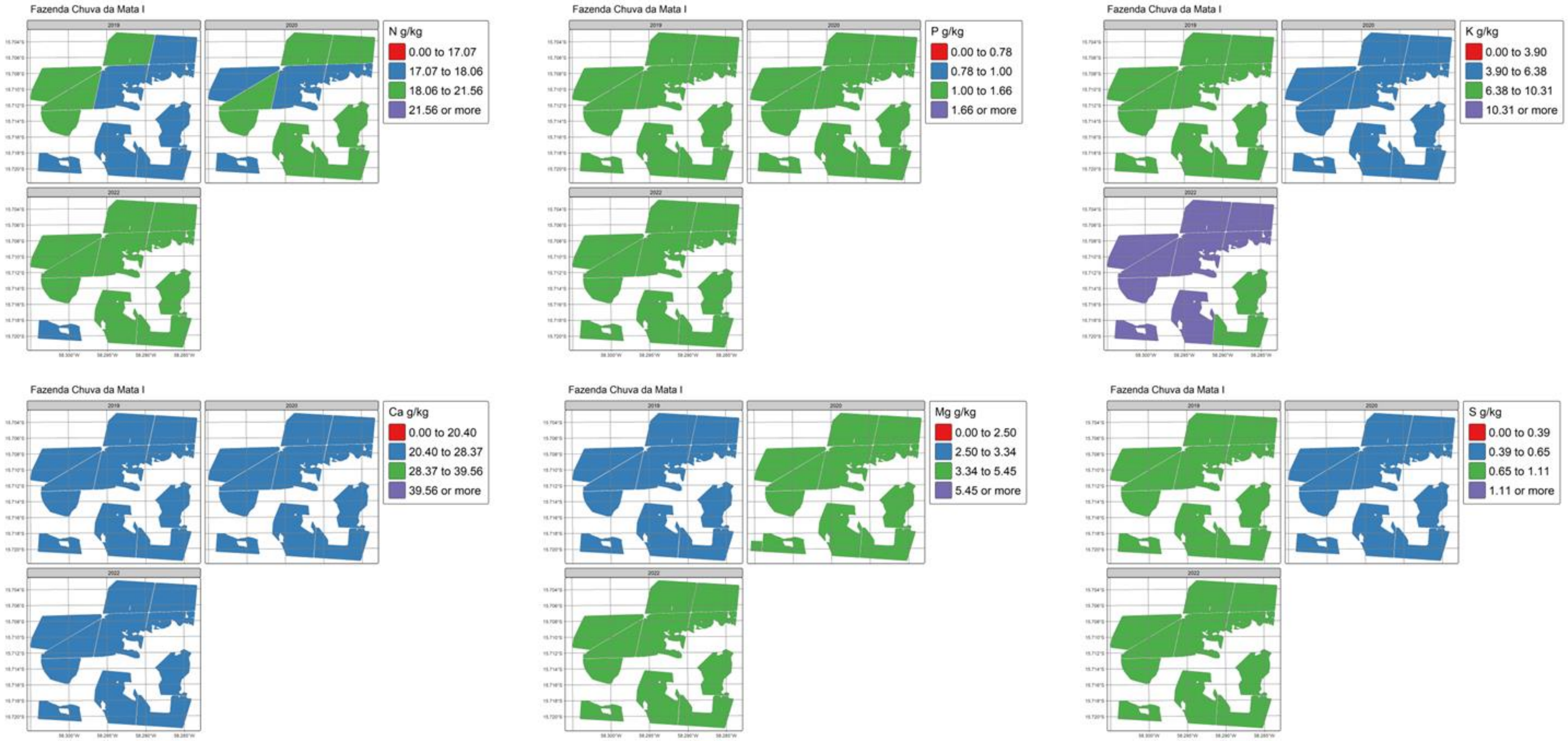

Figure 15. Map for predicted macronutrients (N, P, K, Ca, Mg and S) for Farm "Fazenda Chuva da Mata I" in Mato Grosso, Brazil. Color in red, blue, green and purple represent the low, sufficient, high and excessive ranges, respectively.

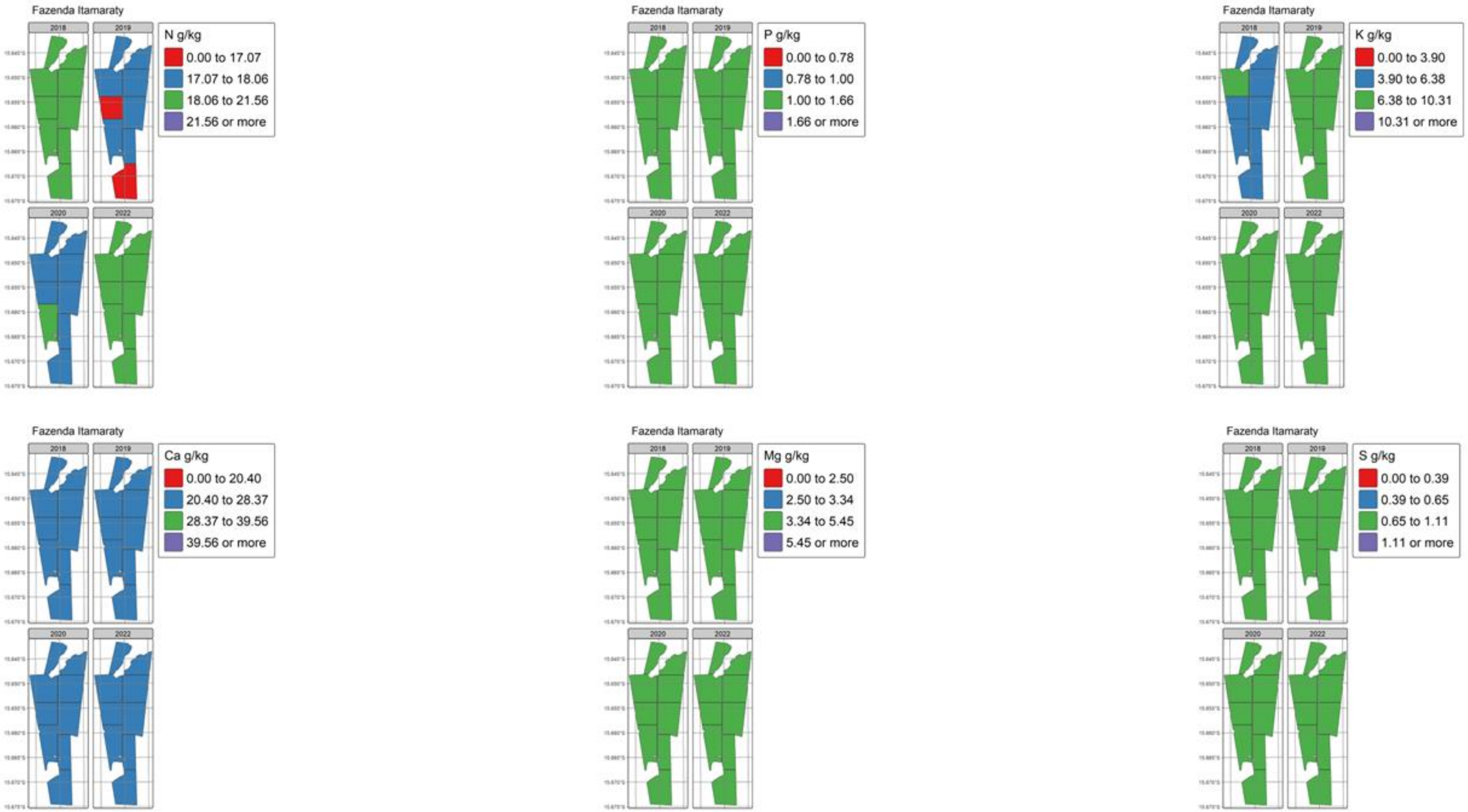

Figure 16. Map for predicted macronutrients (N, P, K, Ca, Mg and S) for Farm "Fazenda Itamaraty" in Mato Grosso, Brazil. Color in red, blue, green and purple represent the low, sufficient, high and excessive ranges, respectively.

Figure 17. Map for predicted macronutrients (N, P, K, Ca, Mg and S) for Farm "Fazenda Rancho Alegre " in Mato Grosso, Brazil. Color in red, blue, green and purple represent the low, sufficient, high and excessive ranges, respectively.

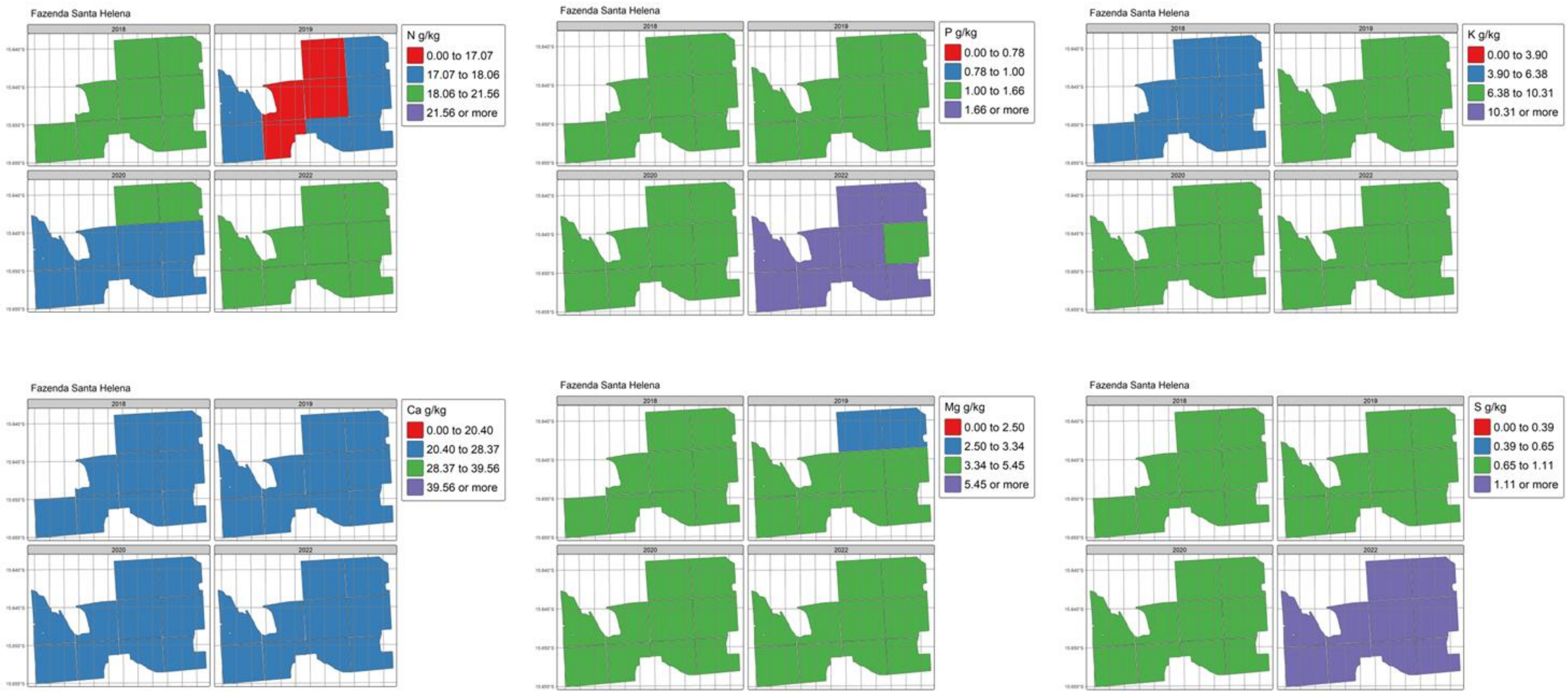

Figure 18. Map for predicted macronutrients (N, P, K, Ca, Mg and S) for Farm "Fazenda Santa Helena" in Mato Grosso, Brazil. Color in red, blue, green and purple represent the low, sufficient, high and excessive ranges, respectively.

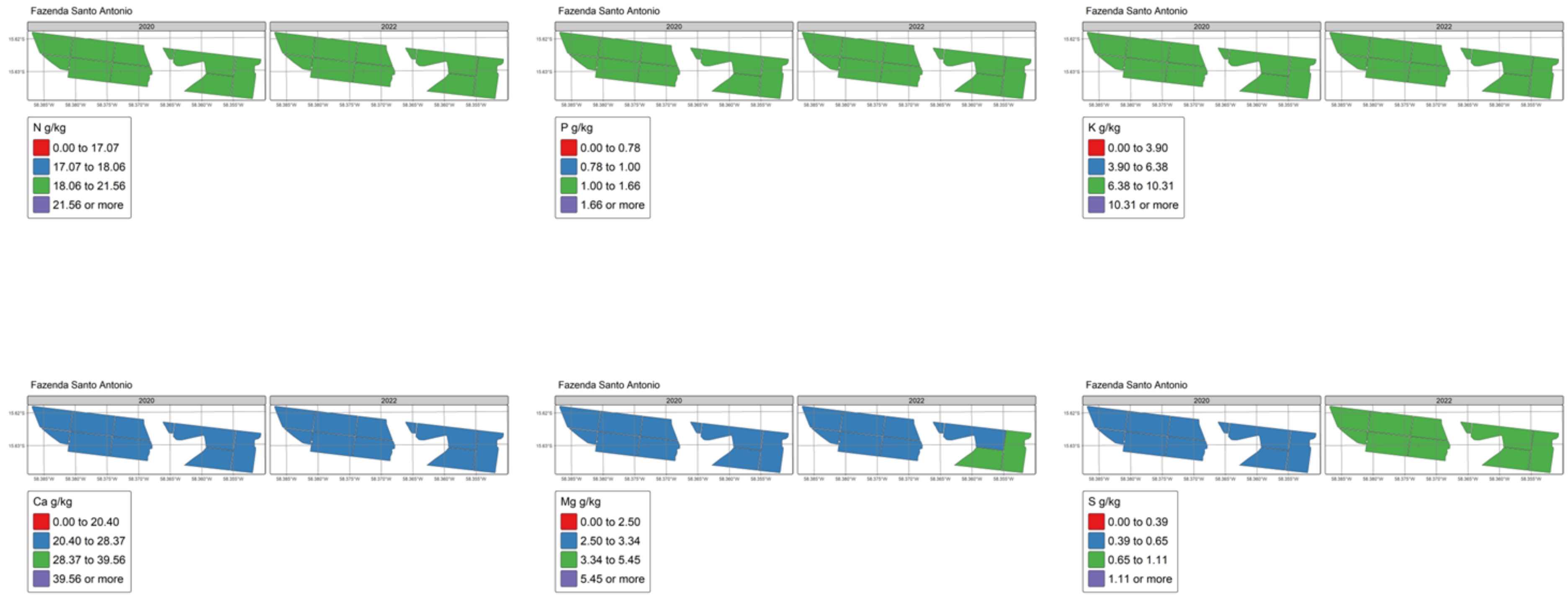

Figure 19. Map for predicted macronutrients (N, P, K, Ca, Mg and S) for Farm "Fazenda Santo Antonio" in Mato Grosso, Brazil. Color in red, blue, green and purple represent the low, sufficient, high and excessive ranges, respectively.

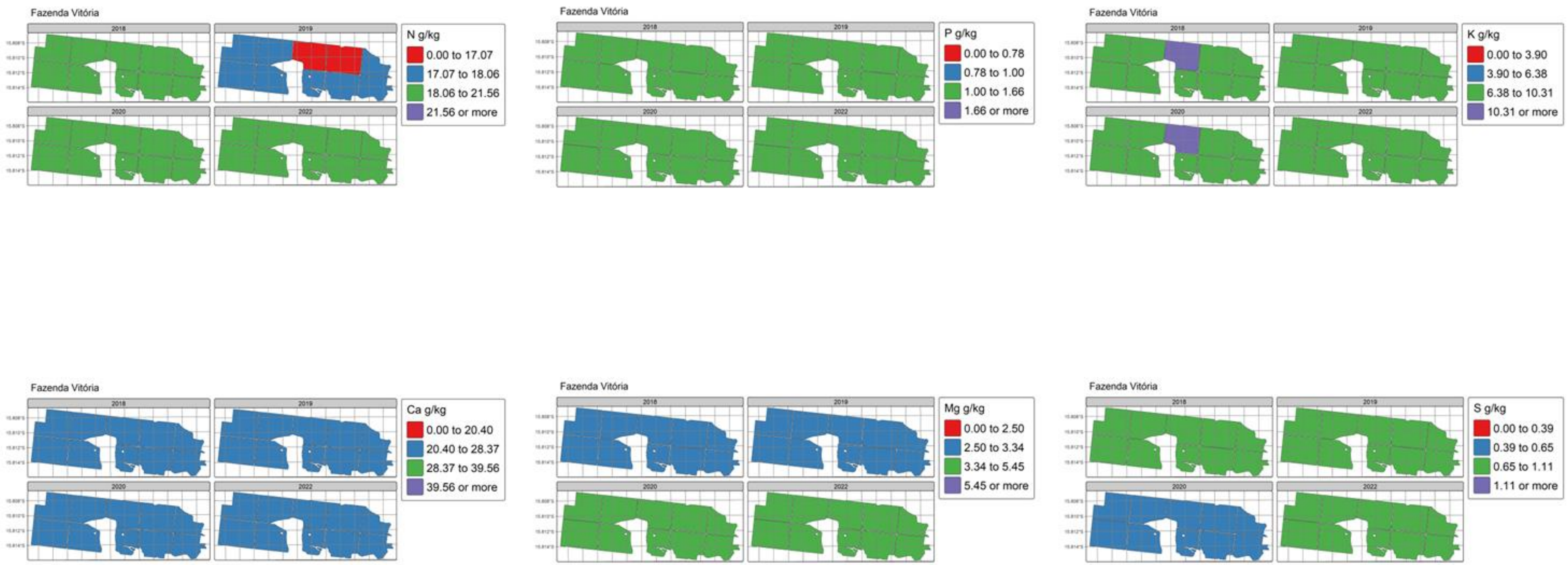

Figure 20. Map for predicted macronutrients (N, P, K, Ca, Mg and S) for Farm "Fazenda Vitoria" in Mato Grosso, Brazil. Color in red, blue, green and purple represent the low, sufficient, high and excessive ranges, respectively.

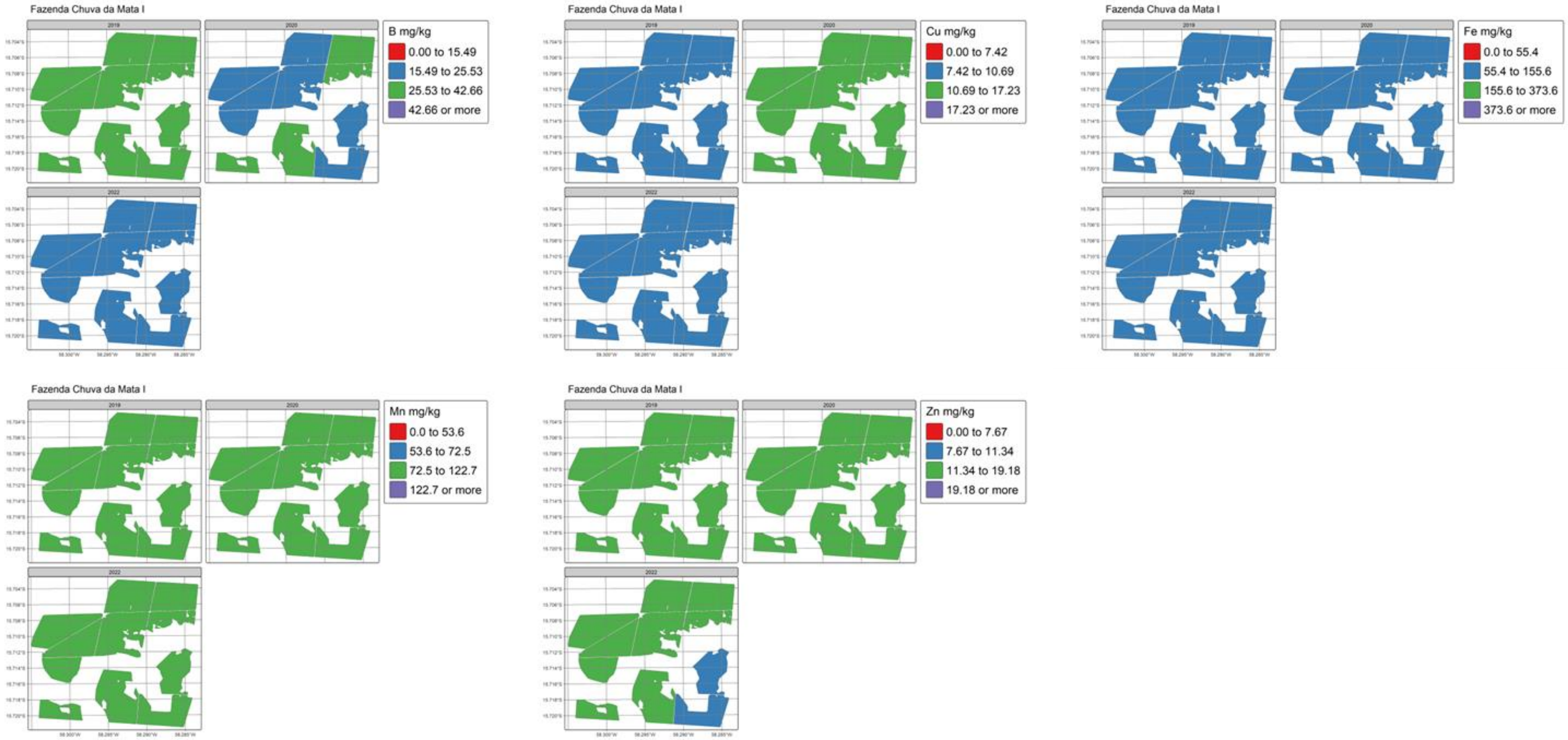

Figure 21. Map for predicted micronutrients (B, Cu, Fe, Mn and Zn) for Farm "Fazenda Chuva da Mata I" in Mato Grosso, Brazil. Color in red, blue, green and purple represent the low, sufficient, high and excessive ranges, respectively.

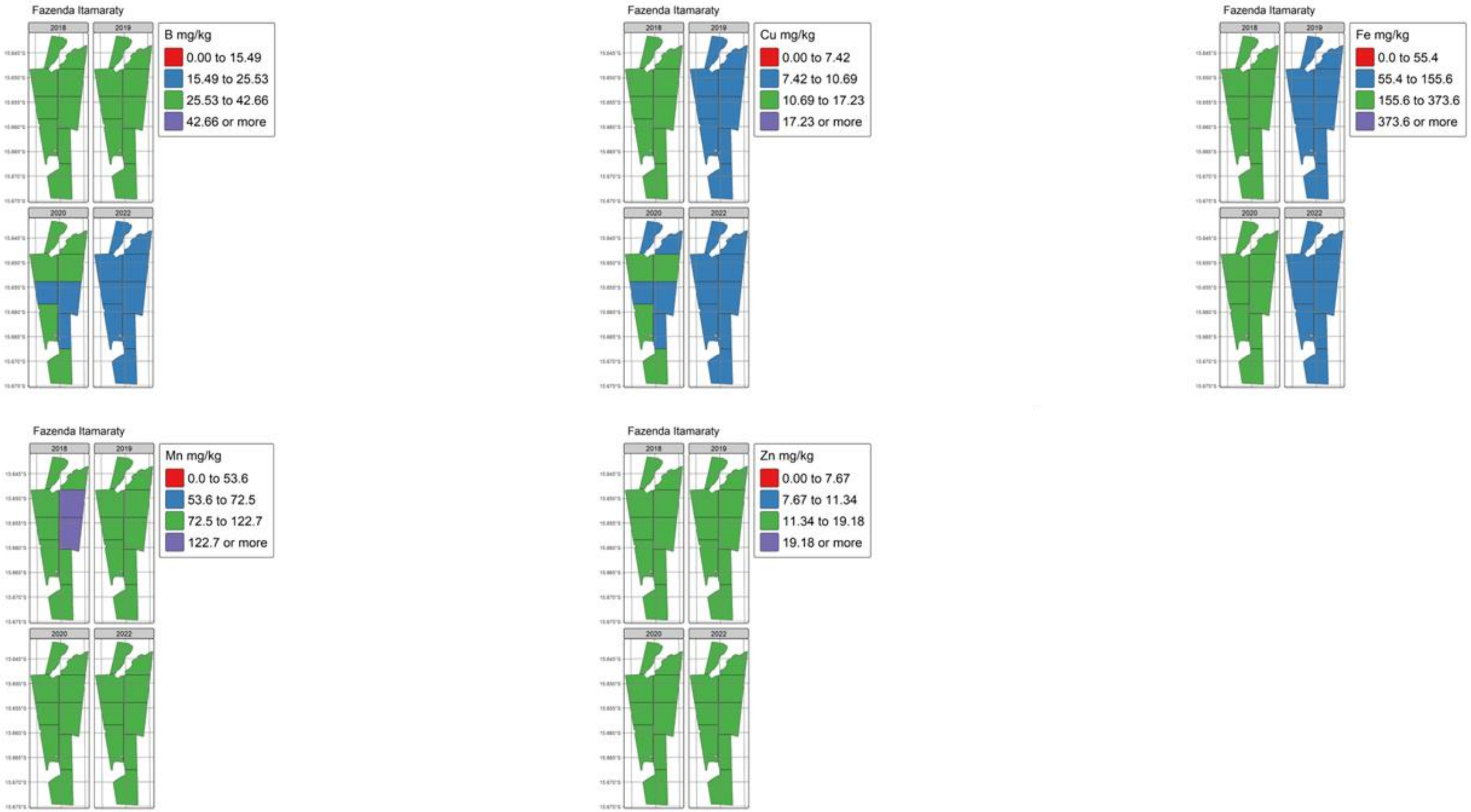

Figure 22. Map for predicted micronutrients (B, Cu, Fe, Mn and Zn) for Farm "Fazenda Itamaraty" in Mato Grosso, Brazil. Color in red, blue, green and purple represent the low, sufficient, high and excessive ranges, respectively.

Figure 23. Map for predicted micronutrients (B, Cu, Fe, Mn and Zn) for Farm "Fazenda Rancho Alegre" in Mato Grosso, Brazil. Color in red, blue, green and purple represent the low, sufficient, high and excessive ranges, respectively.

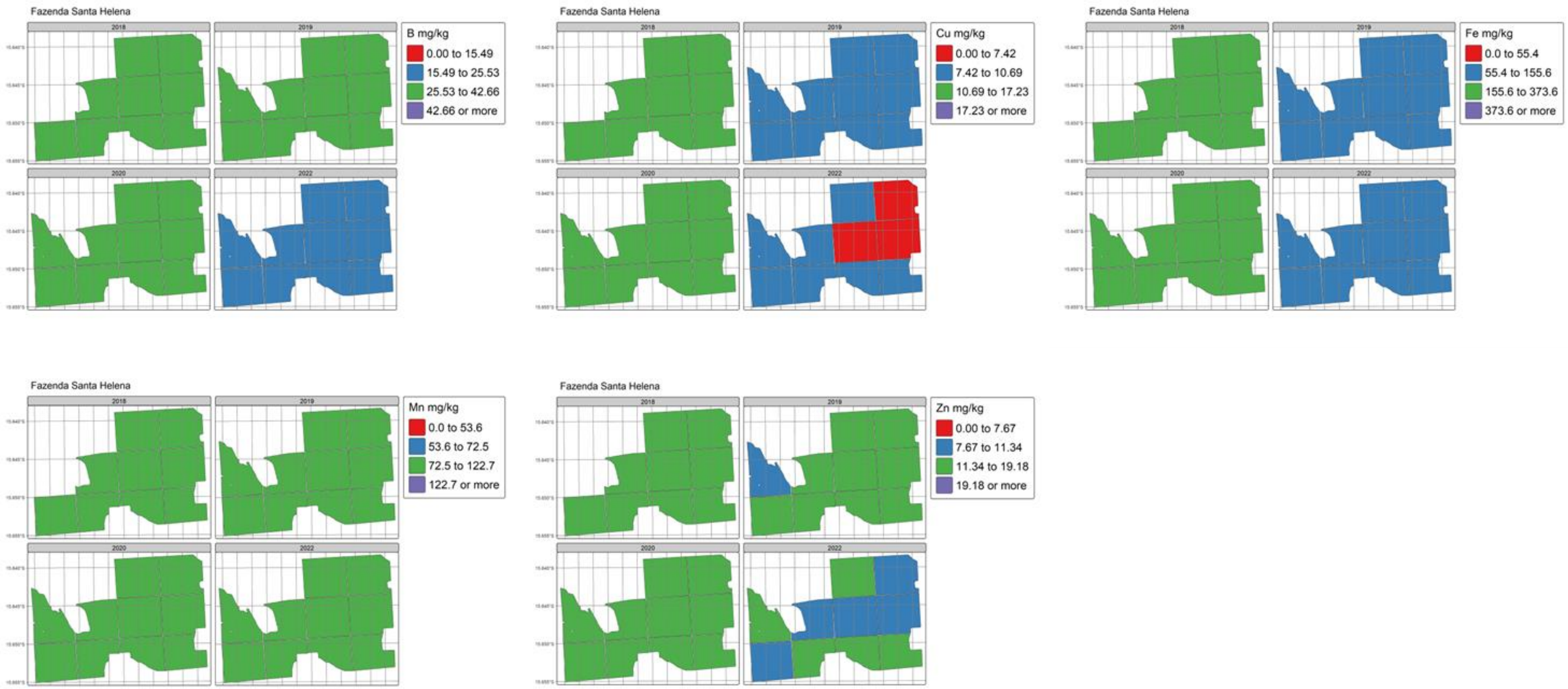

Figure 24. Map for predicted micronutrients (B, Cu, Fe, Mn and Zn) for Farm "Fazenda Santa Helena" in Mato Grosso, Brazil. Color in red, blue, green and purple represent the low, sufficient, high and excessive ranges, respectively.

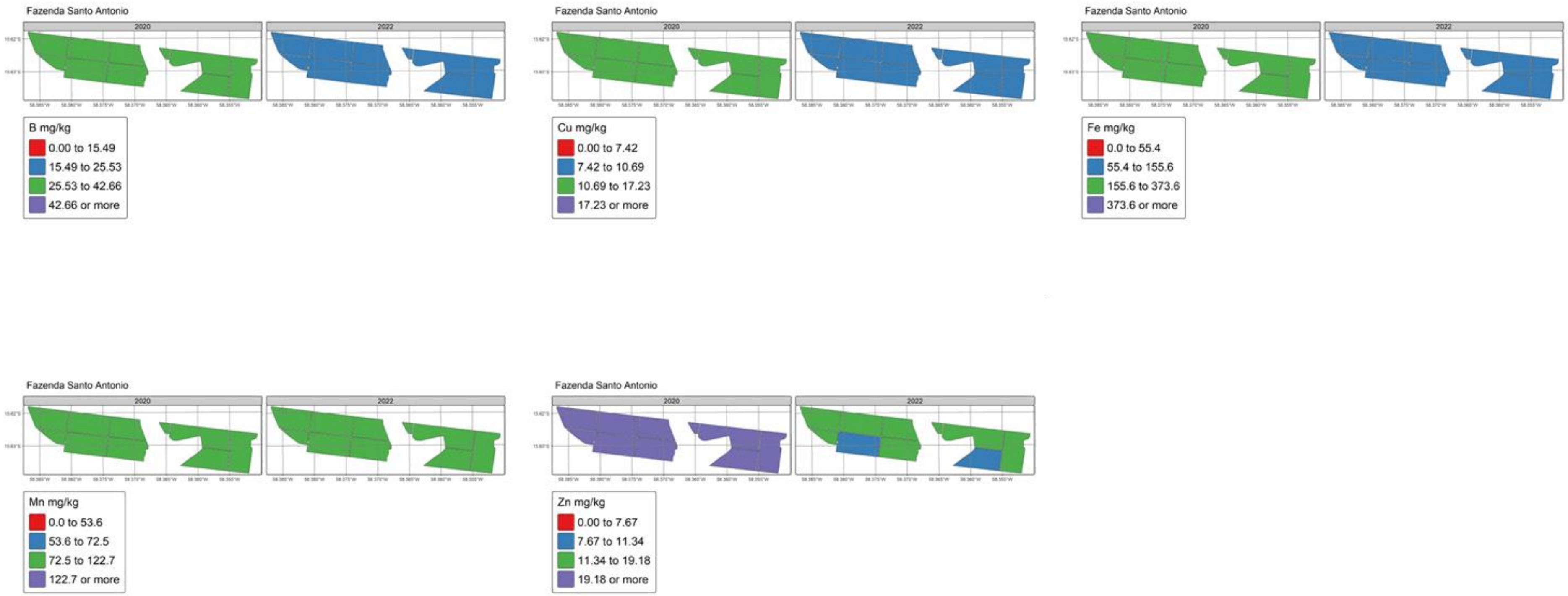

Figure 25. Map for predicted micronutrients (B, Cu, Fe, Mn and Zn) for Farm "Fazenda Santo Antonio" in Mato Grosso, Brazil. Color in red, blue, green and purple represent the low, sufficient, high and excessive ranges, respectively.

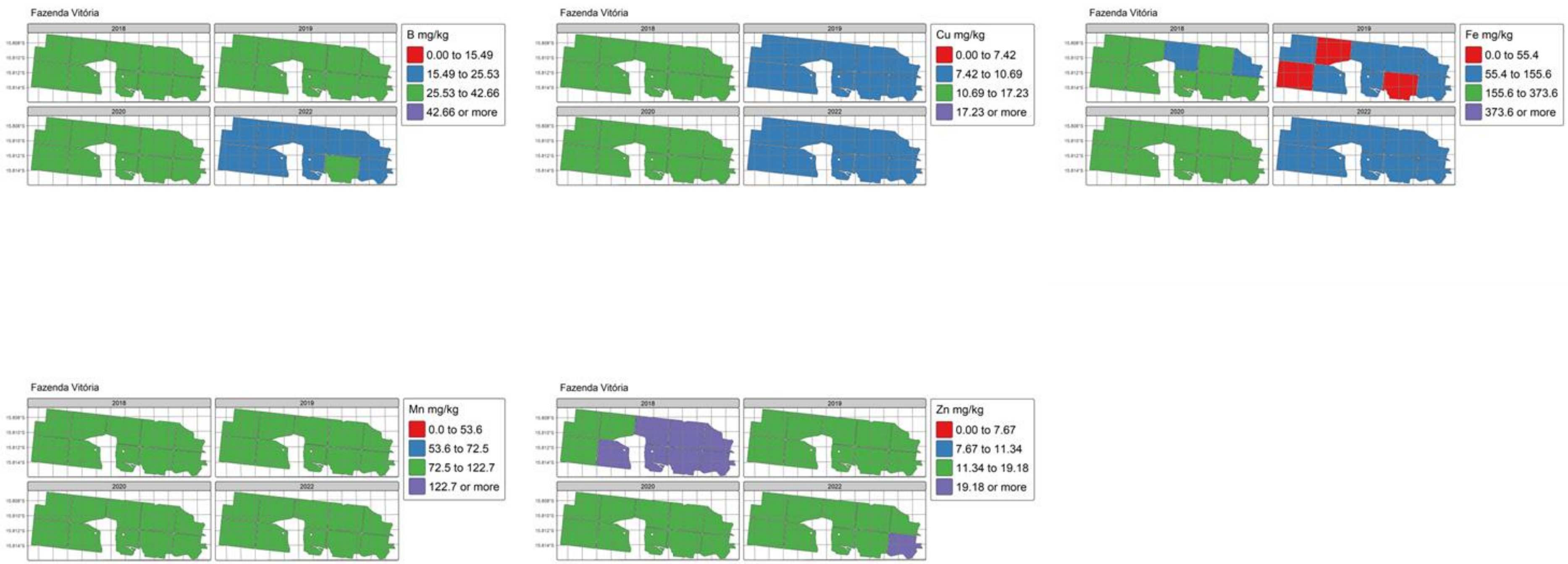

Figure 26. Map for predicted micronutrients (B, Cu, Fe, Mn and Zn) for Farm "Fazenda Vitoria" in Mato Grosso, Brazil. Color in red, blue, green and purple represent the low, sufficient, high and excessive ranges, respectively.

DISCUSSION

Concentration of nutrients in Teak

Forest growth depends on many factors, but they can be summarized in climate, topography and soil conditions (Kusbach et al., 2021), being the latter the only one that can be modified through cultural practices such as the use of cover crops, application of fertilizers, amendments among others (Palviainen et al., 2020). However, even though soil analysis may indirectly represent the nutrient absorption by plants, it can only be confirmed by foliar analysis that can be expensive. To observe the relative nutrition conditions in this study the norms reported in other work (Arevalo-Hernandez et al., 2024) were used, since the values were determined using data from a similar region (Mato Grosso). Nutrients such as N, K, Ca, Mg, S, B, Cu, Fe and Mn were in the "sufficient range", indicating good nutrition of the teak forests. Nevertheless, P and S, presented values below the "normal range" in some years and sites, which can be summarized as 1.01-1.39 g/kg for P and 0.57-0.92 g/kg for S. For P, it moves in the soil mostly through diffusion while S have mixed movement (diffusion and mass flow) through the soil (Mengel et al., 2001). Eventhough, concentration of these elements are relatively good in the soil, climatic conditions may have limited absorption of these elements, since diffusion is greatly affected by water availability and transpiration rates (Marschner, 2011; Mengel et al., 2001).

Modelling of teak nutrition

Plant nutrition is generally assessed by chemical analysis of leaves, which is a costly and slow procedure in comparison to the use of remote sensing. In the case of nutrients, the use of remote sensing is not new and have widely used mainly for crops such as maize, cotton, sugarcane, rice, among others (Feng et al., 2020; Liu et al., 2023; Sharifi, 2020; Zhao et al., 2018). However, its benefits have also been used for the improvement of forest plantations and their nutrition (Alvarado, 2015; Peterson et al., 1988; Watt et al., 2019). In the case of species, work have been carried out mostly on commercial species being Pine, Spruce, Eucalyptus and Maple the most studied worldwide (Guevara-Bonilla et al., 2023;

Singh et al., 2022; Walshe et al., 2020; Watt et al., 2019, 2020). In South America, the same trend is observed, where Eucalyptus has been the most studied species in terms of remote sensing for plant nutrition (Damasceno et al., 2023; Oliveira et al., 2019). However, in the case of teak, a lot of work is observed in terms of traditional plant nutrition and its assessment (Cavalcante et al., 2021; Fernández-Moya et al., 2014, 2016; Zhou et al., 2017). Nevertheless, little work has been done using remote sensing for nutrition modelling and less with the use of machine learning. The only work found to date is the work of Thakur & Swamy (2012), in India, where they found a good correlation between NDVI and N using regression analysis.

In general, in terms of nutrients, most of the research has focused mainly on N, while the other nutrients have received little or no attention at all, specifically in the case of micronutrients (Feng et al., 2020; Watt et al., 2019). The most studied species (Pine and Eucalyptus) present research focused mainly on macronutrients, with good performance (R^2>0.7) for N, P, K, Ca and S (Oliveira et al., 2017, 2019; Ramos et al., 2023), fairly good (R^2>0.5) for B and low (R^2<0.2) for Fe, Mg and Zn. Also, Oliveira & Santana, (2020), assessed all macro and micronutrients in Eucalyptus using hyperspectral images and found good results (R2>0.7) for macronutrients and fairly good for micronutrients (R^2>0.5), with exception of Fe and Zn (R^2<0.2). These values obtained in Eucalyptus are like the ones found in this research, except for Mg, Fe and Zn, where values were higher (R^2>0.5) than previously reported.

These results obtained using random forest algorithms are partially explained by the high performance of these models when results are heterogeneous and highly variable. They are robust, and their ensemble learning helps to reduce overfitting and can increase generalization of data. Also, they are less sensitive to outliers, missing data and can capture complex and nonlinear relationships which can outperform other models (Hastie et al., 2009).

Teak nutrition main predictors

Main variables selected as predictors prevail either as soil or climate variables, specifically water deficit (Deficit) or days without rain (Dia_SEMCH) and some vegetation indexes. In the case of precipitation variables, available water affects directly nutrient movement and availability in the soil. It’s necessary to have soil water conditions near field capacity (-33kPa) for nutrients to be released from the solid phase of the soil and absorbed by plants (Reichardt & Timm, 2020). Also, the age of the stand is important for many nutrients (P, K, Ca, Mg, S, B, Cu and Fe) it may reflect the nutrient use efficiency of teak plants. They tend to improve with passing years until they reach a maximum of 11 years and then decline (Jha, 2014). However, the studied teak plantations had a maximum of 10 years (2013-2022), explaining the effect on nutrient acquisition.

For N, available B and S, were the most important. Boron has direct influence on N uptake in plants either by improving or reducing N concentration (Long & Peng, 2023). While S, has a direct relationship with N, with these elements acting synergistically since it is directly linked to nitrate reductase and S is a constituent of methionine, an initiation amino acid (Fazili et al., 2008).

For P and Mg, precipitation variables and the age of teak (Tectona grandis) were the most important, the latter may be related to nutrient acquisition efficiency.

For K, S and Zn, had as major predictor age, available S and Deficit. In the case of K and S, their available values in the soil had a direct relationship with the absorption, which was not the case for Zn. However, the importance of available S for K and Zn may be related to the xylem loading of these elements and its translocation that can be determined by the amount of sulfate in the shoot (Reich et al., 2016). Also, specifically in the case of Zn, synergistic interactions with S have been reported, since Thiols (-SH) are essential compounds and required for several physiological functions (Hübner & Haase, 2021) and sulfur deficiency tend to reduce growth and Zn and K absorption in plants (Khampuang et al., 2023; Reich et al., 2016).

For Ca, Age (Id_inv), Clay and available S were the most important. The studied soils tend to neutral pH and have similar exchangeable Ca levels. Clay concentration is directly linked to CEC (Cation exchange Capacity) and different levels may lead to a different buffer capacity and different levels in Ca in soil solution and plant absorption (Jing et al., 2024). Also, S in high concentration can lead to Calcium deficiency by the formation of insoluble compounds (Jing et al., 2024).

For boron (B), precipitation variables were the most important with available sulfur, but available B was present, even though it was not as important as the previous mentioned. There is few information about sulfur and boron interactions, however evidence points out that Sulfur promotes B absorption in plants (Long & Peng, 2023) and may be crucial for B nutrition.

For Cu and Fe, the age, available S and Mn were the most important. Available Mn has a high correlation with available Cu and Fe and in many cases an antagonistic effect that could lead to lower Cu and Fe uptake (Ghasemi-Fasaei & and Ronaghi, 2008). Also, S tend to form bonds with Cu (CuS) and Fe (FeS) to form amino acids and proteins such as Ferredoxin and Rieske having an essential function in the uptake and translocation of these elements (Abdin et al., 2003; Chorianopoulou & Bouranis, 2022). However, in the case of Cu, the MTCI (MERIS Terrestrial Chrolophyll Index) vegetation index has been also important. The latter has been designed for detecting changes in photosynthetic activity of plants and can be more sensitive than other indexes such as NDVI (Dash & Curran, 2007).

Finally, for Mn, Organic matter, RGVI (Rice Growth Vegetation Index) and water deficit were the most important, however pH in water (pH_ag), clay and the age were also important. These results are expected because pH, Organic Matter and clay content controls overall bioavailability of Mn (Millaleo et al., 2010). Of all the nutrients, Mn and Cu were the only ones that presented vegetation indexes of high importance. The RGVI was designed for rice growth monitoring and its very similar to NDVI but optimized for rice phenological conditions (Nuarsa et al., 2011) but presented good concordance for Mn uptake in teak.

Vegetation indexes tend to be sensitive in assessing differences due to reflectance in the canopies of plants by integrating information of the electromagnetic spectrum. However, it is highly affected by several factors such as water content, type of plants, weed, and soil background reflectance (Xue & Su, 2017). Also, research has shown that depending on the overall status of the plants these vegetation indexes may get saturated and may not show any differences at all (Gao et al., 2023). The latter may explain the low importance of Vegetation indexes for the prediction of nutrient concentration in teak, since overall, not great deficiencies are seen in the assessed farms.

CONCLUSION

From all the machine learning algorithms, random forest proved to be better for all the assessed macronutrients (N, P, K, Ca, Mg, S) and micronutrients (B, Cu, Fe, Mn, Zn). This algorithm presented the lowest RMSE and MAE and the highest R^2. The nutrients with the highest validation values were P, Mg, B, intermediate K, Ca, S, Cu and Zn and the lowest N and Mn. In terms of variable importance, Available S, Age, Days without rain and Water Deficit were the most important variables for most nutrients. Finally, this study highlights the importance of utilizing machine learning algorithms to predict the nutrient uptake of forest species and could furthermore reduce the costs for monitoring. This is the First published study in Teak (*Tectona grandis*) that uses machine learning algorithms for nutrition prediction. However, further research is needed to improve the current models and the use of other technologies to improve the current state of the art.

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CAPITULO 4. SOIL CHARACTERISTICS AND ALLOMETRIC MODELS FOR BIOMETRIC CHARACTERISTICS AND NUTRIENT AMOUNTS FOR HIGH YIELDING "BOLAINA" (*GUAZUMA CRINITA*) TREES

ABSTRACT

The Peruvian amazon is very diverse in native forestry species, the Guazuma crinita "Bolaina" being one of the most planted species in the country; however, little or no information about soil requirements and nutrient demands is known. The objective of this work was to assess the general conditions of soil fertility, biomass and macro- and micronutrient amounts in high-productivity Guazuma crinita plantations. Fields of high yielding Bolaina of different ages (1–10 years) were sampled in two regions. Soil and plant samples were collected in each field and biometric measurements of fresh weight, diameter at breast height and height were performed. For soil and plant analysis, both macro- (N, P, K, Ca, Mg, S) and micronutrients (B, Cu, Fe, Mn, Zn) were determined. Finally, allometric equations were constructed for biometric and nutrient amounts. This study is the first to assess and model macro- and micronutrient amounts in the productive cycle in this species, which grows in fertile soils. In the case of biometric equations, the logarithmic and logistic models performed better. For nutrient amounts, this species followed a pattern of Ca>N>K>P>S>Mg for macronutrients and Fe>B>Mn>Zn>Cu for micronutrients. The best prediction models for nutrients were the square root and logistic models.

Keywords: soil fertility; nutrient prediction; native Amazon tree; nonlinear models.

INTRODUCTION

The Peruvian Amazon covers the largest area in Peru, representing nearly 60% of the total territory. The Amazon is characterized by high diversity in both flora and fauna, being one of the most diverse ecosystems worldwide (Asner et al., 2017). This region is characterized by a multitude of native trees that have several purposes, such as conserving biodiversity, carbon stocks, water cycling, traditional medicine and wood (Fearnside, 2008; Skirycz et al., 2016). Recently the Peruvian government has focused on promoting forestry plantations and exploitation by assigning resources in terms of credits, funds for projects and loans for each purpose, all of which were considered in the “Plan for Promoting Commercial Forestry Plantations 2021-2050” (SERFOR, 2021). However, this promotion for forestry business has been focused on some species with some level of knowledge about their management and cultivation, such as Eucalyptus sp., “Capirona” (Calycophyllum spruceanum), “Cedro” (Cedrela odorata), Pinus sp. and “Bolaina” (Guazuma crinita). The latter has been greatly promoted by the government in the last decade because of its rapid growth, feasibility of work and a relatively new demand on the market based on white wood (Alberto et al., 2019),

In general, forestry plantations in Peru are small in comparison to the areas dedicated to agriculture and of the 117,495.59 ha of plantations in 2022 the areas dedicated to Guazuma crinita amounted to 15,109.46 ha, representing nearly 12.86% of forestry plantations in the country, and it is also the most planted species in Peru (SERFOR, 2023). Even with its high importance, research on this species has focused mostly on genetics (Coral et al., 2016; Rochon et al., 2007; Tuisima-Coral et al., 2020), developing allometric models (Casas et al., 2022; Revilla-Chávez et al., 2021), carbon storage (Timoteo et al., 2016), propagation (Ramos-Huapaya & Torrejón, 2016), wood characteristics (Tuisima-Coral et al., 2017) or management (Putzel et al., 2011; Vidaurre Arévalo, 1992), with little known about soil fertility, nutrition requirements or fertilization management in this species, which represent very important issues for future commercial plantations.

Nutrition management is a particularly important topic in the case of forestry plantations, even though in the past it was considered that trees could grow without inputs and in very infertile soils. (Alvarado, 2015) Nowadays, the use of fertilizers and soil amendments is known to improve growth, development and wood quality (Chambi-Legoas et al., 2021; Reyes Moreno et al., 2021). Also, temperature regimes in the tropics are very high (in the coldest month, >18°C) in comparison to other latitudes, which benefits trees by operating at its optimum condition, allowing them to grow faster and making nutrition requirements more critical when water supply is not limiting (Toledo et al., 2011; Way & Oren, 2010).

In the case of tropical native species, an extensive review by (Alvarado, 2015) summarizes that most species in the tropics demand nutrients in the order N>K>Ca>Mg>P and that concentrations of nutrients on the litter are higher in Ca and N and higher in deciduous species in comparison to evergreen species. In the case of Guazuma crinita, few studies on nutrition or fertilizer requirements exist; most are related to the response to organic and inorganic fertilizers in greenhouse (Ortiz Córdova, 2009) and field conditions (Centeno Avendaño, 2012; Cueva Cartagena, 2011; Sánchez, 1995), where all the authors found positive responses for biometric measurements (height, diameter, dry weight, foliar area, root growth) when fertilizers or amendments were used. From these studies, only (Cueva Cartagena, 2011; Ortiz Córdova, 2009) analyzed foliar concentration of nutrients, but only for N, P and K, where they reported concentrations of nutrients in the order N>K>P.

Soil fertility is important for ecology restoration in tropical ecosystems because soil conditions may limit the establishment and growth of new forestry trees in degraded areas. Therefore, general knowledge of basic soil conditions may improve the selection of areas for reforestation of tree species (Alvarado, 2015; Matichenkov & Bocharnikova, 2021). General nutrition requirements are important for establishing fertilization programs in commercial crops worldwide to efficiently apply fertilizer and avoid excessive doses that can cause serious problems in the environment, such as salinity, contamination of groundwater, eutrophication, etc (Savci, 2012).

Therefore, taking into consideration the need for basic information related to the nutrition demands of Guazuma crinita, we hypothesized that high productivity stands of this species may reflect adequate conditions in terms of soil fertility, growth and nutrition in order to build prediction models that can be used for improving management in this important native tree. Therefore, this work had the following objectives: to assess the general conditions of soil fertility in high-productivity Guazuma crinita plantations; to explore the accumulation of biomass and nutrients (macro- and micronutrients) in different ages of high-productivity

Guazuma crinita plantations; and to develop allometric models for biomass and nutrient uptake in Guazuma crinita.

MATERIALS AND METHODS

Location

The study was located at three regions in Peru: San Martin, Huánuco and Ucayali. The climates of the collected areas are similar, with temperatures of 21–33°C and precipitations higher than 1400 mm per year, classified as Am (Köppen, 1931).

The plantations selected were trees of seminal origin and the data collection places in the San Martin, Ucayali and Huanuco regions. Nevertheless, as there was only one data collection site in Huanuco the data for analysis were combined with the Ucayali data due to the similarities in environmental conditions.

Soil and plant sampling

"Bolaina" trees of 1, 3, 5, 7 and 10 years were selected for study. Plots were selected according to their productivity based on the highest forest volume over time; as no reference exists relating to high, medium or low productivity, the highest values were used. Five trees were selected based on the highest circumference in each plot. In the case of plant sampling, the procedures are according to institutional guidelines and the Peruvian national legislation (Law 29763), which does not require permission to work with this species because the samples were collected from commercial plantations.

The selected specimens were harvested and cut into different pieces for biometric assessment: trunk, branches and leaves.

For plant sampling, three circular sections from the trunk (base, middle and top) were collected; for branches and leaves, samples of 2 kg and 1 kg were sampled, respectively.

For soil sampling, four samples of 250 g were taken at 0.20 m depth, in the north, south, east and west of the tree at 20 cm distance from the trunk base. Soil sampling was performed for each tree sacrificed in the study. All the samples were stored in boxes at a temperature of 4°C and then sent to the Instituto de Cultivos Tropicales laboratory for soil and plant analysis.

Determination of biometric variables

The main variables determined were the height, diameter and dry weight of the trunk, branches and leaves.

Regarding height, the trees were measured in meters (m) after they were sacrificed. Circumference was measured at a height of 1.30 m and diameter was estimated by dividing the circumference by the value of pi.

Fresh weight was measured in the field and sections of different parts of the tree were preserved at 4°C and delivered to the laboratory for assessing the dry weight proportion in relation to fresh weight. For calculating the proportion of dry tissue and humid tissue, the tissue was oven dried at 60°C until reaching constant mass and then the dry weight was calculated by discounting the humidity in each sample.

Determination of soil attributes

The physical and chemical attributes of the soil were determined using the procedures described in previous publications. (Anderson & Ingram, 1993; Arévalo-Gardini et al., 2015; EMBRAPA, 2009) Attributes determined were pH, organic matter (OM), CaCO3, granulometric analysis (sand, clay and lime), exchangeable bases (Ca, Mg, Na, K), exchangeable acidity, cation-exchange capacity (CEC) and available P, S, B, Cu, Fe, Mn and Zn.

Granulometric analysis was performed via the Bouyoucos method using $(NaPO_3)_6$ + Na_2CO_3 as a dispersant. Soil pH (1:2.5 H_2O) was measured using a potentiometer and organic carbon (OC) with the Walkley and Black method by titration, utilizing the factor of 1.7624 to calculate OM. Carbonates in soil were determined using a calcimeter and CEC and base cations (Ca2+, Mg2+, Na+, K+) were determined using extraction with 1.0 mol L^{-1} NH_4OAc and then flame atomic absorption spectrophotometry (FAAS). To determine exchangeable acidity (Al3+, H+), Yuan's method (Yuan, 1959) was used. Available P was extracted with the Olsen method (0.5 mol L-1 $NaHCO_3$, pH 8.5) and determined using UV-VIS spectrophotometry. Available B was extracted with hot water and available S-SO_4^{2-} with 500 mg L-1 P [$Ca(H_2PO_4)$][$2H_2O$] + 2.0 mol L-1 CH_3COOH, and determined using UV-VIS spectrophotometry. The selected microelements (Cu, Fe, Mn, Zn) were extracted with diethylenetriaminepentaacetic acid (DTPA) and then analyzed using FAAS. For soil chemical analysis, reference material AG-1 from SPC-Science was used to assure quality control.

Determination of nutrient concentrations and uptake in "Bolaina" trees

After the tissues were dried (trunk section, branches and leaves), they were milled at 20 mesh and stored for plant analysis. Aliquots of 500 mg of each dried tissue were used to determine the macro (N, P, K, S, Ca, Mg) and micronutrients (B, Cu, Fe, Mn, Zn). For plant analysis, wet digestion methods were used (HNO3) and the procedures are detailed on Embrapa. (EMBRAPA, 2009) Determination of the elements can be summarized as follows: N was determined by the Kjeldahl method; P was determined by the ascorbic-molybdate color development method using UV-VIS spectrophotometry; and Ca, Mg, K, Cu, Fe, Mn and Zn were determined by FAAS using the Spectra 55B instrument from Varian. Concentrations are presented as the mean of three replicates from each repetition. In order to ensure analytical quality, a certified NIST material was used (Apple leaves).

For calculation of the macro- and micronutrient amounts, the following formula was used: (Arévalo-Hernández et al., 2022)

$$Amount\ (\text{mg per plant}) = Concentration\ of\ element\ * Dry\ weight\ (\text{g})\ * m$$

Where Concentration = results of chemical analysis of plant tissues (trunk, branches and leaves), in g kg^{-1} for macronutrients and mg kg^{-1} for micronutrients; m = 1 for macronutrients and 100 for micronutrients.

Allometric models

The nonlinear regression models used to build the allometric models are presented in Table 1. For the case of biometric models, except for commercial height (CH) and diameter at breast height (DBH), all models were tested at a significant level of 0.05 for the best prediction algorithm. However, in the case of nutrient amounts, only Models 1, 2 and 7–10 was used.

Table 1. Nonlinear regression models used for the construction of allometric models, where diameter at breast height (DBH) and commercial height (CH) were used as independent variables (X)

Number	Model formula	Name and reference
1	$Y = a + b * DBH$	Linear model (Archontoulis & Miguez, 2015; Miguez et al., 2018)
2	$Y = a + b * DBH^{0.5} + c * DBH$	Square root model (Archontoulis & Miguez, 2015; Miguez et al., 2018)
3	$Y = a + b * log(DBH^2 * CH)$	Logarithmic model (Archontoulis & Miguez, 2015; Miguez et al., 2018)
4	$Y = a\,(DBH^2 * CH)^b$	Modified power model (Archontoulis & Miguez, 2015; Dos Santos et al., 2022; Miguez et al., 2018)
5	$Y = a + b * DBH^2 * CH$	Modified power model (Archontoulis & Miguez, 2015; Dos Santos et al., 2022; Miguez et al., 2018)
6	$Y = a * DBH^b * CH^c$	Power model (Archontoulis & Miguez, 2015)
7	$Y = a * DBH^b$	Power model (Archontoulis & Miguez, 2015; Dos Santos et al., 2022; Miguez et al., 2018)
8	$Y = a + b * log(DBH)$	Logarithmic model (Archontoulis & Miguez, 2015; Miguez et al., 2018)
9	$Y = \frac{a}{1 + e^{b-c*DBH}}$	Logistic (Verhulst, 1838) (Archontoulis & Miguez, 2015; Miguez et al., 2018)
10	$Y = a(1 - e^{-c(DBH-b)})$	Mitscherlich model (Sileshi, 2021)

Statistical analysis

All statistical analyses and graphics were calculated using R software, version 4.1.2. (R Core Team, 2021) For samples taken in the Huanuco region, owing to the proximity to the Ucayali region it was considered part of this region for all statistical analyses. Chemical and physical attributes of the soil were compared between the sampled regions by analysis of variance (ANOVA). In the case of biometric measurements and macro- and micronutrient amounts, linear and nonlinear regression models were constructed and compared using the Akaike information criterion (AIC) and the root-mean-square error (RMSE); the model with the lowest AIC and RMSE was selected as the best fit and the equation was presented for all the variables studied. Also, an F-test at a 0.05 significance level was performed in the selected models to verify the significance of the model.

RESULTS

Soil characteristics of high-yield stands

Physical and chemical soil characteristics for the San Martin (SM) and Ucayali (UC) regions are presented in Table 2. With regard to physical characteristics, soils in SM had more sand and less silt compared to UC; no significant differences were observed ($P > 0.05$) for clay but the silt/clay ratio is higher in UC (1.48) than in SM (0.78), reflecting younger soils in the case of UC. In relation to chemical characteristics, soils from the collected areas had similar pH values and no significant differences ($P > 0.05$) were reported; the pH was around neutral (pH 7.0), indicating that even though this species had emerged from the Amazon region it may have a preference for neutral soils. Also, in the case of organic matter (OM) in the soil, no significant differences ($P > 0.05$) were observed between the regions and values were above the normal levels found in tropical soils (OM > 30 g kg-1), which may be related to the high C values required for this species. For P and S, significant differences were indicated, where the SM region had higher values than the UC region. In the case of exchangeable bases (Ca, Mg and K), significant differences ($P \leq 0.05$) were observed only for K, where the SM region had higher values (6.2 $mmol_c\ kg^{-1}$) in comparison to UC (4.0 $mmol_c\ kg^{-1}$). In the case of available micronutrients (B, Cu, Fe, Mn and Zn), only B showed significant differences ($P \leq 0.05$), with the SM region reporting higher values (0.15 mg kg^{-1}) in comparison to UC (0.02 mg kg^{-1}); however, both regions showed low available concentrations of this element.

Table 2. Physical (sand, silt and clay proportions) and chemical [pH, CaCO3, organic matter (OM), Ca, Mg, K, P, S, B, Cu, Fe, Mn and Zn] characteristics of soils in the San Martin (SM) and Ucayali (UC) regions

Region	Sand	Silt	Clay	pH	$CaCO_3$	OM	Ca	Mg	K	P	S	B	Cu	Fe	Mn	Zn
	------- g kg^{-1} -------				--- g kg^{-1} ---		mmol$_c$ kg^{-1}			--------------------- mg kg^{-1} ---------------------						
SM	378 ± 116	273 ± 67	349 ± 68	7.00 ± 0.56	13.8 ± 12.6	42.2 ± 14.7	244 ± 104	21 ± 5	6.2 ± 3.7	18.1 ± 10.4	18.9 ± 14.6	0.15 ± 0.10	0.95 ± 0.95	28.3 ± 21.8	26.2 ± 14.8	3.3 ± 2.2
UC	243 ± 120	45.1 ± 190	30.6 ± 121	6.77 ± 0.41	11.5 ± 17.3	38.8 ± 10.2	254 ± 73	23 ± 6	4.0 ± 1.3	8.4 ± 3.7	7.0 ± 7.9	0.02 ± 0.02	0.94 ± 0.52	38.4 ± 13.9	28.8 ± 12.3	2.5 ± 1.6
P	*	*	ns	ns	ns	ns	ns	ns	*	*	**	*	ns	ns	ns	ns

ns = not significant; *significant at 0.05; **significant at 0.01. Granulometric analysis (Bouyoucos method), pH (potentiometer 1:2.5), $CaCO_3$ (calcimeter), OM (Walkley and Black), P (0.5 mol L^{-1} $NaHCO_3$, pH 8.5), Ca, Mg, K (1.0 mol L^{-1} NH_4OAc), S [500 mg L^{-1} P with $Ca(H_2PO_4)$ $2H_2O$ + 2.0 mol L^{-1} CH_3COOH], B (hot water) and Cu, Fe, Mn and Zn (diethylenetriaminepentaacetic acid: DTPA).

Biometric measurements

The mean biometric measurements per selected age are presented in Table ESI-1 (see Supplementary Information). In the case of biometric measurements, allometric models were developed using data from both regions (SM and UC) as non-significant differences were observed (P > 0.05) between the biometric measurements in these regions and, in this way, the constructed models can be improved with more data. The tested models, formulae, Akaike information criterion (AIC) and root-mean-square error (RMSE) are presented in Table 15 [commercial height (CH) and diameter at breast height (DBH)] and Table 16 (dry weight). For CH and DBH estimation, the best model was the square root model (Model 2), with R2 values of 0.91 and 0.79 for CH and DBH, respectively.

Table 3. Allometric model evaluation with the Akaike information criterion (AIC) and root-mean-square error (RMSE) for commercial height (h_c) and diameter at breast height (dbh) of “Bolaina”

(Guazuma crinita) trees, based on dbh and age, respectively, from 1 to 10 years in the sampled areas of the San Martin and Ucayali regions

Models	Commercial height (m)		Diameter at breast height (cm)	
	AIC	RMSE	AIC	RMSE
1	26.68	0.33	-41.73	0.12
2	**-33.76**	**0.13**	**-42.03**	**0.12**
7	20.92	0.30	-36.73	0.13
8	15.53	0.28	-34.76	0.14
9	-19.15	0.16	-41.64	0.12
10	-13.30	0.18	-41.73	0.12
Best model formula*	$Ln\ (ht) = -11.4774 + 5.7708 * dbh^{0.5} - 0.5806 * dbh$, R^2=0.90		$Ln\ (dbh) = 2.4259 + 0.1012 * Years^{0.5} - 0.0632 * Years$, R^2=0.79	

*The selected models were significant by the *F*-test at 0.05. Values in bold indicate the best model, with the lower AIC and RMSE values.

In the case of dry weight estimation (Table 4), poor predictive models were constructed for leaves and branches. However, trunk and total weight had good prediction estimations, with R^2 values of 0.96 and 0.93, respectively, and the best predictive models were the logarithmic model (Model 3) and the logistic model (Model 9), respectively. In the case of leaves, the best model was the power model (Model 7), with R^2 = 0.62, whereas for branches it was the power model (Model 6), with R^2 = 0.25. In general, the highest proportion of biomass in these trees is represented by the trunk, with a lesser proportion for leaves and branches; with increasing age this relation is higher, accounting for 56.80% of the total biomass of the tree in the first year to 77.70% at 10 years. In the case of leaves and branches, this relation accounts for 5.07% and 38.13% in the first year to 10.11% and 12.19% at 10 years, respectively.

Table 4. Allometric model evaluation with the Akaike information criterion (AIC) and root-mean-square error (RMSE) for trunk, branches, leaves and total dry weight (Dw; in kg) of “Bolaina”

(Guazuma crinita) trees from 1 to 10 years in the sampled areas of the San Martin and Ucayali regions

Models	Trunk		Branches		Leaves		Total	
	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE
1	34.04	0.36	67.78	0.58	99.16	0.86	12.28	0.26
2	-21.23	0.16	68.55	0.57	100.83	0.87	-27.63	0.15
3	**-32.68**	**0.14**	70.69	0.61	102.36	0.89	-19.69	0.17
4	-28.76	0.15	68.76	0.65	102.76	0.89	-22.51	0.16
5	19.38	0.14	69.75	0.55	101.59	0.88	2.78	0.15
6	-28.37	0.14	**65.03**	**0.55**	100.54	0.87	-23.59	0.15
7	24.95	0.32	68.38	0.59	**98.89**	**0.86**	-0.04	0.22
8	11.45	0.26	68.60	0.59	100.01	0.87	-10.89	0.19
9	-22.33	0.16	72.33	0.57	101.33	0.88	**-28.46**	**0.14**
10	-16.72	0.17	86.72	0.57	108.72	0.94	-26.20	0.15
Best model formula	$Ln(Dw) = -370.18 + 55.52 * \log(\mathrm{dbh}^2 * hc)$, R^2=0.96		$Ln(Dw) = 0.0008 * \mathrm{dbh}^{2.9435}$, R^2=0.62		$Ln(Dw) = 1.1165 * dbh^{1.4163} * hc^{-0.5786}$, R^2=0.27		$Ln\ (Dw) = \frac{5.6277}{1+e^{1.5581-0.1675*dbh}}$, R^2=0.93	

*The selected models were significant by the *F*-test at 0.05. Values in bold indicate the best model, with the lower AIC and RMSE values.

Macronutrient amounts

The mean concentrations and amounts of each macronutrient according to age are presented in Table ESI-2 (see Supplementary Information). In the case of nutrient amounts, the tested equations in terms of AIC and RMSE for each nutrient are presented in Table ESI-3 and the best-selected allometric equations are presented in Figure 1. For nutrient amounts, the square root model obtained the best fit for trunk and total amounts of N, K, Ca and Mg whereas the logistic model obtained better results for P and S. In general, at a younger age (*dbh* < 15 cm), the accumulation of macronutrients was as follows: N>Ca>K>P>S>Mg. However, at a later age or higher *dbh*, macronutrient amounts followed the order Ca>N>K>P>S>Mg.

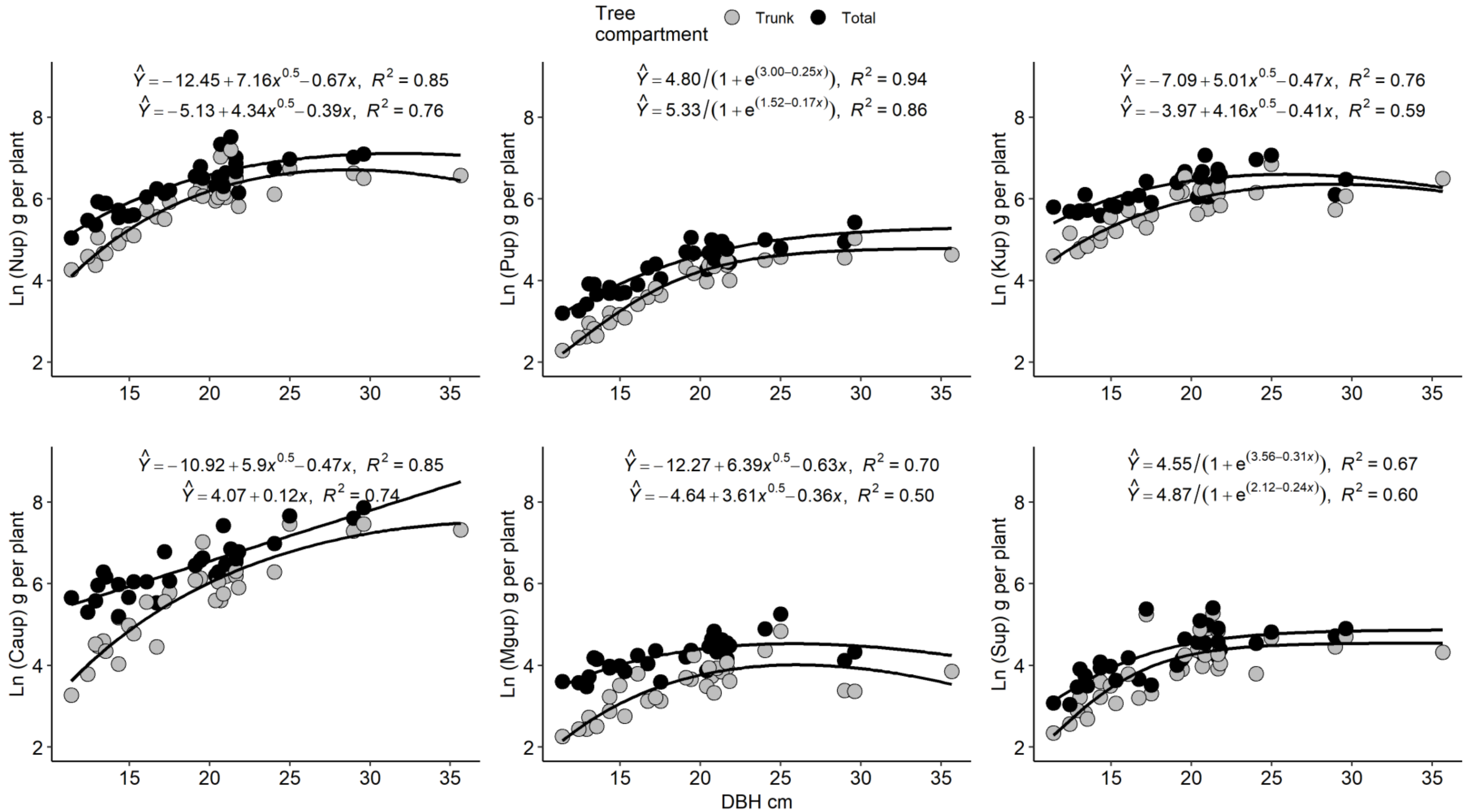

Figure 1. Allometric equations for macronutrient (N, P, K, Ca, Mg, S) amounts (in g per plant) in relation to diameter at breast height (*dbh*) in Guazuma crinita "Bolaina blanca" plants. The square root model was used for N, K, Ca and Mg and the logistic model fo P and S.

For nutritional demand, the best models for estimating the absorption of nutrients in Guazuma were used. To calculate the optimal nutrient demand in the Guazuma crinita productive cycle, some considerations were made. For the square root equation, a derivative of the equation was used to calculate the maximum DBH, whereas for the exponential and logarithmic equations the asymptote was considered as this value. However, in all equations, a value of 3 Baule units (87.5%) was used in relation to the maximum *dbh* to estimate the optimal demand rate and avoid excessive calculations for fertilizer programs in this species. The overall macronutrient demands (trunk and total) are summarized in Table 5. In the case of Ca, the total estimation was by taking into consideration the maximum value obtained by the square root model and then using the linear formula for total Ca uptake estimation.

Table 5. Macronutrient (N, P, K, Ca, Mg, S) demands in “Bolaina” (Guazuma crinita) over the productive cycle, considering 400 plants per hectare

N		**P**		**K**		**Ca**		**Mg**		**S**	
g per plant											
Trunk	Total	Trunk	Total	Trunk	Total	Trunk	Total	Trunk	Total	Trunk	Total
757.1	1163.7	66.5	106.2	545.0	702.3	1705.3	4093.1	51.6	89.1	53.4	71.0
kg ha^{-1}											
Trunk	Total	Trunk	Total	Trunk	Total	Trunk	Total	Trunk	Total	Trunk	Total
302.8	465.5	26.6	42.5	218.0	280.9	682.1	1473.5	20.6	35.6	21.4	28.4

Micronutrient amounts

The mean concentrations and amounts of each micronutrient according to age are presented in Table ESI-2 (see Supplementary Information). In the case of micronutrient amounts, the tested equations for each nutrient are presented in Table ESI-4 and the best-selected allometric equations are presented in Figure 2. For nutrient amounts, the square root model obtained the best fit for trunk and total amount of Cu, Fe and Mn whereas for B it was the logistic model and for Zn it was the power model. In general, micronutrient amounts were observed in the order Fe>B>Mn>Zn>Cu. In this case, there were no variations in the order of absorption of these nutrients with higher *dbh* and age. With regard to the models, the prediction was lower in comparison to macronutrients (R^2 > 0.60); this could be related to the higher variation in micronutrient amounts and the spatial variability normally observed for this type of variable in research.

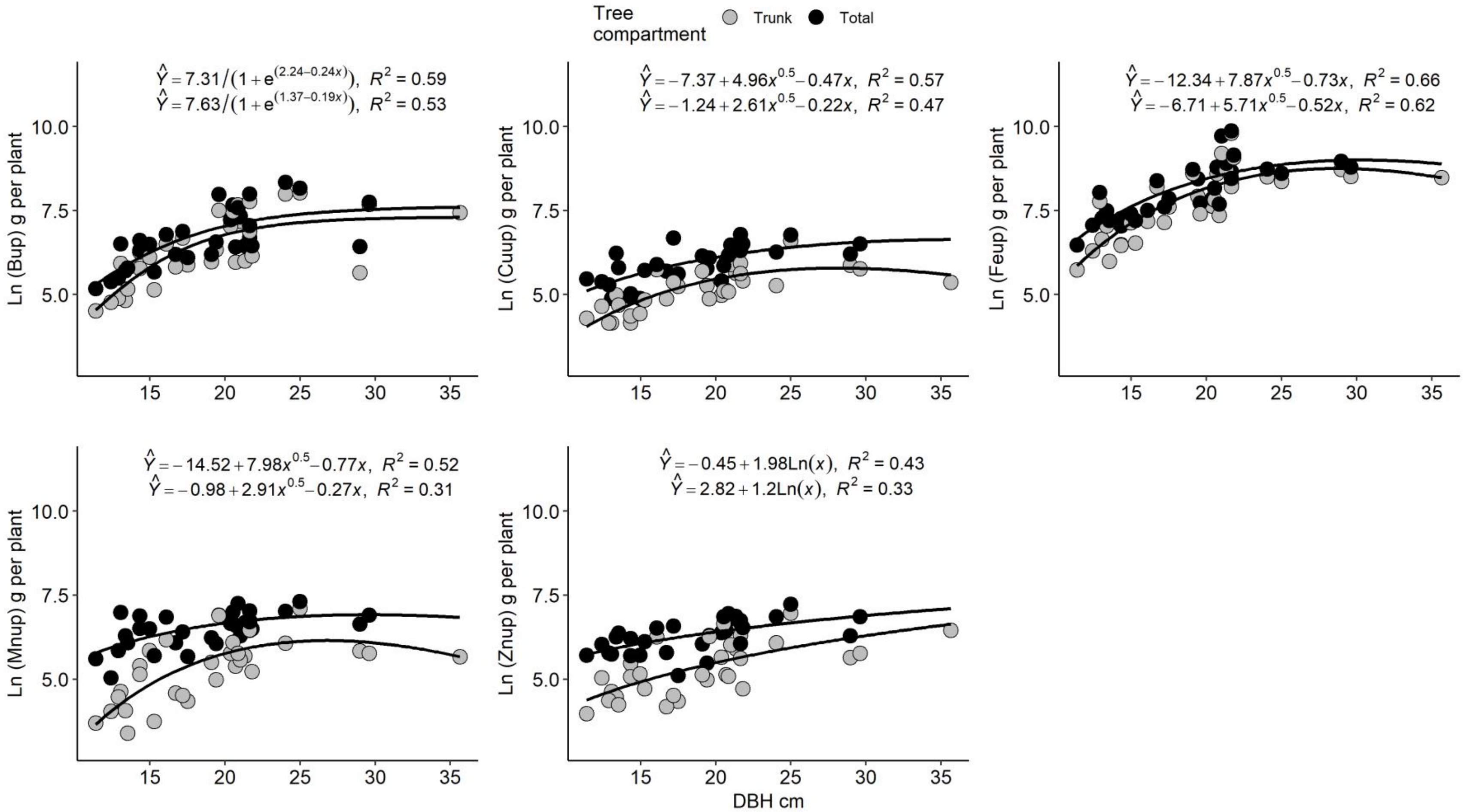

Figure 2. Allometric equations for micronutrient (B, Cu, Fe, Mn, Zn) amounts (in g per plant) in relation to diameter at breast height (*dbh*) in Guazuma crinita "Bolaina blanca" plants. The logistic model was used for B, the square root model for Cu, Fe and Mn and the logarithmic model for Zn.

As in the case of macronutrients, the micronutrient demands were calculated by taking into consideration the same assumptions. The results of the micronutrient demands for Guazuma crinita are presented in Table 6, expressed in mg per tree and g ha^{-1}.

Table 6. Micronutrient (B, Cu, Fe, Mn, Zn) demands in "Bolaina" (Guazuma crinita) over the productive cycle, considering 400 plants per hectare

B		Cu		Fe		Mn		Zn	
mg per plant									
Trunk	Total	Trunk	Total	Trunk	Total	Trunk	Total	Trunk	Total
599.9	793.0	309.0	737.9	5792.2	7630.3	429.8	775.5	240.0	610.9
g ha^{-1}									
Trunk	Total	Trunk	Total	Trunk	Total	Trunk	Total	Trunk	Total
240.0	317.2	123.6	295.2	2316.9	3052.1	171.9	310.2	96.0	244.4

DISCUSSION

Soils in "Bolaina" stands

In terms of the physical attributes of soil, the values of particle size analysis (sand, silt and clay) indicate that SM soils may have higher water infiltration and drainage, which can reduce water accumulation and prevent root diseases and anoxia conditions while enhancing growth (Kreuzwieser & Rennenberg, 2014). Also, the higher concentration of silt in UC soils may indicate younger soil (in terms of geologic time) and higher quartz concentrations. Higher values of silt can be negatively correlated to growth in Eucalyptus grandis (Delgado-Caballero et al., 2009). Furthermore, the silt/clay ratio for these soils was higher, which may be related to higher tree mortality in some tropical species (Júnior et al., 2022). With regard to clay, the values were higher than 250 g kg-1 in both regions and, as specified by, Soong et al.(Soong et al., 2020) this may be related to lesss leaching of nutrients, which can improve overall nutrient stocks and tree growth. These observations indicate that SM-sampled soils present better conditions for Guazuma crinita growth. Nevertheless, even though the physical properties of soil are important for the root development of trees, its chemical attributes, especially nutrient availability, are also key players in terms of overall tree survival and growth (De Toledo et al., 2011; Soong et al., 2020). In general, all the chemical attributes of soil were at a good level for the growth of any plant, with the exception of B that was found at a low level (< 0.2 mg kg-1); also, specifically for UC, P was at a low level (< 10 mg kg-1) and S at a medium level (< 20 mg kg-1), according to Horneck et al. (Horneck et al., 2011). These chemical results in both sampled sites partly explain the high growth in these areas, since all collected plots were attributed as high productivity plantations. In general, forestry species require low levels of P, S and B in comparison to K and Ca (Alvarado, 2015). In particular, K is generally scarce in tropical soils due to the dominance of ultisols and oxisols (Sombroek, 1984). However, in these plantations this element was not limited, a fact that can be associated with the less weathered soils present in these areas. With regard to Ca, this element is especially important in teak plantations (da Favare et al., 2012; Zhou et al., 2012a), this species being one of the main exceptions to this rule.

Biometric measurements in "Bolaina"

In general, there is scarce research regarding allometric models for estimating biomass in this species, except for the work of (Revilla-Chávez et al., 2021)(Revilla-Chávez et al., 2021). However, the latter has only considered plants of 31 months old, with a wide range of biometric measurements to obtain R^2 of the same magnitude as this work. Our research is the first to consider a wide range of age (1–10 years) for dry weight estimation in this species, making it possible for general estimations of biomass and possibly also for carbon stock estimations in these types of plantations. Also, research on allometric models in this species has focused more on the determination of commercial volumes of wood rather than dry weight, (Casas et al., 2022; Chávez et al., 2021; Revilla-Chávez et al., 2021) so the literature is very scarce. In general, the first equations (1–4) are commonly used in the literature for estimating height, *dbh* and weight, as shown by the work of Huang et al. 38 & Vorster et al. (Huang et al., 2022; Vorster et al., 2020). However, the logarithmic and logistic models have shown very good results for estimating all the variables, especially for trunk and total weight in *Guazuma crinita*, indicating that their use may be interesting in further research with this species.

Macro- and micronutrient amounts in "Bolaina"

In the case of accumulation of macronutrients in other tropical cultivated species, teak presented a similar trend to Guazuma: at younger ages (5 years), N>Ca>K>P>Mg>S; at later ages (10 years), Ca>N>K>Mg>P>S. (Dos Santos et al., 2022; Fernández-Moya et al., 2014). For six different Eucalyptus (age 3.5 years) genotypes the order was Ca>N>K>Mg>S>P at age 3.5 years (Santos et al., 2020) but in Europe at 18 years it was N>Ca>K>Mg>P, (Merino et al., 2005) so a shift of Ca for N demand was observed. For Larix the order was N>Ca>K>P>Mg (Yan et al., 2017) but for Pinus radiata at 35 years it was N>K>Ca>Mg>P. (Merino et al., 2005) Guazuma reported a high demand for Ca that can only be compared with teak; although other tree species accumulated Ca it was not on the scale of Guazuma and N prevailed as the nutrient in the most demand for this species.

All nutrients are important for plant growth and development but in general N and K are the most in demand, as was observed for Guazuna in the early years. Nitrogen is a key element for plant metabolism and is the main component of many organic compounds, such as amino acids, proteins, enzymes, etc. (Javed et al., 2022; Kraiser et al., 2011). Also, the absence of this element can significantly diminish tree growth and development (The et al., 2021; Zhou et al., 2012b), making it necessary to apply fertilizers in order to combat this limitation. On the other hand, K^+ is a dominant cation in plant cells; it does not have a structural role as N does, but it features in several metabolic functions such as stomatal regulation, stress alleviation, water economy, enzymatic and photosynthetic activity (Sardans & Peñuelas, 2021). However, in this species the dominance of another element was observed: the absorption of Ca was superior in comparison to N, which decreased exponentially with passing years and higher DBH. Cultivated soils with this species presented high Ca, and sometimes also $CaCO_3$ (in low concentrations of < 2%), which could partly explain these higher concentrations. However, some forest species have been reported as high Ca-demanding species, such as teak (Tectona grandis), caoba (Swietenia macrophylla), Pinus patula and others (Alvarado, 2015; Dos Santos et al., 2022). Calcium is an important nutrient in plants for their growth and development because it forms important structural molecules, such as the cell wall and membranes (Thor, 2019), and participates actively in metabolism as a secondary messenger, the oscillatory concentrations in cytosolic Ca^{2+} being the signal for responses to abiotic and biotic stress (Ghosh et al., 2022; Thor, 2019; Xu et al., 2022) and its sufficiency in tropical woody plants such as Guazuma being important for its survival and establishment in this highly competitive environment.

In general, the literature related to micronutrient amounts in forestry is scarce in comparison to macronutrients. Nevertheless, the accumulation of micronutrients for teak (Tectona grandis) was in the order Fe>Zn>Mn>B>Cu, (Fernández-Moya et al., 2014) for Eucalyptus it was Mn>Fe>B>Zn>Cu, (Merino et al., 2005; Santos et al., 2020) for Pinus sp. it was Mn>Fe>Zn>Cu, (Merino et al., 2005; Węgiel et al., 2019) for Pinus pinaster it was Mn>Fe>Zn>B>Cu (Saur et al., 1992) and for Larix it was Mn>Fe>Zn>Cu. (Yan et al., 2017) The main difference for Guazuma in comparison to other tree species is the relatively high requirement for B, this being the second most demanded micronutrient throughout its production cycle.

Micronutrients are very important for plant development and are required in lesser amounts, with both Fe and Mn generally being the most in-demand micronutrients for all plants; (Marschner, 2011) these elements are very important and can be very scarce in neutral to alkaline soils (as the sampled soils) because their availability decays drastically at high pH. Iron is one of the most abundant elements on Earth and in plants it participates in photosynthesis, respiration and, with its high reactivity, helps to transport and balance oxygen (Lapaz et al., 2022; Liang, 2022). On the other hand, Mn is important for its functions as an enzyme cofactor in numerous enzymes, such as arginase, pyruvate carboxylase and Mn superoxide dismutase, among others (Alejandro et al., 2020). However, it can also act to prevent biotic stress, hormone signaling and detoxification of reactive oxygen species (Socha & Guerinot, 2014). In general, in Amazon soils, both Fe and Mn occur in adequate to high concentrations; however, B is generally scarce. (Shorrocks, 1997; Sombroek, 1984). Boron has a structural role in the cell wall and plasma membrane and plays an important role in carbohydrate metabolism, bloom, fructification and hormonal activity; a deficiency in B can diminish wood quality (Wang et al., 2015). Furthermore, woody trees use their reserves of B to overcome deficiency and this factor may be one of the most important when estimating the requirement for B (Riikonen et al., 2013; Wang et al., 2015). In addition, B management is difficult due the narrow limit between deficiency and toxicity in plants; however, in the case of woody species, their ability to store this element may help to reduce the effect of high B application.

CONCLUSION

“Bolaina” (Guazuma crinita) is a very important forest tree in the Peruvian Amazon, being the most planted tree in the country, and has interesting advantages such as rapid growth and its use for wood and construction. This research collected samples in different high-yielding Guazuma plantations in order to explore the general soil conditions and construct allometric equations for biometric variables and nutrient amounts. Overall, it was observed that this species grows in fertile soils. In the case of biometric equations, the logarithmic and logistic models performed better. For nutrient amounts, this species followed a pattern of Ca>N>K>P>S>Mg for macronutrients and Fe>B>Mn>Zn>Cu for micronutrients. The best models for prediction were the square root model (N, K, Ca, Mg, Cu, Fe, Mn), logistic model (P, S, B) and logarithmic model (Zn). This study is the first to assess and model macro- and micronutrient amounts in the productive cycle of this species and the high Ca accumulation in relation to N needs to be researched further by exploring the physiological, anatomical or molecular drivers that explain this behavior.

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Table ESI-1. Mean ± standard deviation of diameter at breast height (DBH), commercial and total height, dry weight (trunk, leaves, branches and total) and wood volume per plant of Bolaina plants from different ages

Age	DBH	Commercial height	Total height	Trunk dry weight	Leaves dry weight	Branches dry weight	Total dry weight	Wood volume
	cm	kg	m	kg	kg	kg	kg	m^3
1	13.2 ± 1.3	5.7 ± 1.0	11.2 ± 1.3	22.4 ± 5.1	2.0 ± 0.8	15.0 ± 5.5	39.3 ± 8.7	0.79 ± 0.30
3	16.9 ± 3.0	11.3 ± 3.8	18.1 ± 6.4	65.4 ± 39.1	6.2 ± 4.1	10.5 ± 4.8	82.1 ± 39.8	2.83 ± 1.87
5	19.7 ± 1.4	15.4 ± 2.3	23.4 ± 3.7	99.4 ± 19.0	5.0 ± 4.1	15.8 ± 8.5	120.2 ± 19.1	4.68 ± 1.00
7	21.9 ± 1.8	16.4 ± 2.0	24.8 ± 3.0	130.1 ± 23.1	4.3 ± 4.3	27.8 ± 17.6	162.2 ± 29.3	6.13 ± 1.45
10	31.4 ± 3.7	13.5 ± 3.2	22.1 ± 5.2	185.9 ± 41.9	22.3 ± 8.5	24.7 ± 19.6	232.9 ± 47.7	10.07 ± 0.84

Table ESI-2. Mean ± standard deviation concentration of nutrients and nutrient uptake of N, P, K, Ca, Mg, S, B, Cu, Fe, Mn and Zn of Bolaina plants from different ages

Age	N			P			K			Ca			Mg			S			B			Cu			Fe			Mn			Zn		
	Leaves	Branches	Trunk	Leaves	Branches	Trunk	Leaves	Branches	Trunk	Leaves	Branches	Trunk	Leaves	Branches	Trunk	Leaves	Branches	Trunk	Leaves	Branches	Trunk	Leaves	Branches	Trunk	Leaves	Branches	Trunk	Leaves	Branches	Trunk	Leaves	Branches	Trunk
	NUTRIENT CONCENTRATION																																
	g kg^{-1}																		**mg kg^{-1}**														
1	26.8 ±4.8	7.5±2.7	4.6±0.4	2.9±0.1	0.9±0.1	0.7±0.1	13.6 ±4.3	10.2±2.6	6.2±0.9	23.6 ±4.1	15±3.3	3.3±1.3	2.8±0.4	1.9±0.3	0.6±0	1.5±0.2	0.8±0.1	0.7±0.1	14.0 ± 2.6	6.5 ± 1.0	6.1 ± 0.9	9.4 ± 1.6	11.2 ± 1.9	4.7 ± 1.1	78.3 ± 22.7	38.0 ± 11.2	42.99 ± 41.11	41.2 ± 11.7	13.0 ± 4.5	2.5 ± 1.2	24.5 ± 5.3	19.8 ± 3.3	4.2 ± 1.5
3	24.6 ±2.7	5.7±1.8	5.8±1.5	3.2±0.6	1±0.2	0.6±0	13.2 ±2.7	8.3±4.2	4.9±1	19.2 ±2.7	5.9±2.4	3.5±1.5	4±1.5	1±0.4	0.6±0.2	1.3±0.2	0.9±0.4	0.7±0.2	12.5 ± 1.6	8.5 ± 3.5	9.3 ± 4.0	9.3 ± 2.5	6.8 ± 4.3	3.1 ± 1.7	94.1 ± 43.4	41.4 ± 23.6	33.76 ± 15.35	84.0 ± 43.4	11.1 ± 6.6	4.8 ± 3.0	22.9 ± 6.7	10.4 ± 4.6	4.3 ± 3.0
5	27.7 ±2.4	5.9±2.3	4.1±0.6	3.3±0.6	1.1±0.2	0.7±0.1	12.7 ±1.2	10.3±4.7	3.8±0.7	22.4 ±1.7	11±8.9	3.8±0.4	2.7±0.6	1.2±0.6	0.4±0	1.3±0.4	0.8±0.3	1±0.8	11.6 ± 2.6	8.3 ± 4.6	8.9 ± 4.8	11.4 ± 2.7	11.1 ± 8.2	2.2 ± 0.7	94.1 ± 42.7	30.0 ± 9.0	39.88 ± 31.45	61.0 ± 39.5	14.1 ± 7.6	2.4 ± 1.2	21.2 ± 11.9	14.4 ± 7.9	2.5 ± 2.0
7	24.6 ±3.2	5.8±2.1	4.9±2.3	3±0.2	0.9±0.1	0.6±0	9.3±2.2	8.1±4.9	3.9±1.5	18.6 ±7	13.5±7.2	5.4±3.4	3±1.4	1.1±0.7	0.5±0.2	1.3±0.6	0.8±0.1	0.8±0.4	12.7 ± 3.8	12.4 ± 7.4	13.8 ± 6.1	11.1 ± 3.9	9.1 ± 4.4	2.3 ± 1.1	66.5 ± 10.6	40.1 ± 10.1	30.0 ± 9.2	35.6 ± 8.9	8.9 ± 5.5	4.7 ± 2.8	22.1 ± 9.1	12.8 ± 6.6	3.4 ± 1.7
10	20.8 ±0.5	5.8±0.5	4±1	2.7±0.1	0.8±0	0.6±0	7.4±0.4	3.5±0.1	2.6±1.2	29.1 ±5.2	12.8±5.2	8.6±1	1.8±0	0.6±0.1	0.2±0.1	1±0.4	0.6±0.1	0.5±0.1	8.7 ± 4.1	9.1 ± 9.3	7.1 ± 4.5	7.0 ± 0.6	8.3 ± 5.5	1.7 ± 0.6	66.7 ± 22.8	112.4 ± 233.1	45.5 ± 37.9	26.9 ± 2.6	5.0 ± 1.3	1.8 ± 0.4	18.5 ± 3.9	6.9 ± 5.6	2.3 ± 1.3
	NUTRIENT UPTAKE																																
	g per plant																		**mg per plant**														

1	59.2 ± 10.5	122.3 ± 67.1	104.0 ± 32.6	6.4 ± 1.0	15.3 ± 7.1	15.0 ± 4.0	29.5 ± 6.8	159.8 ± 73.1	137.8 ± 33.6	53.4 ± 13.8	246.7 ± 123.1	76.4 ± 35.1	6.3 ± 1.6	30.6 ± 14.2	12.2 ± 2.0	3.5 ± 1.1	13.3 ± 5.8	15.8 ± 4.0	32.4 ± 10.8	100.5 ± 30.6	135.7 ± 32.0	21.0 ± 5.00	182.9 ± 94.3	104.4 ± 31.3	179.9 ± 77.0	559.0 ± 141.2	912.9 ± 777.2	90.8 ± 25.9	212.3 ± 115.3	52.6 ± 20.2	55.4 ± 17.3	311.6 ± 112.0	92.8 ± 36.0
3	147.2 ± 109.9	51.3 ± 18.7	386.2 ± 354.3	21.0 ± 18.0	9.3 ± 3.0	38.7 ± 24.9	86.6 ± 73.1	68.5 ± 19.1	286.0 ± 168.5	110.4 ± 72.2	63.3 ± 49.2	203.9 ± 136.2	21.2 ± 15.6	10.0 ± 7.1	30.2 ± 13.2	7.2 ± 4.7	9.5 ± 7.8	35.0 ± 11.9	75.3 ± 56.0	94.1 ± 74.5	452.9 ± 148.2	62.8 ± 53.7	53.0 ± 23.0	197.2 ± 208.2	469.4 ± 326.3	323.7 ± 88.0	2,170.3 ± 1,773.0	370.2 ± 174.0	121.9 ± 120.9	260.1 ± 192.9	125.4 ± 98.6	91.1 ± 45.1	227.5 ± 184.4
5	174.5 ± 151.2	112.2 ± 73.6	403.4 ± 105.5	21.8 ± 19.9	18.9 ± 8.9	69.9 ± 22.4	74.7 ± 62.2	196.8 ± 152.6	385.2 ± 131.6	129.5 ± 102.5	226.8 ± 235.6	376.5 ± 94.8	18.2 ± 16.6	24.3 ± 19.6	38.2 ± 9.1	6.4 ± 4.2	16.1 ± 10.7	92.6 ± 56.7	60.1 ± 42.0	157.4 ± 119.5	860.7 ± 513.8	68.5 ± 59.5	225.4 ± 224.1	211.8 ± 62.8	622.1 ± 730.3	509.2 ± 255.3	3,889.8 ± 2,866.2	219.2 ± 67.6	290.6 ± 203.2	243.0 ± 128.3	91.5 ± 86.5	274.6 ± 223.8	265.6 ± 258.7
7	115.8 ± 124.5	158.4 ± 110.8	610.3 ± 200.2	13.0 ± 13.3	23.6 ± 14.1	81.4 ± 12.9	42.6 ± 48.2	241.3 ± 198.5	516.2 ± 219.6	69.2 ± 80.9	310.1 ± 159.7	705.6 ± 485.5	9.9 ± 11.8	31.8 ± 22.4	62.8 ± 30.8	3.6 ± 2.4	21.3 ± 13.4	94.9 ± 35.0	62.3 ± 67.8	422.0 ± 418.0	1,869.2 ± 969.3	56.6 ± 63.1	217.6 ± 96.5	305.2 ± 197.4	277.5 ± 274.4	1,498.9 ± 1,944.4	6,041.1 ± 5,497.5	134.3 ± 131.5	280.7 ± 248.9	614.3 ± 371.2	117.3 ± 133.4	300.8 ± 151.2	445.3 ± 274.1
10	474.2 ± 260.4	178.8 ± 112.6	715.4 ± 45.2	62.2 ± 34.7	25.9 ± 18.1	117.3 ± 32.2	171.1 ± 98.9	108.7 ± 73.1	467.7 ± 181.6	691.7 ± 468.0	350.0 ± 117.4	1,571.8 ± 146.5	40.7 ± 22.0	17.3 ± 10.2	35.3 ± 10.3	21.3 ± 3.2	17.0 ± 8.8	90.7 ± 17.9	172.6 ± 11.2	187.1 ± 95.7	1,389.7 ± 984.3	162.8 ± 98.2	322.1 ± 354.5	296.8 ± 73.8	1,376.5 ± 283.9	1,159.4 ± 557.9	5,343.5 ± 706.7	625.2 ± 382.5	143.1 ± 67.7	317.7 ± 28.1	443.8 ± 310.7	278.4 ± 326.4	413.8 ± 195.9

Table ESI-3. Allometric models evaluation with Akaike Information Criterion (AIC) and Root Mean Squared Error (RMSE) for macronutrient (N, P, K, Ca, Mg, S) amounts of trunk and total in g per plant of “bolaina” (*Guazuma crinita*) trees from 1 to 10 years in the sampled areas in San Martin and Ucayali department

	N				**P**				**K**				**Ca**				**Mg**				**S**			
Models	Trunk		Total		Trunk		Total		Trunk		Total		Trunk		Total		Trunk		Total		Trunk		Total	
	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE
1*	50.05	0.48	25.36	0.33	37.13	0.39	11.04	0.26	36.22	0.39	21.56	0.31	53.20	0.51	**25.37**	**0.33**	48.67	0.47	20.79	0.31	61.29	0.57	41.20	0.43
2	**21.43**	**0.30**	**19.04**	**0.29**	-9.33	0.18	0.94	0.22	**17.25**	**0.28**	**14.90**	**0.27**	**39.97**	**0.40**	26.69	0.33	**27.75**	**0.33**	**16.32**	**0.28**	46.10	0.44	36.55	0.38
7	37.76	0.40	19.87	0.30	18.47	0.29	2.50	0.23	27.22	0.34	17.81	0.29	41.75	0.42	29.07	0.35	41.34	0.42	17.90	0.29	54.53	0.52	37.58	0.40
8	42.90	0.43	21.41	0.31	30.45	0.35	6.30	0.24	29.90	0.35	18.45	0.30	48.27	0.47	27.43	0.34	44.70	0.44	18.56	0.30	57.95	0.54	39.03	0.41
9	21.56	0.30	19.06	0.29	**-11.61**	**0.18**	**0.56**	**0.21**	17.48	0.28	16.47	0.28	40.44	0.40	26.67	0.38	29.13	0.34	17.41	0.28	**46.08**	**0.44**	**36.39**	**0.38**
10	23.34	0.31	19.31	0.29	-6.64	0.19	0.92	0.22	18.41	0.28	16.93	0.28	40.81	0.40	26.93	0.38	30.18	0.34	17.58	0.28	46.69	0.44	36.34	0.38

*The selected models were significant by F-test at 0.05. Values in bold represent the best model, with the lower AIC (Akaike Information Criterion) and RMSE (Root Mean Squared Error)

Table ESI-4. Allometric models evaluation with Akaike Information Criterion (AIC) and Root Mean Squared Error (RMSE) for micronutrient (B, Cu, Fe, Mn, Zn) amountamount of trunk and total in g per plant of “bolaina” (*Guazuma crinita*) trees from 1 to 10 years in the sampled areas in San Martin and Ucayali department

	B				**Cu**				**Fe**				**Mn**				**Zn**			
Models	Trunk		Total		Trunk		Total		Trunk		Total		Trunk		Total		Trunk		Total	
	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE	AIC	RMSE
1	77.30	0.74	62.94	0.61	50.02	0.48	37.23	0.40	73.53	0.70	54.76	0.53	79.71	0.77	42.59	0.44	64.86	0.61	37.22	0.40
2	69.11	0.63	59.72	0.56	**40.80**	**0.40**	**37.38**	**0.39**	**61.06**	**0.55**	**51.44**	**0.49**	**69.87**	**0.64**	**41.66**	**0.42**	64.07	0.58	38.88	0.40
7	72.24	0.68	60.13	0.58	45.02	0.45	36.87	0.39	66.98	0.63	51.46	0.50	75.19	0.71	41.38	0.43	**62.75**	**0.59**	**36.94**	**0.40**
8	74.15	0.70	61.01	0.59	46.43	0.46	38.08	0.39	69.12	0.65	52.30	0.51	76.96	0.73	41.57	0.43	63.33	0.59	36.95	0.40
9	**68.93**	**0.63**	**59.10**	**0.56**	42.11	0.41	37.25	0.39	62.18	0.56	51.59	0.49	71.47	0.65	41.59	0.49	64.03	0.58	38.74	0.40
10	69.02	0.63	60.13	0.56	42.58	0.42	37.44	0.39	62.79	0.57	51.86	0.49	71.79	0.66	42.71	0.42	64.10	0.58	38.80	0.40

*The selected models were significant by F-test at 0.05. Values in bold represent the best model, with the lower AIC (Akaike Information Criterion) and RMSE (Root Mean Squared Error)