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Papers

Use of logistic regression and GIS techniques in the analysis of forest cover dynamics in Mabote and Funhalouro, Inhambane, southern Mozambique

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Logistic regression
Forest cover dynamics
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Abstract
This article seeks to use logistic regression and GIS techniques as a way to understand the influence of forest policy on the dynamics of forest cover in the study area. For this, we chose the following variables: Dynamics of forest cover as the dependent variable; precipitation, temperature, simple license, forest concession, volume of charcoal exploited, agricultural areas, villages, and population dynamics as independent variables. From the correlation, the variables that showed significance in the model are simple license, temperature, and volume of charcoal exploited. But the logistic regression model showed that the simple license and temperature variants are significantly important for the model. This does not rule out the existence of other variables that may explain the phenomenon. Thus, the constructed logistic regression model points out that the simple license predictor is statistically more significant in explaining the variation in forest cover compared with temperature. Simple licensing is one of the modalities that forestry policy in Mozambique has adopted for forest licensing. And many of the operators prefer this type of license. Temperature inversely influences the dynamics of forest cover, causing water stress in plants. While the variable volume of coal explored, its influence is significantly smaller.

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INTRODUCTION

The degradation of forest cover, especially in tropical regions, worries the world (CARRERE, 2002; MORAN, 2010; FAO, 2020). The region should contribute to carbon sequestration, mitigating the effects of global warming, but this local ecosystem service is compromised due to intensive logging activity. In Mozambique, the works of Macqueen and Falcão (2017), Mackenzie (2006), Sitoe et al. (2012), Sheila de Menezes Advogados (2017), Banco Mundial (2018), and FAO (2020) highlight this environmental problem. In the 2007 forest inventory, the country had an area of native forests that occupied about 45% of its territory (MARZOLI, 2007), but this percentage has decreased in the last ten years, given the average annual loss of 222,000 hectares of forest (FAO, 2020).

It is important to conserve and monitor forest ecosystems because they provide ecological goods and ecosystem services for other plants and animals, and for humans (MORAN, 2010; SONG; GRAY; GAO, 2011).

The use of remote sensing products is a viable means for studies on forest cover dynamics, especially for temporal-spatial analysis at different scales (INPE, 2002). The detection of changes, both in time and space, allows for analyzing the behavior of phenomena on the land (MALDONADO; DOS SANTOS, 2005; LIU et al., 2004).

Images from optical sensors, mainly those from the Landsat satellite series, due to their temporal resolution, make it possible to capture the dynamics of phenomena (CAPANEMA, 2017; SONG et al., 2011), while statistical methods help to determine the importance of variables that influence forest cover dynamics.

Studies related to forest cover dynamics using spatial information technologies and statistical models (BAVAGHAR, 2015, CRONEMBER; VICENS, 2015; KUMAR et al. 2014; RODRIGUES, 2005) gain importance, currently.

Kumar et al. (2014) studied the status of forest cover conversion in Kanker, district of Bhanupratppur, India’s province of Chhattisgarh. In their methodology, the authors applied spatial information technology and a logistic regression model. Bavaghar (2015), in turn, studied forest degradation in Hyrcanian, west of Gilan, Iran, and used a similar methodology. These studies used natural and anthropogenic variables in nature.

The adoption of remote sensing technique and statistical methods help to broaden the range of factors that influence the forest cover dynamics.

The main objective of this work is to analyze the association of natural and anthropogenic explanatory variables to achieve the analysis of forest cover dynamics using the binary logistic regression model.

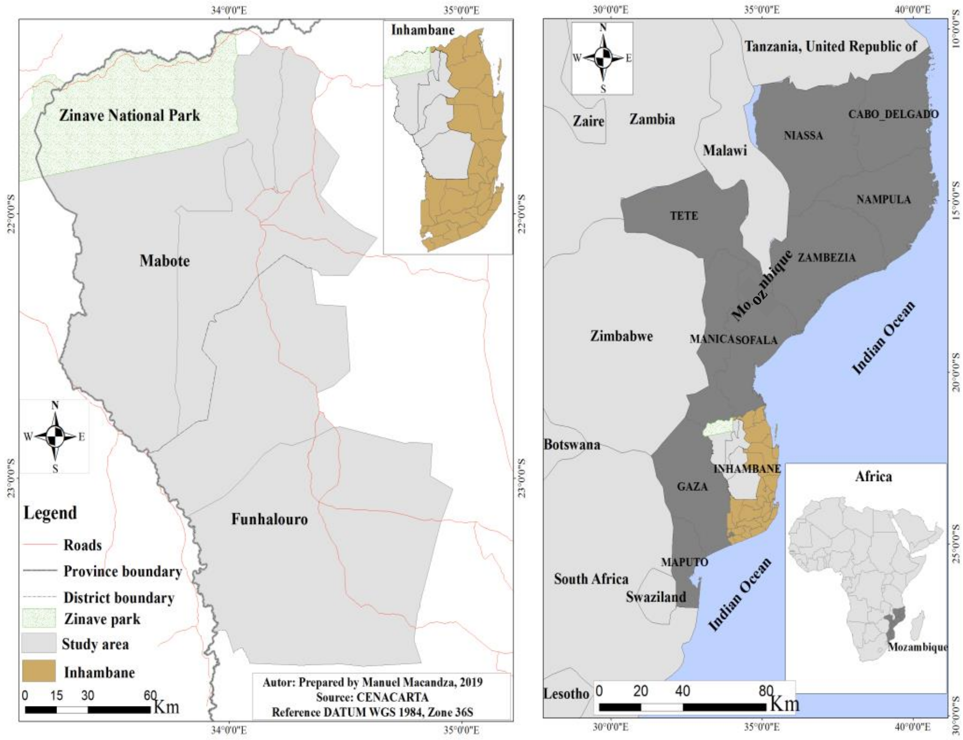
MATERIALS AND METHODS

Location of the study area

The study area, the Mabote and Funhalouro districts, is located in the northwest of Inhambane province, in the southern region of Mozambique, and is bordered to the north by the Zinave National Park (Figure 1).

The area has a surface area of 28,943 km² (MOÇAMBIQUE, 2005) and is located on a large sedimentary plain, characterized by recent soils with constant changes in shape (MUCHANGOS, 1999).

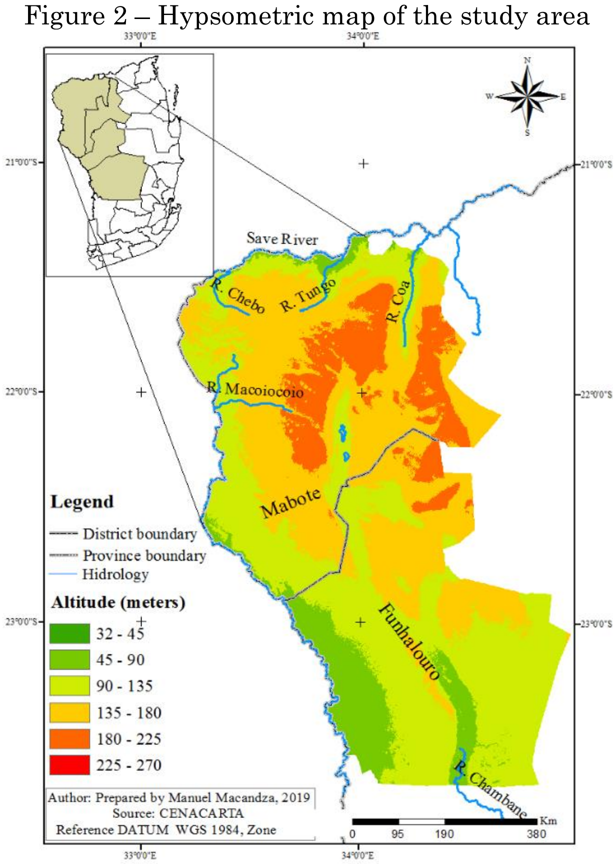
Figure 1 – Location of the study area



Source: The author (2020)

Altimetry shows that altitudes vary from 32 to 270 meters (Figure 2). The hypsometric classes [90-135] and [135-180] are the ones that occupy the largest areas, located in the central part, being relatively high. Higher is the hypsometric class [180-225], predominant in Mabote. The hypsometric class [45-90] constitutes flooding surfaces.

Figure 2 – Hypsometric map of the study area



Source: The author (2019).

The predominant vegetal formation is the miombo (MUCHANGOS, 1999). Mozambique has a hot and rainy season that starts in October and ends in March, with rainfall reaching an average of 600 mm per year, and the months of December and January have the highest temperatures (from 30ºC to 40ºC), and another, a dry and cool season, in which rainfall is rare and reaches an annual average of 430 mm, and the months of June and July have the lowest temperatures.

In Mozambique, forests and land are the property of the State. For forest exploitation, operators require forest licensing, which can be either a simple license or a forest concession. For land use, users need to apply for the "Direito do Uso e Aproveitamento da Terra" (DUAT) (this document allows the use and benefit of land), but there are other forms of land access: customary law and good-faith occupation, in which access to land is granted when the person has been using the land for at least ten years.

RESOURCES AND WORK METHODOLOGY

Knowing the information on land cover is essential for the correct management, planning, and monitoring of natural resources. Satellite images are a viable source of land cover information (YACOUBA et al., 2009). From the website of the Earth Resources Observation and Science (EROS) project of the United States Geological Survey - USGS, (2018) it was downloaded images from the Landsat TM 4 and 5 satellites, sensor TM C1 level 1, corresponding to the dates of 07/10/1989, 07/03/1998, and 09/07/2008, while from Landsat 8, sensor OLI/TIRS C1 level 1, from 09/28/2018. The bands used for the images from Landsat 4 and 5 satellites were 5, 4, and 3, and for Landsat 8, it was used bands 6, 5, and 4. The images are from the months of July and September, as these coincide with the dry period, in the study area.

The images were georeferenced in the cartographic projection Datum WGS 1984, UTM, zone 36S, and had a spatial resolution of 30 meters. The shapefile was obtained from the database of the National Center for Remote Sensing and Cartography (CENCARTA), an institution that is currently part of the Mozambican Ministry of Land, Environment and Rural Development. With the help of GIS software tools (ArcGIS, version 10, and QGIS, version 2.6), it was possible to process the images. There was, successively, the radiometric calibration of the images, the stacking of the bands, and, to highlight the target under analysis - the forest -, we used the Normalized Difference Vegetation Index (NDVI) technique to classify the images using two classes: forest and non-forest.

The spectral information in both Landsat TM and ETM+ satellite images is determined from the red (RED) and near-infrared (NIR) spectral bands because it is in these bands that vegetation best reflects sunlight (SONG et al., 2011).

During the field visit, we observed the forest cover and, with the help of GPS, we collected 100 points to validate the maps, considering the process described by Maldonado and Dos Santos (2005). The 100 sample points, randomly drawn on the maps, were checked in the field one by one.

The exploratory analysis consisted in describing the patterns or characteristics of the data contained in the images (INPE, 2002), from which we raised hypotheses, that required confirmatory analyses (ROGERSON, 2012), such as statistical models.

Regression model

Regression is a conditional distribution of the response variable. It changes when one or more independent variables also change (HOSMER et al., 2013; WASSERMAN, 2004). The method is important in any analysis that concerns describing the relationship between the response variable and one or more explanatory variables (HOSMER et al., 2013).

This concern is well founded because, according to Tobler's first law, all things are related to all other things, but things nearby are more related than far away things (TOBLER, 1970, p. 234 apud FISCHER; WANG, 2011). Furthermore, Rogerson (2012, p. 2) clarifies that "[...] the study of geographical phenomena requires the application of statistical methods to produce new understanding".

From these bases, we deduce the hypothesis that the dynamics of forest cover in the study area are a response to the new forest policy, the increase in agricultural areas of the family sector, charcoal production, the dynamics of the population, settlements in forest areas, and climate (precipitation and temperature).

The process of explaining the relationships between the variables is based on models. These provide a simplified view of the relationships between variables (ROGERSON, 2012). In this sense, we can highlight simple regression, multiple regression, and logistic regression.

When there is only one response variable and one explanatory variable, the relationship is linear and known as a simple regression model (CRONEMBER; VICENS, 2015; HOSMER et al., 2013). The equation describing this linearity is as follows:

$$Y = a + \beta x \qquad \text{(Equation 1)}$$

In this equation, Y is the predicted value of the dependent variable, x is the observed value of the independent variable, a is the intercept, and ß is the slope of the straight line. The quantities a and ß represent the parameters that describe the straight line.

In multiple linear regression, more than one independent variable affects the dependent variable. The equation that translates this preposition is (ROGERSON, 2012):

$$Y = a+b1x1+b2x2+\ldots+bpxp \qquad \text{(Equation 2)}$$

In the logistic regression model, the response variable is categorical and can be explained by more than one independent variable, some of which, at different scales, for example, the discrete and nominal variables. The relationship is represented by Equation 3 (ROGERSON, 2012):

$$Y = \beta 0 + \beta 1x1 + \beta 2x2 +\ldots+\beta pxp \text{(Equation 3)}$$

In this equation, Y is the predicted value of the dependent variable. The problem and solution are identical to those of bivariate regression in concept, except that there are more parameters to estimate and the geometric interpretation is performed in a larger dimensional space.

The value of ß1 describes how much the value of y changes in the plane, when x1 increases by one unit, along any line, where x2 is constant. Similarly, the value of ß2 describes the change in y, when x2 varies by one unit, while x1 remains constant (ROGERSON, 2012; WASSERMAN, 2004).

For the present work, we will use the binary or dichotomous logistic regression model. The dependent variable takes two values (0 and 1), where "0" represents the absence of the phenomenon and "1", its presence. In this study, the dependent variable assumes that "0" is *no forest* and "1" is the *existence of the forest* (BAVAGHAR, 2015; KUMAR et al., 2014).

For the dependent variable and the various independent variables to be linearly related, a logistic transformation is required (HOSMER et al., 2013; ROGERSON, 2012). This consists in transforming the response variable into a linear one, following the expression ȳ/(1-ȳ). This expression is known as odd (in favor of the event), according to Rogerson (2012), so the new variable is known as the "logarithm of the odd". Using Z to define the new variable, we have Equation 4:

$$Z = \ln \bar{y}/(1- \bar{y}) = \alpha + \beta x \qquad \text{(Equation 4)}$$

In this case, the interpretation of the slope coefficient occurs at each change of the logit function (Z=ln ȳ/(1- ȳ), which corresponds to each unit change of the independent variable (HOSMER et al., 2013).

Binary logistic regression assesses the probability of occurrence of a given event, as well as the influence of each independent variable on this event.

The variable data were processed in SPSS version 21.

Multicollinearity analysis of the variables

We analyze the explanatory variables within the correlation matrix to see whether or not multicollinearity exists between them (ROGERSON, 2012). For Salvian (2016) and Rogerson (2012), multicollinearity is defined as the presence of a high degree of correlation between the independent variables. The inexistence of multicollinearity means that the model is well designed, but when two explanatory variables are highly correlated, it is not possible to estimate the coefficients (ROGERSON, 2012). This author adds that the low tolerance and the high variance inflation factor (VIF) near five indicate the existence of multicollinearity.

To elevate multicollinearity, one or more highly correlated variables must be excluded (HOSMER et al., 2013; ROGERSON, 2012).

Accuracy of the logistic regression model

The models allow us to build a simplified view of reality, but it is necessary to observe their quality (HOSMER et al., 2013, ROGERSON, 2012). Multicollinearity survey was one of the steps to observe the quality of the model.

The ρ -value allows us to evaluate the importance and adjustment of the variable to the model. Hosmer et al. (2013) recommend using a significance level between 0.2 and 0.25, as this allows variables to be fit to the model. However, for the present work, we adopt the significance level of 0.05, which is commonly used. The most important independent variable is the one with the lowest ρ-value (HOSMER et al., 2013).

The tests are equally important for gauging model fit. The Wald test is used to assess the degree of significance of each coefficient in the logistic regression equation, including the constant (HOSMER et al., 2013).

The maximum likelihood ratio test assists in analyzing the overall significance of the independent coefficients (WASSWERMAN, 2004).

The coefficient of determination R^2 allows us to interpret, in percentage form, the relationship between the dependent variable and the independent variables (WASSWERMAN, 2004).

The Receiver Operator Characteristics (ROC) curve is a test that consists, more completely, of classifying the accuracy of the model (HOSMER et al., 2013). The ROC curve has become the standard for assessing the quality of model fit. The area of the curve is composed of two perpendicular lines: sensitivity and specificity (HOSMER et al., 2013).

The variables we use are forest cover dynamics; precipitation; temperature; simple license; forest concession; the volume of charcoal exploited; agricultural areas; settlements in the forests; and population dynamics (Chart 1).

Chart 1 – Variables used in the analysis of the dynamics of forest cover in the study area

Groups of variable types	Variable characteristic	Variable	Variable types	Measurement unit	Source
Dependent					
Spatial	Environmental	Forest cover dynamics	Category		USGS (2018)
Independent					
Physical aspects	Precipitation	Precipitation	Continuous	mm	CHIRPS (2019)
	Temperature	Temperature	Continuous	°C	
National Forest Policy	Operating licenses	Simple License	Discrete	Number of operators	SPFFB (2019)
		Forest Concession	Discrete		
		The volume of charcoal exploited	Continuous	kg	Ministério da Agricultura de Moçambique (2019), which means Ministry of Agriculture of Mozambique
Land policies		Agricultural areas	Continuous	Hectares	
Population Policy	Human	Forest settlements	Discrete	Number of settlements	INE (2017)
		Population dynamics	Discrete	Number of populations	INE (2017)

Source: The author (2019).

The dynamics of forest cover is an indicator that quantifies changes in forest cover caused by natural or anthropological factors.

Both precipitation and temperature affect vegetation because strong insolation in the tropical region, especially in the dry tropical climate, leads plants to experience the phenomenon of water stress (CHAZDON, 2016).

The dynamics of population and settlements within forests, with an upward trend, contribute to increasing the pressure on natural resources (CRONEMBERGER; VICENS, 2005).

As for agricultural areas, Cronember and Vicens (2005) recognize that forest variations have some correlation with the dynamics of agricultural areas.

The volume of charcoal exploited induces disturbances that gradually degrade the forest cover.

Both Simple License and Forest Concession exploration regimes are modalities of forest license within Mozambique's forest policy.

RESULTS

Variable selection for the model

From Pearson's correlation matrix the following coefficients were obtained: the Simple License variable (SL), with r = 0.898, r = 0.919, and r = 0.890 for the agricultural areas, population dynamics, and settlements within forest areas variables, respectively.

The variable population dynamics has r = 0.901 and r = 0.949 with respect to the volume of charcoal exploited and settlements within forest area variables, respectively, as well as the variable agricultural areas is highly correlated with both volume of charcoal exploited and settlements within forest area variables (r = 0.806 and r = 0.885, respectively).

Checking for multicollinearity, we removed highly correlated variables, which are population dynamics, agricultural areas, forest concessions, and forest settlements, using the *stepwise* method of the SPSS statistical software. The variables in Table 1 have potential for model quality.

Table 1 – Result of the multicollinearity survey

Models	**Non-standardized coefficients**		**Standardized coefficients**	**Sig**	**95.0% Confidence Interval for β**		**Collinearity statistics**	
	B	Standard Error	Beta		Lower	Upper	Tolerance	VIF
Constant	5.663	4.315			0.201 - 3.206	14.532		
Simple License	-.017	.018	-.349		0.378 -.055	.021	.217	4.608
Temperature	-.204	.0179	-.215		0.263 -.572	.163	.926	1.080
Charcoal	.000	.001	.085		0.827 -.002	.002	.224	4.473

Note: dependent variable: Forest Cover.

Source: The author (2021).

For the exclusion of variables, we observe both the tolerance and the variance inflation index. A tolerance lower than 0.1 and values close to 5 in the VIF indicate problems with multicollinearity (ROGERSON, 2012).

Next, we run the binary logistic regression model with the variables in Table 1 to verify that they have the power to explain the phenomenon under analysis.

Analysis of binary logistic regression models

To analyze the quality of the model, we assume that the significance level is 0.05. Coefficients that have a ρ-value less than that have greater statistical significance for the model, while coefficients with a greater ρ-value have less significance for the model (HOSMER et al., 2013).

The SL and temperature have ρ-values smaller than 0.05 (0.021 and 0.013, respectively), revealing the statistically significant association between these two variables and the response variable, forest cover dynamics. However, the volume of charcoal exploited variable presents a ρ-value of 0.113 (greater than 0.05), so its association with the response variable is not statistically significant (Table 2). From these coefficient values, the null hypothesis (H0) is rejected.

Table 2 – Result of the logistic regression model

	B	S. E	Wald	Sig	Exp (B)	95,0% C.I for Exp (B)	
						Lower	Upper
Simple License	1.307	.564	5.368	1.021	3.695	1.223	11.163
Temperature	-.001	.001	6.136	1.013	.999	.997	1.000
Charcoal	.012	.008	2.515	1.113	1.012	.997	1.027
Constant	91.885	36.806	6.233	1.013	8.042E+3		

Source: The author (2021).

Wald test values are: Wald = 5.368 and degree of freedom (df) = 1 for SL; Wald = 6.136 and df = 1 for temperature; and Wald = 2.515 and df = 1 for the volume of charcoal exploited (Table 2). These values reveal the level of significance of the coefficients individually and for the overall model (HOSMER et al., 2013).

To see the fit of the model, the Hosmer-Lemeshow test was also used, using the chi-square (χ^2) (BAVAGHAR, 2015). The correct rank of the coefficients is high (63.3%) and indicates that the model is perfect to explain the relationship between the dependent and independent variables (Table 2).

Another evaluation of the model involved the use of the Nagelkerke coefficient of determination (R^2). According to Bavaghar (2015), its value is lower in the logistic regression model due to the binary response variable. According to Kumar et al. (2014), an R^2 value greater than 0.2 indicates that the model is relatively good. The Simple License variable has R^2 = 0.229, the volume of charcoal exploited has R^2 = 0.240, and the temperature variable has R^2 = 0.385.

On the other hand, delineates the model's discrimination. For ROC = 0.5, discrimination is poor; between 0.5 and 0.7, better; between 0.7 and 0.8, acceptable; between 0.8 and 0.9, excellent; and an ROC $\geq$ 0.9 represents exceptional discrimination (HOSMER et al., 2013). The ROC curve area for the present model is 0.72, which means the accuracy of 72% of the predictors, is acceptable discrimination.

Kumar et al. (2014), citing Loza (2006), state that a model with a ROC curve of 71.5% has a good discrimination ability. In Bavaghar's (2015) study on forest degradation in Hyrcanian, the ROC curve of the model was 0.807, which means an accuracy of 80.7%.

The coefficient of the temperature variable indicates a significantly negative probability of influence on the dynamics of forest cover. The coefficients of SL and volume of charcoal exploited variables were used to indicate a significantly positive probability (Table 2).

The coefficient of SL (β = 1.307) is shown to be a predictor of significant importance on forest cover, while the coefficient of the volume of charcoal exploited variable (β = 0.12) indicates less importance. The interpretation is that for every one-unit increase in the Simple License variable or the explored charcoal volume variable, the change in forest cover also increases. Although the coefficient of the temperature variable (β = -0.001) means that with every increase in temperature, there is a probability of a decrease in the change in forest cover. From the column Exp (β), we have the probability of the changes happening (Table 2).

DISCUSSION

Variation of forest cover

The variation of forest cover was characterized by both a reduction and an increase in forest areas over the 30 years of observation (1989 to 2018) (Table 3). The forest class lost an area of 1,645 km², however, from 1998 to 2018, a recovery of the area covered by the class has been observed. In this period, it is about 1,137 km² of the area gained.

Table 3 – Land cover classes in the study area from 1989 to 2018

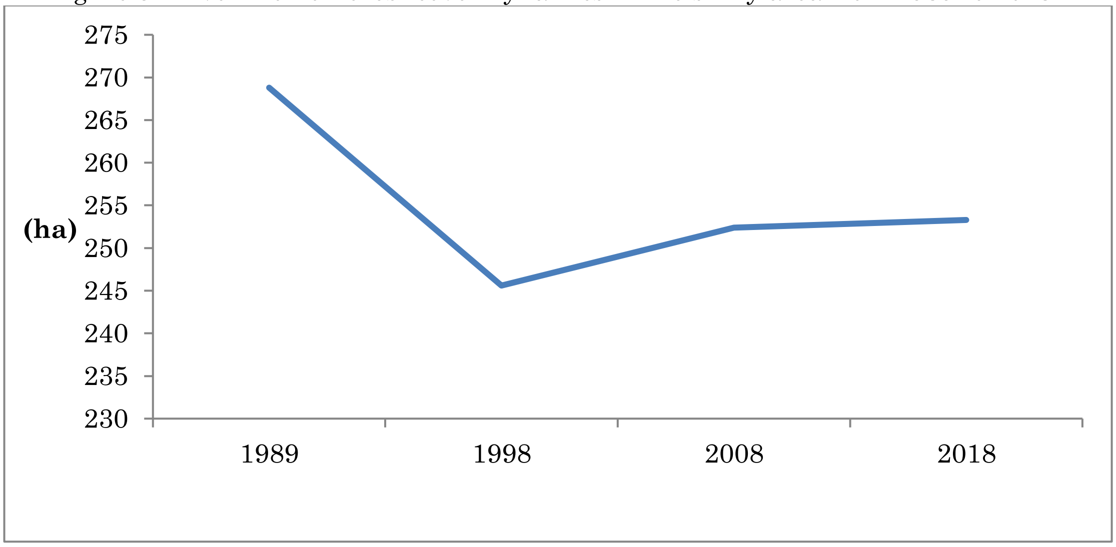
Class	1989	1998	2008	2018
Forest	15,971	14,326	15,293	15,463
Non-forest	12,952	14,607	13,650	13,480
Total	28,943	28,943	28,943	28,943

Source: The author (2022).

This variation in forest cover follows the behavior of temperature, precipitation, and the dynamics of the national forest policy.

Inhambane has the highest number of trees per hectare (856/ha) (MAGALHÃES, 2018), and the existence of a forest brings many benefits, such as carbon capture, climate improvement, water recycling, watershed and soil protection, and diversity of economic resources (...) (MORAN, 2010; PORTO-GONÇALVES, 2017).

Figure 3 – Evolution of forest cover dynamics in the study area from 1989 to 2018

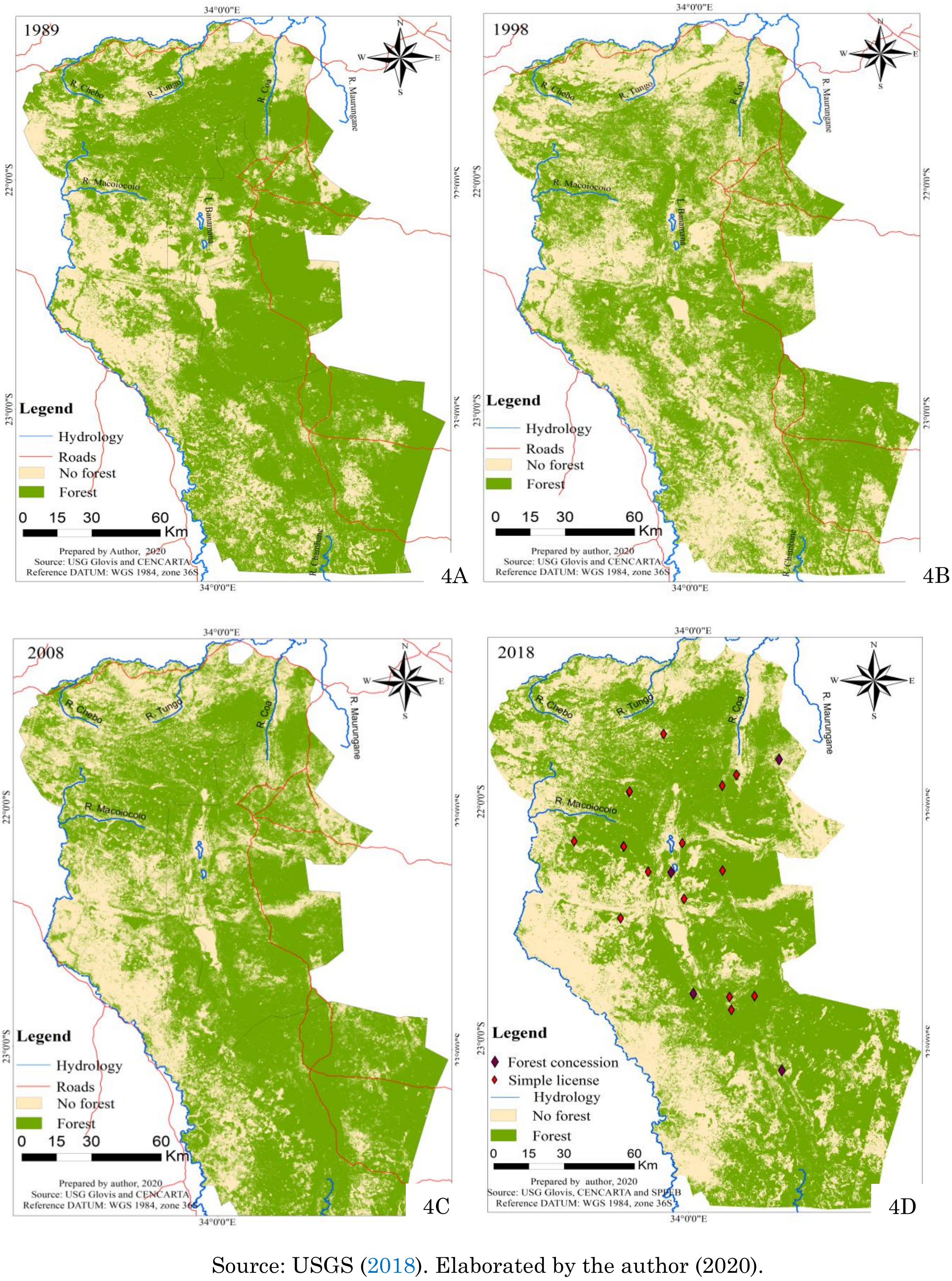


Source: The author (2021)

The phenomenon described in Figure 3 and Table 3 is also reflected in the maps of forest cover variation. Information on forest cover validates the accuracy of the maps, which is demonstrated from the points superimposed on the forest cover area.

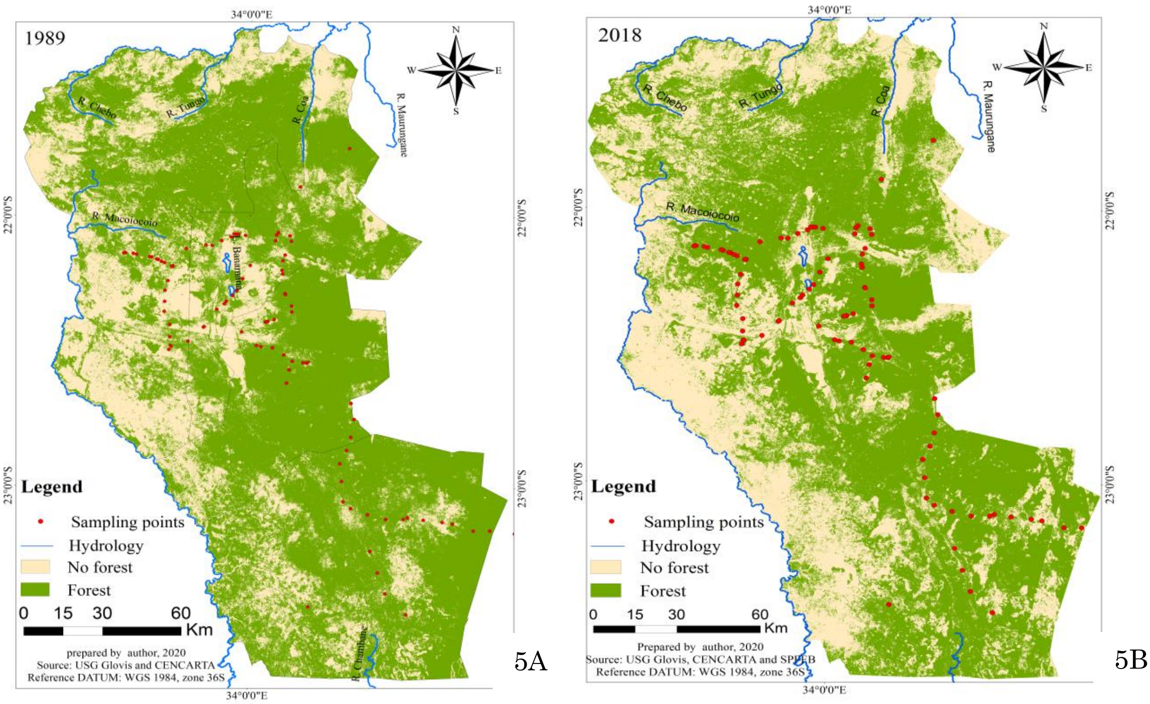
Figure 4D shows the spatial distribution of forest licenses, both by Simple License and by Forest Concession regime, in 2018. The north of the study area has more forest operators than the south. Until 1999, only one company exploited the forests through the Simple License: Madeira de Moçambique.

Figures 4A, 4B, 4C, and 4D – Maps of forest cover variation in the study area from 1989 to 2018



Source: USGS (2018). Elaborated by the author (2020).

Figures 5A and 5B – Maps of forest cover variation, with accuracy points (in 1989 and 2018)



Source: USGS (2018).Elaborated by the author (2020).

The logistic regression model highlights the variables SL and temperature as being important in explaining the situation of forest cover variation. However, other variables can explain the phenomenon. In the analysis of forest cover in the country, both the national literature (MACQUEEN; FALCON, 2017; MACKENZIE, 2006; MAGALHAES, 2018; SITOE et al., 2012), (BANCO MUNDIAL, 2018) and international literature give relevance to other factors, such as itinerant agriculture, uncontrolled burning, hunting, and poverty.

Variable Simple License

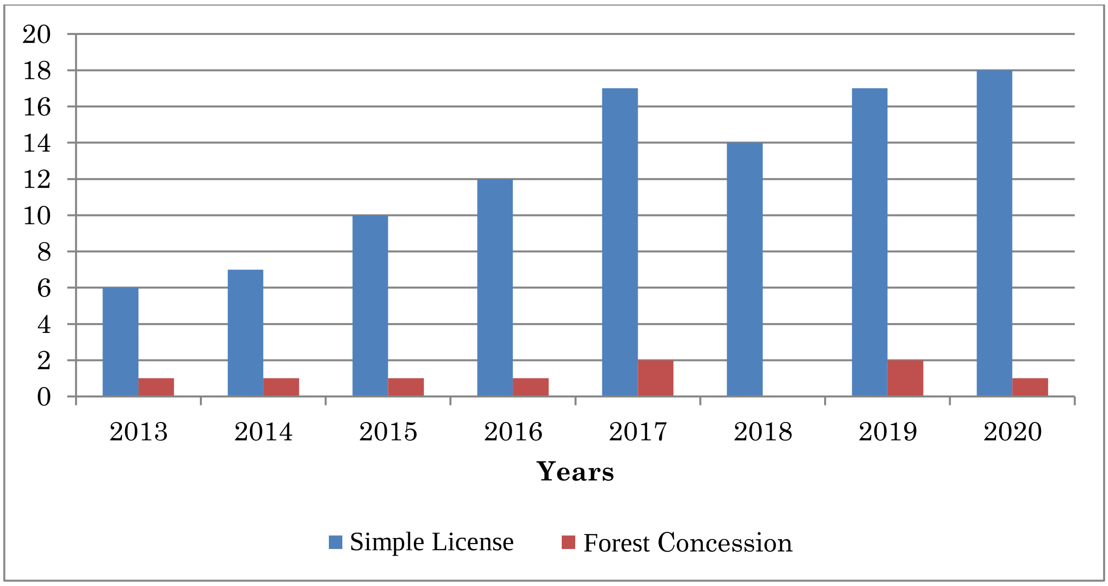
The SL predictor is statistically significant in explaining the variation in forest cover in the study area and, indeed, throughout the country. The Simple License is one of the modalities of forest exploitation, along with the Forest Concession (FC), adopted by the Forest and Wildlife Policy of 1999 for forest licensing. In 2012, the modality changed: the period of forest exploitation increased from one year to five and the extension, from 500 m³ to 10,000 hectares (MOÇAMBIQUE, 2012).

Forest operators, stimulated by the policy, prefer the SL. The forest law requires operators to take environmental responsibility by implementing the management plan, but poor supervision of forestry activity does not ensure compliance with legal requirements.

The SL is passed on to Mozambicans to exploit three forest products: wood, stakes, and charcoal, but there are cases in which locals use this license to act in partnership with foreigners.

From 2013 to 2018, the Inhambane Provincial Forestry and Wildlife Services Directorate received 134 requests for SL forest licenses, versus six for the FC regime. From 2017 to 2020, the SPFFB registered 16 to 18 SL operators only in the study area (Figure 6). The modality accounts for 80% of local forest exploitation.

Figure 6 – Evolution of the number of forest operators in the study area from 2013 to 2020



Source: Provincial Forest and Wildlife Services - SPFFB (2019).

According to Chazdon (2016), anthropogenic disturbances vary greatly in extent, frequency, and intensity. Operators take advantage of the fact that land and forests are owned by the State and of the inefficiency of forest activity enforcement to evade their environmental responsibilities.

The uncontrolled extractive action of forest species, both by Mozambicans and foreigners, led the State to carry out the reform of forest policy (MOÇAMBIQUE, 2012).

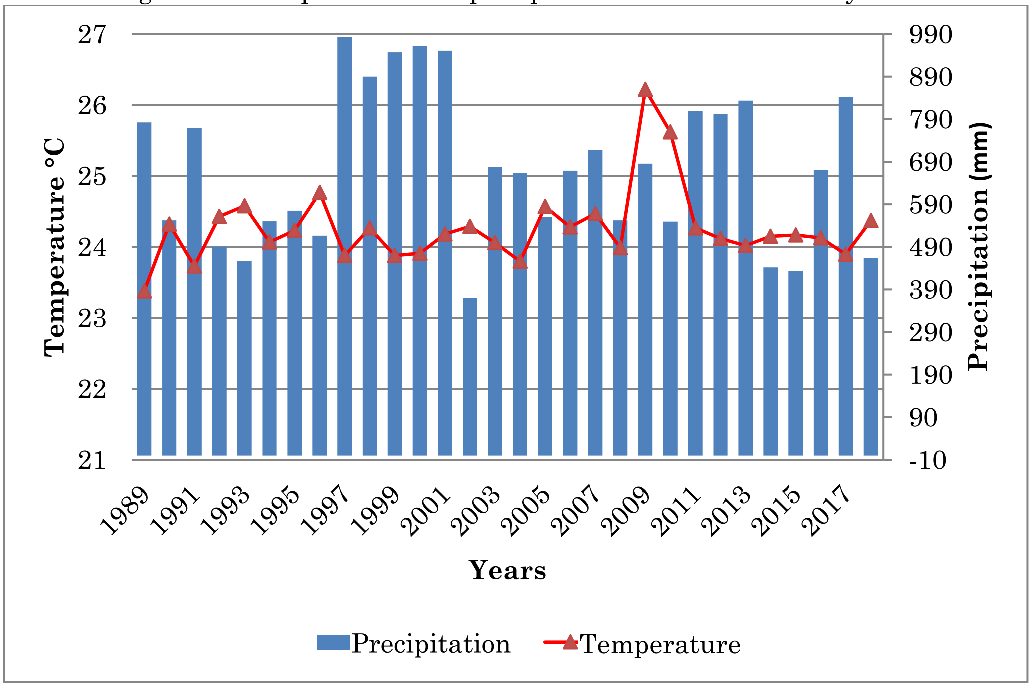
Variable Temperature

Climate variability in tropical regions during the Early and Middle Holocene is strongly related to changes in the distribution of forests and savannas (CHAZDON, 2016, p. 44). In the African continent, from Madagascar to West Africa, where Mozambique falls, the droughts of the period shrank the rain forests and expanded the savannas.

Temperature behavior influences the variation of forest cover in an inverse way, so when the average temperature passes 25.4°C, the growth rate of plants is at a high level, and longevity decreases (LOCOSSELLI et al., 2020). Water availability influences, because when the site dries out, it creates stress on the plant, so it reaches smaller sizes and dies younger. Tree growth rates in tropical forests may be decreasing because of physiological stress caused by high temperatures and severe droughts in certain years (CHAZDON, 2012).

In the 1998 map, we observe that forest cover has substantially regressed, and, in association with Figure 7, we note that the study area recorded rainfall below 400 mm per year and a mean annual temperature of almost 25°C, between 1992 and 1996, which may have led the plants to a water stress situation (LOCOSSELLI et al., 2020). However, in the following years (from 1997 to 2001), periods of average annual precipitation above 700 mm were recorded, which explains the increase in forest cover (see figures 4A to 4D).

Figure 7 – Temperature and precipitation levels in the study area



Source: CHIRPS (2019), elaborate by the author (2019).

Considering the possibility that the dynamics of the forest cover is related to the behavior of temperature is important because vegetation, the main factor influencing atmospheric processes, in the study area, is less and less present. In the tropics, the forest acts as a conduit for the movement of water from the soils to the atmosphere, and the cycling of water from the forest soils back to the atmosphere is interrupted after deforestation or vegetation disturbance (CHAZDON, 2016). SL explains the intensity of deforestation. Tree extraction creates conditions for the temperature to have positive variations, that is, to increase it.

Variable Volume of charcoal exploited

This variable has a statistically non-significant influence on our significance level, but we observe that, as there is an increase in the volume of charcoal exploited, there is an increase in the variation of forest cover. Studies prove that the further away from the main charcoal-consuming urban centers and the main roads, the lower the exploitation of this fuel (BANCO MUNDIAL, 2018). The distance of the study area to one of the main urban centers of Inhambane, the city of Maxixe, is about 400 km, of which nearly 150 km are traveled on a dirt road. This makes the commercialization of charcoal expensive. However, charcoal is sold along secondary and tertiary roads in the study area.

FINAL CONSIDERATIONS

It is not the objective of this study to draw definitive conclusions about the explanatory variables that influence the dynamics of the Mozambican forest cover, but rather to seek other variables that will help provide useful information for the management and monitoring of local forest landscapes.

The variables in the present model are not the only ones; the model can be refined by introducing new ones that can improve it.

The analysis of forest cover dynamics using spatial information technologies and the logistic regression model was useful because it allowed new dimensions to interpret forest cover dynamics. The model showed that the SL and temperature variables have a statistically significant weight for the explanation of the model, but the SL variable was the one that best fitted the model because its ρ-value and Wald test indicated better performance of the variable in the model. The discrimination capacity of the phenomenon under study, observed from the ROC curve, was 72%, revealing good accuracy.

Thus, the results of the present work can serve as a basis for forest policy making. Also, they bring the need to point out other causes for the forest dynamics and make us not get stuck to the factors often pointed out as causing forest degradation such as itinerant agriculture, uncontrolled burning, hunting, and poverty. We do not invalidate these factors, but we believe that it is necessary to look for other factors to broaden our understanding of the problem of forest cover variation in Mozambique.

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AUTHORS CONTRIBUTION

Manuel Madeira Macandza conceived the study, analyzed the data, and wrote the text. Ulisses Bremer commented on the data.