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Articles

Using drones for estimating fuel material in Cerrado grasslands

Uso de drone para a estimativa do material combustível em formações campestres no Cerrado

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ABSTRACT

In the quest to advance fire prevention and control strategies, new techniques for quantifying combustible material are being explored. Among these, the use of multispectral sensors and red, green, and blue (RGB) cameras has emerged as promising solutions to streamline both cost and time expenditures in the field. This study aimed to assess the feasibility of employing an airborne multispectral sensor and an airborne RGB digital camera, mounted on a multirotor drone, to estimate combustible material load in a Cerrado area through linear regression analysis. Conducted within a savanna formation, the study involved evaluating 40 samples of combustible material load in 1 m² plots. Aerial surveys were conducted to capture images, facilitating the derivation of reflectance variables, vegetation indices, and descriptive parameters of the three-dimensional model. The resulting equation, customized to predict total combustible material within the study area, exhibited considerable significance ($p < 0.001$), accompanied by a determination coefficient (R^2) of 0.70 and an adjusted R^2 of 0.65. Upon analyzing the variables' impact on the model, it became evident that while the point density of the model showed higher correlations, the normalized difference vegetation index wielded notable influence, as indicated by its prominent weight within the adjusted equation.

Keywords: Remote sensing; UAV; Estimation

RESUMO

Em busca de alternativas para aprimorar o controle e gerenciamento das ações de prevenção aos incêndios, novas técnicas para quantificação do material combustível têm sido estudadas. Para reduzir os custos e tempo gasto em campo, o uso de sensores multiespectrais e câmera RGB (Red, Green e Blue) vêm se destacando como ferramentas úteis e eficazes na estimativa do material combustível. Nesse contexto, objetivou-se neste trabalho avaliar a viabilidade da utilização de um sensor multiespectral e câmera digital *RGB* aerotransportada por um multirrotor, para estimativa de carga de material combustível em área de Cerrado por meio de regressão linear. O trabalho foi conduzido em área de formação savânica, onde foram avaliadas 40 amostras de carga de material combustível em parcelas de 1 m^2, coletando-se também imagens, mediante a um aerolevantamento, para obtenção de variáveis de reflectância, índices de vegetação e variáveis descritivas do modelo tridimensional. A equação ajustada para prever o conteúdo de material combustível (MCT) na área de estudo revelou-se relevante, com significância estatística ($p < 0,001$), um coeficiente de determinação (R^2) de 0,70 e R^2 ajustado de 0,65. Ao analisar a influência das variáveis no modelo, observou-se que, embora a densidade de pontos no modelo (DPM) apresentasse correlações superiores entre as variáveis, o índice de vegetação NDVI exerceu uma influência mais significativa, evidenciada pelo seu maior peso na equação ajustada.

Palavras-chave: Sensoriamento remoto; VANT; Estimativa

1 INTRODUCTION

The Cerrado biome is renowned as one of the world's most diverse savannas but faces significant threats as one of the most endangered ecosystems, largely due to human activities leading to habitat loss and fragmentation (Strassburg *et al*., 2017). Human activity in the Cerrado biome has resulted in significant alterations in fire management practices, which depend on the timing and frequency of occurrences, and are greatly influenced by fire behavior dynamics (Schmidt *et al*., 2016). While fire is a natural and essential element that has played a pivotal role in shaping the Cerrado biome over thousands of years, the expansion of urbanization has made humans the primary drivers of wildfires, causing extensive harm to this biome (Soares *et al*., 2017).

The repercussions of wildfires are multifaceted, encompassing biodiversity depletion due to habitat destruction, disruptions in the hydrological cycle leading to water scarcity, soil erosion from vegetation cover removal, and substantial greenhouse gas emissions contributing to climate change. In response to these challenges, novel techniques for understanding fire behavior have been explored to enhance control and management strategies in wildfire prevention efforts (Tavares, 2017).

A study by Santos *et al*. (2018) exemplifies investments in procedures aimed at enhancing our comprehension of fire behavior. This research investigated the relationship between moisture content and the flammability of species inhabiting the Cerrado grasslands in the Jalapão region. Through tests covering ignition frequency, average time to ignition, combustion duration, and flame height across six species at four moisture levels, the researchers deepened our understanding of fire dynamics.

According to Soares *et al*. (2017), fire behavior involves three primary elements of combustion: fuel, oxygen, and heat, collectively known as the fire triangle. Fuel encompasses any organic material susceptible to combustion, including branches, twigs, fallen logs, grasses, herbs, shrubs, humus, and peat, and it can be managed. However, quantifying combustible material within the Cerrado area presents challenges due to the biome's heterogeneity and diversity, making conventional quantification methods costly and intricate (Ferraz *et al*., 2014).

In this context, indirect methods are notable for their ability to establish correlations between vegetation parameters and easily accessible variables, particularly through remote sensing techniques (Souza *et al*., 2018). Multispectral sensors provide insights into the interactions between the target and its spectral response, enabling the characterization of vegetation based on its spectral features (Bendig *et al*., 2014). Consequently, the utilization of airborne sensors offers an alternative that provides images with enhanced spatial and spectral resolutions, thereby allowing for more precise quantification of vegetation attributes (Berni *et al*., 2009).

In the field of digital image processing (DIP), advancements in airborne multispectral sensors and high-resolution digital cameras are noteworthy due to their user-friendliness and data accessibility, making them invaluable tools for field research endeavors (Banu *et al*., 2016). The significant advantage of aerial photogrammetry over traditional measurement methods lies in the high density of data points acquired through DIP, resulting in meticulous data processing and rendering it a cost-effective alternative for target characterization (Rodrigues and Gallardos, 2018).

The application of aerial photogrammetry for estimating vegetation parameters finds exemplary validation in the studies of Bendig *et al*. (2014), Li *et al*. (2016), and Souza *et al*. (2018). These studies, focusing on biomass estimation in summer barley, canopy height and biomass assessment in corn plantations, and combustible material quantification in "campo sujo" areas of the Cerrado, distinctly demonstrate the practical and innovative utility of this technology in agricultural and ecological analyses.

Building upon this foundation, our study assumes that the use of an airborne multispectral sensor and an airborne red, green, and blue (RGB) photographic sensor, both deployed via a multirotor drone, enables the acquisition of vegetation parameters within a "campo sujo" area of the Cerrado. Furthermore, it is hypothesized that these parameters can be integrated into statistical models to accurately estimate the load of combustible material.

Therefore, the aim of this study was to evaluate the feasibility of employing an airborne multispectral sensor and an airborne RGB digital camera, both mounted on a multirotor drone, for estimating combustible material load in "campo sujo" areas within the Cerrado biome. This evaluation will be conducted through linear regression analysis.

2 MATERIALS AND METHODS

2.1 Study area

The research was conducted in July 2017, during the dry season period in the Cerrado, specifically within the Xerente Indigenous Land. Located in the municipality of Tocantínia, in the southern region of the state of Tocantins, the study area is centrally positioned at coordinates 9°39'00" South latitude and 48°07'12" West longitude.

Within this region, there are areas undergoing recovery, predominantly characterized by low-growing herbaceous vegetation in a state of senescence. Both are situated within a "campo sujo" zone of the Cerrado. According to the Köppen classification, the prevailing climate in the study region is C2wA´a´, indicating a sub-humid climate with moderate water deficiency in winter, an average precipitation of 1,500 mm, and an average temperature of 26.6°C (Alvares *et al*., 2014).

2.2 Data collection

For aerophotogrammetry, a Survey3W multispectral sensor with a resolution of 4,000 × 3,000 pixels was utilized. This sensor can detect near-infrared light (NIR) around 850 nm, red light (Red) at 660 nm, and green light (Green) at 550 nm. Additionally, an FC6310 camera with a resolution of 5,472 × 3,648 pixels and a focal length of 8.8 mm was deployed. Both devices were mounted on a multirotor drone, and an external USB GPS receiver was integrated into the sensor to accurately geotag each captured image.

In the flight plan, an altitude of 100 m was established with an 85% overlap both longitudinally and laterally. This configuration resulted in a ground sample distance of 2.3 cm, representing the value of each pixel in the image in ground units. Additionally, artificial targets measuring 1 m^2 (1 × 1 m) were strategically positioned across all the plots. These targets, consisting of plates with distinctive markings, were utilized to enhance their identification in the images, thereby augmenting the accuracy and interpretability of the acquired data.

The sampling of combustible material involved 40 plots measuring 1 m^2 (1 × 1 m), randomly distributed as defining quadrants. All the plant material within each plot was collected on the same day, at 10 a.m., immediately following the flight of the multirotor drone. Following collection, the material was weighed, divided into sub-samples, and stored in Kraft paper bags. Subsequently, the samples underwent oven drying at 70°C until a constant mass was achieved. This approach aimed to estimate the load of total combustible material (TCM) in each plot, allowing for extrapolation to tons per hectare ($t.ha^{-1}$).

2.3 Data analysis

After capturing the images with the Survey3W multispectral sensor, it was necessary to prepare them before generating the digital model through the MAPIR Camera Control software. This involved converting the photos from RAW to TIFF format, followed by image calibration. This critical procedure significantly contributes to enhancing image quality and mitigating spectral variability (Jorge and Inamasu, 2014).

Following image preparation, a three-dimensional model was generated by executing the Structure from Motion (SfM) algorithm. This technique utilizes multiple overlapping photographs to reconstruct the area in three dimensions. Subsequently, the three-dimensional model was converted into a digital red, green, and NIR (NGR) model. As a result, each pixel contains a known reflectance value expressed as a percentage. Upon completion of this process, the normalized difference vegetation index (NDVI) was calculated following the methodology outlined by Rouse *et al*. (1974) (Equation (1)), and the normalized green-red difference index (NGRDI) was determined in accordance with Hunt *et al*. (2005) (Equation (2)):

$$NDVI = \frac{Nir - Redx}{Nir + Red} \tag{1}$$

$$NGRDI = \frac{Green - Red}{Green + Red} \tag{2}$$

Where: Nir, is the near-infrared spectral region (850 nm); Red, is the red spectral region (660 nm); Green, is the green spectral region (550 nm).

The NDVI, derived from a mathematical expression ranging between –1.0 and 1.0, is widely used in vegetation cover studies. This index is segmented into various classes and can be adjusted based on the specific vegetation characteristics, as outlined in Table 1. Leveraging NDVI values enables the assessment of leaf area index, biomass, soil cover percentage, photosynthetic activity, and productivity.

Table 1 – Classification of NDVI values

NDVI	Interpretation
-1.0 – 0.0	Lack of vegetation cover
0.0 – 0.2	Low vegetative vigor
0.2 – 0.4	Moderate vegetative vigor
0.4 – 0.6	High vegetative vigor
0.6 – 1.0	Very high vegetative vigor

Source: Aquino (2017)

The NGRDI, proposed by Motohka *et al*. (2010), serves as both a complement and an alternative to the NDVI, owing to its sensitivity in detecting changes in vegetation colors. Therefore, the applicability of the NGRDI is crucial for enhancing vegetation cover assessment.

The FC6310 camera-captured images underwent processing using the same SfM algorithm, resulting in the generation of a three-dimensional model. This model was exported in LAS format to derive new variables: Zmin, Zmax, and Zmean, representing the minimum, maximum, and mean altitudes in centimeters within the digital elevation model, respectively. Additionally, point density of the model (PDM) was generated, indicating the density of points in the dense point cloud per square meter. Subsequently, data from each spectral band (NIR, Green, and Red), vegetation indices (NDVI and NGRDI), and descriptive statistics from the three-dimensional model were extracted for each plot and organized using GIS software.

A descriptive analysis encompassed the variables TCM, Red, Green, Nir, NDVI, NGRDI, Zmin, Zmax, Zmean, and PDM, followed by Pearson correlation analysis ($p < 0.05$) between the dependent variable TCM and the other variables. To increase the pool of estimators for analysis, the variables underwent transformations into Ln(x), Log(x), 1/x, x^2, and x^3. The Stepwise selection method was then used to adjust the linear regression equations, considering the dependent variable TCM in tons per hectare (t.ha–1) alongside the aforementioned estimators and their respective transformations.

The selection of the adjusted model was based on graphical analysis of the residuals in percentage, the standard error of estimate in percentage (Syx%), the coefficient of determination (R^2), the adjusted coefficient of determination (R^2adj), and the histogram of the residuals in percentage. To identify the most influential predictor variables in the regression model, the coefficients' values were standardized. This standardization enables comparison of predictors on different scales upon their coefficients. Additionally, the hypothesis of non-collinearity was examined (Myers, 1990; Bowerman and O'Connell, 1990; Menard, 1995).

3 RESULTS AND DISCUSSIONS

3.1 Descriptive analysis

The results of the descriptive analysis of the used parameters are presented in Table 2. The average reflectance values, expressed as percentages for Red (21.98%), Green (11.47%), and NIR (25.23%), shed light on the physicochemical attributes of the vegetation. Absorbance, the process by which plants absorb electromagnetic radiation, is prominently observed in the Red and NIR wavelengths. These bands are associated with the photosynthesis process and, consequently, with the vegetative vigor of the plant (Geipel *et al.*, 2014).

Table 2 – Descriptive analysis

Parameters	Minimum	Average	Maximum	CV%
Red	13.18	21.98	30.26	22.03
Green	5.97	11.47	16.20	22.13
Nir	14.68	25.23	33.04	20.46
NDVI	-0.03	0.07	0.14	61.08
NGRDI	-0.48	-0.22	0.39	56.70
Zmin (cm)	199.04	255.70	320.91	14.36
Zmax (cm)	358.35	492.68	607.16	15.39
Zmean (cm)	300.79	360.39	421.46	10.17
DPM (p m^{-2})	201.00	406.56	655.00	26.55
MCT (t ha^{-1})	1.79	4.66	7.60	29.97

Source: Authors (2022)

Where: Red, Green and Nir refer to reflectance values in percentage; NDVI and NGRDI to vegetation indices; Zmin, Zmáx and Zmean, altitude in centimeters; DPM, number of points per square meter; MCT, load of combustible material in ton per hectare.

Examining the average values, it is evident that the NDVI (0.07) and NGRDI (–0.22) vegetation indices classify the vegetation as having low vegetative vigor and no vegetation cover, respectively, based on the NDVI value classification.

The seasonality of the Cerrado biome is primarily marked by two distinct periods: the dry season, spanning from April to September, and the rainy season, occurring from

October to March (SEPLAN, 2012). This characteristic directly impacts the descriptive values of the data, particularly the reflectance and vegetation index variables, which are influenced by the vegetation's vigor (Marcussi *et al*., 2010).

3.2 Pearson Correlation and linear regression

Table 3 presents the results of the Pearson correlation between the dependent variable TCM and the independent variables: Red, Green, NIR, NDVI, NGRDI, Zmin (cm), Zmax (cm), Zmean (cm), and PDM (p.m-^{2}), along with their respective transformations.

Table 3 – Descriptive analysis

Variable	r	Variable	r
Red	-0.37*	1 / NDVI	-0.31*
Ln (Red)	-0.36*	NGRDI^2	-0.31*
Log (Red)	-0.36*	Z Mean	-0.32*
Red^2	-0.37*	Z Mean^2	-0.33*
Red^3	-0.36*	Z Mean^3	-0.35*
1 / Red	0.35*	DPM	0.49**
Green^2	-0.31*	Ln (DPM)	0.49**
Green^3	-0.33*	Log (DPM)	0.49**
NDVI	0.42**	DPM^2	0.48**
NDVI^2	0.41**	DPM^3	0.46**
NDVI^3	0.36*	1/ DPM	-0.47**

Source: Authors (2022)

Where: Red, Green and Nir refer to reflectance values; NDVI and NGRDI to vegetation indices; Z Mean and DPM to the statistics of the three-dimensional model; Red^2, Green^2, NDVI^2, NGRDI^2, Z Mean^2 and DPM^2 to squared variables; Red^3, Green^3, NDVI^3, Z Mean^3 and DPM^3 to variables cubed; 1/Red, 1/NDVI and 1/PointCount in inverse of Red, NDVI and DPM, respectively; Log = logarithm in base 10; Ln = natural logarithm; r = Pearson correlation; * and ** = significant at 5% and 1% by T test, respectively.

The Pearson correlation coefficient between the dependent variable TCM and the independent variables of Red reflectance, Ln (Red), Log (Red), Red^2, Red^3, Green^2, and Green^3 revealed weak and inverse correlations, significant at a 5% probability level (r = –0.37, r = –0.36, r = 0.36, r = –0.37, –0.31, and –0.33, respectively), except for the variable 1/Red, which displayed a weak and positive interaction (r = 0.35).

The association between the variable TCM and the NDVI, $NDVI^2$, and $NDVI^3$ vegetation indices demonstrated a positive correlation (r = 0.42, r = 0.41, and r = 0.36, respectively). In contrast, 1/NDVI and $NGRDI^2$ exhibited a weak and inverse correlation, with an r = –0.31 for both. Notably, only the NDVI variable was found to be significantly relevant at the 1% level according to the T-test.

The descriptive variables derived from the three-dimensional model, namely PDM, Ln(PDM), Log(PDM), PDM^2, PDM^3, and 1/PDM, exhibited higher correlations, albeit still considered weak (r = 0.49, r = 0.49, r = 0.49, r = 0.48, r = 0.46, and r = –0.47, respectively) compared to reflectance variables and vegetation indices. Conversely, variables Zmean, $Zmean^2$, $Zmean^3$, displayed inverse and weak correlations (r = –0.32, r = –0.33, and r = –0.35, respectively). Notably, similar to NDVI, the PDM variable demonstrated statistical significance at a 1% probability level.

Interestingly, manipulation and transformation of the Red and NIR spectral bands into NDVI resulted in an increase in correlation with the variable TCM. Tumlisan (2017) emphasizes the importance of combining and transforming variables into new indices for improved interpretation of vegetation cover.

Ponzoni *et al*. (2015) elucidate that healthy vegetation undergoes photosynthesis, absorbing approximately between 80% and 90% of the visible spectrum while reflecting between 40% and 50% of the NIR light. Consequently, applying the normalized difference index expression enhances vegetation, with brightness directly proportional to its vigor.

The correlation coefficient between combustible material and NGRDI revealed a weak association. In precision agriculture studies, Li *et al*. (2016) and Jannoura *et al*. (2015) observed indices with moderate interactions, ranging from r = 0.55 to r = 0.74. Conversely, Souza *et al*. (2018) achieved an r = 0.41 for the interaction between combustible material and NGRDI in a “campo sujo” area in the Cerrado. Tumlisan (2017) suggests that RGB wavelengths reflect less as chlorophyll availability increases in plants, hence associating NGRDI with photosynthetic activity akin to NDVI.

The variable ZMean, representing elevation in centimeters, exhibited a weak correlation (r = 0.32). This required an improvement in the classification of points, similar to the approach employed by Bendig *et al*. (2014), Cunliffe *et al*. (2016), Geipel *et al*. (2014), and Souza *et al*. (2018), resulting in a normalized digital elevation model.

The variable PDM emerged as a focal point in this study, showcasing a correlation coefficient of r = 0.49. The increased granularity of data points within the plots facilitated finer segmentation of the vegetation, thereby directly correlating with the quantity of combustible material within those plots.

In the realm of Pearson correlation analyses, the equation refined through the stepwise method for estimating the combustible material load from multispectral sensor data and RGB camera inputs is delineated in Table 13. Notably, the model's F-adjustment (interaction) exhibits a significant p-value of < 0.01, signifying the relevance of the interrelationship between the variables in elucidating the response variable TCM. Upon evaluating the hypothesis of non-multicollinearity, it is discernible that the variance inflation factor (VIF) values remain below 10, affirming the absence of collinearity. Notably, scholars such as Myers (1990) and Bowerman and O'Connell (1990) suggest caution against VIF values exceeding 10, which may introduce bias into the regression model, while Menard (1995) states that a tolerance threshold of 0.20 is indicative for concern.

Table 4 - Adjustment of the regression equation

Y	**X**	**C**	**C.P**	**R^2**	**R^2aj**	**Syx%**	**F**	**M.C**	
								T	**FIV**
	ß0	-12.31***					16.06		
	Ln (DPM)	2.69***	0.54				(p <0.01)	0.95	1
MCT	NDVI	18.81***	0.6	0.7	0.65	17.56		0.74	1.3
	Red^3	-6.93e-5**	-0.36					0.84	1.1
	1/NGRDI	-0.19**	-0.32					0.71	1.4

Source: Authors (2022)

Where: C, coefficient; C.P, standardized coefficient; M.C, multicollinearity; T, tolerance and IVF, Variance inflation factor; **, significant at 1% and ***, significant at 0.1% probability.

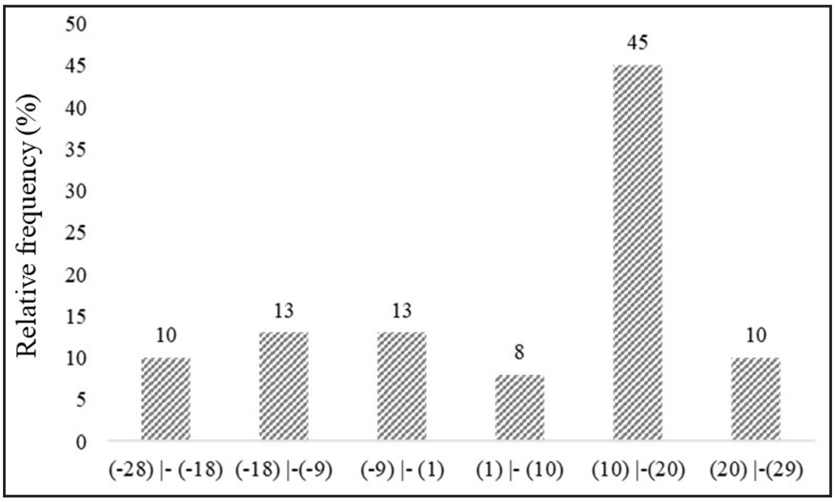
The determination coefficient for the equation stands at R^2 = 0.70, with an adjusted R^2aj = 0.65. Through an appraisal of the variables' significance, all were found to be highly significant per the T-test. Furthermore, when analyzing the relevance of each variable in the model, it is evident that although Ln (PDM) exhibits significant correlation, as presented in Table 13, NDVI wields a greater influence in refining the model compared to the other variables as evidenced by the standardized coefficient column.

Yue *et al*. (2017) and Bendig *et al*. (2015), in their efforts to estimate vegetation biomass using the NDVI, attained R^2 values of 0.37 and 0.48, respectively. Furthermore, Yue *et al*. (2017) used Green and Red wavelengths for the same purpose, achieving determination coefficients of 0.56 and 0.59, respectively.

The error frequency histogram depicted in Figure 1 reveals that 45% of the errors fall within the 10% to 20% range, indicating no discernible trend in errors. With a Syx% value of 17.56 for the smallest error range of 1% to 10%, approximately 8% of the errors were observed in this region.

Geipel *et al*. (2014), Bendig *et al*. (2015), and Souza *et al*. (2018) underscore the importance of combining variables, highlighting that integrating diverse factors significantly enhances model performance. This integration leads to improvements in adjustments and a reduction in the standard residual error.

Figure 1 - Error Frequency Histogram



Source: Authors (2022)

3 CONCLUSIONS

The utilization of remote sensors mounted on drones showcases potential for the quantitative assessment of combustible material in "campo sujo" vegetation areas within the Cerrado region. Specifically, the Survey3W and FC6310 multispectral sensors emerge as viable options for data collection through image capture. In light of the hypotheses and objectives set for this study, the following conclusions are drawn:

1– The NDVI and NGRDI vegetation indices exhibit a moderate correlation with the load of combustible material;

2– The PDM variable demonstrates the highest correlation with the combustible material load;

3– The adjusted equation devised for estimating the combustible material load demonstrates significant potential for facilitating fuel management in "campo sujo" areas within the Cerrado.

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