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Spatial distribution of wood volume in Brazilian savannas

EDUARDA M.O. SILVEIRA[1,2], ALINY A. DOS REIS[1,3], MARCELA C.N.S. TERRA[1], KIERAN D. WITHEY[4], JOSÉ M. DE MELLO[1], FAUSTO W. ACERBI-JÚNIOR[1], ANTONIO CARLOS FERRAZ FILHO[5] and CARLOS R. MELLO[6]

[1]Forest Science Department – DCF, Federal University of Lavras – UFLA, University Campus, 37200-000 Lavras, MG, Brazil
[2]SILVIS Lab, Department of Forest and Wildlife Ecology, University of Wisconsin, 1630 Linden Drive, Madison, WI, 53706, United States of America
[3]Interdisciplinary Center of Energy Planning – NIPE, University of Campinas – UNICAMP, 330 Cora Coralina Street, University City, 13083-896 Campinas, SP, Brazil
[4]Lancaster Environment Centre (LEC), Lancaster University, Lancaster, LA1 4YQ, United Kingdom
[5]CPCE, Federal University of Piauí, Manoel Gracindo Avenue, Km 01, 64900-000 Bom Jesus, PI, Brazil
[6]Water Resources Department, Federal University of Lavras – UFLA University Campus, 37200-000 Lavras, MG, Brazil

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Abstract: Here we model and describe the wood volume of Cerrado *Sensu Stricto*, a highly heterogeneous vegetation type in the Savanna biome, in the state of Minas Gerais, Brazil, integrating forest inventory data with spatial-environmental variables, multivariate regression, and regression kriging. Our study contributes to a better understanding of the factors that affect the spatial distribution of the wood volume of this vegetation type as well as allowing better representation of the spatial heterogeneity of this biome. Wood volume estimates were obtained through regression models using different environmental variables as independent variables. Using the best fitted model, spatial analysis of the residuals was carried out by selecting a semivariogram model for generating an ordinary kriging map, which in turn was used with the fitted regression model in the regression kriging technique. Seasonality of both temperature and precipitation, along with the density of deforestation, explained the variations of wood volume throughout Minas Gerais. The spatial distribution of predicted wood volume of Cerrado *Sensu Stricto* in Minas Gerais revealed the high variability of this variable (15.32 to 98.38 m^3 ha^{-1}) and the decreasing gradient in the southeast-northwest direction.

Key words: cerrado *sensu stricto*, forest inventory, geostatistics, regression kriging, volumetry.

INTRODUCTION

The Brazilian Savanna biome, also known as Cerrado, occupies about 2.5 million square kilometres, which represents approximately 25% of the country's territory. This biome is among the most endangered eco-regions in the world due to high conversion rates and few protected areas (Hoekstra et al. 2005), and is considered one of the world's biodiversity hotspots (Myers et al. 2000). Its large area extent, climatic variability, vegetation mosaics and proximity to other tropical biomes result in high heterogeneity of the vegetation types

Correspondence to: Aliny Aparecida dos Reis
E-mail: alinyreis@hotmail.com
ORCID: https://orcid.org/0000-0002-7115-1485

in this biome (Silva et al. 2006), ranging from dry grassland to densely wooded Savanna (Ferreira et al. 2004, Arantes et al. 2016).

Since the 1970s this biome has suffered large losses of its natural vegetation due to agricultural expansion (Fearnside 2001, Silva et al. 2006). Currently, the rate of deforestation is about 1.6% per year (Arantes et al. 2016), leading to large-scale conversion of native vegetation to agricultural land, which has already affected more than 40% of the original area of this biome (Ferreira et al. 2004, Sano et al. 2010). This high conversion rate of primary vegetation threatens the stability of the ecosystem, along with ecological services, such as carbon sequestration and climate regulation (Schwieder et al. 2016).

Good indicators of priority areas for conservation require accurate estimates of important factors, such as wood volume (Gizachew et al. 2016). However, due to the great heterogeneity of Brazilian Savannas, estimates of wood volume of its remnants over large geographic regions are expensive, time consuming, and labour intensive. Thus, it is necessary to develop new techniques and approaches for estimating wood volume over large areas that combine field-based forest inventory data with more robust techniques in solving problems previously resolved by traditional statistical modeling.

Traditionally, information of diameter and total height of trees measured in field plots established according to a pre-defined sampling system are used to estimate wood volume using classical statistical methods. However, these procedures assume that the spatial variability of the variables of interest are random and do not consider them to be spatially dependent (Guedes et al. 2015). Previous studies have shown that biometric variables are spatially structured and, therefore, this spatial dependence should not be disregarded in the statistical analyses (Alvarenga et al. 2012, Scolforo et al. 2015). To solve this issue, several geostatistical methods and techniques have been developed over the last fifty years, and are widely used in forest management, leading to significant improvements in estimation accuracy of wood volume (Alvarenga et al. 2012, Reis et al. 2015). Among these geostatistical techniques, kriging is the most widely used (Scolforo et al. 2016). However, in highly heterogeneous areas, like Brazilian Savannas, more robust techniques are necessary, such as those based on multivariate kriging, e.g. regression kriging (Galeana-Pizaña et al. 2014, Meng et al. 2009, Viana et al. 2012).

Regression kriging is a hybrid method that includes the combination of a linear regression between the target variable and auxiliary variables and ordinary kriging of the regression residuals, which is then used to correct the map developed based on the regression model (Palmer et al. 2009, Viana et al. 2012). The regression model should be able to capture the spatial behaviour of the target variable (Mello et al. 2013), assuming that the residuals of the regression model are spatially distributed and combines information from the relationships between the target and auxiliary variables through deterministic models, local components and error (Scolforo et al. 2016).

Here, we model the wood volume of Brazilian Savannas in the state of Minas Gerais, southeast Brazil, using spatial and environmental datasets, multivariate regression and geostatistical regression kriging. This study contributes to a better understanding of the variables that affect the volumetric spatial distribution of Brazilian Savanna as well as improving our knowledge of the spatial heterogeneity of this biome.

MATERIALS AND METHODS

STUDY AREA AND DATA COLLECTION

This study was conducted in a Brazilian Savanna vegetation type, known as Cerrado *Sensu Stricto*, which falls within the state borders of Minas

Gerais. According to the Brazilian Institute of Geography and Statistics (IBGE), it represents an area of approximately 54,500 km². Cerrado *Sensu Stricto* is a type of woodland Savanna characterized by vegetation dominated by trees and shrubs often 3-8 m tall with more than 30% crown cover and a continuous grass layer (Oliveira-Filho and Ratter 2002). The Cerrado *Sensu Stricto* in the state of Minas Gerais is located between latitudes -14.25 ° and -21.50 ° south and between longitudes -41.80 ° and -50.91 ° west (Figure 1).

The average annual temperature is between 21 and 23 °C. Rainfall is highly seasonal, concentrated between the months of October and March, with annual averages between 1,200 and 1,800 mm of rainfall. The topographic conditions present altitudes ranging between 900 and 1500 meters.

A total of 641 plots of 1000 m² (10x100 m) in 57 remnants of Cerrado S*ensu Stricto* were sampled (Figure 1), during the Project "Forest Inventory of Minas Gerais", conducted by the Universidade Federal de Lavras (Federal University of Lavras, UFLA), in 2006 and 2007 (Scolforo et al. 2008). During the field surveys, the diameter at breast height (DBH; 1.3 m) and the total height of all trees with a minimum DBH of 5 cm were measured. Total wood volume for all the trees was estimated by applying Eq. 1, developed by Rufini et al. (2010) for Cerrado *Sensu Stricto*.

$$V = e^{(-9.7289673246 + 2.4207715832 * \ln(DBH) + 0.4608810281 * \ln(H))} \quad (1)$$

where V is the volume (m³); *e* is the base of the natural logarithm; ln is the natural logarithm; DBH is the diameter measured at 1.3 meters above the ground (cm); and H is the total tree height (m).

We used 19 climatic variables (Table I; 1 km² spatial resolution) which were acquired from WorldClim (Hijmans et al. 2005). We used

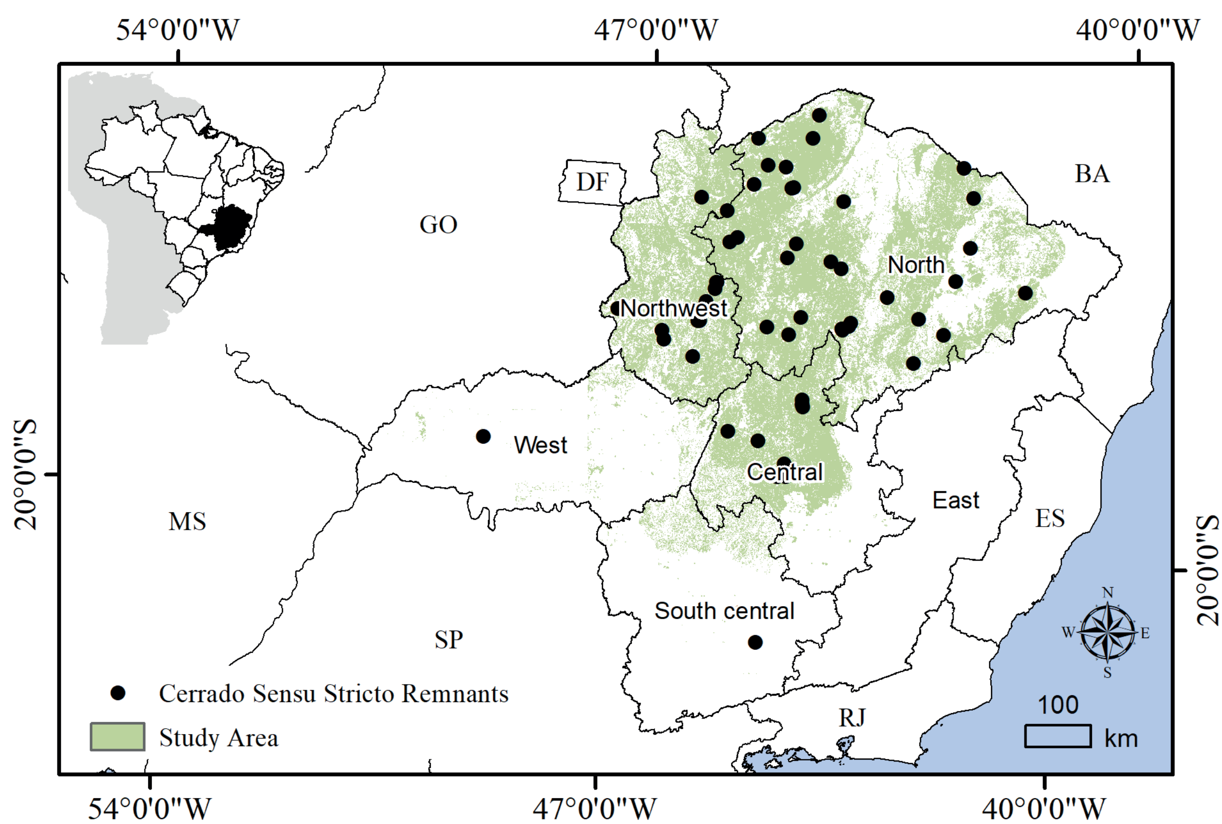

Figure 1 - Location of the state of Minas Gerais in Brazil and remnants of Cerrado *Sensu Stricto* measured by the project *Forest Inventory of Minas Gerais*.

additional spatial variables, and a topographic and deforestation density map generated by the Project “Forest Inventory of Minas Gerais - Monitoring of Native Flora 2006-2007”. The deforestation density map was developed by Carvalho and Scolforo (2008), who developed a computational algorithm for semi-automatic detection and segmentation of areas that were subjected to drastic land-use/cover changes.

WOOD VOLUME MODELLING AND REGRESSION KRIGING

We used a stepwise regression technique based on the Akaike information criterion (AIC) to select the most significant independent variables to build the wood volume model. The total database was randomly divided into a fitting set (70% of the database) and a validation set (30% of the database). The best model was subjected to successive variance inflation factor (VIF) tests for the removal of those variables with VIF values greater than or equal to 10, which ensures that the final model is free of multicollinearity (Dormann et al. 2012).

To spatialize the model residuals, firstly we verified whether the data were non-biased and isotropic in different directions. We then spatialized the residuals obtained with the multivariate model using ordinary kriging by fitting theoretical semivariogram models (Gaussian, Spherical, and Exponential) using the weighted least squares method. The selection and validation of the best semivariogram model was based on reduced mean error (ER) and standard deviation of reduced mean error (SDE), which were calculated on the basis of the cross validation process described by Cressie (1991) and McBratney and Webster (1986).

Semivariograms express the variation of a given attribute as a function of the distance between the points in the sampling field. The total variance of the attribute is dismembered into different distances and used to estimate the spatial structure of the variance. The semivariance is characterized by three parameters: sill, range and nugget effect (Isaaks and Srivastava 1988). Sill is the plateau reached by the values of semivariance, and indicates the amount of variation that can be explained by the spatial structure of the data. Range is the distance at which the semivariogram reaches the plateau, indicating the distance at which the

TABLE I
Variables used for modelling the wood volume in Cerrado *Sensu Stricto* in the state of Minas Gerais, southeast Brazil.

Variables	Description
Bio 1	Annual Mean Temperature (ºC)
Bio 2	Mean Diurnal Range (Mean of monthly) (ºC)
Bio 3	Isothermality (BIO2/BIO7) (* 100) (ºC)
Bio 4	Temperature Seasonality (standard deviation *100) (ºC)
Bio 5	Max Temperature of Warmest Month (ºC)
Bio 6	Min Temperature of Coldest Month (ºC)
Bio 7	Temperature Annual Range (BIO5-BIO6) (ºC)
Bio 8	Mean Temperature of Wettest Quarter (ºC)
Bio 9	Mean Temperature of Driest Quarter (ºC)
Bio 10	Mean Temperature of Warmest Quarter (ºC)
Bio 11	Mean Temperature of Coldest Quarter (ºC)
Bio 12	Annual Precipitation (mm)
Bio 13	Precipitation of Wettest Month (mm)
Bio 14	Precipitation of Driest Month (mm)
Bio 15	Precipitation Seasonality (Coefficient of Variation) (mm)
Bio 16	Precipitation of Wettest Quarter (mm)
Bio 17	Precipitation of Driest Quarter (mm)
Bio 18	Precipitation of Warmest Quarter (mm)
Bio 19	Precipitation of Coldest Quarter (mm)
Dec	Declivity (%)
Elev	Elevation (m)
Lat	Latitude
Long	Longitude
Prec	Annual Mean Precipitation (mm)
Temp	Annual Mean Temperature (ºC)
Dd	Deforestation density (Number/m²)

points are spatially correlated. The nugget effect is the combination of sampling errors and variations on small scales, whose distance values are smaller than the shortest distance between the points sampled.

The selected semivariogram model was used for the ordinary kriging of the regression residuals, introducing a stochastic aspect to the wood volume maps. For the regression kriging application, continuous georeferenced cells with dimensions of 100 x 100 m were created for the Cerrado *Sensu Stricto* vegetation in the state of Minas Gerais. In each of these cells, the variables selected in the multivariate model were extracted and the regression model was applied to them, generating the global map of wood volume. The final step was the correction of this map by adding the residual ordinary kriging map.

The accuracies of predicted wood volume maps were evaluated using Root Mean Square Error (RMSE) calculated in percentage based on field-based inventory wood volume estimates with the validation set. We used R (R Core Team 2016) and ArcGis version 10.1 (Esri 2010) for the analyses.

RESULTS AND DISCUSSION

EXPLORATORY ANALYSIS

The statistics of the wood volume (m^3 ha^{-1}) obtained from field-based forest inventory indicate that average (48.5 m^3 ha^{-1}) and median (44.7 m^3 ha^{-1}) values are close to one another, indicating a symmetry in the distribution of the wood volume data (m^3 ha^{-1}). The minimum value was 15.9 m^3 ha^{-1} and the maximum value was 107.2 m^3 ha^{-1}, which led to a high coefficient of variation (42.8%), and thus, a high variability of the wood volume throughout this biome. Alvarenga et al. (2012) and Reis et al. (2015) studied remnants of Cerrado *Sensu Stricto* in the northern region of the state of Minas Gerais, and found a coefficient of variation for wood volume per hectare of 72.2% and 60.9%, respectively. Thus, the results found here corroborate these studies, confirming the high volumetric variability of Cerrado *Sensu Stricto* in the state of Minas Gerais. Scolforo et al. (2008) reported that this vegetation type presents great variation in its wood volume, both within the same remnant and among remnants, due to the differences in tree density, which can range from 407 to 2316 individuals per hectare in the state of Minas Gerais.

WOOD VOLUME MODELLING

All parameters used in our multivariate regression model had significant coefficients (Table II) and the residuals were normally distributed (Shapiro-Wilk, p = 0.98), with a coefficient of determination (R^2) of 0.55 and a mean absolute error (MAE) of 34.5%. Figure 2 illustrates the one-to-one relationship between observed and estimated wood volume of Cerrado *Sensu Stricto* as obtained using the selected multivariate regression model. This model resulted in a predictable dispersion of the observed values in relation to the field-measured values close to the axis of 45°, indicating increased predicted value precision in comparison to observed values.

The coefficient of determination (R^2), as well as the mean absolute error (MAE), are considered

TABLE II
Coefficients estimated by the regression model and their statistical significance.

Coefficients	Variable	Values	p-value
b0	Intercept	-395.6202	0.0073
b1	Bio 10	11.9302	0.0076
b2	Bio 17	0.3919	0.0911
b3	Bio 3	49.0357	0.0039
b4	Temp	-8.9337	0.0105
b5	Dd	2.8011	0.0664

Bio 10 = Mean Temperature of Warmest Quarter (ºC); Bio 17 = Precipitation of Driest Quarter (mm); Bio 3 = Isothermality (%); Temp = Annual Mean Temperature (ºC); Dd = Deforestation density (Number/m²).

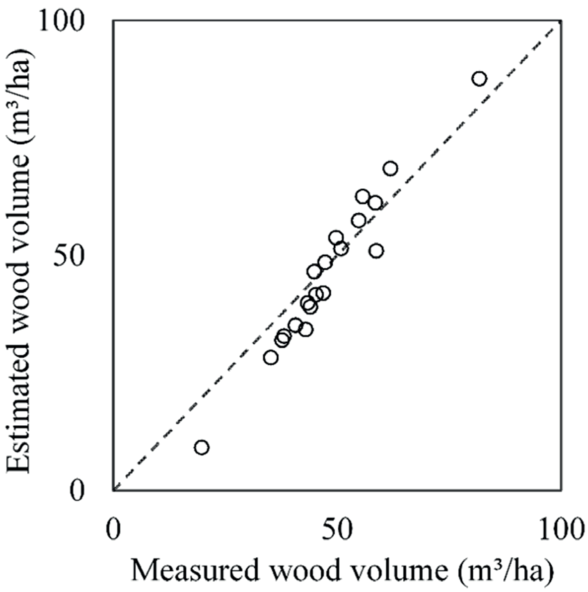

Figure 2 - Scatterplots of the predicted vs. observed wood volume in Cerrado *Sensu Stricto* in the state of Minas Gerais.

acceptable due to the wide variation found for the target variable in this region. This wide variation reflects the heterogeneity of the natural conditions of the Cerrado *Sensu Stricto* remnants in the state of Minas Gerais, which directly affects the wood volume (Scolforo et al. 2008). In addition, it is important to note that the wood volume values do not only respond to the environmental conditions considered, but also to other environmental variables, such as chemical and physical soil characteristics (Berner and Law 2016), as well as structural conditions of the remnant, such as different vegetation successional stages with different age structures (Schwieder et al. 2016).

In general, climate seasonality (in terms of both temperature (Bio 3, Bio 10, and Temp) and precipitation (Bio 17)), and deforestation are the main drivers of the variation in wood volume in the state of Minas Gerais (Figure 3). These specific climate variables, mainly precipitation seasonality, mean temperature, and isothermality (Bio 3) – a measure of reduced temperature seasonality – increase environmental stress in the north of the state, and are directly related to the limitations of tree growth and number of trees, as a consequence of reduced water availability (Esquivel-Muelbert et al. 2016, Terra et al. 2018).

On the other hand, deforestation detected between 2006 and 2007 has a direct influence on the wood volume, since it implies significant losses in the vegetation stock (Arantes et al. 2016). These deforestation events are generally concentrated to productive areas, which makes them more desirable for wood exploitation. Rocha et al. (2011) analysed the spatial distribution of deforestation in the Cerrado from 2002 to 2009 in order to understand the processes responsible for the transformation of this biome. They found that 70% of deforestation was concentrated in only 100 municipalities and occurred mainly in areas of dense vegetation and predominantly flat relief, favouring the advance of mechanized agriculture and, to a lesser extent, extensive livestock. This tendency for agricultural frontiers to occur in areas of dense vegetation with greater biomass was also observed by Aguiar et al. (2012) for the Brazilian Amazon.

REGRESSION KRIGING

The variographic analysis indicates that the residuals of the model were spatially structured (nugget effect = 147.38 m^6 ha^{-2}, sill = 480.73 m^6 ha^{-2}, and range = 20.71 m) (Figure 4), and the spherical model presented the best performance of all fitted models (ER = 0.019 m^3 ha^{-1}; SER = 0.920 m^3 ha^{-1}). The degree of spatial dependence of the volume residual variable (GDE%) represents the magnitude of the structure of spatial dependence, and can be obtained from the ratio (sill)/(nugget effect + sill). According to Cambardella et al. (1994), if the GDE is greater than 75%, there is a strong spatial correlation between the points sampled. In this study, the GDE was equal to 78.2%, which indicates a strong spatial dependence of the residuals. The GDE also indicates that from the 45% ($1 - R^2$) of the variation in wood volume that

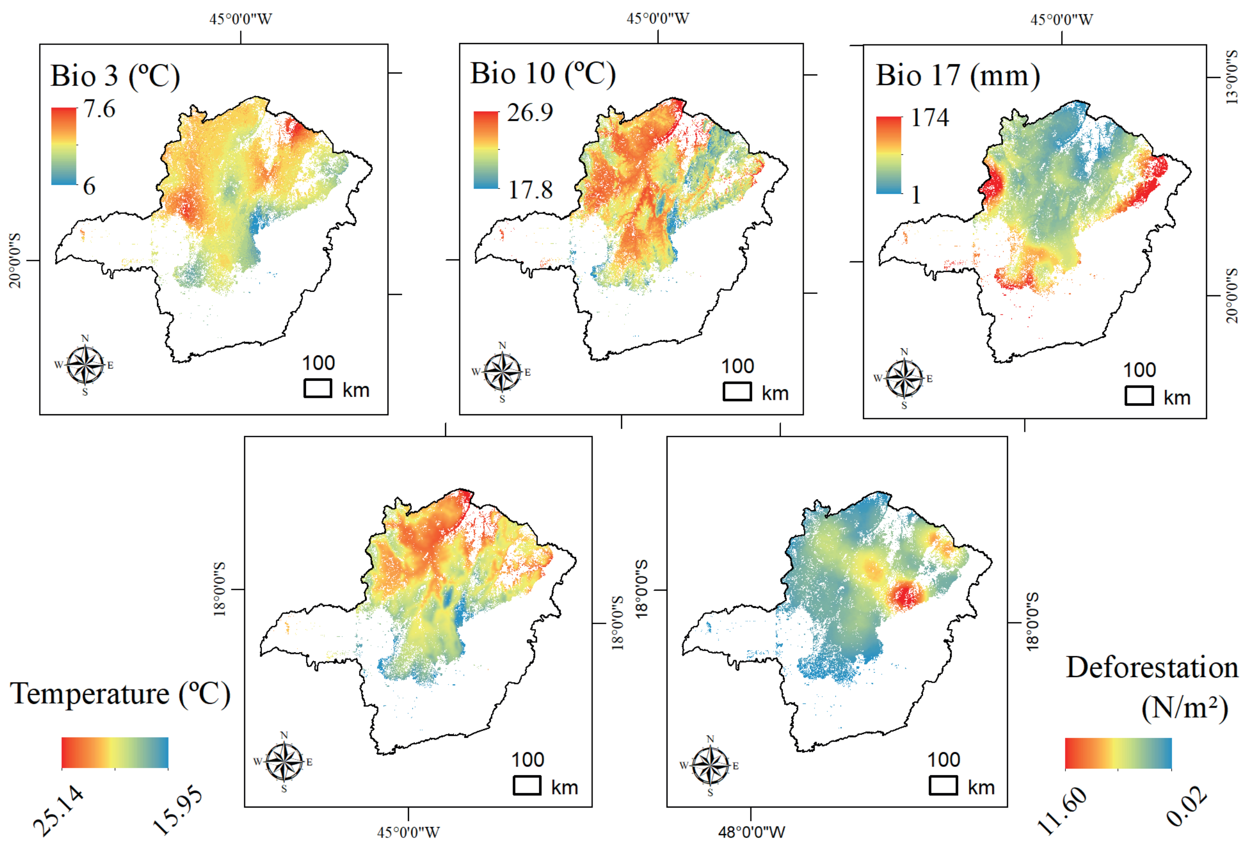

Figure 3 - Selected variables by multivariate regression model for wood volume estimation: Bio 3= Isothermality; Bio 10 = Mean Temperature of Warmest Quarter (ºC); Bio 17= Precipitation of Driest Quarter (mm); Temp=Annual Mean Temperature and Dd= Deforestation density.

were not explained by the regression model, 78% were explained by the spatial model. Therefore, 35% of the original variation in wood volume were explained by the spatial component.

From the spatial distribution map of the residuals (Figure 5), it is possible to observe a balance between the under and overestimates, meaning that the model is adequate as there is no bias produced by the regression model. Meusburger et al. (2012) and Mello et al. (2013) both applied regression kriging for rainfall erosivity mapping in Switzerland and Brazil, respectively, and concluded that the residuals should have a balanced, trendless spatial distribution, so that the regression kriging can be more expressive. In addition to this characteristic, it is important to note that the low values of estimation errors, both underestimates (negative values) and overestimates (positive values), demonstrate not only the good performance of the multivariate regression model,

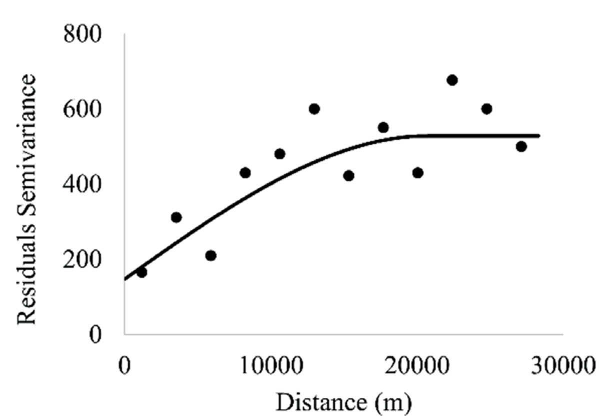

Figure 4 - Theoretical and experimental univariate semivariogram for wood volume residuals (m^3/ha) as a function of environmental variables in Cerrado *Sensu Stricto* of the state of Minas Gerais.

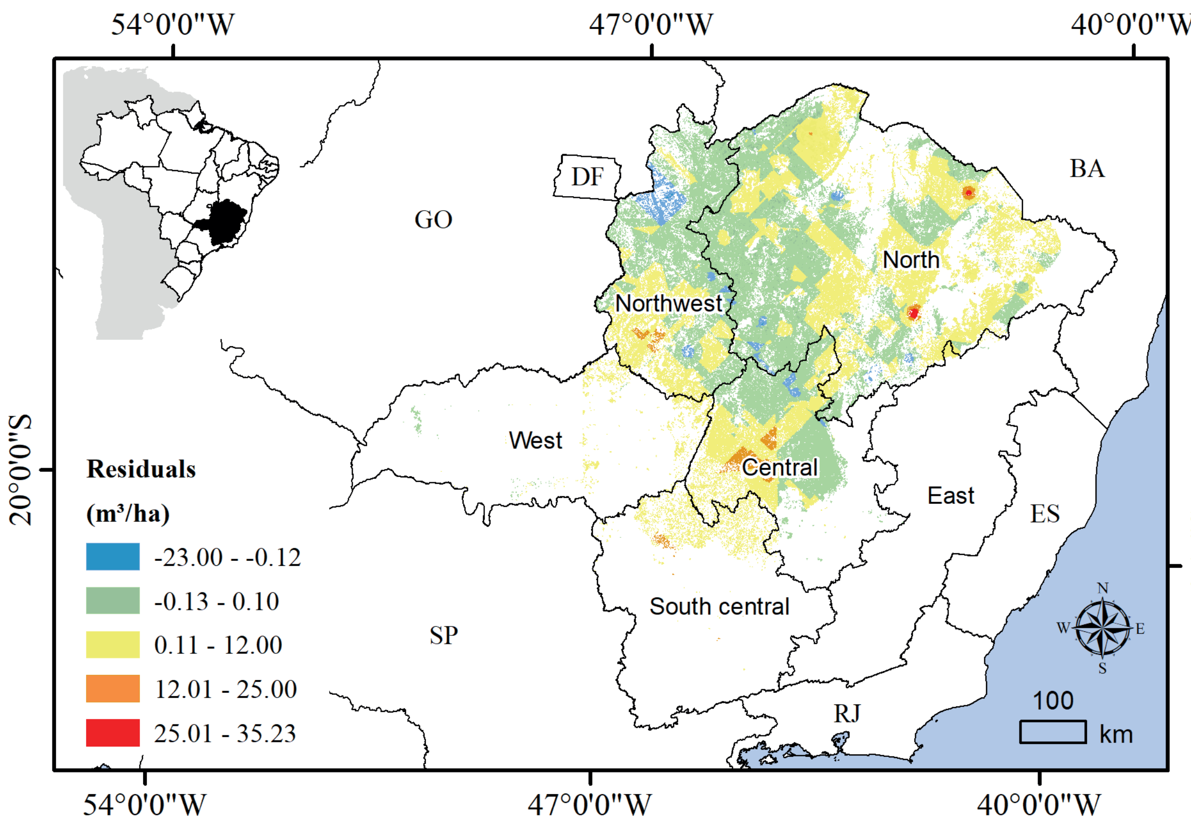

Figure 5 - Spatial distribution of wood volume residuals in Cerrado *Sensu Stricto* in the state of Minas Gerais.

but also the good performance of the ordinary kriging map of wood volume residuals.

SPATIAL DISTRIBUTION OF WOOD VOLUME

Both the global map generated by the regression model (RMSE = 11.6 %) (Figure 6) and the map corrected by the regression kriging technique (Figure 7) revealed a decrease in the wood volume from the middle towards the northern portions of the state. This is primarily related to the effects of the seasonality of precipitation (Esquivel-Muelbert et al. 2016), as indicated by the regression model. Furthermore, low soil water availability in these regions (Skorupa et al. 2012) also represents a limiting factor for the growth of biometric characteristics, leading to low wood volume values (Wagner et al. 2012).

The western portion of the Central region of the state and the southern portion of the Northeast region hold the remnants with the highest wood volumes, ranging from 45 to 98.2 m^3 ha^{-1}. These regions have increased water availability, which provides more favourable conditions for plant growth (see Bio 17 variable in Figure 2). In the northern part of the state lies a region with wood volumes of less than 30 m^3 ha^{-1}. These areas have experienced anthropogenic disturbances, such as exploitation of vegetation for charcoal production, cattle grazing, and conversion for agricultural practices and they are in an advanced degradation stage leading to lower wood volume in this region.

The low wood volume obtained for the middle region of the state occurred due to climatic effects related to a geographical barrier, which generates an unfavourable situation for vegetation growth. This geographical barrier consists of an extensive mountain range known as the Espinhaço Range, which produces an orographic effect

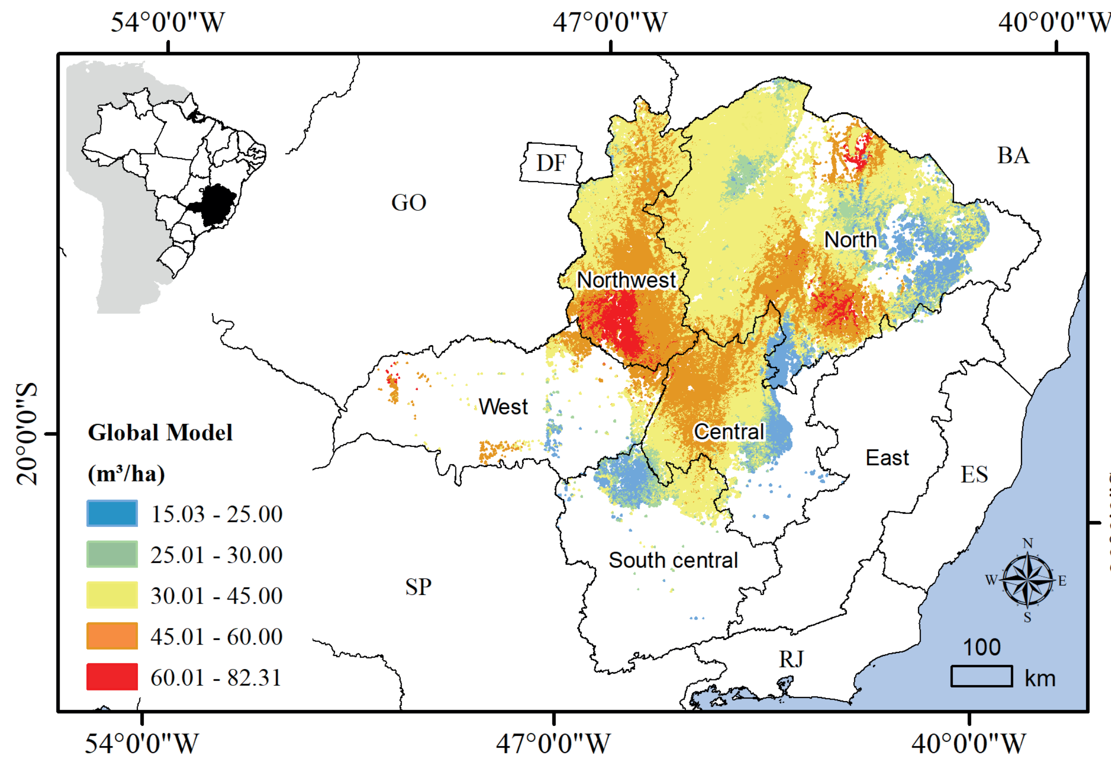

Figure 6 - Global model for wood volume (m^3/ha) for the Cerrado *Sensu Stricto* in the state of Minas Gerais.

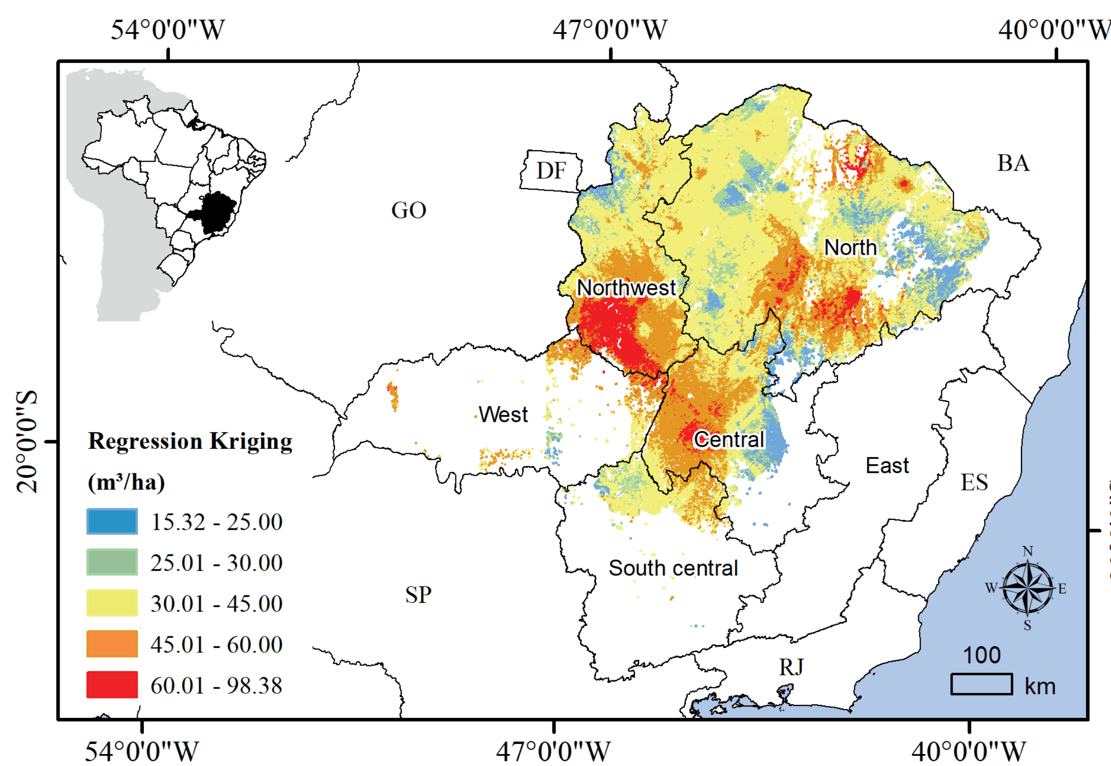

Figure 7 - Map of wood volume (m^3/ha) obtained by regression kriging for the Cerrado *Sensu Stricto* in the state of Minas Gerais.

on the precipitation regime in the east of Minas Gerais, impeding the transportation of moisture from the Atlantic Ocean over the mountains. The lower overall humidity and the stronger climate seasonality certainly have a negative impact on plant growth (Esquivel-Muelbert et al. 2016). Additionally, the cold fronts that come from the south of the country affect the Cerrado *Sensu Stricto* region in Minas Gerais, causing a decrease in humidity in the winter months and thus reduced favourability for plant growth.

Regarding the northern part of the state, the effect of the seasonality of precipitation is remarkable. Also, the edaphic component plays an important role in vegetation structure. Therefore, despite the presence of 'enclaves' of highly fertile soils, where dry forests predominate (Apgaua et al. 2014; Santos et al. 2012), there is a general trend towards sandier soils, like the Cambisol (Inceptsols) and Lythollic Neossol. These soils generally have low fertility that, together with the physical characteristics of the soils, low precipitation and high temperatures, create conditions that are unfavourable for plant growth in almost all of the São Francisco River basin. This basin accounts for 35% of the state area, and is the region with the largest remnants of the Cerrado in the state of Minas Gerais.

CONCLUSIONS

The predicted wood volume distribution of the Cerrado *Sensu Stricto* is characterized by high variability, ranging from 15.32 to 98.38 $m^3 ha^{-1}$, and a climatically driven gradient of decreasing wood volume in the southeast-northwest direction, due to the effects of precipitation and temperature seasonality. The deforestation density map also played an important role in explaining the variation in Cerrado *Sensu Stricto* wood volume throughout the state.

The high variability of wood volume in this vegetation type reinforces the importance of the use of methods that consider the influence of environmental variables on the spatial distribution of wood volume.

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AUTHORS CONTRIBUTIONS

All authors contributed substantially to the work reported here. EMOS, AAR, and MCNST analysed, interpreted the data, and wrote the manuscript. KDW, JMM, FWAJ, ACFF, and CRM reviewed and edited the manuscript. All authors read and approved the final manuscript.

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