ISSN 1808-8546 (ONLINE) 1808-3765 (CD-ROM)

AGROMETEOROLOGICAL-SPECTRAL MODEL FOR ESTIMATING SUGARCANE PRODUCTIVITY IN BRAZILIAN SEMI-ARID

ANDERSON SANTOS DA SILVA [1]; MARIANA ALVES DA COSTA [2]; GEBER BARBOSA DE ALBUQUERQUE MOURA [3]; PABRÍCIO MARCOS OLIVEIRA LOPES [4]; MIGUEL JÚLIO MACHADO GUIMARÃES [5] E ANTHONY WELLINGTON ALMEIDA GOMES [6]

[1] Professor Dr. da Universidade Federal do Agreste de Pernambuco, Avenida Bom Pastor, s/n°, Bairro: Boa Vista, CEP.: 55292-270,Garanhuns/PE/Brasil, anderson.silva@ufape.edu.br;
[2] Mestranda no Programa de Pós-Graduação em Ciências Ambientais, Universidade Federal do Agreste de Pernambuco, Avenida Bom Pastor, s/n°, Bairro: Boa Vista, CEP.: 55292-270,Garanhuns/PE/Brasil, maac.cic@gmail.com;
[3] Professor Dr. do departamento de Agronomia, Universidade Federal Rural de Pernambuco, Rua Dom Manuel de Medeiros, s/nº, Bairro: Dois Irmão, CEP.: 52171-900, Recife/PE/Brasil, geber.moura@ufrpe.br;
[4] Professor Dr. do departamento de Agronomia, Universidade Federal Rural de Pernambuco, Rua Dom Manuel de Medeiros, s/nº, Bairro: Dois Irmão, CEP.: 52171-900, Recife/PE/Brasil, pabriciope@gmail.com;
[5] Professor Dr. do Instituto Federal de Educação, Ciência e Tecnologia do Maranhão, Campus São Raimundo das Mangabeiras, Rodovia BR-230, Km 319, Zona Rural, CEP.: 65840-000, São Raimundo das Mangabeiras/MA/Brasil, miguel.guimaraes@ifma.edu.br;
[6] Professor Dr. da Universidade Federal do Agreste de Pernambuco, Avenida Bom Pastor, s/n°, Bairro: Boa Vista, CEP.: 55292-270, Garanhuns/PE/Brasil, anthony.gomes@ufape.edu.br

1 ABSTRACT

This work aimed to develop an agrometeorological-spectral model, through a multiple linear regression, to estimate sugarcane productivity in the semi-arid region of Brazil. Annual agricultural yield data (2005/2006 to 2011/2012), monthly agrometeorological and spectral data (2005 to 2012) were used. In the calibration period of the model, the correlation between agrometeorological and spectral data in conformity with the real agricultural yield was the criterion chosen for the independent variables: irrigation plus rain precipitation, average air temperature, air vapor saturation deficit, and normalized difference vegetation index. In the calibration of the model, satisfactory results were observed with mean relative differences below 0.87% and an estimated standard error of 0.7806 tons of sugarcane in all crop years analyzed. In the model validation, the best performance was obtained for the crop year 2004/2005 compared to 2013/2014 and 2014/2015, what can be justified by the renewal of planting in this period. The model was adjusted through a correction factor and had its performance optimized in the 2013/2014 and 2014/2015 crop years. Multiple linear regression represents an excellent tool to be used in association with agrometeorological and spectral data for the estimation of agricultural productivity.

Keywords: remote sensing, multiple linear regression, northeast.

SILVA, A. S.; COSTA, M. A.; MOURA, G. B. A.; LOPES, P. M. O.; GUIMARÃES , M. J. M.; GOMES, A. W. A.
MODELO AGROMETEOROLÓGICO-ESPECTRAL PARA ESTIMATIVA DA PRODUTIVIDADE DE CANA-DE-AÇÚCAR NO SEMIÁRIDO BRASILEIRO

Recebido em 25/01/2021 e aprovado para publicação em 03/11/2021
DOI: http://dx.doi.org/10.15809/irriga.2021v26n3p490-506

2 RESUMO

O trabalho objetivou desenvolver um modelo agrometeorológico-espectral através de uma regressão linear múltipla para estimar a produtividade da cana-de-açúcar na região semiárida do Brasil. Foram utilizados dados anuais de rendimento agrícola (safras 2005/2006 até 2011/2012), dados mensais agrometeorológicos e espectrais (2005 até 2012). No período de calibração do modelo, a correlação existente entre os dados agrometeorológicos e espectrais em conformidade com o rendimento agrícola real foi o critério escolhido para as variáveis independentes: irrigação mais precipitação pluvial, temperatura média do ar, déficit de saturação de vapor do ar e índice de vegetação por diferença normalizada. Na calibração do modelo foram observados resultados satisfatórios com diferenças relativas médias inferiores a 0,87% e um erro padrão de estimativa de 0,7806 toneladas de cana-de-açúcar em todos os anos-safras analisados. Na validação do modelo, o melhor desempenho foi obtido no ano-safra de 2004/2005 quando comparado aos anos-safras de 2013/2014 e 2014/2015, o que pode ser justificado pela renovação de plantio nesse período. Por intermédio de um fator de correção, o modelo foi ajustado e seu desempenho otimizado nos anos-safras de 2013/2014 e 2014/2015. A regressão linear múltipla representa uma excelente ferramenta que pode ser utilizada em associação com dados agrometeorológicos e espectrais para estimativa de produtividade agrícola.

Palavras-chaves: sensoriamento remoto, regressão linear múltipla, nordeste.

3 INTRODUCTION

Sugarcane *(Saccharum* ssp.) has been cultivated in much of the Brazilian semi-arid because it presents high biomass production according to local edaphoclimatic conditions, subsidized by efficient irrigation technology in the production system (SILVA *et al*., 2014). It is a sexual breeding plant, but it is asexually multiplied by vegetative propagation when cultivated commercially. It is characterized by panicle-like inflorescence, hermaphrodite flower, and cylindrical growing stem composed of nodes and internodes. Also, alternating leaves, opposite, attached to the stems knots, with silica blades on their edges and open sheath (DANTAS NETO; TEODORO; FARIAS, 2010).

Sugarcane has adapted well to the climatic conditions found in Brazil in all regions, especially the Southeast, which concentrates on the leading producing states, *São Paulo* and *Minas Gerais*. The Northeast region, in recent years, has come with the introduction of new crops such as soybeans and corn, highlighting the region known as MATOPIBA (composed of the states of *Maranhão*, *Tocantins*, *Piauí*, and *Bahia*). And recently, the state of *Alagoas* has been implementing grain crops, but about the planted area, there was an increase of 0.8% and 2.8%, with productivity predictability to about 51 million tons for the 2020/21 crop year (CANA-DE-AÇUCAR, 2020).

According to the National Supply Company (Conab) (CANA-DE-AÇÚCAR, 2020), with the expectation of 61,800 hectares of planted area for the crop year 2020/21, the state of *Bahia* has an average productivity of approximately 60 t ha^{-1} in regions using rescue irrigation with dependence on rainfall. It differentiates this scenario in privileged areas with full irrigation where the yields are above 100 t ha^{-1} quietly, as can be observed in sugarcane fields in the municipality of *Juazeiro-BA* (SIMÕES *et al*., 2018).

Simões *et al*. (2018) highlight that, generally, the estimation of agricultural yields in sugarcane areas of certain companies and farms are made close to the beginning of the harvest by technicians who go through the sugarcane fields. They observe the vegetative vigor of the crop, attributing to its productivity values based on the experience gained and information from previous harvests. However, this type of analysis can be unfair and does not allow evaluating errors involved in the process.

In addition to the meteorological conditions, which play a vital role in productivity, the spectral variables also influence the final yield of an agricultural area. They represent agronomic handling, cultivars types, spatial situation, and certain elements not included in the agrometeorological components (MELO *et al*., 2008). The implementation of remote sensing in monitoring the space-time variability of the biophysical parameters inherent to the phenological phases of sugarcane corroborates the importance of this spectral supervision in optimizing water use. Through irrigation depths, due to the daily actual evapotranspiration obtained by the energy balance, which in turn correlates directly with the production of plant biomass responsible for productivity (MARTINS *et al*., 2019).

Agrometeorological and spectral models are based on the statistical relationship between dependent variables, which should be estimated (e.g., grain yield or phenological development) with independent variables (rainfall, air temperature, solar radiation, and vegetation indices). However, multiple linear regression aims to establish the relative importance and magnitude of the effect of independent variables on the dependent variable (MOREIRA, 2008).

According to Garcia and Reichardat (1989), the use of multiple linear regression in statistical modeling presents great responses between dependent and independent variables in the quantification and simulation of agricultural productivity of any crop. It was observed through its agroclimatic model using meteorological data.

In controlled environments, through a greenhouse experiment with sugarcane crop, the correlation between biometric and industrial parameters collected with their respective productivity through the multiple linear regression technique, allowed the achievement of satisfactory results. Moreover, they are quite practical and presented an acceptable degree of accuracy (DALCHIAVON *et al*., 2014).

The MODIS (Moderate-resolution Imaging Spectroradiometer) offers various products for remote sensing applications, including the product MOD13. It incorporates the vegetation indices NDVI (Normalized Difference Vegetation Index) and EVI (Enhanced Vegetation Index) produced globally with resolutions of 1km, 500 m, and 250 m, in image compositions or mosaics of 16 days since the year 2000 (RUDORFF; SHIMABUKURO; CEBALLOS, 2007).

NDVI is generally more sensitive to chlorophyll and other vegetation pigments responsible for absorbing solar radiation in the red spectrum. The EVI is more sensitive to variation in canopy structure, including LAI (Leaf Area Index), plant physiognomy, and canopy architecture (HUETE *et al*., 2002). Multiple linear regression associated with satellite imaging data from Landsat-8/OLI (Operational Land Imager) was used to model sugarcane yield. It showed that the NDVI, EVI, and MSAVI2 (Modified Soil-adjusted Vegetation Index 2) vegetation indexes can efficiently estimate productivity when the canopy is dense (LEDA; GONÇALVES; LIMA, 2019).

Thus, the objective of this work was to develop an agrometeorological-spectral model through a multiple linear regression to estimate sugarcane productivity in the semi-arid region of the northeast area of Brazil.

4 MATERIAL AND METHODS

The research was conducted in a commercial area of sugarcane located in the *Sertão* of *Bahia*, in the municipality of *Juazeiro - BA*. The study area consisted of 11 lots with a total area of 131.06 hectares, of which 121.50 hectares were planted with sugarcane, 9.34 hectares of streets and drains, plus 0.22 hectares of stones.

The study area presented the same: soil type (vertisol); drip irrigation system, spacing (0.90m x 2.10m), cultivated variety (SP 79-1011), and type of harvest (manual). From the 2014 harvests, after planting renewal in the field, 93% of the area was filled by the VAT 90-212 variety, and the remaining 7% was composed of several other varieties.

Productivity data for crop yields from 2005/2006 to 2011/2012 (calibration period of the models) and the 2004/2005 crop years, 2013/2014, 2014/2015, 2015/2016, and 2016/2017 (model validation period) were made available by the property owner, expressed in tons per hectare (t ha^{-1}), both estimated and measured values.

Table 1 shows the productivity history of the area under study, from the first harvest in 1998/1999 to the last harvest in 2011/2012. In addition, it can be observed that the renewal period of planting with the new variety occurred in the crop year 2012/2013, with the first harvest (plant cane) in 2013/2014 and with the second harvest (ratoon cane) in 2014/2015.

Table 1. Sugarcane productivity data for the crop years 1998/1999 to 2016/2017.

Crop year	Varieties	Harvest	Harvest season	Productivity (t ha^{-1})
1998/1999	SP 79-1011	1ª	-	146.00
1999/2000	SP 79-1011	2ª	-	105.00
2000/2001	SP 79-1011	3ª	-	113.00
2001/2002	SP 79-1011	4ª	-	101.00
2002/2003	SP 79-1011	5ª	-	117.00
2003/2004	SP 79-1011	6ª	-	93.00
2004/2005 PV	SP 79-1011	7ª	November/2005	98.00
2005/2006 PC	SP 79-1011	8ª	October/2006	101.51
2006/2007 PC	SP 79-1011	9ª	October /2007	113.20
2007/2008 PC	SP 79-1011	10ª	October /2008	96.20
2008/2009 PC	SP 79-1011	11ª	September/2009	82.73
2009/2010 PC	SP 79-1011	12ª	September /2010	83.36
2010/2011 PC	SP 79-1011	13ª	August/2011	84.48
2011/2012 PC	SP 79-1011	14ª	July/2012	74.28
2012/2013	-	-	Planting renewal	-
2013/2014 PV	VAT 90-212	1ª	June/2014	261.86
2014/2015 PV	VAT 90-212	2ª	July/2015	171.77
2015/2016 PV	VAT 90-212	3ª	July/2016	156.03
2016/2017 PV	VAT 90-212	4ª	July/2017	148.83

PC = Calibration period of the models and; PV = Validation period of the models.
Source: The authors (2022).

The meteorological variables considered in this study were: average air temperature (°C); mean relative humidity (%); insolation (hours day^{-1}); solar radiation (W m^{-2}); rainfall (mm day^{-1}), and evapotranspiration (mm day^{-1}). In addition, data from the irrigation depth (provided by the agricultural property owner) were used.

Data on meteorological variables were obtained from the Semiarid Tropic Agricultural Research Center, they are collected daily at the automatic agrometeorological station in commercial area (09º19'S and 40º11'W) located in the municipality of *Juazeiro-BA*.

A portable GPS (Global Positioning System) device, version eTrex10 from Garmin®, was used to collect the points that delimited the entire region. Data were downloaded in the free software QGIS version LTR (LongTerm Release) 3.16.11(QGIS, 2021) to create the file .shp of the site. These points were collected in the Coordinate Reference System (CRS), UTM (Universal Transverse Mercator) in the Datum SIRGAS 2000 (Geocentric Reference System for the Americas, year 2000).

Spectral information was extracted from orbital images obtained by the MODIS sensor onboard the Earth platform. These MODIS sensor images (MOD13Q1 - calculated from the 16-day time series) were acquired over the corresponding crop year.

Using the Application MODIS Reprojection Tool (MRT), all the preprocessing of the images was carried out. It includes georeferencing, reprojection, resampling, and conversions of file formats, HDF (Hierarchical Data Format), original format when the image are downloaded, for GeoTIFF, standard format that preserves information with CRS and Datum.

With the vector and matrix data of the study area, presenting CRS and compatible dates, the image clipping was overlaid and processed in the free software QGIS version LTR 3.10.7, thus generating the attributes necessary to calculate NDVI.

Knowing that the MOD13 product provides valid NDVI pixel values in the range of 2000 to 10000, MOD13 has 16-bit radiometric resolution, so it must be multiplied by the conversion factor, according to Equation 1:

$$NDVI = VP \times 0.0001 \quad (1)$$

Where: NDVI is the normalized difference vegetation index, and VP are the pixel values of NDVI.

Next, an NDVI analysis was performed throughout the crop cycle, observing the spectral behavior in the three months preceding the harvest, choosing the images, and the most representative month according to the best adjustments of the model.

The meteorological and spectral data were organized in a worksheet in the Microsoft Office Excel software, then imported into Statistica software, version 10. Finally, a correlation analysis was performed to see the significant influence of these variables on the final productivity of sugarcane culture.

The test of all independent variables correlated with agricultural productivity (dependent variable) and its choice was conditioned to the significance of the model (coefficients of determination and correlation), the probability ≤ to 5%, and a low estimate standard error.

Then, the values found were used to construct the agrometeorological-spectral model based on the multiple linear regression technique, according to Equation 2, in order to estimate agricultural productivity.

$$Y_i' = \alpha + X_1.\beta_1 + X_2.\beta_2 + X_3.\beta_3 + X_4.\beta_4 + \varepsilon \quad (2)$$

Where: Y_i' is the estimated agricultural productivity index (dependent); X_1, X_2, X_3, and X4 are the independent variables (irrigation plus rain precipitation - IP; average air temperature - T Vapor pressure déficit – DEF; and normalized difference vegetation index – NDVI; α, β_1, β_2, β_3, and β_4 are the parameters to be estimated and ε are the residues).

Subsequently, the definition of the independent variables that defined the model and the model's calibration was made. This study analyzed the three months preceding the harvest in the corresponding crop year, choosing that most significant time. It also selected the second-month preceding harvest because it presented the satisfactory results mentioned above.

According to the parameters found, these results were evaluated by calculating the Mean Absolute Deviation (MAD), the Relative Mean Difference (RMD), and the Root Mean Square Error (RMSE), between the productivity estimated by the models and the productivity considered real, calculated with values collected from the field. The Equations 3, 4, and 5 for calculating these parameters are described below:

$$MAD = \frac{1}{n}\sum_{i=1}^{n} |Y_i' - Y_i| \quad (3)$$

$$RMD = \frac{1}{n}\sum_{i=1}^{n} \frac{|Y_i' - Y_i|}{|Y_i|} \quad (4)$$

$$RMSE = \left[\frac{\sum_i^n (Y_i' - Y_i)^2}{n}\right]^{1/2} \quad (5)$$

Where: Y_i corresponds to the observed or actual productivity value (data collected in the field); Y'_i corresponds to the productivity value estimated by the model, and n corresponds to the number of crop years of productivity data.

Pearson coefficient was calculated to verify the performance of the models (Equation 6), *r* ($p<0.05$). It measures the degree of correlation and its direction, whether positive or negative, between two variables of the metric scale. This coefficient assumes values between -1 and 1: 1 means a perfect positive correlation between the two variables, and -1 means a perfect negative correlation between the two variables, that is, if one increases, the other continuously decreases, and 0 (zero) means that the two variables do not depend linearly on each other.

$$r = \frac{C_X}{S_X S_Y} \quad (6)$$

Where: C_{XY} is the covariance or joint variance of variables X and Y; S_X is the standard deviation of variable X, and S_Y is the standard deviation of variable Y.

The accuracy is related to the distance from the estimated values to those observed and was statistically given by the concordance index "d" proposed by Willmott, Ackleson and Davis (1985). Its values vary from zero for no agreement, to 1, for perfect agreement. The index is given by Equation 7:

$$d = 1 - \left[\frac{\sum (Y_i' - Y_i)^2}{\sum(|Y_i' - Y| + |Y_i - Y|)^2}\right] \quad (7)$$

Where: Y'_i is the estimated value; Y_i is the observed value; and Y is the average of the experimental values.

According to Camargo and Sentelhas (1997), the following statistical indicators were considered to correlate the estimated values with the measured values: accuracy - Willmott index "d" and confidence or performance index "c". The "c" is calculated according to Equation 8:

$$c = r \times d \quad (8)$$

Based on the value found in the Equation 8, they are classified on a scale according to Table 2.

Table 2. Classification of agricultural productivity estimation methods performance by index c.

c values	Performance
>0.85	Excellent
0.76 to 0.85	Very good
0.66 to 0.75	Good
0.61 to 0.65	Intermediate
0.51 to 0.60	Tolerable
0.41 to 0.50	Poor
≤0.40	Extremely poor

Source: Camargo and Sentelhas (1997).

Adjustment or forecast errors were measured by deviation according to equation 9:

$$\text{Deviation} = (\text{Measured productivity}) - (\text{Estimated productivity}) \quad (9)$$

5 RESULTS AND DISCUSSION

5.1 Calibration of the agrometeorological-spectral model

For the calibration period, Table 3 presents the agrometeorological-spectral model (MAE) parameters of multiple linear regression for the estimated productivity in the second month before harvest. The model was significant at the 5% probability level ($p < 0.05$) with a 95% confidence interval for the estimated value, presenting a good coefficient of determination (R^2), around 99%.

Table 3. Coefficients of the agrometeorological-spectral model (MAE) with the respective probabilities of error (p), linear correlations (r), Willmott concordance index (d), and standard error of the estimate.

Independent variables (MAE)	β	p value
α	749.3973	0.000558
IP	0.1778	0.031276
T	-2.6623	0.001017
DEF	2.4028	0.001382
NDVI	0.1649	0.051588
r = 0.99 R² = 0.99	p < 0.0023	d = 0.99
Standard error of estimate: 0.7806		

α and β = model parameters; IP = Irrigation + Rain precipitation (mm); T = Average air temperature (Cº); DEF = Vapor pressure deficit (hPa); NDVI = Normalized Difference Vegetation Index.
Source: The authors (2022).

Table 3, cited above, shows the correlation coefficient (r) and the concordance index (d) of the models; according to Camargo and Sentelhas (1997), the performance or confidence index (c) of the productivity estimation model was around 0.9801, classified as excellent for the period analyzed.

All variables present in the agrometeorological-spectral model were highly significant, contributing, consequently, to the best performance in estimating yields in the face of real yields.

Fiorio *et al*. (2018) evaluated the spectral behavior of sugarcane leaves as a function of the imposition of water deficit with the assignment of irrigation for longer and observed that high reflectances in the infrared region (a range responsible for the NDVI) were compute, evidencing the importance of adequate handling of full irrigation in the cultivation of this crop.

As the semi-arid region presents low and irregular rainfall regime, irrigation with adequate depths according to the crop's need strengthened the relationship between surface temperature and NDVI, with a strong positive correlation, corroborating the study developed by *Gomes et al*. (2019) in the semi-arid northeast region of Brazil with the aplications of satellite images and remote sensing techniques.

Antunes, Lamparelli and Rodrigues (2016) evaluated the sugarcane crop through MODIS time series. They realized that the use of NDVI, correlating with typical rainfall values, was important to identify the vegetative peak of the crop during the growth phase, maintaining the maturation phase at its correct phenological stage. Thus, it is similar to the study area, where the water regime is controlled through full irrigation throughout the crop year.

Sugarcane requires adequate water availability inherent to each stage of its cycle to maintain its efficient physiological functions. Therefore, in regions with rainfall irregularities, similar to those found in the Brazilian semi-arid, irrigation plays an excellent role, corroborating the results of Silva *et al*. (2021) that observed that as the culture canopy increases, water storage in the soil is greater, and its uniformity distribution is more representative.

Santiago *et al.* (2021), evaluating probabilistic models for reference evapotranspiration (ETo) in the region of *Petrolina-PE* and *Juazeiro-BA*, observed that January presented the highest probable water need, around 8.6 mm day^{-1} for the municipality of *Juazeiro-BA*. This region is near to the studied area, justifying the importance of variable irrigation in the development of the crop and the explanation through the agrometeorological-spectral model.

Table 4 compares the actual and estimated results from 2005/2006 to 2011/2012 by the MAE.

Table 4. The measured values versus estimated values for the agrometeorological-spectral model (MAE), from 2005/2006 to 2011/2012.

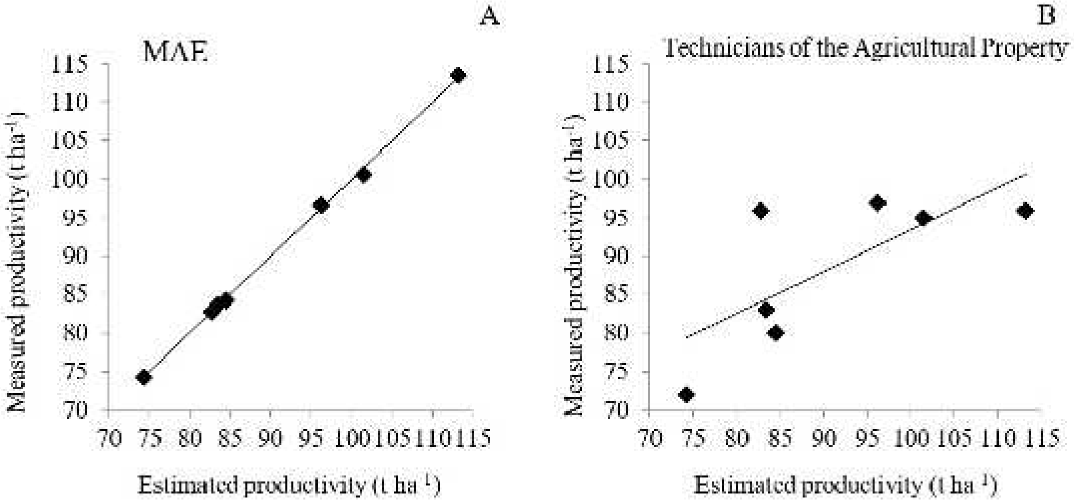
Crop Year	Productivity (t ha^{-1})		Residuals	Standardized Residuals
	Measured	Estimated (MAE)		
2005/2006	101.51	100.63	0.880325	1.127783
2006/2007	113.20	113.54	-0.337509	-0.432382
2007/2008	96.20	96.64	-0.434731	-0.556933
2008/2009	82.73	82.79	-0.060150	-0.077058
2009/2010	83.36	83.61	-0.251274	-0.321907
2010/2011	84.48	84.22	0.264946	0.339422
2011/2012	74.28	74.34	-0.061600	-0.078915

Source: The authors (2022).

As described in Table 4, it is observed that in most of the crop years studied, adjustment errors did not reach 1 standard deviation, a consequence of the good significance attributed to the model.

Figure 1A shows the graphs of the values corresponding to measured and estimated yields, respectively. Because it has an optimal coefficient of determination (R^2), the variables of the agrometeorological-spectral model (MAE) explain 99% without significant deviations of adjustments, being considered satisfactory, approaching the measured productivity provided by the agricultural property owner, corroborating the adjustment close to 1 from the methodology proposed by Willmott, Ackleson and Davis (1985).

Figure 1. Agrometeorological-spectral model (MAE) and the estimation of agricultural property productivity with the measured values versus the estimated values.



With the subsidy of Figure 1B, the performance of the agricultural property productivity was represented, presenting proximity of the measured values with those estimated by the technicians, thus justifying the coefficient of 99% of the agreement index of Willmott, Ackleson and Davis (1985). It was possible to identify some crucial deviations of adjustment. On the other hand, this may occur for the prediction of future values.

These results reflect an optimal fit of the model used, validating several studies. Fontana and Junges (2011) concluded that agrometeorological-spectral models could be used to estimate wheat yield with adequate precision.

Sarmiento *et al*. (2020) state that the incorporation of NDVI in agrometeorological models to estimate productivity favored the identification and monitoring of phenological phases of crops, performing time studies to obtain more accurate estimated values. Estimates of NDVI presented themselves as a good tool for monitoring sugarcane because its behavior is correlated with agronomic parameters of the crop, such as leaf area index, the number of tillers per meter, productivity, and biomass (SIMÕES *et al.*, 2005).

The incorporating spectral variables into the agrometeorological model can make it more efficient and consistent with the agricultural scenario in which the crop development occurs (RIZZI, 2004; SILVA; LOPES, 2022). Furthermore, it agrees with the performance of the agrometeorological-spectral model illustrated earlier in Figure 1, showing that it is more dynamic in spatial and time terms.

The crop years tested for calibration of the agrometeorological-spectral model (MAE) for productivity estimation are found in Table 5, considering the corresponding mean absolute deviation (MAD), the relative mean difference (RMD %), and the root mean square error (RMSE).

Table 5. Values of measured productivity (t $ha^{-1}_{measured}$) and productivity estimated by the Agrometeorological-spectral model (MAE), with their respective mean absolute deviation (MAD), the relative mean difference (RMD %), and the root mean square error (RMSE), for the crop years studied.

Crop Year	Productivity (t ha^{-1})		MAD	RMD (%)	RMSE
	Measured	Estimated (MAE)			
2005/2006	101.51	100.63	0.88	0.87	0.77
2006/2007	113.20	113.54	0.34	0.30	0.12
2007/2008	96.20	96.64	0.44	0.46	0.19
2008/2009	82.73	82.79	0.06	0.07	0.00
2009/2010	83.36	83.61	0.25	0.30	0.06
2010/2011	84.48	84.22	0.26	0.31	0.07
2011/2012	74.28	74.34	0.06	0.08	0.00

Source: The authors (2022).

Among the crop years tested by the agrometeorological-spectral model (MAE), all crops obtained good performance, especially the 2008/2009 and 2011/2012 crop years, which showed the lowest relative mean differences, 0.07 and 0.08%, respectively.

As shown in Table 5, the 2005/2006 crop year showed the highest relative average difference of 0.87%, and both, the 2006/2007 and 2009/2010 crop years showed the mean relative difference of 0.30%.

In Table 6, by analyzing the actual values and comparing those estimated in particular by the property techinicians, the smallest mean relative differences found were 0.43% in the 2009/2010 crop year, followed by 2007/2008, which was 0.83%, whose highest relative average differences were 15.19% and 16.04%, in 2006/2007 and 2008/2009, respectively.

Table 6. Values of measured productivity (t $ha^{-1}{}_{measured}$) and productivity estimated by the agricultural property technicians, with their respective mean absolute deviation (MAD), the relative mean difference (RMD %), and the root mean square error (RMSE), for the crop years studied.

Crop Year	Productivity (t ha^{-1})		MAD	RMD (%)	RMSE
	Measured	Estimated			
2005/2006	101.51	95.00	6.51	6.41	42.38
2006/2007	113.20	96.00	17.20	15.19	295.84
2007/2008	96.20	97.00	0.80	0.83	0.64
2008/2009	82.73	96.00	13.27	16.04	176.09
2009/2010	83.36	83.00	0.36	0.43	0.13
2010/2011	84.48	80.00	4.48	5.30	20.07
2011/2012	74.28	70.00	2.28	3.07	5.20

Source: The authors (2022).

When observing the mean differences related to the model, it was noticeable that there was no abrupt difference between the values compared with the values found in the estimation of the agricultural property productivity performed by the technicians.

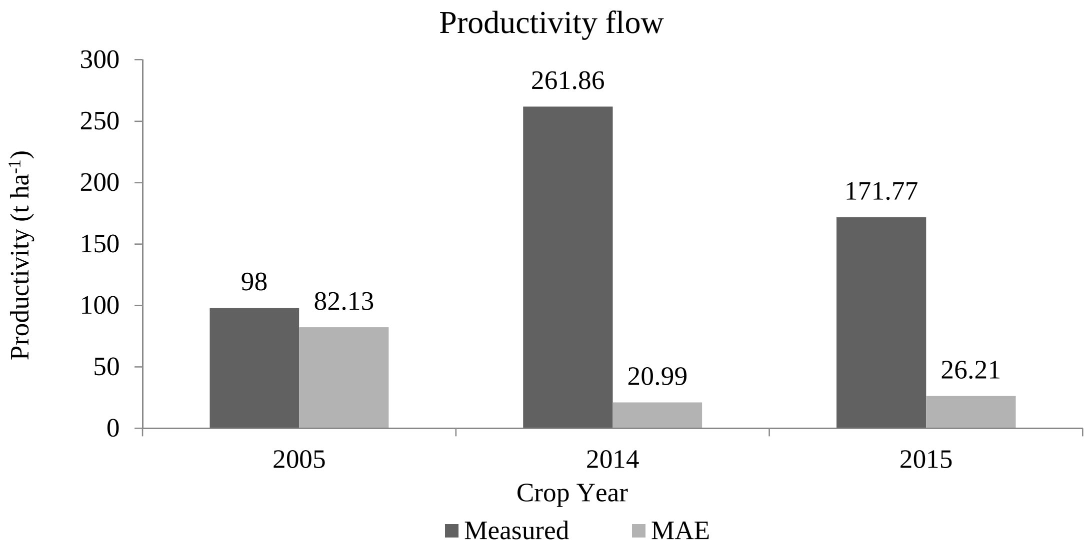
As observed, through the values found in the calibration process of the statistical models in estimating agricultural productivity of sugarcane, it can be infer that there is the possibility of a quantitative relationship between productivity and climatic variability associated with agronomic handling, supporting studies developed by Oliveira Mantovani and Sediyama (2013).

The use of agrometeorological variables in association with spectral indices in the calibration of models to evaluate and estimate the productivity of large crops is a viable alternative. It can assist the rural producer in decision-making within the property in several crops, such as rice (KLERING *et al*., 2016), wheat (FONTANA; JUNGES, 2011), soybeans (SARMIENTO *et al*., 2020), corn (MALIBANA; FONTANA; FONSECA, 2012), and sugarcane (SIMÕES *et al*., 2005). This use is efficient for environmental assessments such as desertification risks and soil degradation in cultivated areas (SILVA *et al*., 2022).

5.2 Validation of the agrometeorological-spectral model

As illustrated in Figure 2, we presented the performances of the agrometeorological-spectral model regarding the measured productivity harvested by the agricultural property included in the validation period in the crop years 2004/2005, 2013/2014, and 2014/2015.

Figure 2. Measured agricultural productivity and that estimated by the Agrometeorological-spectral model (MAE).



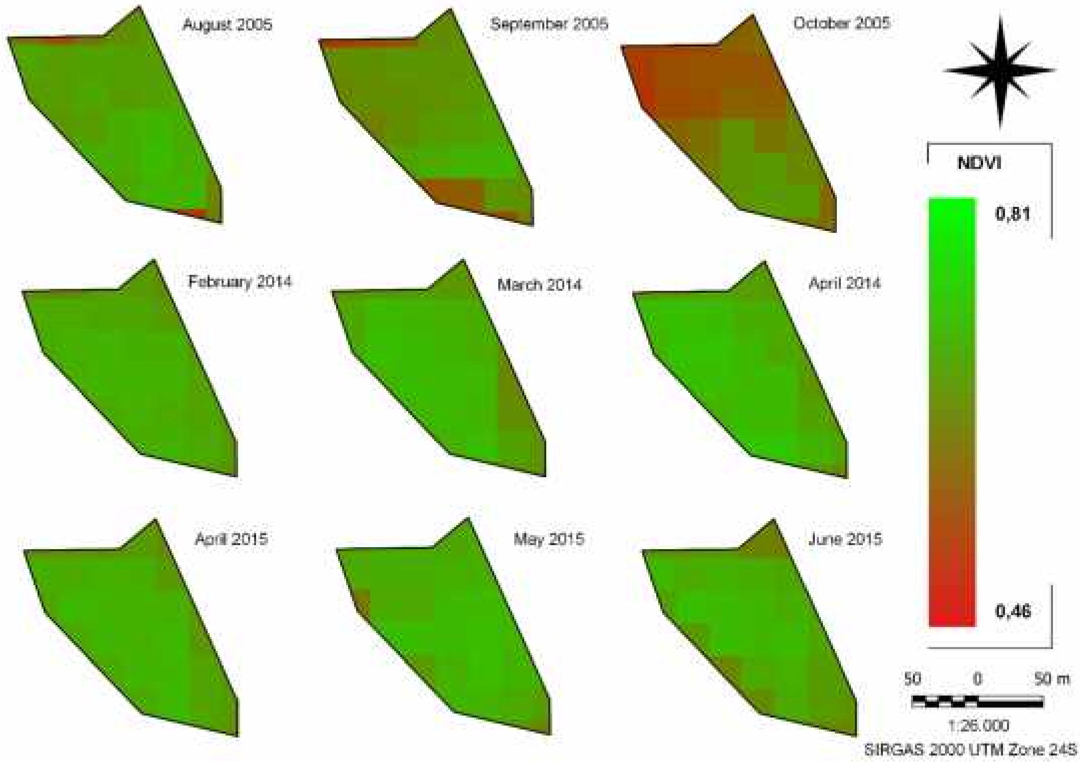
Source: The authors (2022).

Reflected by the renewal of the field with new planting at the end of 2012, the first harvest occurred from 2014, i.e., a field harvested with 18 months of planting with new variety and differentiated productive physiology. Thus justifying the significant yields for the crop year 2013/2014 and 2014/2015, the field was harvested 12 months later.

Figure 3 outlines the trajectory of NDVI in the three months preceding the harvest, where the irrigation depths are being reduced until it ceases, handling adopted in the crop years validated by the model. Through NDVI, it was possible to understand the behavior and vegetative vigor of the new variety in the first (2013/2014) and second (2014/2015) crop year of the new canopy. That is, in the first harvest (sugarcane plant or 1st leaf) and second harvest (ratoon cane or 2nd leaf) when correlated with NDVI in the crop year

2004/2005, in which the crop was in the 7th harvest (in the condition of ratoon cane). These differences were noticeable through the reflectance of the canopy leaves.

Figure 3. Normalized Difference Vegetation Index (NDVI) trajectory of the study area in the three months preceding harvest in the crop years 2004/2005, 2013/2014, and 2014/2015.



Source: The authors (2022).

As observed in Table 6, the value of agricultural productivity obtained by the agrometeorological-spectral model was close to the real productivity. These results agree with those obtained by Malibana, Fontana and Fonseca (2012), in which spectral variables subsidize agrometeorological variables in explaining the annual variations in the average yield of corn grains.

When comparing 2013/2014 and 2014/2015 harvests, it was possible to observe a production fall of 0.65596 or –65%, that represents, a reduction of approximately 90 tons of sugarcane, explained because, in 2013/2014, the harvested field had an age of 18 months (called 1.5-year sugarcane) once the renovation of the field was carried out in 2012 and 2014/2015 crop year, the area was harvested 12 months after the first harvest.

Confirming what Fontana *et al.* (2001) report, differences between varieties, handling, soil type, fertility, climate, and other variables, even within the same locality or region, highlight the importance of calibration and/or the closely observation of different aspects of each locality in order to obtain more accurate estimates.

Table 7 describes the actual and estimated values of the agricultural productivity by the agrometeorological-spectral model (MAE) and their differences.

Table 7. Values of measured productivity (t $ha^{-1}{}_{measured}$) and productivity estimated by the the Agrometeorological-spectral model (MAE), with their respective mean absolute deviation (MAD), the relative mean difference (RMD %), and the root mean square error (RMSE), for the crop years 2004/2005, 2013/2014 and 2014/2015.

Crop Year	Productivity (t ha^{-1})		MAD	RMD (%)	RMSE
	Measured	Estimated (MAE)			
2004/2005	98.00	82.13	15.87	16.19	251.86
2013/2014	261.86	20.99	240.87	91.98	58018.36
2014/2015	171.77	26.21	145.56	84.74	21187.71

Source: The authors (2022).

The highest percentages of the relative mean difference were found for the 2013/2014 and 2014/2015 harvests, respectively, ranging from 70.36% to 91.98%, an oscillation due to the new variety planted and the plant age. These results demonstrate a limitation in applying the model since its use to estimate the productivity of crops outside the conditions for which it was calibrated or developed (plant age and specific variety) can cause high error values, justifying this difference in the crop years mentioned.

The Table 8 describes the values of measured and estimated productivity by the technicians of the agricultural property and their corresponding differences.

Table 8. Values of measured productivity (t $ha^{-1}{}_{measured}$) and productivity estimated by agricultural property technicians, with their respective mean absolute deviation (MAD), the relative mean difference (RMD %), and the root mean square error (RMSE), for the crop years 2004/2005, 2013/2014, and 2014/2015.

Crop Year	Productivity (t ha^{-1})		MAD	RMD (%)	RMSE
	Measured	Estimated			
2004/2005	98.00	96.00	2.00	2.04	4.00
2013/2014	261.86	235.00	26.86	10.26	721.46
2014/2015	171.77	180.00	8.23	4.79	67.73

Source: The authors (2022).

Using the productivity simulation model DSSAT/CANEGRO, Gomes, Saad and Barros (2014) analyzed the behavior of four sugarcane varieties in different planting times and two distinct production environments (irrigated and rainfed) in the northeastern of Brazil. They observed that in a rainfed environment, productivity was significantly affected compared to irrigated areas because of the water deficit, either due to low precipitation and/or lack of irrigation.

In Table 9, to meet the need for a better adjustment in the crop years 2013/2014 and 2014/2015, the agrometeorological-spectral model presented correction factors of 12.48 and 6.55 (respectively), derived from the ratio of measured productivity by the estimated. The correction factor also recorded a significant reduction of 52.48%, corroborating the representative decrease in the production of 90 tons of sugarcane from one crop to another. It is probably associated with crop handling that went from 1.5-years sugarcane (cultivated up to 18 months) to 1-year sugarcane (every 12 months to harvest).

Table 9. Crop correction by the Agrometeorological-spectral model (MAE).

Crop Year	Productivity (t ha^{-1})		Factor	Productivity$_{Corrected}$
	Measured	Estimated		
2013/2014	261.86	20.99	12.48	261.95
2014/2015	171.77	26.21	6.55	171.68

Source: The authors (2022).

These values of correction factors will be reduced and adjusted over the years of cultivation. Consequently, the model will adjust to measured productivity without the need for such factors to correct them.

The cultivation of sugarcane has significant socioeconomic importance in the region studied, so the predictability of harvesting through the proposed model should consider the period in balance. In other words, when the corrected productivity is adjusted to the real coinciding with the calibration values, it favors efficient logistics in labor, agricultural machinery, and other variables inherent to the production system.

6 CONCLUSIONS

1. The agrometeorological-spectral model showed a good explanation of the estimated productivity of sugarcane in relation to the measured productivity for the calibration period;
2. The agrometeorological-spectral model showed a good response of the sugarcane estimated productivity of 82.13 t ha^{-1} when compared to the measured productivity of 98 t ha^{-1} in the validation period, for the crop year 2004/2005;
3. Agrometeorological-spectral models can be used to estimate sugarcane yields in semi-arid regions once they are calibrated and validated for the local planting characteristics. For conditions of using different varieties from those used in the calibration of the models, adjustments can be made to ensure the accuracy of the results generated.

7 REFERENCES

ANTUNES, J. F. G.; LAMPARELLI, R. A. C.; RODRIGUES, L. H. A. Representação de ciclos harmônicos de séries temporais Modis para análise do cultivo da cana-de-açúcar. **Pesquisa Agropecuária Brasileira**, Brasília, v. 51, n. 11, p. 1868-1879, 2016.

CAMARGO, A. P.; SENTELHAS, P. C. Avaliação do desempenho de diferentes métodos de estimativa da evapotranspiração potencial no estado de São Paulo, Brasil. **Revista Brasileira de Agrometeorologia**, Santa Maria, v. 5, n. 1, p. 89 - 97, 1997.

CANA-DE-AÇUCAR. **Acompanhamento da Safra Brasileira**: cana-de-açucar, Brasília, DF, v. 7, n. 3, p. 1-62, dez. 2020. Safra 2019/20, Terceiro Levantamento. Available at: https://www.conab.gov.br/info-agro/safras/cana/boletim-da-safra-de-cana-de-acucar. Acessed on: 2 apr. 2021.

DANTAS NETO, J. D.; TEODORO, I.; FARIAS, C. H. A. Sistema produtivo da cana-de-açúcar. *In*: José Dantas Neto. **Curso de especialização em gestão na indústria sucroalcooleira**. Campina Grande: UFCG, 2010. mod. 3, cap. 1, p. 1-7.

DALCHIAVON, F. C.; CARVALHO, M. P.; MONTANARI, R.; ANDREOTTI, M.; PANOSSO, A. R. Produtividade da cana-de-açúcar: variabilidade linear e espacial entre componentes tecnológicos e da produção. **Bioscience Journal**, Uberlândia, v. 30, suplemento1, p. 390-400, 2014.

FIORIO, P. R.; COELHO, R. D.; BARROS, P. P. S.; BONILLA, M. M. Z.; GADY, A. P. B. Comportamento espectral de folhas da cana-de-açúcar na presença do déficit hídrico. **Revista Irriga**, Botucatu, v. 23, n. 3, p. 609-621, 2018.

FONTANA, D. C.; BERLATO, M. A.; LAUSCHNER, M. H.; MELLO, R. W. Modelo de estimativa de rendimento da soja no Estado do Rio Grande do Sul. **Pesquisa Agropecuária Brasileira**, Brasília, v. 36, n. 3, p. 399-403, 2001.

FONTANA, D. C.; JUNGES, A. H. Modelo agrometeorológico-espectral de estimativa de rendimento de grãos de trigo no Rio Grande do Sul. **Revista Ceres**, Viçosa, MG, v. 58, n. 1, p. 9-16, 2011.

GARCIA, J. V.; REICHARDT, K. Modelo Agroclimático de Regressão Linear Múltipla para previsão de produtividade de culturas de sequeiros. **Pesquisa Agropecuária Brasileira**, Brasília, v. 24, n. 7, p. 779-786, 1989.

GOMES, A. W. A.; SAAD, J. C. C.; BARROS, A. C. Simulação da produtividade de cana-de-açúcar (*saccharum officinarum l.*) na região nordeste do brasil, utilizando o modelo DSSAT. **Revista Irriga**, Botucatu, v. 19, n. 1, p. 160-173, 2014.

GOMES, A. R. S.; ALVES, J. M. B.; SILVA, E. M.; GOMES, M. R. S.; GOMES, C. R. S. Estudo da Relação entre a Variabilidade dos Índices de Vegetação e Temperatura da Região Nordeste do Brasil. **Revista Brasileira de Meteorologia**, São José dos Campos, v. 34, n. 3, p. 359-368, 2019.

HUETE, A. R.; DIDAN, K.; MIURA, T.; RODRIGUEZ, E. P.; GAO, X.; FERREIRA, L. G. Overview of the radiometric and biophysical performance of the MODIS vegetations indices. **Remote Sensing of Environment**, New York, v. 83, n. 1-2, p. 195-213, 2002.

KLERING, E. V.; FONTANA, D. C.; ROGLIO, V. S.; ALVES, R. C. M.; BERLATO, M. A. Modelo agrometeorológico-espectral para estimativa da produtividade de grãos de arroz irrigado no Rio Grande do Sul. **Bragantia**, Campinas, v. 75, n. 2, p. 247-256, 2016. DOI: http://dx.doi.org/10.1590/1678-4499.287. Available at: https://www.scielo.br/j/brag/a/j7Pp6zJSHXpm5bPJMNCZSBr/?lang=pt. Acessed on: 18 jan 2022.

LEDA, V. C.; GOLÇALVES, A. K. G.; LIMA, N. S. Sensoriamento remoto aplicado a modelagem de produtividade da cultura da cana-de-açúcar. **Revista Energia na Agricultura**, Botucatu, v. 34, n. 2, p. 263-270, 2019.

MALIBANA, H. A.; FONTANA, D. C.; FONSECA, E. L. Desenvolvimento de modelo agrometeorológico espectral para estimativa de rendimento do milho na Província de Manica-Moçambique. **Revista Ceres**, Viçosa, MG, v. 59, n. 3, p. 337-349, 2012.

MARTINS, C. M. R.; LOPES, P. M. O.; MOURA, G. B. A.; SILVA, Ê. F. F.; NÓBREGA, R. S.; SILVA, J. L. B. Evapotranspiration of sugarcane in different phenological phases by remote sensing in the São Francisco Sub-medium Valley. **Journal of Hyperspectral Remote Sensing**, Recife, v. 9, n. 3, p. 156-165, 2019.

MELO, R. W.; FONTANA, D. C.; BERLATO, M. A.; DUCATI, J. R. Na agrometeorological–spectral model to estimate soybean yield, applied to southern Brazil. **International Journal of Remote Sensing**, Basingstoke, v. 29, n. 14, p. 4013-4028, 2008.

MOREIRA, L. F. Multicolinearidade em análise de regressão. *In*: 12º Encontro Regional de Matemática Aplicada e Computacional, 12., 2008, Foz do Iguaçu. **Anais** [...]. Cascavel: Unioeste, 2008. p. 61-75.

OLIVEIRA, H. F.; MANTOVANI, E. C.; SEDIYAMA, G. C. Avaliação de modelos de estimativa de produtividade da cana-de-açúcar irrigada em Jaíba-MG. **Revista Brasileira de Agricultura Irrigada**, Fortaleza, v. 7, n. 2, p. 112-127, 2013.

RIZZI, R. **Geotecnologias em um sistema de estimativa da Produção de soja: estudo de caso no Rio Grande do Sul**. 2004. Tese (Doutorado em Sensoriamento Remoto) – Instituto Nascional de Pesquisas Espaciais, São Jose dos Campos, 2004.

QGIS. **Sistema de Informações Geográficas QGIS**. versão LTR 3.16.11. QGIS, 2021. Available at: http://qgis.osgeo.org. Acessed on: 18 jan 2022.

RUDORFF, B. F. T.; SHIMABUKURO, Y. E.; CEBALLOS, J. C. **O sensor Modis e suas aplicações ambientais no Brasil**. São José dos Campos: Bookimage, 2007.

SANTIAGO, E. J. P.; SILVA, F. G.; SILVA, A. S. A.; CANTALICE, J. R. B.; CUNHA FILHO, M.; AGUIAR, J. D. A. A adequação de modelos probabilísticos à evapotranspiração de referência no submédio do Vale do Rio São Francisco. **Revista Irriga**, Botucatu, v. 1, n. 1, edição especial Nordeste, p. 144-154, 2021.

SARMIENTO, C. M.; COLTRI, P. P.; ALVES, M. C.; CARVALHO, L. G. A spectral agrometeorological model for estimating soybean grain productivity in mato grosso, Brazil. **Engenharia Agrícola**, Jaboticabal, v. 40, n. 3, p. 405-412, may/jun. 2020. DOI: http://dx.doi.org/10.1590/1809-4430-Eng.Agric.v40n3p405-412/2020. Available at: https://www.scielo.br/j/eagri/a/N6PjNtXy3pqcv6zHdS6bQjC/?lang=en. Acessed on: 18 jan 2022.

SILVA, T.G. F.; ZOLNIER, S.; MOURA, M. S. B.; SOUZA, L. S. B.; CARMO, J. F. A. Índices morfofisiológicos e uso de radiação solar por um cultivo de cana-de-açúcar irrigada no semiárido brasileiro. **Revista Brasileira de Geografia Física**, Recife, v. 7, n. 4, p. 764-773, 2014.

SILVA, M. M.; SANTOS JÚNIOR, J. A.; MELO FILHO, M. S.; SILVA, E. F. F.; SANTOS, J. B. Uniformidade da irrigação por aspersão em função da altura do dossel da cana-de-açúcar. **Revista Irriga**, Botucatu, v. 26, n. 1, p. 195-209, 2021.

SILVA, J. L. B.; MOURA, G. B. A.; LOPES, P. M. O.; FRANÇA E SILVA, Ê. F.; ORTIZ, P. F. S.; SILVA, D. A. O.; SILVA, M. V.; GUEDES, R. V. S. Spatial-Temporal Monitoring of the Risk of Environmental Degradation and Desertification by Remote Sensing in a Brazilian Semiarid Region. **Revista Brasileira de Geografia Física**, Recife, v. 13, n. 2, p. 544-563, 2020. DOI: https://doi.org/10.26848/rbgf.v13.2.p544-563. Disponível em: https://periodicos.ufpe.br/revistas/rbgfe/article/view/242500. Acesso em: 22 jan. 2022.

SILVA, K. J. C.; LOPES, P.M.O. Spatiotemporal variation of the vegetation index by normalized difference in the hydrographic basin of Pernambuco semiarid, Brazil. **Journal of Hyperspectral Remote Sensing**, Recife, v. 11, p.292-301, 2021. DOI: https://doi.org/10.29150/jhrs.v11.5.p292-301. Disponível em: https://periodicos.ufpe.br/revistas/jhrs/article/view/251965. Acesso em: 22 jan. 2022.

SIMÕES, W. L.; CALGARO, M.; GUIMARÃES, M. J. M.; OLIVEIRA, A. R.; PINHEIRO, M. P. M. A. Sugarcane crops with controlled water deficit in the Submiddle São Francisco Valley, Brazil. **Revista Caatinga**, Mossoró, v. 31, n. 4, p. 963-971, 2018.

WILLMOTT, C. J.; ACKLESON, S. G.; DAVIS, R. E. Statistics for the evaluation and comparison of models. **Journal of Geography Research**, Alicante, v. 90, n. 5, p. 8995-9005, 1985.