ESTIMATION OF CORN PRODUCTIVITY IN THE MIDWEST OF BRAZIL USING SPECTRAL DATA

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ABSTRACT: The objective of this work was to determine a specific range or vegetation index with Landsat 8 data that best estimates the productivity of the corn crop. The study was carried out in a corn field of 111 ha located in the municipality of Santa Helena de Goiás, Brazil. Three times of the crop cycle were determined for Landsat 8 image acquisition and yield estimation: 32, 57 and 96 DAP (days after planting). Productivity was obtained through sensors built into the harvester. On each date, the green, red, near infrared and thermal bands were analyzed and the NDVI was calculated. Data were subjected to Pearson correlation (r) between productivity (y) and spectral bands/NDVI (x). The green band shows the best response with corn yield at 57 and 96 DAP. The spectral bands present better responses (r) to the estimate of corn productivity in the intermediate phase of the crop (57 DAP). In the final phase of the crop (96 DAP), the productivity estimate is better with the green band and the NDVI. Remote sensing products are promising for determining productivity as well as crop response variations in heterogeneous areas.

KEYWORDS: Precision Agriculture, Cerrado, *Zea mays*.

ESTIMATIVA DE PRODUTIVIDADE DE MILHO NO CENTRO-OESTE DO BRASIL UTILIZANDO DADOS ESPECTRAIS

RESUMO: O objetivo deste trabalho foi determinar uma faixa específica ou índice de vegetação com dados Landsat 8 que melhor estime a produtividade da cultura do milho. O estudo foi realizado em uma lavoura de milho de 111 ha localizada no município de Santa

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Helena de Goiás, Brasil. Três épocas do ciclo da cultura foram determinadas para aquisição de imagens Landsat 8 e estimativa de produtividade: 32, 57 e 96 DAP (dias após o plantio). A produtividade foi obtida por meio de sensores embarcados na colheitadeira. Em cada data foram analisadas as bandas verde, vermelho, infravermelho próximo e thermal e o NDVI foi calculado. Os dados foram submetidos à correlação de Pearson (r) entre produtividade (y) e bandas espectrais/NDVI (x). A banda de cor verde apresenta melhor reposta com a produtividade do milho aos 57 e 96 DAP. As bandas espectrais apresentam melhores respostas (r) a estimativa da produtividade do milho na fase intermediaria da cultura (57 DAP). Na fase final da cultura (96 DAP), a estimativa da produtividade é melhor com a banda verde e o NDVI. Os produtos de sensores remotos são promissores para determinar a produtividade, assim como as variações da resposta da cultura em áreas heterogêneas.

PALAVRAS-CHAVE: Agricultura de Precisão, cerrado, *Zea mays*.

INTRODUCTION

Corn (*Zea mays* L.) is one of the most important crops in Brazil, and growing areas are constantly increasing (PUERARI et al, 2015). In addition, corn is the main crop used for rotation or succession with soybean (*Glycine max* (L.) Merril) (PASQUALETTO & COSTA, 2001).

The remote sensing allows obtaining vegetation information for the monitoring and forecasting of productivity of the agricultural crops to identify the agricultural areas and their dynamics (YI et al., 2007). For crop monitoring and pastures, such studies involve the use of radiometric techniques, which use specific spectral bands, or vegetation indices based on digital images (SENA JÚNIOR et al., 2008; GIONGO et al., 2022).

Vegetation indices are arithmetic combinations of spectral bands developed to evaluate the vegetation cover and have a good relation with the spectral signature and measurable parameters in the field (RISSO et al., 2012; CARAMÉS et al., 2015). These arithmetic combinations are performed between bands in the visible and near infrared range of the electromagnetic spectrum (EPIPHANIO et al., 1996).

Higher NDVI values are related to greater biomass accumulation and, consequently, greater productivity potential (KLERING et al., 2016). Some authors have obtained good results for estimating crop productivity using spectral data on soybeans (MERCANTE et al., 2010) and sugarcane (ALMEIDA et al., 2006; FERNANDES et al., 2011).

Within this context, this work aimed to determine the best specific band or vegetation index with data from Landsat 8 that best estimates the productivity of the corn crop.

MATERIALS AND METHODS

The study was carried out in a corn field of 111 ha (Figure 1a) during the 2018 harvest located at Santa Helena Farm's, Countryside of the municipality of Santa Helena de Goiás, Goiás, Brazil. The 30F53 corn hibrid (DuPont Pioneer, Johnston, Iowa, USA) was planted on February 15, 2018, spacing 0.5 m and population of 60.000 plants ha^{-1} in a dystrophic red latosol. Cultural practices and management practices such as pest control, invasive diseases and plants, and fertilization were carried out according to the crop needs and production practices of the corn producing region (SILVA et al., 2017). The corn harvest was carried out on June 14, 2018.

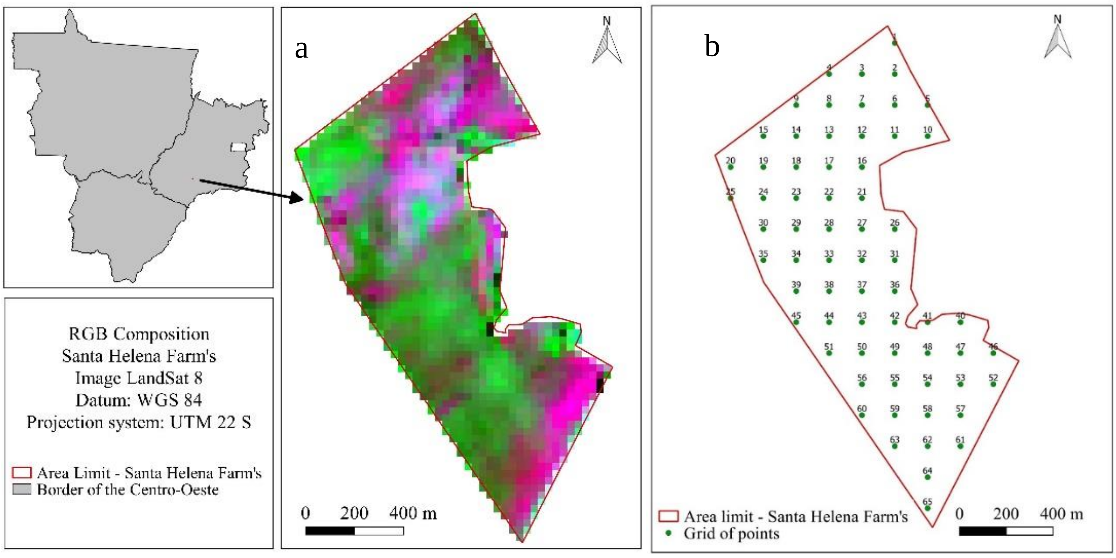

Figure 1. Geographic location of the study area, in Landsat 8 image (a) of Santa Helena Farm's, with LandSat 8 pass on the day March 19, 2018 and Grid of georeferenced points for information collection (b).

Productivity data were obtained from the Harvest Monitor™ crop monitor and manufacturer's brand sensors embedded in the John Deere S660 harvester (Deere and Company, Moline, Illinois, USA), which performs real-time area mapping as the harvest is carried out. The data recorded by the harvest monitor were manipulated and converted into shapefile format files and then exported to Qgis (QGIS Development Team, Boston, USA) for corn productivity information. Images of the Landsat 8 satellite were obtained using the Land Viewer tool (www.eos.com/landviewer). Three seasons were determined during the crop cycle for image acquisition and productivity estimation: 32, 57 and 96 DAP (days after planting). The following scenes with crossing and orbit / point dates, March 19, 2018 (223/72) (32 DAP, growth stage V7), 13 April 2018 (222/72) (57 DAP, growth stage of tasseling) and 22 May 2018 (223/72) (96 DAP, growth stage at R5, dent). At each date the bands green (B3), red (B4), near infrared (B5) and thermal (B10) were analyzed. The abbreviation for each band corresponds to the identification of the LandSat8 band. Through the red (B4) and near infrared (B5) bands of Landsat 8 the NDVI (Equation 1) was calculated.

$$NDVI = (R_{nir} - R_{red})/(R_{nir} + R_{red}) \quad (1)$$

Where: Rnir corresponds to the reflectance in the infrared band and Rred corresponds to the reflectance in the red band.

After downloading at images, the information about the limit of the study area was cut. A regular grid of points was performed by the "Soil Collecting" application (Figure 1b) to sample information with representative of approximately 1 point for every 2 hectares. These points were used to collect the information of the reflectance (B3, B4, B5 and B10), NDVI and productivity in the pixel corresponding to the geographic coordinate referring to the points of the grid. All the information was analyzed and submitted to Pearson correlation between yield (y), spectral bands and NDVI (x).

RESULTS AND DISCUSSION

Among the three seasons of productivity estimation, the one that showed the lowest correlation between the NDVI and the productivity was the 32 DAPs due to the very small plant and the average spatial resolution of the satellite used. At 57 DAP (Figure 2b), the western region of the study area shows a relationship between NDVI and productivity. At 96 DAP there is an increase in the trend between NDVI and productivity (Figure 2d), with a high correlation mainly with points with high and low productivity. Visually, much of the area with the lowest NDVI values in the northern region of the area and a small part in the southern region is noted. High yields occurred on a large scale in the southern part of the area (Figures 3c, d). In relation to productivity data (Figure 2d), there is a variation between 58 and 154 bags ha^{-1}, with a standard deviation of 18 bags ha^{-1}. The average productivity of the area was 101 bags ha^{-1}, in which, according to CONAB (2019) crop survey, the average productivity for the study region in the 2017/18 crop (second crop year) was 86 bags ha^{-1}, being the productivity of the area considered as high productivity.

Pearson (r) correlations between the bands, NDVI and productivity presented satisfactory results for productivity estimation. The highest correlation values were observed between the green band and productivity at 57 (r = 0.6127) and 96 DAP (r = 0.6119). This can be explained by the fact that the green wavelength, which through chlorophyll pigments absorbs approximately 90% of the incident radiation, and that the lower the absorption, the greater the reflectance (LIU, 2007).

A model showed a decrease in reflectance at the green wavelength with increase in yield. The model that presented the least efficiency in the estimation of productivity with the green wavelength was at 32 DAP. The high values of "r" at 57 and 96 DAP are related to the stage of culture. At 57 DAP the corn crop is at the end of the tipping (VT) and initiating the tipping (R1). At 96 DAP the corn crop is already between the R3 and R4 stages, where the green color is more intense due to the metabolic activities of maize, a crucial period in determining grain yield, also due to the high photosynthetic activity of the leaves, well at this wavelength (OLIVEIRA et al., 2013).

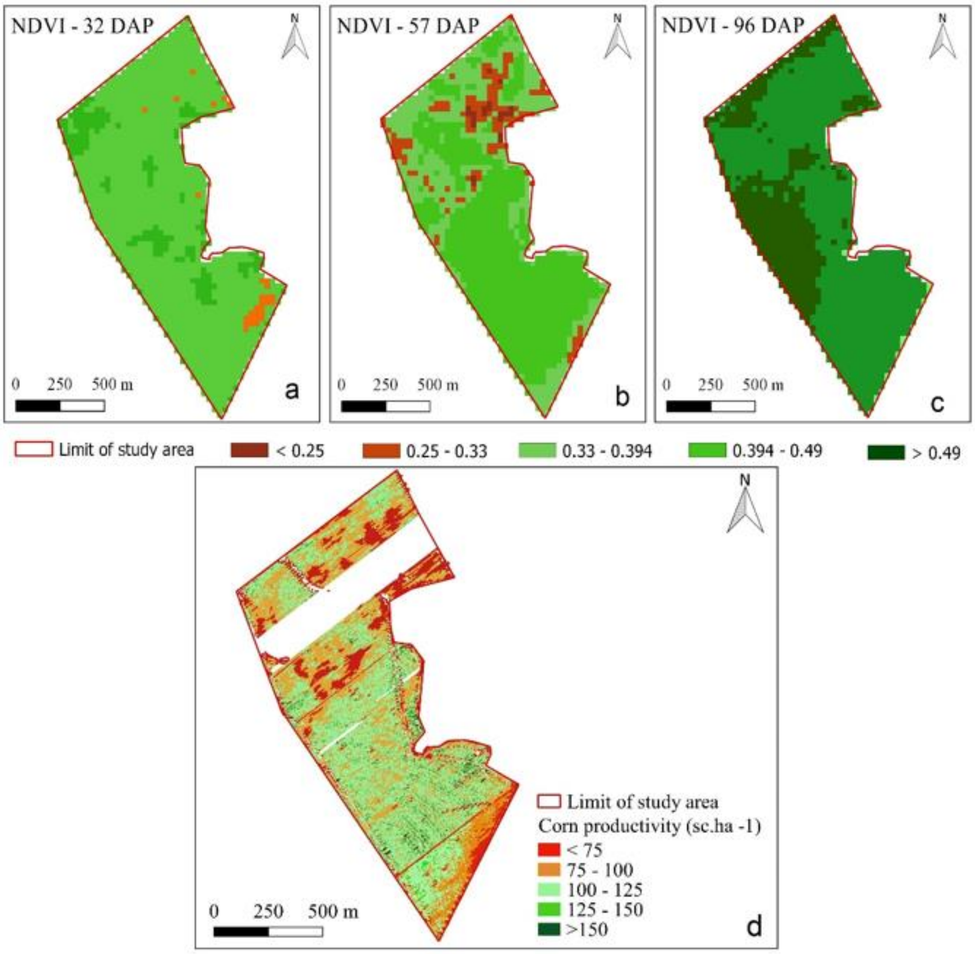

Figure 2. Normalized Difference Vegetation Index maps for 32 (a), 57 (b) and 96 (c) DAP (Days After Planting) images obtained with Landsat 8 satellite and yield map (d) of maize crop, 2017/18 crop in Santa Helena de Goias, Goias, Brazil.

The highest values of reflectance in descending order were obtained at 32, 57 and 96 DAP (Figure 3a). The green wavelength is in the range of the spectrum that the greater the intensity of green in the plant, the greater the reflectance (LIMA et al., 2012). Lower values in green reflectance in the early stages of the crop may be related to low soil cover. In the early stages the plant has not yet reached an architecture that can fully cover soil exposure by interfering with desired results. The low amount of leaves in the initial stages is also a factor that interferes with the values obtained, because the photosynthetic activity of the crop is still low in relation to the other stages (SPADER & VIDAL, 2001).

The red wavelength has low correlation at 32 DAP (r = 0.1706), and then there is an increase for 57 and 96 DAP, with values of r = 0.5563 and r = 0.5208, respectively. The three-year model demonstrated that there was a decrease in reflectance in the wavelength of red with increased productivity. Because the plant when healthy presents a greater absorption capacity in the wavelength of red, and the greater the energy absorption in this wavelength, the greater the transformation of light energy in energy spent by the plant in the photosynthetic processes (TAIZ & ZEIGER, 2013). The red wavelength also presented higher values of reflectance at 32 DAP, being also related by the same reason of the reflectance in the green wavelength, with the exposed soil interference.

The model that best correlated with the near infrared wavelength was at 96 DAP (r = 0.4748). This model demonstrated that the reflectance at the near infrared wavelength increased with increasing productivity. When plants have high productive potential (high vigor), they will reflect more energy at the infrared wavelength than absorb, and plants with low productive potential exhibit greater energy absorption at the near infrared wavelength (CARTER & KNAPP, 2001). Due to the degradation of photosynthetic pigments, most of the energy in the near-infrared wavelength will be absorbed by the plant (CARTER & KNAPP, 2001). For 32 and 57 DAP, the models demonstrated that the energy reflected in the near infrared wavelength decreases with the decrease in productivity. The models showed that the increase of the independent variable (productivity) caused the increase in the dependent variable (reflectance).

Near-infrared is the most sensitive wavelength to identify nutritional, physiological, and structural deficiencies of the plant (HMIMINA et al., 2013). The highest reflectance values of this band occurred at 57 DAP (Figure 3c), where the best spectral response period in maize crop occurs at the phenological stage corresponding to the phases between VT and R1. In general, the corn crop begins to initial reproductive phase (R1) when it reaches approximately 60 days, next period of data obtained at 57 DAP (RITCHIE et al., 2003).

The Landsat8 thermal band has a higher correlation with productivity at 57 DAP (r = 0.4415). For the three seasons, the model verified that there was a decrease in productivity with the increase in the temperature of the canopy of the plants, that is, as there was an increase in the temperature of the canopy of the plants, there was a decline in corn yield. In addition, the plant presents some stress, with a decrease in the water content of the leaves, and consequently causing the canopy temperature to increase (LAMB et al., 2014), reflecting the low productive potential.

The highest temperatures were observed at 32 DAP (Figure 3d). The thermal wavelength is related to the surface temperature (corn canopy). In the early stages of corn cultivation, the temperature tends to be higher due to direct sun exposure (NUMMER FILHO & HENTSCHKE, 2006). The lowest temperatures were obtained at 57 DAP, being related to the stage of the crop in which the leaf architecture covers the whole soil and creates a microenvironment around the leaves (NUMMER FILHO & HENTSCHKE, 2006). The values of the reflectance of the thermal band at 96 DAP increased again, since the culture began the senescence phase (RITCHIE et al., 2003), beginning to lose leaves and consequently there was soil interference.

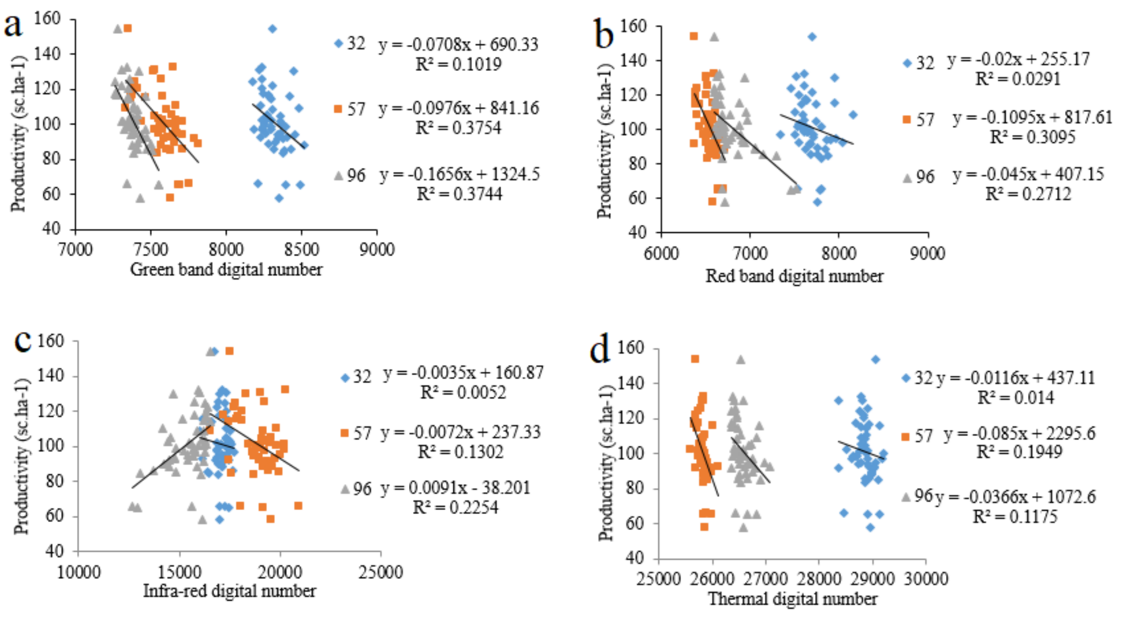

Figure 3. The linear correlation of corn yield (sc ha^{-1}) reflectances of band 3 (a) (green), band 4 (b) (red), band 5 (c) (infra-red near) (d) (thermal), for images obtained at 32, 57 and 96 DAP (days after planting).

According to Figures 3c and 5, there was better efficiency in the estimation of productivity with NDVI at 96 DAP. The model showed that the higher the NDVI, the higher the corn crop productivity. At 32 and 56 DBH the correlations between NDVI and productivity were r = 0.1166 and r = 0.2261, respectively, (Figure 4a). The best correlation was obtained at 96 DAP (r = 0.4798), where the plant was a crucial stage, because in the full reproductive cycle, and with all the productivity response expressed by the characteristics of the plant, (and beginning of senescence) (RITCHIE et al., 2003). In order to determine productivity, the crop still presents high water demand and nutrient accumulation for ear formation.

The stage that the culture best represents the spectral response, corresponds to the stage of vegetative growth, in which the culture exhibits a greater amount of leaf area and photosynthetic activity (SILVA et al., 2017), occurring in this study to 57 DAP. The NDVI values at 96 DAP had higher dispersion and variation between minimum and maximum, which reflects that NDVI variation is also observed in the productivity map variability (Figure 2d) and NDVI at 96 DAP (Figure 2c).

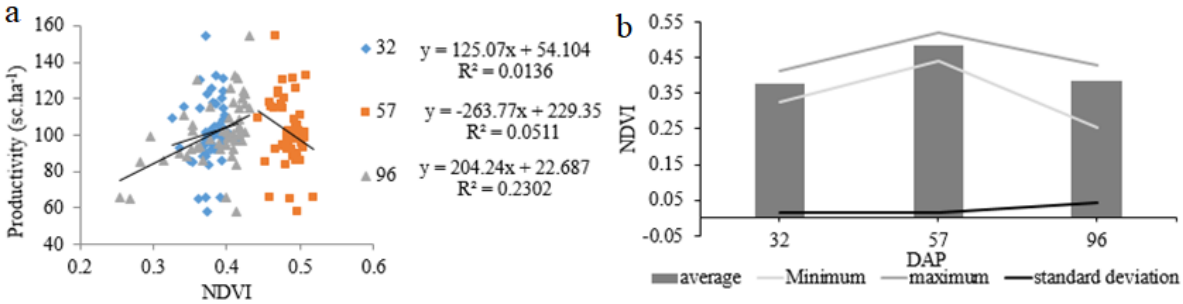

Figure 4. Linear correlation of corn yield (sc ha^{-1}) with NDVI vegetation index (a) and mean NDVI (b) at 32, 57 and 96 DAP.

CONCLUSIONS

The spectral bands present better responses (r) to the estimate of corn productivity in the intermediate phase of the crop (57 DAP). In the final phase of the crop (96 DAP), the productivity estimate is better with the green band and the NDVI.

Remote sensing products are promising for determining productivity as well as crop response variations in heterogeneous areas.

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