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REMOTE SENSING AND GEOSTATISTICS APPLIED TO NDVI, KC AND PRODUCTIVE PARAMETERS IN IRRIGATED CORN CROP

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1 ABSTRACT

Remote sensing (SR) has contributed to digital agriculture, associated with the use of geostatistical techniques that allow data acquisition, analysis and decision making. In view of this, the objective of this work was to evaluate the spatial variability of soil physical attributes, NDVI and second crop corn productivity in the territory of Santa Helena de Goiás, and to estimate values of crop coefficient (KC) through the NDVI, and to evaluate the spatiality. Soil samples were collected in a georeferenced way using a regular grid. The images were from the Sentinel 2A satellite. The Normalized Difference Vegetation Index (NDVI) was calculated, the Kc values of the crop were estimated, using two methodologies Toureiro *et al*., (2017) and Kamble, Kilic, Hubbard (2013), and later the values were extracted through a regular GRID, with which the geostatistical analyzes and correlations with productivity were submitted. The NDVI showed an increase up to 69 days after planting, in addition to proving the spatial variability and spatial dependence. With the geostatistics it was possible to generate a map of the spatial distribution of productivity. The NDVI allowed to obtain the Kc corresponding to the different phases of cultivation, sensitive to the methodologies used. The Kc obtained presents a high response and potential to the management of irrigated corn.

Keywords: Precision agriculture, Interpolation, Center Pivot.

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SENSORIAMENTO REMOTO E GEOESTATISTICA APLICADO A PARAMETROS DE NDVI, KC E PRODUTIVOS NA CULTURA DO MILHO IRRIGADO

2 RESUMO

O sensoriamento remoto (SR) tem contribuído com a agricultura digital, associado ao uso de técnicas de geoestatística que permitem a aquisição de dados, analise e tomada de decisão. Diante disso o objetivo deste trabalho foi avaliar a variabilidade espacial dos atributos físicos do solo, NDVI e produtividade de milho de segunda safra no território de Santa Helena de

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Goiás, e estimar valores de coeficiente de cultivo (KC) por meio do NDVI, e avaliar a espacialidade. As amostragens de solos foram coletadas de forma georreferenciada por meio de um gride regular. As imagens foram do satélite Sentinel 2A. Foi calculado o Índice de Vegetação da Diferença Normalizada (NDVI), foi estimado os valores de Kc da cultura, por meio de duas metodologias Toureiro *et al*. (2017) e Kamble, Kilic, Hubbard (2013), e posteriormente foi realizado a extração dos valores através de um GRID regular, com o qual foi submetido as análises de geoestatistica e as correlações com a produtividade. O NDVI apresentou-se crescente até os 69 dias após o plantio, além de comprovar a variabilidade espacial e dependência espacial. Com a geoestatística foi possível gerar o mapa da distribuição espacial da produtividade. O NDVI permitiu obter o Kc correspondente as diferentes fases de cultivo, sensível as metodologias utilizadas. O Kc obtido apresenta uma alta resposta e potencial ao manejo do milho irrigado.

Palavras-chave: Agricultura de precisão, Interpolação, Pivô Central.

3 INTRODUCTION

Corn is one of the main cereals produced in the world, used in human and animal food due to its nutritional characteristics, and for the production of fuels such as ethanol and biodiesel in some countries such as the United States of America. The use of aerial images in monitoring and decision-making is increasingly used in agriculture as highlighted by several authors, (Moraes *et al*., 2019; Oliveira *et al*., 2020). Precision agriculture (AP) is a form of rural property management. For Klerkx, Jakku and Labarthe (2019) the AP goes through the digitization process, ensuring more accurate decision-making.

In addition to promoting the technical optimization of agricultural production systems. Precision agriculture provides the producer with a way out of the conventional cultivation system, providing tools for better crop management, according to the spatial variability of the area (Arantes *et al.,* 2020).

Remote sensing (SR) is a way of capturing data without direct contact with the research target. With the SR it is possible to obtain information about the area through images, and other data by capturing and recording the reflectance of the surface of the area (Giongo *et al*., 2022). Vegetation indices (VI) are mathematical models based on spectral bands, with the aim of showing the vigor and attributes of vegetation (Candiago *et al*., 2015). According to Ihuoma and Madramootoo (2017), IVs provide the physiological assessment of crops, favoring the definition of management zones, and can be applied in variable rate application of fertilizers, localized disease control and irrigation management.

Thus, it aimed to evaluate the spatial variability of the physical attributes of the soil and the corn yield, and to correlate it with the NDVI, which was also used to estimate the Kc of the crop in an irrigated system.

4 MATERIALS AND METHODS

The survey was carried out at the Santa Cecilia farm, a property located in the municipality of Santa Helena de Goiás - GO, Brazil, with an average altitude of 575 meters (Figure 1). The climate is tropical classified as Aw with an average temperature of 24.3°C, with average annual rainfall of 1539 mm according to Köppen and Geiger. In this research, an irrigated area via center pivot with 2nd crop corn was evaluated, with an area of 69 hectares.

Corn planting was carried out on 02/10/2020, being considered the 2nd harvest, which was carried out in a no-tillage system, with 50 cm spacing between rows and a final population of 50,000 pl ha^{-1}. The cultural treatments for pest, disease and fertilization management followed the recommendations for the corn crop. Soil samples were collected according to the sampling points in Figure 1 (Grid), a total of 57 points were collected, and an Etrex Legend H model navigation GPS was used. Soil samples were sent to the laboratory, which issued the following results: Clay, sand and silt contents.

The research, images were obtained from the Sentinel-2A satellite MSI sensor, during the 2019/2020 harvest, acquired through the Land Viewer / EOS, available on the website (https://eos.com/landviewer/). The collection of satellite images was obtained in the orbit and point corresponding to the study area (orbit/point 22KEF), with passage on a clear sky day. Images corresponding to the Days after Planting (DAP) were obtained: 17, 31, 36, 69, 76, 91, 96, 106, 111 and 121. Images were processed using QGis v. 3.10. To calculate the NDVI, bands 8A (NIR) and 4 (RED) were used, according to Equation 1.

$$NDVI = (NIR - RED)/(NIR + RED) \quad (1)$$

Where: NIR: Reflectance value of the near infrared band; RED: Band reflectance value in red.

After computing the NDVI, the Kc (cultivation coefficient) was calculated using Equations 2 and 3, developed by Toureiro *et al*. (2017) and Kamble, Kilic and Hubbard (2013), respectively.

$$Kc = 0{,}918 * NDVI + 0{,}303 \quad (2)$$

$$Kc = 1{,}457 * NDVI - 0{,}1725 \quad (3)$$

The Corn harvest for calculating productivity was carried out in June 2020 according to the sampling grid shown at Figure 1. Three ears were collected from each point of the (GRID), to be converted into unit area (m^2) and later for ha. They were threshed manually, the moisture content of the samples was determined using the universal standard method, and the weight of the grains was corrected for a moisture content of 13% and converted to kg ha^{-1}. Descriptive statistics were performed using an Excel spreadsheet, calculating the mean, median, minimum value, maximum value, coefficient of variation, standard deviation, coefficient of asymmetry and kurtosis, analyzing the distribution of data (Burak; Santos; Passos, 2016). The criteria adopted for classifying the coefficients of variation (CV) of the variables will follow the magnitude classes downwards (CV≤12%); medium (12%≤CV≥62%) and high (CV≥62%) according to the classification adapted by Lima *et al*. (2015). The evaluation was performed using a Pearson correlation matrix, and with the aid of electronic spreadsheets, simple linear correlations (r) were calculated.

To characterize the spatial variability, geostatistical analysis was used for the parameters, identifying their spatial dependence by calculating simple semivariograms. The semivariograms were adjusted based on the assumption of the intrinsic hypothesis (USOWICZ; LIPIEC, 2017). The choice of the mathematical model of the adjusted semivariograms will follow the selection criteria of the lowest sum of squared residuals (RSS); higher coefficient of determination (r^2) and higher degree of spatial dependence (GDE), according to Monteiro, Menezes and Silva, (2017). The adjusted mathematical model of the semivariograms of each attribute provided the parameters of the nugget effect

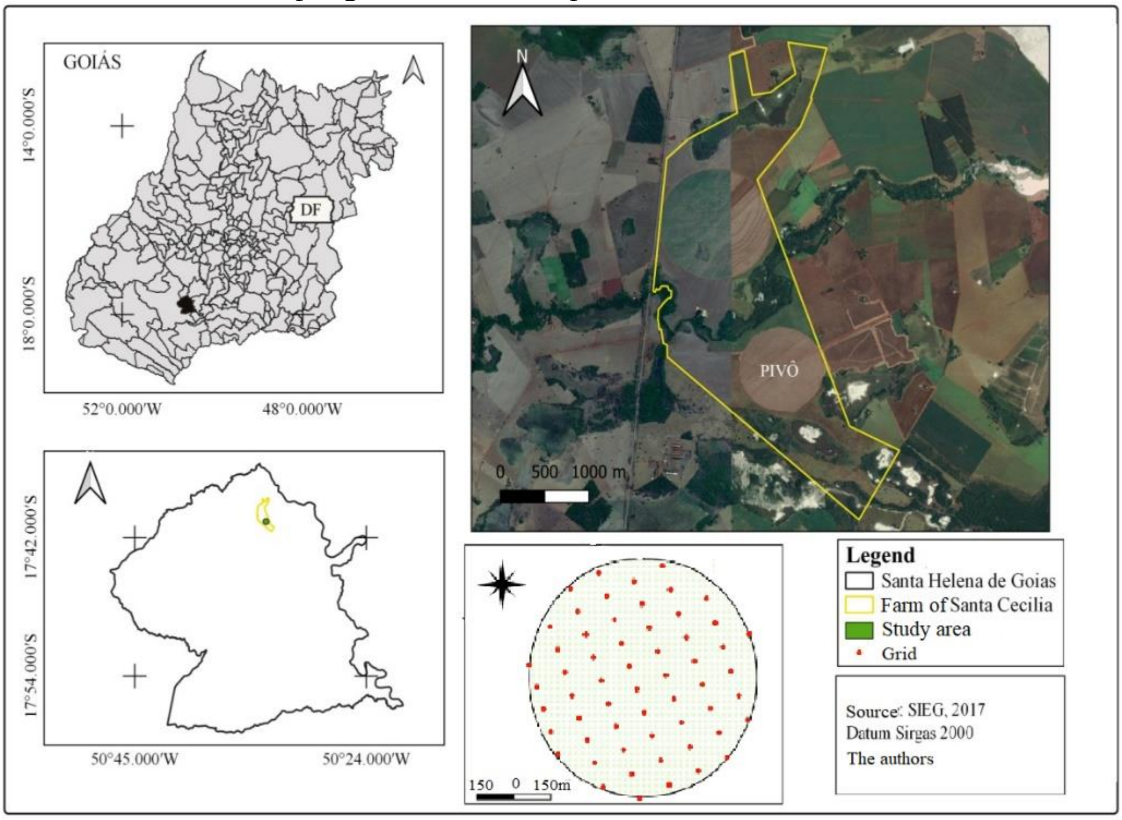
(C0); structural variance (C1); threshold (C0+C1) and range (A).

The degree of spatial dependence (DSD) was analyzed by the relationship between structural variance and threshold according to Dalchiavon and Carvalho (2012), according to Equation 4.

$$DSD = \left[\left(\frac{C0}{C0+C1}\right) \times 100\right] \quad (4)$$

Where: GDE - degree of spatial dependence; C0: nugget effect; C0 + C1: threshold

Figure 1. Geographical location of the study area in the municipality of Santa Helena de Goiás and sample grid of the center pivot.

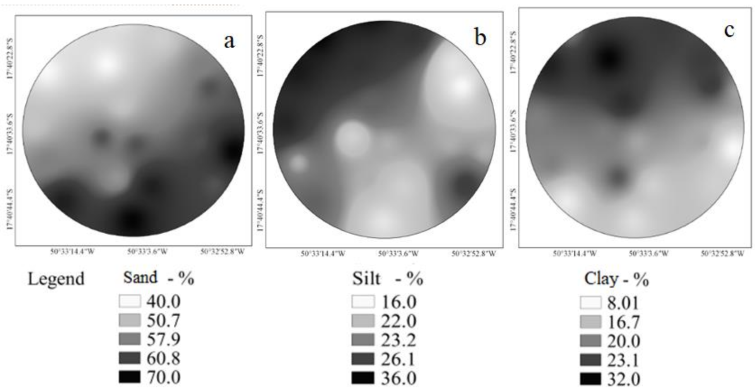


5 RESULTS AND DISCUSSION

In Figure 2a, it can be seen that the highest percentage of sand is located in the southern region of the pivot, and in the northern part practically the entire region has a average sand of 55.9% (SD 9.41). In the southern region, a large part of the pivot has a high percentage of sand, thus indicating a sandy soil. In figure 2c, where the clay content is observed, it is also possible to identify a great variability for the studied area, with Average clay of 19.7% (SD 6.03), values between 10 and 30%. The Average silt of 24.4% (SD 5.68).

The physical parameters of the soil, Sand, Silt and Clay, as well as corn productivity, showed spatial dependence, indicating the variability that geostatistics allowed to identify. It is important to observe not only the average value, but the variation in the regions that concentrate the highest sand/clay content, as they help to define soil management. In this scenario, Azevedo and Bueno (2016) in the survey and classification of soils, show that the potential to collaborate with the use and management of soils has been offering better conditions for the development of areas effectively, when using the correct techniques according to the physical and chemical characteristics of each production area.

Figure 2. Maps of spatial distribution of Sand (a), Silt (b) and Clay (c) percentages for a central pivot in Santa Helena de Goiás.



In Figure 3 it can be seen that from the 17 DAP the study area presented variation in the values of the NDVI starting from the interval with the value 0.07 to 0.59, such amplitude due to the staggering of planting, being identified a difference between the dates of planting, thus allowing it to be identified up to 36 DAP and after 91 DAP.

Mean NDVI values showed Pearson correlation between -0.41 (17DAP) to 0.64 (106DAP). The coefficients of variation of the NDVI images ranged from 2.04 (76DAP) to 34.91 (17DAP).

The NDVI showed a high correlation with the Kc values, thus allowing them to be used as a reference in estimating this parameter in heterogeneous areas, as well as in identifying areas in different phenological stages of the corn crop. Er-Raki *et al*. (2007) using the Kcb-NDVI model overestimated the basal cultivation coefficient by 10.7%. Water demand at the initial stage of the crop is lower and increases as the plant develops, reaching its peak at stage 2 and stage 3.

According to Table 1, it can be seen that the correlation between productivity and NDVI values during the corn cycle has shown to increase with the increase in days after planting (DAP). With 17 DAP it was – 0.41 being considered an average negative correlation, at 69 DAP with a value of 0.32 it exhibits an average positive correlation, which continues to grow up to 121 DAP with 0.60 classified as a strong correlation, according to the Pearson classification adapted by Bermudez-Edo, Barnaghi and Moessner (2018).

Silva *et al*. (2016) in their research work pointed out that the NDVI is a tool that can be used to estimate corn productivity, between stages V3 and V9, with correlations equal to or greater than 0.65 classified as a strong correlation, the which, shows a result similar to that found in this research. In contrast Santos *et al*. (2019) identified in their study a low correlation between NDVI and productivity.

In Figure 3c, it can be seen that the two methodologies used to estimate Kc had similar behavior, although the beginning and end of the cycle showed the greatest differences between them. Kamble, Kilic and Hubbard (2013) showed a slight trend towards lower values than Toureiro *et al*. (2017), mainly in the initial and final phases of the cycle, highlighting the greater sensitivity of this model for obtaining Kc, while the Toureiro method aims to mitigate the effects of minimums and maximums. It also notes that the standard deviation shown in each image (Figure 3c) is a reflection of the heterogeneity of the vegetation cover in the area (Figure 3a), recorded by the NDVI. Costa *et al*. (2021) obtained an R^2 between KcFAO and KcNDVI of 0.85, which indicates the high performance of these methodologies for obtaining Kc and managing irrigation in corn.

Silva *et al*. (2019) highlight that monitoring irrigated areas also requires efficient ways such as the use of remote sensing for crop management. Still Giongo *et al*. (2022) highlight the use of remote sensing and vegetation indexes such as the NDVI for various large-scale control and monitoring applications of vegetation cover.

Table 1. Descriptive statistics of yield and NDVI from Sentinel 2A satellite images, in off-season corn area.

	DAP	17	31	36	69	76	91	96	106	111	121
Parameters	**Prod. Kg.ha^{-1}**	**NDVI**									
r	-	-0.41	-0.28	-0.11	0.32	0.43	0.56	0.57	0.64	0.65	0.60
Average	8332.27	0.29	0.67	0.80	0.87	0.86	0.82	0.78	0.63	0.49	0.31
Median	8194.92	0.33	0.70	0.83	0.88	0.87	0.82	0.78	0.61	0.46	0.29
Minimum	5248.17	0.08	0.41	0.59	0.78	0.78	0.73	0.65	0.42	0.32	0.24
Maximum	11513.83	0.44	0.82	0.88	0.90	0.89	0.88	0.85	0.81	0.70	0.51
SD	1532.16	0.10	0.11	0.07	0.02	0.02	0.04	0.05	0.11	0.11	0.07
Variance	2347509.2	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.00
CV (%)	18.39	34.91	16.39	8.93	2.65	2.04	4.32	6.24	17.14	21.77	21.09

r= Pearson's correlation between NDVI and corn yield; SD= Standard Deviation; CV: coefficient of variation.

Checks through Table 2, that all NDVI images, as well as the productivity showed spatial dependence, with the Spherical and linear models, which described them. As for range, the models allowed distances between 181.5m (productivity) to 654.618m (NDVI DAT 36), showing that geostatistics allows identifying NDVI and productivity zones for different operations and management. Costa *et al*. (2021) also evaluated the influence of NDVI and other scale parameters Spatiotemporal variability in corn crop and emphasize how zones with different growth can be identified, as well as zones for management.

Figure 3. Spatial maps of NDVI (a), average of NDVI (b) and Kc estimated using the NDVI (c) values, for irrigated corn under cerrado conditions.

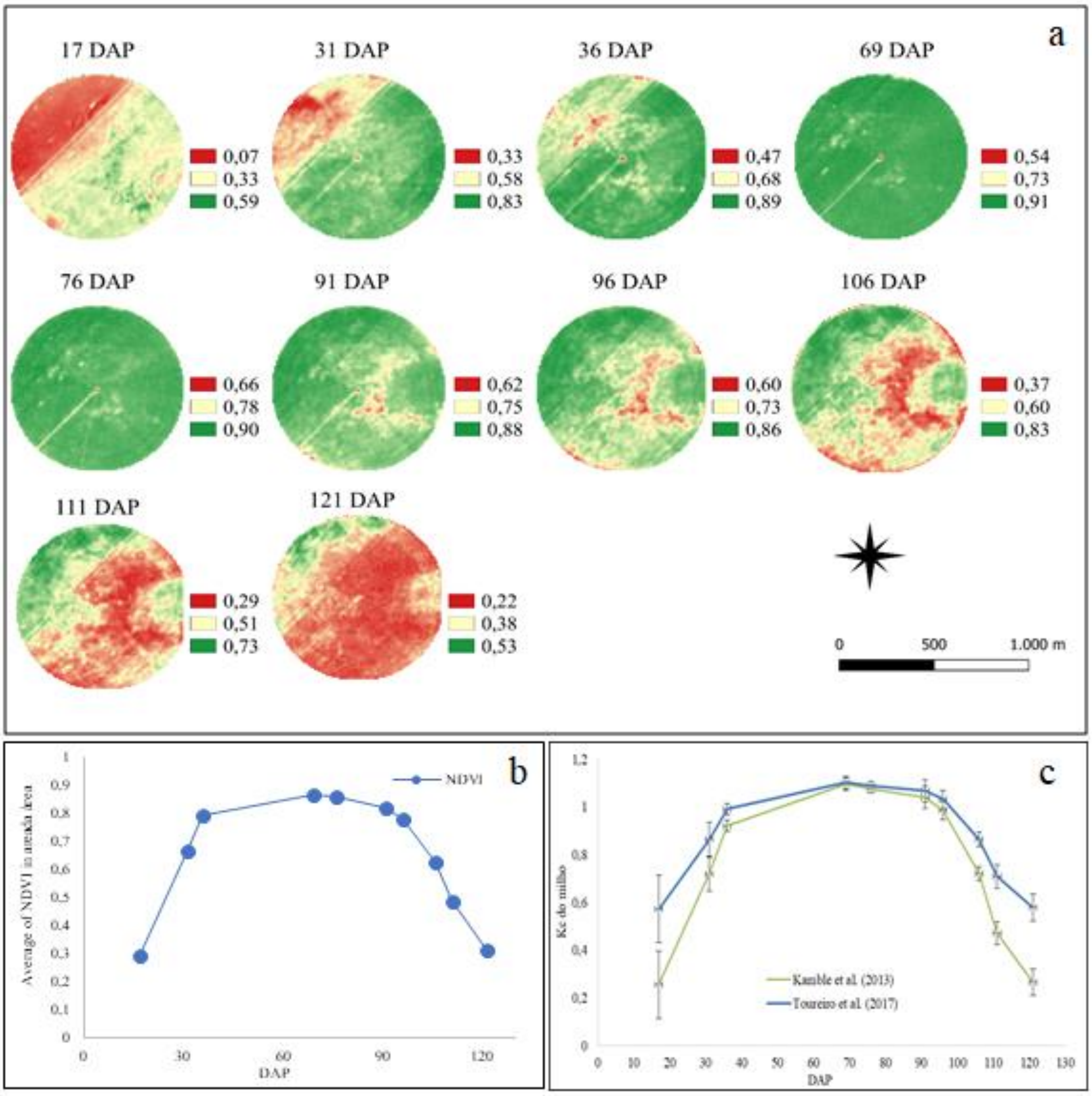


Table 2. Semivariogram model and degree of spatial dependence (DSD) of NDVI and productivity of irrigated corn under cerrado conditions.

Parâmetro	Model	Co	Co + C	Lenght (m)	R^2	RMSE	DSD (%)
Productivity	Spherical	6300	21280	181.500	0.926	0.198	29.605
DAP 17	Linear	0.081	0.101	280.067	-0.181	0.110	80.198
DAP 31	Linear	0.070	0.091	397.034	0.263	0.350	76.923
DAP 36	Spherical	0.401	0.464	654.618	0.477	0.240	86.422
DAP 69	Spherical	0.120	0.425	443.660	0.649	0.147	28.235
DAP 76	Spherical	0.052	0.102	523.221	0.556	0.203	50.980
DAP 91	Spherical	0.235	0.276	600.215	0.432	0.321	85.145
DAP 96	Spherical	0.314	0.385	580.254	0.385	0.402	81.558
DAP 106	Spherical	0.612	0.644	432.124	0.562	0.156	95.031
DAP 111	Linear	0.051	0.105	398.265	0.701	0.416	48.571
DAP 121	Spherical	0.251	0.321	289.356	0.235	0.012	78.193

Co: Nugget effect; Co + C1: threshold; R^2: coefficient of determination; RMSE: root mean squared error; DSD - degree of spatial dependence.

6 CONCLUSIONS

With geostatistics it was possible to identify the variability and spatial dependence for the physical parameters of the soil, the NDVI and the productivity of irrigated corn.

The NDVI images obtained by satellite images show a stronger correlation at 106 and 121 DAP, flowering and grain filling phases.

As presented, the NDVI is indicated for obtaining the Kc of the crop, as well as the phenological phase of the corn crop.

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