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ARTICLE

Geostatistical analysis of aboveground carbon stock in Mopane forests

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Abstract

Tropical forests play a crucial role in regulating the climate and maintaining the global carbon cycle. Carbon is primarily stored in plant biomass. In Africa, these forests still present significant uncertainty in the carbon balance. This is due to scarce inventories and a lack of continuous monitoring. Mopane forests (*Colophospermum mopane*) are typical of dry tropical regions and have important ecological and socioeconomic roles. They are widely used by local communities. In Mozambique, charcoal production mainly drives degradation of these forests and loss of aboveground carbon (AGC). The aim of this study is to analyze aboveground carbon stock in Mopane forests in the Chicualacuala District, Southern Mozambique. The data used refer to georeferenced tree locations in a fragment of native forest. Aboveground biomass was individually estimated through a pantropical equation, using as predictor variables: diameter at breast height (DBH), total height, and basic wood density. From the biomass estimates, AGC was calculated and subsequently analyzed using geostatistical methods such as variograms and ordinary kriging. The results indicated that the ordinary kriging model partially captured the spatial pattern of AGC and, as evidenced by cross-validation, showed a moderate positive correlation (54.66%) between observed and predicted values. This level of correlation suggests that while the model provides a reasonable prediction of AGC, there is still considerable unexplained variability, which highlights areas for further model refinement or additional data collection.

Keywords: Spatial dependence; Interpolation; Tropical forest; Chicualacuala district.

1. Introduction

Forest structure refers to the three-dimensional arrangement of tree components, such as leaves, branches, and stems, which are distributed over areas of different scales (Kay *et al.,* 2021). This configuration is essential for understanding the functioning of forest ecosystems, particularly with respect to carbon stocks and fluxes (Means *et al.,* 1999). In particular, tropical forests play a key role in regulating the global climate and the carbon cycle, being one of the main terrestrial reservoirs of this element, stored in the form of organic compounds present in plant biomass (Fischer, 2021; Anderson-Teixeira *et al.,* 2016; Malhi, 2012).

Seasonally dry tropical forests, which represent about 40% of the planet's tropical forest area, also play a relevant role in climate change mitigation, as recognized by the Paris Agreement under the United Nations Framework Convention on Climate Change (UNFCCC) (Ciais *et al.,* 2011; Grainger, 1999). However, these ecosystems face alarming levels of deforestation and degradation (McNicol et al., 2018), which compromise their function as carbon sinks and threaten global climate stabilization efforts (Millar *et al.,* 2007; Njana *et al.,* 2021). In the African context, tropical forests represent a significant source of uncertainty in the global carbon balance, largely due to the scarcity of forest inventories and the absence of long-term monitoring strategies (Ciais *et al.,* 2011; Valentini *et al.,* 2014; Pelletier *et al.,* 2018).

Land Use (LU) and Land Cover Change (LULCC) has direct impacts on the global carbon cycle, especially in light of the continuous increase in atmospheric carbon dioxide (CO_2) concentration (Houghton *et al.,* 2012; Gasser *et al.,* 2020). The role of land-use changes in CO_2 emissions has motivated several studies aimed at quantifying the global carbon budget and understanding the impacts of human activities on terrestrial ecosystems (Gumbo *et al.,* 2018; Lisboa *et al.,* 2025).

The assessment of carbon stocks is thus fundamental for mapping stored carbon and sequestration potential, constituting a strategic tool to support environmental policy formulation and land-use planning (Asner *et al.,* 2016). Such estimates are significant for preventing carbon-rich ecosystems from becoming net sources of emissions as a consequence of inappropriate management practices or land-cover changes, such as deforestation (Powlson *et al.,* 2012; Vashum & Jayakumar, 2012). Moreover, the ongoing increase in greenhouse gas concentrations and the impacts associated with global warming underscore the urgent need to identify, conserve, and sustainably manage ecosystems with a high capacity for carbon storage (Canadell & Raupach, 2008; Hilmi *et al.,* 2021).

In this context, particular attention is given to Mopane forests, dominated by the species *Colophospermum mopane* (J. Kirk ex Benth J. Léonard), typical of dry tropical regions. This vegetation formation is widespread in Southern Africa, including Angola, Namibia, Botswana, Zimbabwe, Mozambique, South Africa, Zambia, and Malawi, covering an estimated area of 555,000 km^2 and forming part of the Zambezian Regional Center of Endemism (Makhado *et al.,* 2014; Stevens, 2021). In Mozambique, Mopane woodlands occurs in the provinces of Tete, Manica, and Gaza, comprising one of the main phytogeographic regions of the country (Maquia *et al.,* 2019). Mopane woodlands play a crucial role for local communities, providing resources such as food, medicine, grazing, construction materials, and serving as an important source of household energy (fuel wood and charcoal) (Woollen *et al.,* 2016; Stevens, 2021; Macôo *et al.,* 2025). However, Mopane forests are under threat due to selective harvesting for charcoal production, leading to forest degradation and the reduction of carbon stocks (Woollen *et al.,* 2016; Sedano *et al.,* 2020).

Conducting forest inventories in Mopane woodlands is not an easy task, and therefore, analyses of these biomes are based on data obtained from sample of experimental plots located within the study region (Gibbs *et al.,* 2007). Thus, to obtain a complete map of aboveground carbon (AGC) stocks in Mopane forests, it is necessary to use some type of spatial interpolator.

Thus, the main aim of this study is to use geostatistical methods such as variogram and kriging to analyze AGC stocks in Mopane forests (*Colophospermum mopane*), in the Chicualacuala district, located in southern Mozambique, in order to get a complete spatial characterization of this variable.

2. Materials and Methods

2.1 Data

The study was conducted in the village of Chihondzoene (Chicualacuala district), in Gaza Province, Mozambique. The study area is located in a semi-arid region, with mean annual precipitation ranging from 300 to 700 mm/year and mean annual temperatures between 20°C and 26°C (Woollen *et al.,* 2016; Sedano *et al.,* 2020).

The forested area covers 37,983 ha. The main forest type in the region is Mopane, which has scattered forest fragments of Mecrusse (*Androstachys johnsonii*, Prain) and forest formations composed of *Guibourtia conjugata* (Bolle, J. Leonard), along with species of *Combretum spp.*, *Acacia spp.*, and others. Mopane forests are predominantly dominated by *Colophospermum mopane*, while Mecrusse forests are generally monospecific, composed of *A. johnsonii*.

Local populations depend on the forest for their livelihoods. Subsistence agriculture, livestock rearing, and charcoal production are the main economic activities.

Mozambique is located on the eastern coast of Africa, between latitudes 10°–26° South, in the Southern African region. The climate ranges from humid tropical to dry, including some semi-arid regions. Native forest covers a total of 31,693,872 ha, of which Gaza Province accounts for 3,096,817 ha (9.8%). The main biomes of Gaza Province include Miombo, Mopane, and Mangrove (Macôo *et al.,* 2025).

Field surveys were carried out between February and April 2019, based on the methodology of the National Forest Inventory (NFI) (Marzoli, 2007), aiming at the development of a community forest management plan. The area was stratified according to the main vegetation types: (i) Mopane, dominated by *Colophospermum mopane*; (ii) Mecrusse, dominated by *Androstachys johnsonii*; and (iii) Mixed forest, composed of a combination of *Acacia spp.*, *Guibourtia conjugata*, *Combretum spp.*, and other species.

Sentinel-2A MSI images were used to classify the forest types. Based on this classification, 55 clusters were established through random sampling with a minimum distance restriction of 500 m between points (Maniatis & Mollicone, 2010), to avoid overlap. Each square cluster contained four plots of 100×20 m, located at the corners and spaced 400 m apart, as well as one subplot of 15×10 m each (Figure 1).

In each plot, GPS coordinates were recorded (accuracy ± 3 m), and diameter at breast height (DBH $\geq$ 10 cm) and total tree height were measured, following the NFI protocol. In the subplots, individuals with $5 \leq$ DBH < 10 cm were included. Species were identified by their scientific names, with the support of botanical guides (Burrows *et al.,* 2018; Van Wyk & Van Wyk, 1997), and also by their local names, with the assistance of community residents, as described by Woollen *et al.* (2016).

Aboveground carbon (AGC) stock estimation was based on aboveground biomass (AGB; kg), calculated for each tree using the pantropical equation of Chave *et al.* (2014), with the following predictor variables: diameter at breast height (DBH; cm), total height (H; m), and basic wood density (ρ; $g \cdot cm^{-3}$), as described by Pelletier *et al.* (2017).

Aboveground carbon (AGC; $Mg \cdot ha^{-1}$) was obtained by multiplying each tree's AGB by a conversion factor of 0.475, following Guedes *et al.* (2018). It is estimated that between 45% and 50% of plant biomass corresponds to carbon (Guedes *et al.,* 2018; Chave *et al.,* 2014). The AGC for each plot was determined by summing the AGC of all trees present and subsequently converting this value to a per-hectare basis, according to plot and subplot sizes, following the approach of Gizachew *et al.* (2016). Finally, AGC per cluster was calculated as the mean AGC of its constituent plots, a method adopted to minimize variability, as recommended by Pelletier *et al.* (2017).

Further information on the dataset can be found in Macôo *et al.* (2025).

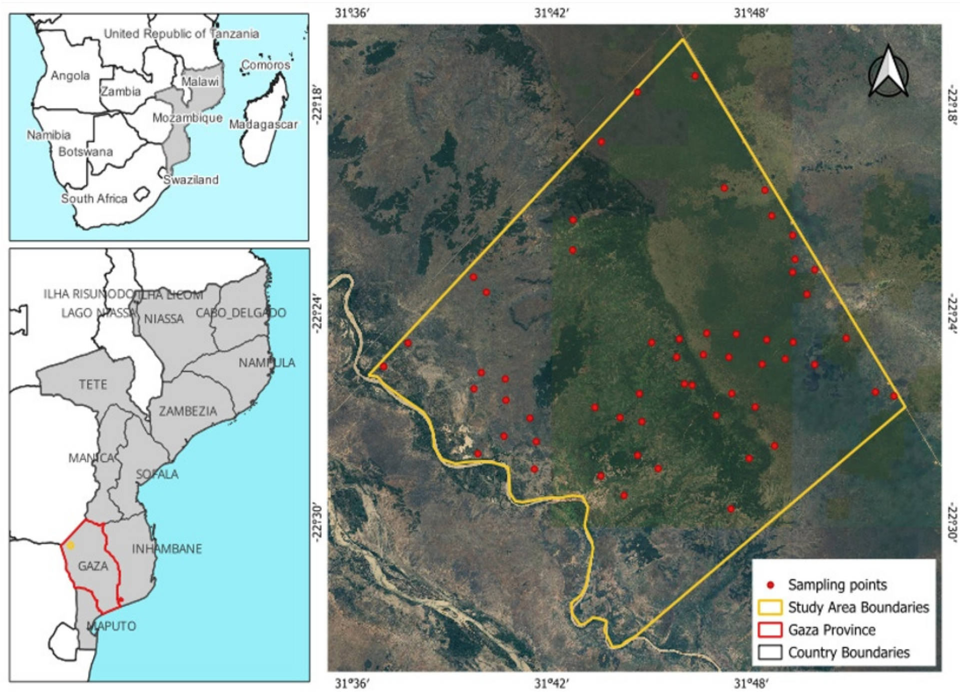

Figure 1. Map of the study area: on the left, it indicates the general location of the study area in Gaza Province, southern Mozambique; on the right, it shows the study site in Chihondzoene, Chicualacuala district.

2.1.1 Statistical Methods

An exploratory data analysis was first carried out in order to characterize the distribution of the sample data of aboveground carbon (AGC), and to detect the presence of outliers that could affect the quality of the geostatistical analysis. For this purpose, descriptive statistics were calculated such as mean, median, range, standard deviation, standard error, skewness, and kurtosis. To complement this approach and to facilitate the understanding of the distribution of aboveground carbon (AGC), histograms and boxplots were also used (Oliveira *et al.*, 2023; Tuzine *et al.*, 2022; Scalon, 2024).

After the exploratory data analysis, a geostatistical analysis was performed in order to quantitatively represent the spatial variation of AGC in the study area.

Initially, Matheron's classical predictor of semivariance (Matheron, 1963) was carried out to characterize the spatial dependence of AGC. Under the assumption of the intrinsic hypothesis, Matheron's estimator is given by the Expression 1:

$$\hat{\gamma}(h) = \frac{1}{2\left|N(h)\right|} \sum_{N(h)} \left[Z(s_i) - Z(s_j)\right]^2, \tag{1}$$

where h represents the distance measured only in magnitude, $N(h)$ is the set of all pairs of Euclidean distances $|x_i - x_j| = h$, $|N(h)|$ is the number of distinct pairs in $N(h)$, and $Z(x_i)$ and $Z(x_j)$ are data values at spatial locations s_i and s_j.

It is worth noting that the graphical representation of the semivariance $\hat{\gamma}(h)$ as a function of distance h (scatterplot or point diagram) is referred to as the empirical (or experimental) semivariogram (Scalon, 2024).

A recommended practice in geostatistical analysis is the use of simulation envelopes for empirical semivariograms in order to verify the existence of spatial dependence in the studied phenomenon. If such dependence is not identified, the use of geostatistical methods becomes unnecessary, and it is more appropriate to apply conventional statistical techniques (Scalon, 2024).

Once spatial dependence is detected, the next step consists of fitting a theoretical model to the empirical semivariogram. Gaussian, spherical, and exponential models will be fitted. The model parameters will be estimated using the Ordinary Least Squares (OLS) method.

The cross-validation method will be applied to select the best-fitted model, which will be used for interpolation by using ordinary kriging.

Ordinary kriging will be employed using the predictor given in (Expression 3), derived from the general kriging (Expression 2).

$$Z(\boldsymbol{u}_0) = m(\boldsymbol{u}_0) + \sum_{i=1}^{n} \lambda_i \left[z(\boldsymbol{u}_i) - m(\boldsymbol{u}_i) \right], \tag{2}$$

$$\hat{Z}(\boldsymbol{u}_0) = \sum_{i=1}^{n} \hat{\lambda}_i z(\boldsymbol{u}_i), \tag{3}$$

where $\boldsymbol{u}_0$ is the vector of estimation locations, $m(\boldsymbol{u}_0)$ and $m(\boldsymbol{u}_i)$ are the expected values for the estimation sites and the observed values, respectively, and λ_i are the kriging weights assigned to the data $z(\boldsymbol{u}_i)$ to obtain the kriging predictions at the location vector $\boldsymbol{u}_0$. Subsequently, the predicted value and the associated prediction error for the method were estimated.

The predictions obtained were then used to construct the aboveground carbon interpolation map for the entire study region.

Further details on the geostatistical methods applied in this study can be found in Isaaks & Srivastava (1989) and Scalon (2024). All analyses were performed using the *geoR* package (Ribeiro Júnior & Diggle, 2001) in the *R* software environment (R Core Team, 2025).

3. Results and Discussion

Mopane forests play an important role in the way of life of many people living in African countries such as Mozambique and Malawi (Maquia *et al.,* 2019), and in the climate regulation through their aboveground carbon (AGC) stocks (Fischer, 2021). Unfortunately, the scarcity of inventories in this biome results in uncertainties in the measures of carbon balance (Gibbs *et al.,* 2007). Thus, this work advocates to use geostatistical methods (Matheron, 1963) in order to get a complete spatial characterization of AGC stocks in such forests.

First of all, it is carried out an exploratory data analysis using descriptive statistics and plots. Table 1 presents descriptive statistics of the sample data of AGC and indicates that the mean and median were 10.9442 $\mathrm{Mg \cdot ha^{-1}}$ and 10.3607 $\mathrm{Mg \cdot ha^{-1}}$, respectively, with a standard deviation of 6.4802 $\mathrm{Mg \cdot ha^{-1}}$ and a range of 22.8776 $\mathrm{Mg \cdot ha^{-1}}$. It can also be observed that the distribution of AGC measurements (Figure 2) showed moderate positive skewness (skewness coefficient equal to 0.5133), indicating a greater concentration of observations below the mean and the presence of a longer right-hand tail. Furthermore, the negative kurtosis (−0.8739) characterizes the distribution as platykurtic, that is, flatter compared to the normal distribution and with a lower frequency of extreme values.

Observing Figure 2, Panel (a), it can also be seen that higher values of AGC occur at a lower proportion. In Panel (b), it is noted that the AGC data exhibit a slightly right-skewed distribution without the presence of discrepant values (outliers).

Table 1. Descriptive statistics of aboveground carbon (Mg·ha^{-1}) in mapone forests

Species	n	$\bar{x}$	Md	SD	SE	Rng.	Skew.	Kurt.
C. mopane	55	10.9442	10.3607	6.4802	0.8738	22.8776	0.5133	−0.8739

n: sample size; $\bar{x}$: mean; Md: median; SD: standard deviation; SE: standard error; Rng: range; Skew: skewness coefficient; Kurt: kurtosis.

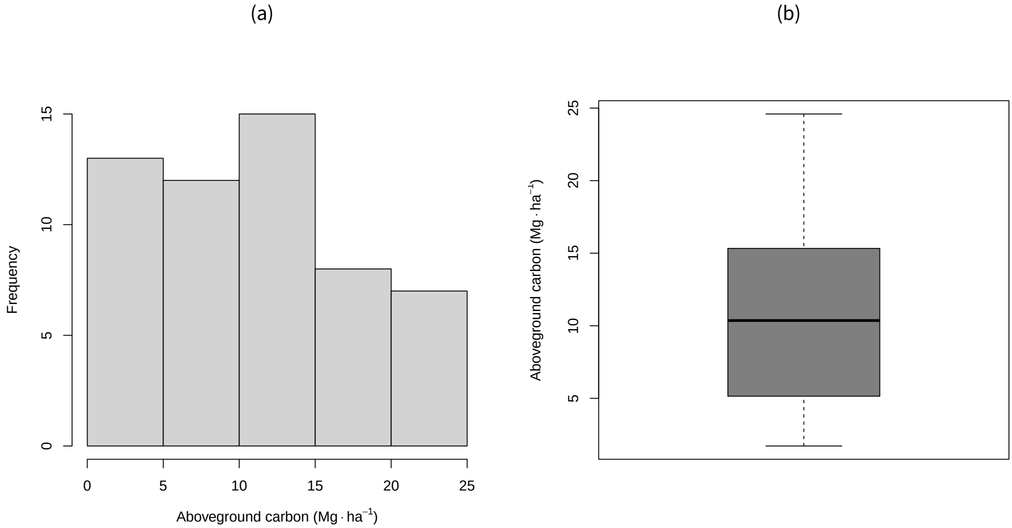

Figure 2. Graphical representations of the distribution of aboveground carbon in Mopane woodlands: (a) frequency histogram and (b) boxplot.

The absence of outliers in the sample data suggests that is possible to use the Matheron´s classical predictor in order to characterize the spatial dependence of AGC in the study region. In Figure 3, Panel (a), the omnidirectional empirical semivariogram can be observed, accompanied by simulation envelopes under the hypotheses of independence.

Figure 3 (Panel (a)), provide evidence that the hypothesis of the absence of spatial dependence in the AGC data is highly unlikely, since the empirical semivariogram exceeds the limits of the simulation envelope for at least one of the distances.

The next step consists of fitting a theoretical model to the empirical semivariogram. We fitted three models (Gaussian, spherical, and exponential) as described in Isaaks & Srivastava (1989). The cross-validation method shown that the exponential model (Equation 4) provided the best fit to the empirical semivariogram. A graphical presentation of this fit can be seen in Figure 3 (Panel (b)).

$$\gamma(h) = 0.0001 + 43.7185\left[1 - \exp\left(-\frac{h}{2042.6705}\right)\right], \tag{4}$$

In Equation 4 the range 2042.67 meters is the distance beyond which sampled points are no longer spatially correlated or related to each other. It represents the extent of spatial continuity of AGC. Sample points separated by a distance shorter than 2042.67 meters exhibit spatial autocorrelation, while those further apart are considered independent. In the best of our knowledge, we understand that it is the first time that spatial dependence of ACG in Mopane Forests is estimated.

The spatial structure of AGC given by the parameter estimations of the exponential model presented in Equation 4 is used in the Kriging method to get the estimates for the unknown values of AGC at unsampled locations.

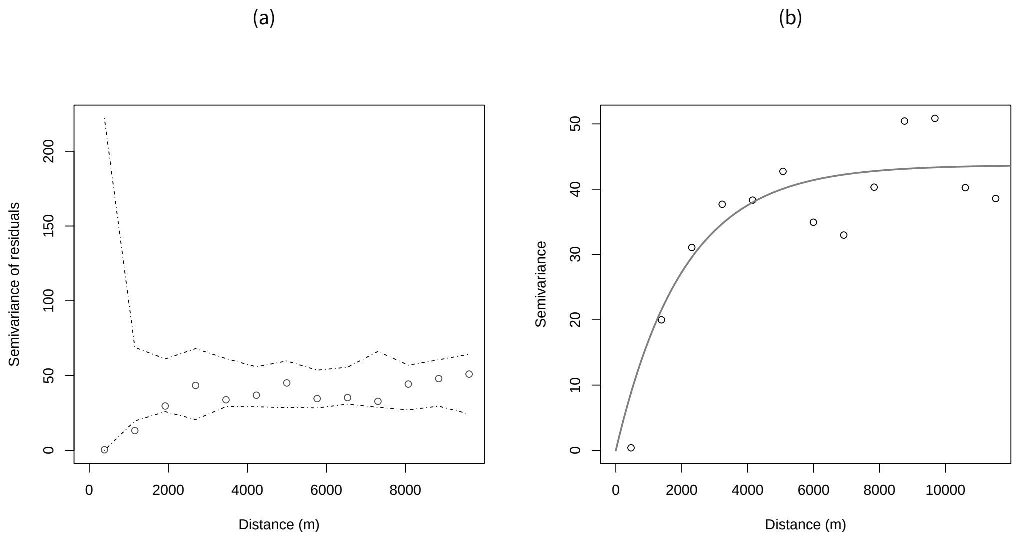

Figure 3. Graphical representations: (a) Omnidirectional empirical semivariogram of residues with simulation envelopes and (b) exponential model fitted to aboveground carbon data in Mopane forests.

We used ordinary Kriging to get the interpolated values that are used to create a continuous surface map of AGC in Mopane forests, located in the Chicualacuala District, as we can see displayed as a raster map (Figure 4, Panel (a)) or contour map (Figure 4, Panel (b)).

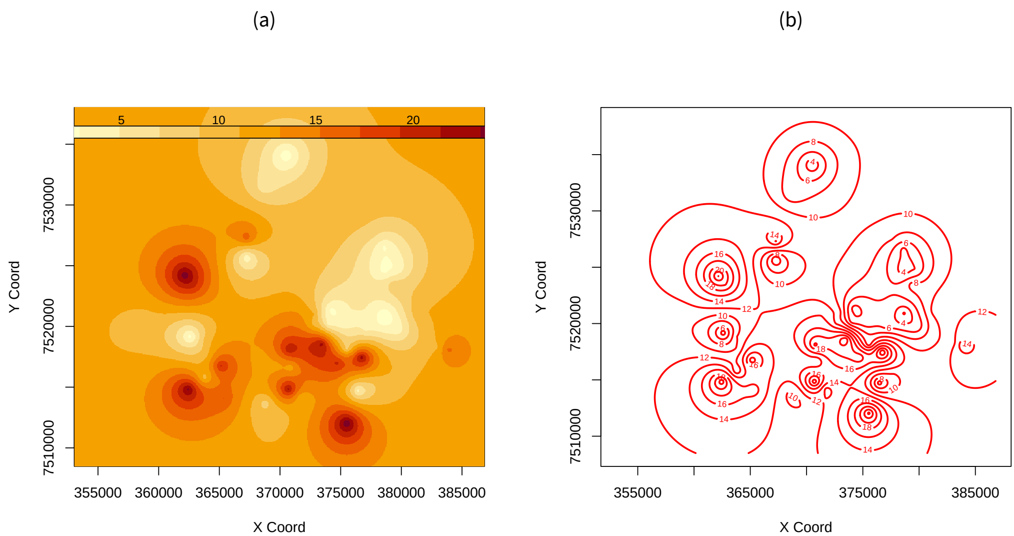

Figure 4. Maps of aboveground carbon in Mopane forests, Chicualacuala district: (a) Raster map and (b) contour map associated with predicted carbon values.

It can be noted that the darker areas on the raster map presented by Figure 4, Panel (a) correspond to higher concentrations of AGC, whereas the lighter regions indicate lower estimated values. This pattern reinforces the usefulness of cartographic products in representing the spatial distribution of biomass and supporting forest management.

Although Figure 4, Panel (a) provides an overview of AGC distribution, its use as an analytical tool should be approached with caution. This is because, despite presenting a measurement scale, the spatial resolution of the map does not allow for precise identification of all local variations. To overcome this limitation, the analysis was complemented with a contour map (Figure 4, Panel (b)), which facilitates the visualization of the continuous spatial distribution of AGC estimates. According to Isaaks & Srivastava (1989), contour maps are widely used in geostatistical studies, as they allow the identification of general patterns, regional trends, and heterogeneities in large spatial datasets.

In Panel (b), it can be observed that predicted AGC values ranged between 4 and 20 Mg·ha^{-1}, highlighting the high spatial heterogeneity of carbon in Mopane woodlands. This variation is consistent with previous studies conducted in similar ecosystems. For example, Kuyah *et al.* (2014) reported carbon stocks ranging from 0.8 to 22 Mg·ha^{-1} in agricultural areas and degraded open forests in Malawi, underscoring the similarity among seasonal tropical environments of Southern Africa. Ribeiro *et al.* (2013) estimated values of approximately 19 Mg·ha^{-1} in undisturbed Miombo forests in the Niassa Forest Reserve, northern Mozambique, suggesting that conservation of these areas plays a crucial role in maintaining carbon stocks. Likewise, Gibbs *et al.* (2007) observed that carbon stocks in open, closed, and seasonal forests of Sub-Saharan Africa vary between 17 and 152 Mg·ha^{-1}. These results indicate that, despite the relatively low values found in Mopane forests, these vegetation formations still contribute significantly to carbon sequestration in semi-arid regions. Moreover, the variation among studies reinforces the importance of ecological context, degree of degradation, and land-use history in determining the carbon storage capacity of different forest types.

Table 2 presents the descriptive statistics of aboveground carbon (AGC) estimates obtained through ordinary kriging.

Table 2. Descriptive statistics of aboveground carbon estimates (Mg·ha^{-1}) in Mopane woodlands predicted by ordinary kriging

Species	n	$\bar{x}$	Md	SD	SE	Rng.	Skew.	Kurt.
C. mopane	360000	11.5134	11.5498	2.5217	0.0042	22.6791	0.1804	2.4747

n: sample size; $\bar{x}$: mean; Md: median; SD: standard deviation; SE: standard error; Rng: range; Skew: skewness coefficient; Kurt: kurtosis.

Table 2 shows that the distribution of predicted values showed a mean and median of 11.5134 Mg·ha^{-1} and 11.5498 Mg·ha^{-1}, respectively, with little difference between them, suggesting an approximately symmetric distribution. This behavior is reinforced by the low skewness coefficient (0.1804), indicating slight positive skewness, with a small concentration of values below the mean. Similar results were observed by Woollen *et al.* (2016), who found mean values close to 11.8 Mg·ha^{-1} of AGC in Mopane forests in the Mabalane district, Gaza Province, when investigating the impacts of charcoal production on local ecosystem services.

The standard deviation (2.5217 Mg·ha^{-1}) indicates moderate variability around the mean, consistent with the heterogeneous nature of Mopane forests, characterized by high structural variation between intact areas and those subject to intensive exploitation. According to Tamene *et al.* (2016), variability in carbon stocks may reflect differences in topography, climate, and land-use regimes across different systems. The standard error of the mean (0.0042) demonstrates the high precision of the estimates, a result of the large sample size (n = 360000), which provides greater statistical robustness to the results. The observed range of 22.6791 Mg·ha^{-1} reveals a wide spread of predicted values, highlighting the influence of environmental gradients and local factors. The positive kurtosis (2.4747), lower than that of the normal distribution (kurtosis = 3), characterizes the distribution as slightly platykurtic, i.e., with lighter tails and a lower frequency of extreme values, suggesting that most areas exhibit AGC values close to the mean, while very high or very low values are less frequent.

It is also important to note that the proximity between mean and median, the low skewness, and the kurtosis lower than the normal distribution suggest that Mopane forests display relatively stable behavior in terms of carbon stock, even under conditions of environmental variability. These findings have relevant implications for monitoring and for the formulation of sustainable management strategies, contributing to climate change mitigation policies in Mozambique and other semi-arid regions of Africa.

Table 3 presents the results of the Pearson correlation test between the observed AGC values and the predictions obtained by ordinary kriging using cross-validation.

Table 3. Pearson correlation between observed aboveground carbon data ($Mg \cdot ha^{-1}$) and estimates obtained by kriging in Mopane woodlands

Species	Corr.	t	gl	$CI(\mu)_{95\%}$	p-value
C. mopane	0.5466	4.7517	53	[0.3289 – 0.7091]	0.0107

Corr.: Pearson correlation; t: Student's t-statistic; gl: degrees of freedom; $CI(\mu)_{95\%}$: 95% confidence interval for μ.

Table 3 shows that the correlation coefficient is equal to 54.66% ($p = 0.0107$), indicating a statistically significant positive association between the empirical data and the predicted values. This performance suggests that, although the kriging model is able to capture part of the spatial pattern of the observed carbon, there remains a significant portion of variability that was not explained. Such limitation may be associated with the intrinsic heterogeneity of seasonally dry tropical forests, in which factors such as floristic composition, vegetation structure, edaphic variations, and disturbance regimes strongly influence the distribution of carbon (Baccini *et al.,* 2017; Wang *et al.,* 2024; Yang *et al.,* 2024).

Despite these limitations, the moderate correlation observed in this study suggests that ordinary kriging still constitutes a useful tool for representing the spatial distribution of aboveground carbon, especially in contexts with limited availability of field data. However, it is recommended that future analyses explore the use of complementary techniques, such as co-kriging and machine learning–based models, which have shown greater capacity to capture the spatial complexity of carbon in heterogeneous ecosystems (Peng *et al.,* 2025; Ho *et al.,* 2025; Parvizi & Fatehi, 2025).

It is worth to point out that the results obtained in this study are consistent with the literature and highlight that the use of geostatistical methods, combined with detailed cartographic representations such as raster and contour maps, may be of fundamental importance for understanding the spatial distribution of forest carbon.

Although the method demonstrates satisfactory performance and practical applicability, its results should be interpreted with caution, particularly in areas of high environmental heterogeneity. The incorporation of additional environmental variables and the use of hybrid approaches may contribute to improving the accuracy of estimates and expanding applicability in carbon monitoring studies and sustainable forest management.

Nevertheless, geostatistical methods may contribute to the development of sustainable management strategies and the formulation of public policies aimed at mitigating climate change, particularly in developing countries with extensive areas of seasonally dry tropical forests.

4. Conclusions

This study has demonstrated the usefulness of geostatistical methods for analyzing and mapping aboveground carbon (AGC) in Mopane woodlands, in the Chicualacuala District, Southern Mozambique. The use of the exponential model, combined with ordinary kriging and cross-validation, has enabled the spatial characterization of AGC stocks, highlighting areas with higher and lower concentrations of AGC based only on a small set of samples. Also, the results shown that there are space to improve these methods in order to incorporate local environmental factors and anthropogenic intervention in the model.

Given the increasing pressure on Mopane Forests for charcoal production, the results obtained here contribute to understanding the stock and distribution of carbon in these vegetation formations, providing support for sustainable management strategies and climate change mitigation policies. However, it is recommended that long-term monitoring be expanded and complementary environmental variables incorporated to improve the accuracy of estimates and strengthen the conservation of these ecosystems.

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Conflicts of Interest

Authors declare no conflict of interest.

Author Contributions

Conceptualization: OSSIFO, M. E.; MACÔO, S. J.; CAU, A. C.; SALVADOR, R. C.; GONZAGA, N. A.; SCALON, J. D. **Data curation**: OSSIFO, M. E.; MACÔO, S. J. **Formal analysis**: OSSIFO, M. E.; SCALON, J. D. **Funding acquisition**: OSSIFO, M. E.; MACÔO, S. J.; CAU, A. C.; SALVADOR, R. C.; GONZAGA, N. A.; SCALON, J. D. **Investigation**: OSSIFO, M. E.; MACÔO, S. J.; CAU, A. C.; SALVADOR, R. C.; GONZAGA, N. A.; SCALON, J. D. **Methodology**: OSSIFO, M. E.; SCALON, J. D. **Project administration**: OSSIFO, M. E.; MACÔO, S. J.; CAU, A. C.; SCALON, J. D. **Software**: OSSIFO, M. E.; SCALON, J. D. **Resources**: **Supervision**: SCALON, J. D. **Validation**: OSSIFO, M. E.; SCALON, J. D. **Visualization**: OSSIFO, M. E.; MACÔO, S. J.; CAU, A. C.; SALVADOR, R. C.; GONZAGA, N. A.; SCALON, J. D. **Writing - original draft**: OSSIFO, M. E. **Writing - review and editing**: SCALON, J. D.

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