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USE OF RGB DRONE SENSORS TO ESTIMATE VEGETATION BIOMASS IN A SEMIARID REGION

USO DE SENSORES RGB EM DRONES PARA ESTIMAR BIOMASSA VEGETAL EM UMA REGIÃO SEMIÁRIDA

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RESUMO - As estimativas dos estoques de biomassa vegetal em pastagens utilizando técnicas de sensoriamento remoto, apesar de serem amplamente utilizadas ultimamente, ainda são incertas devido ao padrão tridimensional e desigual de crescimento da vegetação. Foi definida uma metodologia para estimar os estoques de biomassa no semiárido de Pernambuco, Brasil, utilizando uma câmera RGB de alta definição acoplada a um drone. Os sobrevoos foram realizados em áreas de floresta tropical seca densa e aberta e pastagens, nas estações seca e chuvosa. A biomassa medida em campo foi relacionada a nove índices de vegetação do espectro visível por meio de regressão linear múltipla. Os coeficientes de determinação variaram entre 0,73 e 0,82. Os modelos mostraram-se uma forma viável de estimar a biomassa, considerando a amplitude espacial e temporal do estudo, as características da vegetação e os tipos de cobertura do solo avaliados. Sensores RGB são promissores para estimar biomassa em regiões semiáridas, especialmente integrados a índices de vegetação.
Palavras-chave: Geotecnologias. Espectro visível. Índices de vegetação. Pasto. Floresta seca.

ABSTRACT - Remote sensing techniques are currently widely used in environmental analysis due to the ability to collect accurate data in a cheaper and easier way than conventional techniques. However, estimates of vegetation biomass stocks in rangelands using remote sensing techniques are still uncertain due to the tridimensional and uneven growth pattern of the vegetation. A methodology was defined to estimate biomass stocks in different land cover types in the semi-arid region of Pernambuco state, Brazil, using a high definition RGB camera coupled to a drone. Flyovers 30 m above ground level were performed in three field experiments, in areas of dense and open tropical dry forest and pastures, during the dry and rainy seasons. Biomass measured in field was related to nine visible spectrum vegetation indices as independent variables, using multiple linear regression. The determination coefficients ranged between 0.73 and 0.82. The models proved to be a feasible way to estimate the biomass, considering the spatial and temporal amplitude of the study, the vegetation characteristics and the types of soil cover evaluated, which could be improved with the addition of more sampling points. We conclude that RGB sensors are promising to estimate biomass in semiarid regions, especially integrated with vegetation indices.
Keywords: Geotechnologies. Visible spectrum. Vegetation índices. Pasture. Dry forest.

INTRODUCTION

Remote sensing techniques have become consolidated as versatile tools, and their application in several branches of science is currently becoming more widespread. Remote sensing has enabled a better understanding of the dynamics of environments due to the possibility to collect accurate and robust data, with low cost, covering a large area within a short temporal scale, combined with statistical models (Gaida et al., 2020; McRoberts & Tomppo, 2007). In environmental studies, their positive contribution in monitoring and analysis of the landscape is undeniable, since they facilitate the spatial-temporal visualization of ecological variables important for sustainable ecosystem management (Silva, 1998, Silva et al., 2018).

Remote sensing techniques have traditionally been applied using airplanes and satellites, but the use of unmanned aerial vehicles (UAV) has been increasing in the last decade (Harkel et al., 2020). They have as advantages, compared to airplanes and satellites, the ability to capture images in high spatial resolution, less propense for sampling errors from atmospheric interference, higher flexibility in relation to collection period, and simpler operation (Pádua et al., 2017; Whitehead et al., 2014; Toth & Józków, 2016).

Vegetation is one of the most complex targets analyzed by remote sensing. Therefore, the use of spectral indexes of vegetation has gained space to evaluate the dynamics of plant growth and ground cover (Ponzoni et al., 2010; Epiphanio et al., 1996). Vegetation indexes integrate radiometric measurements composed of values of specific bands of the spectrum, minimizing atmospheric effects Jensen et al., 2011).

The use of RGB cameras as an alternative to infrared in vegetation indices makes research feasible, especially in contexts where the use of high-resolution multispectral or hyperspectral cameras is financially unviable.

The reduced cost and ease of operation of RGB cameras simplify the capture and analysis process. In various situations, these sensors can effectively replace indices that require infrared data, particularly in areas with uniform vegetation, where spectral differences between visible bands can provide reliable estimates of plant health and structure, in some cases satisfactorily replacing indices that need infrared spectrum data (Marcial-Pablo et al., 2019).

This more accessible and practical approach has expanded opportunities for environmental monitoring, especially in sustainable management and conservation initiatives for green areas, where data frequency and accessibility are preferable to high-cost and complex operational systems.

The objective of this study is to define a methodology for estimating biomass stocks using drones in areas with different types of land cover and use in the Caatinga biome of the state of Pernambuco. Specifically, it aims to acquire spectral data for the biome, creating a database that will support future sustainable management plans.

Additionally, the work intends to develop multiple linear regression equations to estimate biomass in different types of land use and cover in the region.

METHODOLOGY

Study area and biomass determination

Nine sites of the network of plots for long-term ecological studies in Northeastern Brazil (PERENE), a regional project led by the National Observatory of Water and Carbon Dynamics in the Caatinga Biome, funded by the Brazilian Ministry of Science and Technology, were selected to collect vegetation field data.

The sites are located at different municipalities in the semiarid region of Pernambuco state, northeast of the Brazil (Figure 1).

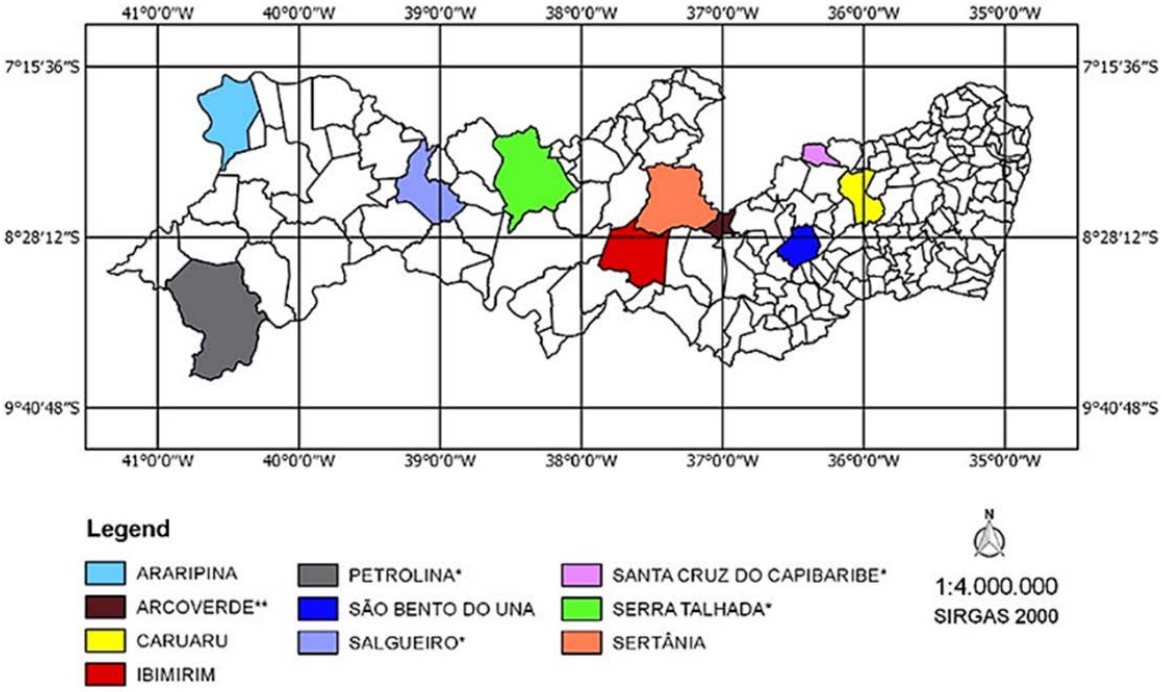

Figure 1 - Municipalities where the data collection sites are located in Pernambuco state, Brazil.

Three plots were selected in each of the ten data collection sites, corresponding to the most important land-use and cover vegetation in the region:

1) Dense Caatinga (DC), deciduous forest with a high density of tall shrubs and trees, forming a heterogeneous but closed canopy, with little areas of exposed soil in an aerial view (Figure 2(a)); 2) Open Caatinga (OC), the same vegetation formation as DC but with lower density of tall shrubs and trees and opener canopy, with points of exposed soil in aerial images, generally corresponding to intermediate stages of forest regeneration (Figure 2(b)), and 3) Pasture fields (P), composed predominantly of herbaceous planted or native species with very low density or absence of tall shrubs and trees (Figure 2(c)).

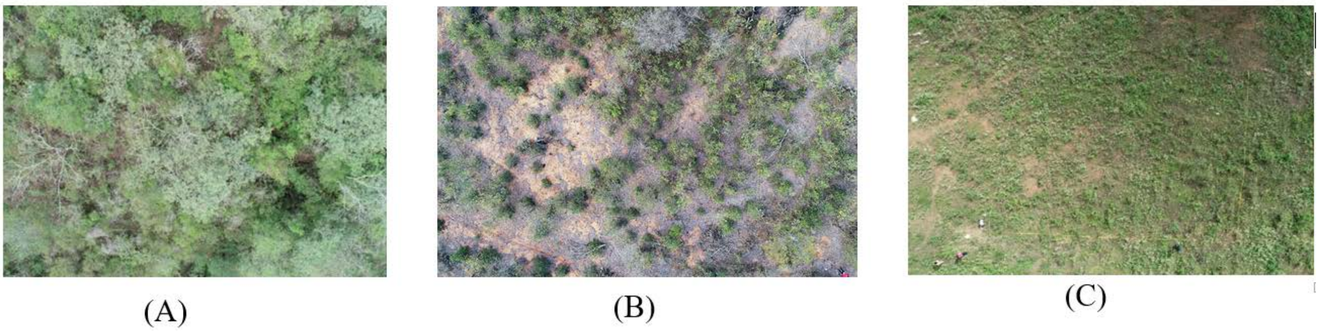

Figure 2 - Aerial images of areas of Dense Caatinga (A), Open Caatinga (B) and Pasture (C) in the semiarid site of Salgueiro municipality, in the Brazilian northeast region.

Each plot had a 20 m x 20 m area, surrounded by a border of at least 5 m without anthropic disturbances and away from floodplains and rock outcrops. Four 1 m² subplots were delimited in each plot corner.

Plant biomass was determined in each plot, measuring the stem diameter at breast height (1.3 m from the ground) of each tall shrub or tree in the plot and using specific alometric equations to calculate the biomass based on the diameter (Sampaio & Silva, 2005, Silva & Sampaio, 2008, Silva, & Cruz, 2018).

and adding the biomass of herbs and small plants determined by direct harvesting and weighing in the four corner subplots, and extrapolating to the plot area.

AERIAL DATA COLLECTION ROUTINE

Drone flight

A Phantom 4 Pro quadcopter drone (DJI, 2016), equipped with a high-definition 20-megapixel camera, capable of capturing in 4K and image size of 5472×3078 pixels with a mechanical shutter, coupled with a wide-angle lens optimized with f/2.8 20 was used to obtain images from the plots.

The overflights always took place at 30 m height, to assure the total imaging of the plot, and were carried out on sunny days and always from 10 am to 2 pm, to minimize possible interference of the amount of incident light on the image area at the time of flight. The images were obtained immediately prior to the biomass determination.

Information processing of spectral analysis

The images collected in the field were processed using the Esri ArcGIS@ software, initially cropping the area of interest in the image, and extracting the average values of the bands of the visible spectrum (green, red, and blue) by the extension module *Zonal Statistic as table*. Once the spectral bands were separated, the values for each band were used in twelve vegetation indices of the visible spectrum (RGB) already described in the literature (Table 1) as estimators of variables associated with plant growth.

Analytic statistical method

Two different methods to categorize the land cover were used. In Method 1 the three different land covers (Dense Caatinga, Open Caatinga, and Pasture) were considered. In Method 2 only two groups were considered, the two types of Caatinga being considered as a single land cover group, and Pastures considered as the second group. For each of the two methods, multiple linear regression analyses were performed considering the total field biomass as the dependent response variable and the values of the vegetation indices as independent explanatory variables together with the land covers as categorical independent variables (dummy variables).

Table 1 - Vegetation indices used as categoric variables to estimate biomass

Indices	Acronym	Equation	Authors
Visible Atmospherically Resistant Index	VARI	(Rg−Rr)/(Rg+Rr−Rb)	Gitelson et al. (2002)
Green Leaf Index	GLI	(2*Rg−Rr−RrRr−RRbRg+Rr+Rb)	Louhaichi et al. (2001)
Normalized Difference Green	NGRDI	(Rg−Rr)/(Rg+Rr)	Tucker (1979)
Coloration Index	CI	(Rr−Rb)/Rr	Escafadal et al. (1991)
Intensity	I	(1/30.5)*(Rr+Rg+Rb)	Escafadal et al. (1991)
Shape Index	IF	(2*Rr−Rg−g−Rr−Rg−Rb)	Escafadal et al. (1991)
Red-Green Ratio	RGR	Rr/Rg	Gamon et al. (1999)
Triangular Greenness Index	TGI	(Rg-0.39)*(Rr-0,61)*Rb	Hunt et al. (2011)
Normalized Pigment Chlorophyll Ratio Index	NCPI	(Rr-Rb)/(Rr+Rb)	Peñuelas et al. (1993)
Simple Ratio Red/Blue Iron Oxide	IO	Rr/Rb	Hewson et al. (2001)
Green Cromatic Coordinate	GCC	Rg/(Rr+Rg+Rb)	Gillespie et al. (1987)
Red Green Blue Vegetation Index	RGBVI	(Rg*Rg)–(Rr*Rb)/(Rg*Rg)+(Rr*Rb)	Bendig et al. (2015)

The stepwise method was applied, via Akaike Information Criterion – AIC (Akaike, 1974), combining the backward and forward procedures, to identify the most significant subset of predictors and to reject those that were not significant, assuming the role of a model quality evaluator and estimating the loss of information. In addition, it was verified whether the residues followed a normal distribution using the Shapiro & Wilk test (1965). The linear forms of heteroscedasticity were detected using the Breusch Pagan (1979) [33] chi-square variance test. Multiple and adjusted R^2 values were also included in the analysis. The statistical software R (R Core Team, 2013) was used in the calculations.

A general method flowchart of the procedures applied for this study are presented in figure 3.

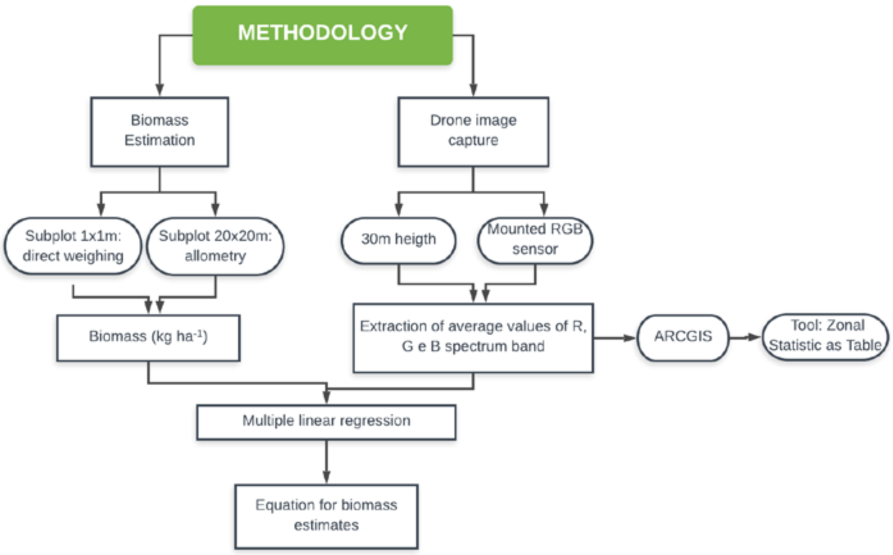

Figure 3 - Routine applied for field activities and information processing.

RESULTS

The biomass stocks directly sampled in the field ranged from 11.89 to 39.40 Mg ha^{-1} for Dense Caatinga, 2.34 to 36.04 Mg ha^{-1} for Open Caatinga and 0.56 to 6.99 Mg ha^{-1} for Pasture. These values are within the range reported for these types of land cover in the Caatinga (Araújo-Filho, 2013). Overall, the biomass stocks estimated through the drone images had ranges similar to those determined in the field: 9.94 to 36.54 Mg ha^{-1} for Dense Caatinga, 0.85 to 20.57 Mg ha^{-1} for Open Caatinga and 0.51 to 7.60 Mg ha^{-1} for Pastures. Model 1, which included the three land cover types as categorical variables, reached a multiple R^2 of 0.7342 and an adjusted R^2 of 0.6738 (F-statistic, 12.15; p value, 1.0 e-09).

The results of the function and their respective coefficients are shown in Table 2. The use of

RGB vegetation indices combined in a regression equation showed high accuracy in predicting the biomass stocks in the vegetation in the Brazilian semiarid region.

Equations for each type of land cover were developed based on the values listed in Table 3.

Table 2 - Coefficients of multiple linear regression of Model 1.

	Estimates	Standard error	T valor	Pr (>|t|)
(Intercept)	5.037e+03	2.363e+03	2.132	0.038630 *
Dense Caatinga	1.607e+01	2.996e+00	5.365	2.86e-06 ***
Pasture	-1.099e+01	3.053e+00	-3.600	0.000803 ***
VARI	-1.169e+03	5.793e+03	-2.018	0.049668 *
NGRDI	1.153e+04	5.740e+03	2.008	0.050799
CI	6.893e+02	3.685e+02	1.871	0.068060
I	2.841e-05	1.758e-05	1.616	0.113231
RGR	7.883e+02	5.080e+02	1.552	0.127847
NCPI	2.447e+03	1.227e+03	1.994	0.052356
RGBVI	-1.649e-04	5.656e-05	-2.915	0.005582 **
GCC	-1.742e+04	8.484e+03	-2.053	0.046010 *

Statistical significance codes: 0’ ***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
VARI - Visible atmospherically resistant index; NGRDI - Normalized Difference Green; CI - Coloration Index; I - Intensity; RGR - Red-Green Ratio. NCPI - Normalized Pigment Chlorophyll Ratio Index; RGBVI - Red Green Blue Vegetation Index; GCC - Green Cromatic Coordinate

Table 3 - Individual equations for each type of cover and land use in Model 1

	EQUATIONS
Dense Caatinga	BDC=5.037e+03+1.607e+01-1.169e+03*VARI+1,153e+04*NGRDI+6.893e+02*CI+2.841e-05*I+7.883e+02*RGR+2.447e+03*NCPI-1.649e-04*RGBVI-1.742e+04*GCC
Open Caatinga	BOC=5.037e+03-1.169e+03*VARI+1,153e+04*NGRDI+6.893e+02*CI+2.841e-05*I+7.883e+02*RGR+2.447e+03*NCPI-1.649e-04*RGBVI-1.742e+04*GCC
Pasture	BP=5.037e+03-1.099e+01-1.169e+03*VARI+1,153e+04*NGRDI+6.893e+02*CI+2.841e-05*I+7.883e+02*RGR+2.447e+03*NCPI-1.649e-04*RGBVI-1.742e+04*GCC

BDC = biomass of Dense Caatinga; BOC= biomass of Open Caatinga; BP= Biomass of Pasture. The description of the independent variables, corresponding to vegetation indices, are in Table 1

The Shapiro-Wilk normality test had a value of 0.9707 and a p-value of 0.1979, indicating the acceptance of the hypothesis of normality of errors. In the analysis of variance, the value of the Breusch Pagan test (7.7431) and p-value (0.6539) indicated that the homogeneity of variance for the residuals was not violated. Therefore, the model followed a normal distribution, most points close to the identity line (Figure 4).

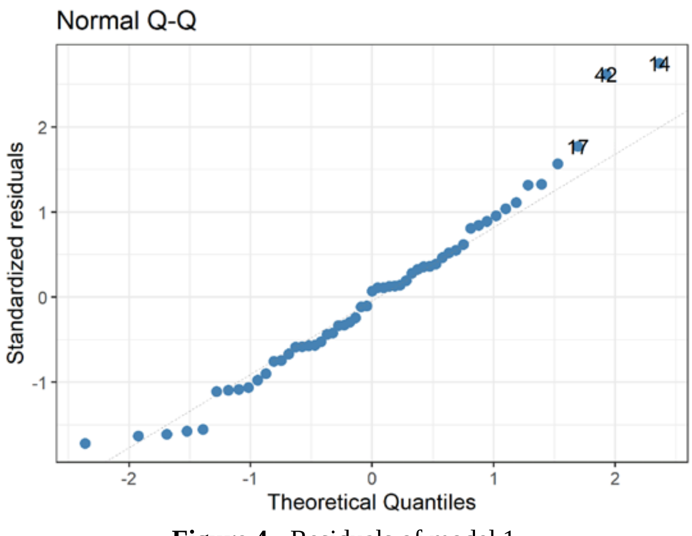

Figure 4 - Residuals of model 1.

In the second Model, considering only two land covers (Caatinga and Pasture), the biomass was estimated using a lower number of explanatory and categorical variables than in Model 1. Merging the open and dense Caatinga into a single land cover group (Caatinga) resulted in a better fitted equation, reaching an R^2 multiple of 0.8521 and an adjusted R^2 of 0.8235 (F-statistic, 29.77; p value, 1.5 e-11). The coefficients are listed in Table 4.

Considering Caatinga as a single land cover reduced the noise in the prediction model, represented by a higher adjusted R^2 in Model 2 than in Model 1. Merging Dense and Open Caatinga as a unique land cover type also resulted in an equation to estimate the biomass stock with less vegetation indices than the equation developed in Method 1. From this information, it was possible to describe the individual equations for each type of land cover (Table 5). The Shapiro Wilk test validated the hypothesis of residue normality, with a value of 0.98241435 and p-value of 0.8011. The residual chart illustrates this statement (Figure 5).

Table 4- Coefficients of multiple linear regression of Model 2.

	Estimatives	Standard error	T valor	Pr (>|t|)
(Intercept)	6.844e+02	2.569e+02	2.664	0.0121 *
Pasture	-2.751e+01	2.462e+00	-11.175	2.12e-12***
NGRDI	9.135e+02	3.723e+02	2.453	0.0200 *
I	2.655e-05	1.487e-05	1.786	0.0839 *
NCPI	4.084e+02	1.626e+02	2.512	0.0174 *
RGBVI	-9.595e-05	5.187e-05	-1.850	0.0739 *
GCC	-1.956e+03	7.696e+02	-2.541	0.0163 *

Statistical significance codes: 0’ ***’ 0.001 ‘**’ 0.01 ‘*’ 0.05

Table 5 - Individual equations for each type of cover and land use in Model 2.

	EQUATIONS
Caatinga	Bca = 6.844e+02 + 9.135e+02*NGRDI + 2.655e-05*I + 4.084e+02*NCPI -9.595e-05 *RGBVI -1.956e+03*GCC
Pasture	Bpa = 6.844e+02 - 2.751e+01 + 9.135e+02*NGRDI + 2.655e-05*I + 4.084e+02*NCPI - 9.595e-05 *RGBVI -1.956e+03*GCC

BCa= Caatinga; PA= Pasture ; Bdc= Biomass of dense caatinga ; Bpa= Biomass of pasture.

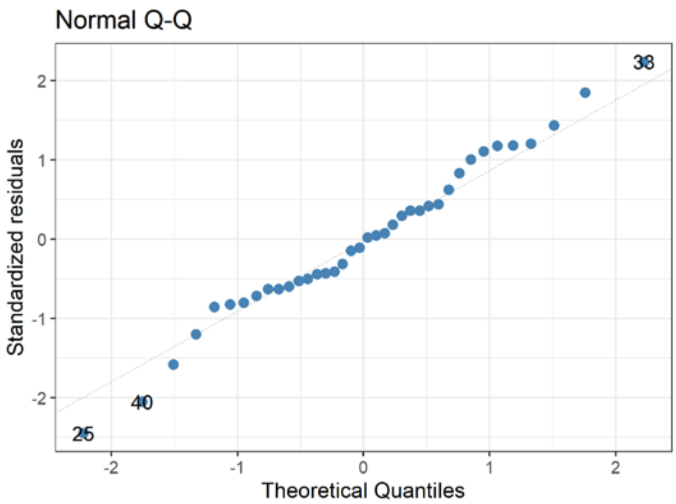

Figure 5 - Residuals of model 2.

However, the variance test showed a violation of the residuals homogeneity considering the 5% significance level (BP = 17.451 and p-value = 0.007762). This implies that the number of samples used to build the model needs to be increased, either in terms of spatial and temporal scale, to achieve a better estimate of the biomass stocks in the region. The violation of homogeneity can be explained by a high percentage of bare soil in the open caatinga areas, which caused differences in the reflectance pattern and increased diffuse radiation from the soil, causing confusion and noise in the reflectance emitted by the vegetation. Based on the violation statistical principle we conclude that Model 1 should be adopted to estimate aboveground vegetation biomass stocks in the Caatinga.

DISCUSSION

Dry forests biomass stock estimations using remote sensing are scarce worldwide, and inexistent for some regions, except for classifications carried out to cover large areas, at the regional, national or continental scales (Kumar & Mutanga, 2017; Smith et al., 2019).

The values estimated using UAV images in our study were similar to those reported by Araújo-Filho (2013) and by Nascimento (2019), who used Landsat 8 images and vegetation indices based in infrared reflectance to estimate the biomass of Caatinga areas and the same vegetation categories: 32.60 ± 9.3, 11.45 ± 9.63 and 4.18 ± 2.23 Mg ha^{-1}, respectively, for Dense Caatinga, Open Caatinga and Pastures.

As show the reference (Luz et al., 2022), used high spatial resolution images of the RapidEye satellite to estimate the aboveground biomass of nine Caatinga areas and found a range of 6.88 to 123.82 Mg ha^{-1}, 50% of the plots varying from 16.77 to 55.92 Mg ha^{-1}.

Presently, the RapidEye satellite offers the highest spatial resolution among satellites images for the Brazilian semiarid area (1.24 meters of resolution).

According to Lima Junior et al. (2014), the large range of values observed in Caatinga areas reflects different edaphoclimatic characteristics, asymmetries in the vegetation growth rate, and anthropic interferences across the biome.

Biomass stock estimates using data from orbital sensors commonly derive from the use of NDVI (Normalized Difference Vegetation Index) integrated with linear regressions. However, as show Nascimento (2015), observed that NDVI was not a good biomass estimator of Caatinga biomass, since he obtained an equation with an R^2 of 0.38 for the same land covers used in the present study.

Similar results were also reported by Accioly et al. (2022) who found a coefficient of 0.36 correlating vegetation indexes of infrared spectrum and biomass of a Caatinga area in the Seridó region of Rio Grande do Norte state (also located in the semiarid region of NE Brazil).

Contrarily, Lima-Junior et al. (2014) applied vegetation indices, using RGB and infrared reflectance data, in a single regression model to estimate the biomass stock of a Caatinga area and obtained a determination coefficient of 0.70.

However, the data used to build the model were from only five sample sites, located only a few hundred meters apart, and, thus, do not reflect the climatic and physiographic diversity of the Caatinga biome and differs from the present study, which had sampling points distributed throughout the state, often separated by hundreds of kilometers.

Even using high spatial resolution, preliminaries studies warn that NDVI is not a good estimator of the aboveground biomass in the Caatinga biome. According to Morais et al. (2021), compared several spectral vegetation indices, including NDVI, to detect changes in land cover in the Caatinga and, concluded that the EVI and SAVI2 indices were the most efficient in distinguishing the vegetation growth pattern, considering seasonality and variation in shrub density.

Nascimento (2019) also identified that the isolate use of NDVI is not the most accurate vegetation index to estimate vegetation growth in the Caatinga.

Baccini et al. (2012), compilated world biomass stocks and referred the Caatinga average biomass as being 44.5 ± 21.7 Mg ha^{-1}, aan average similar to that estimated (40 Mg ha^{-1}) by Sampaio & Costa (2011) and Sampaio (2010). According Sampaio (2010) reviewed biomass values in the literature for specific plots, under different climate and conservation states, and reported a range from 2 to 156 Mg ha^{-1}.

According to Barreto et al. (2018), generalistic predict models to estimate biomass stocks in native vegetations tend to have a low capacity to represent these environments' uniqueness. However, when these models are built contemplating the specificities of the ecosystem, they portray the real variability of these regions. The models obtained in our study were able to catch the heterogeneity of the Caatinga biome.

Both satellite and UAV images can achieve adequate temporal and spatial resolution, while the UAV have a significant restriction in spectral resolution, since most commercial UAV carry only RBG cameras (Li et al., 2020).

Vegetation indices using RGB images captured from UAVs have been used to monitor aboveground biomass in grassland and cultivated pastures (Guo et al., 2021; Maimaitijiang et al., 2019).

Grüner et al. (2019), for example, estimating cultivated pasture biomass with an SfM-based method and RGB image captured by a Phantom

3 quadricopter, found coefficients of determination from 0.59 to 0.81. These coefficients are inferior to those found in the present study, and we have to consider that they were obtained from a single experimental field.

Oldeland et al. (2017) mapped savanna areas in central Namibia using images captured by an RGB-Nir sensor coupled to a fixed-wing drone. They concluded that the Nir spectrum in the UAV did not increase the capacity to determinate biomass stocks in the vegetation and that UAV with RGB cameras could adequately map the arboreal patterns in the ecosystem.

They also concluded that the main reason for the success was the low altitude flights which allow the capture of patterns of the electromagnetic spectrum which would be impossible to be detected from orbital images.

Used a drone equipped with RGB and NIR sensors in a maize field to compare the capacity of the sensors to estimate biomass and to monitor the vegetative stages of the crop (Marcial-Pablo et al., 2019).

They used three vegetation indices based on the visible region and three based on the infrared region and concluded that a simple RGB sensor, depending on the purpose, can be more advantageous, offering high precision to identify the vegetative stages with lower cost than NIR sensors, which were also used in their study. The results of the present research, based only on the visible spectral region, seem to support their conclusion.

Drones coupled with RGB cameras may be an alternative to have fast, cheap, and representative estimates of vegetation biomass stocks in drylands (Chianucci et al., 2016), as demonstrated in our study. Such results diverge from those reported by authors who concluded that RGB images have limited ability to estimate the biomass of dry vegetations, because are highly sensitive to interferences from the soil reflectance (Doughty & Cavanaugh, 2019).

Studies in the Brazilian semiarid region can be further developed using the biomass estimation models proposed in the present study. The models may provide information to support sustainable management plans and to help develop specialized and popularized tools to meet the specific needs of the local population in the face of severe drought problems.

CONCLUSIONS

The use of RGB cameras coupled to UAV and the integration of multiples vegetation indices in two estimating models, one considering three vegetation covers (Dense Caatinga; Open Caatinga; and Pasture) and the other only two vegetations covers (Dense + Open Caatinga; Pasture) proved to be a promising and advantageous method to estimate aboveground plant biomass in the native forest and in pastures established in the semiarid region of northeast Brazil.

In this study the UAV flying 30 m high, offered a spatial resolution of less than 10 cm, advantage for analysis of small areas or when the purpose of the study requires high resolution of the area. The method used in our work differs from used in the most of studies and it is unprecedented for the biome, especially when it is considered the spatial variability of the sampled sites across the biome.

The results obtained are quite satisfactory for an indirect method of this scale, involving the construction of two multiple linear regression models for different land use and cover types in caatinga areas, with determination coefficients of 0.73 and 0.82. These models can be further improved by adding more sampling points, thereby reducing potential intrinsic analysis errors. The application of effective methodologies to estimate biomass in the caatinga is essential and necessary for developing future models for sustainable biome management and creating a spectral database to support future studies.

This technique may be widely used in the management of forested and rangeland areas, due to its higher spatial resolution and lower cost than other types of remote sensors.

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