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Luan Peroni Venancio

Everardo Chartuni Mantovani

Cibele Hummel do Amaral

Christopher M.U. Neale

Ivo Zution Gonçalves

See next page for additional authors

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Authors

Luan Peroni Venancio, Everardo Chartuni Mantovani, Cibeles Hummel do Amaral, Christopher M.U. Neale, Ivo Zution Gonçalves, Roberto Filgueiras, and Fernando Coelho Eugênio

Potential of using spectral vegetation indices for corn green biomass estimation based on their relationship with the photosynthetic vegetation sub-pixel fraction

Luan Peroni Venancio,¹ Everardo Chartuni Mantovani,¹
Cibele Hummel do Amaral,² Christopher Michael Usher Neale,³
Ivo Zution Gonçalves,³ Roberto Filgueiras,¹
Fernando Coelho Eugenio⁴

1 Agricultural Engineering Department, Federal University of Viçosa (UFV), Avenue Peter Henry Rolfs, Viçosa, 36570-900, MG, Brazil

2 Forest Engineering Department, Federal University of Viçosa (UFV), Avenue Peter Henry Rolfs, Viçosa, 36570-900, MG, Brazil

3 Daugherty Water for Food Global Institute, University of Nebraska (UNL), Nebraska Innovation Campus, 2021 Transformation Dr. Ste 3220, Lincoln, NE, 68588, United States

4 Forest Engineering Department, Federal University of Santa Maria (UFSM), Street Ernesto Barros, Cachoeira do Sul, 96506-322, RS, Brazil

Corresponding author — L. Peroni Venancio, Department of Agricultural Engineering, Federal University of Viçosa (UFV), Avenue Peter Henry Rolfs, Viçosa, 36570-900, MG, Brazil

Email addresses: luan.venancio@ufv.br (L. Peroni Venancio); everardo@ufv.br (E. Chartuni Mantovani); chamaral@ufv.br (C.H. do Amaral); cneale@nebraska.edu (C.M. Usher Neale); ivo.zution@gmail.com (I. Zution Gonçalves); roberto.f.filgueiras@ufv.br (R. Filgueiras); fernando.eugenio@ufsm.br (F. Coelho Eugenio).

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Abstract

Crop biomass (Bio) is one of the most important parameters of a crop, and knowledge of it before harvest is essential to help farmers in their decision making. Both green and dry Bio can be estimated from vegetation spectral indices (VIs) because they have a close relationship with accumulated absorbed photosynthetically active radiation (APAR), which is proportional to total Bio. The aims of this study were to analyze the potential capacity of spectral vegetation indices in estimating corn green biomass based on their relationship with the photosynthetic vegetation sub-pixel fraction derived from spectral mixture analysis and to analyze the best interval of VI accumulation (days) for corn grain yield estimation. Field data of center pivots cultivated with corn during the irrigation seasons of 2015 and 2018 and Landsat 8 and Sentinel 2 images were used. The EVI produced the best results; Pearson's correlation coefficient, RMSE and Willmott's index reached 0.99, 6.5%, and 0.948, respectively. Among the nine potential VIs analyzed, the EVI, SAVI and OSAVI were considered the first, second and third best performing for corn green Bio estimation, respectively, based on their comparison to the photosynthetic vegetation sub-pixel fraction (fPV), and the time intervals that extended until 120 days after sowing showed the best results for corn grain yield estimation.

Keywords: *Zea mays* L., spectral unmixing, above-ground green biomass, yield

1. Introduction

Vegetation spectral indices (VIs) can be defined as the arithmetic combination of two or more spectral bands related to the spectral characteristics of vegetation (Matsushita et al., 2007). Applications of remote sensing data in agriculture typically involve the use of VIs because they are normally proportional to the values of several biophysical parameters (Ji and Peters, 2007) such as biomass (Bio) and crop yield (Al-Gaadi et al., 2016; Holzman and Rivas, 2016; Kross et al., 2015; Prabhakara et al., 2015; Wang et al., 2014a).

Bio estimation using VIs is possible because many of them provide a stable and near-linear estimate of accumulated absorbed photosynthetically active radiation (APAR) (Goward and Huemmrich, 1992; Myneni and Williams, 1994; Tan et al., 2013), which represents the energy source for photosynthesis and largely controls vegetation productivity (Akitsu et al., 2017), which is proportional to total Bio (Daughtry et al., 1992; Gallo et al., 1982; Kalaitzidis et al., 2010; Liu et al., 2010, 2004; Monteith, 1972).

For APAR estimation, the most recommended VIs based on their formulation (i.e., spectral index physical meaning), as well as the best

known according to Qin et al. (2018), are simple ratio (SR) (Jordan, 1969), the normalized difference vegetation index (NDVI) (Rouse et al., 1973), the green NDVI (gNDVI) (Gitelson et al., 1996) and the enhanced vegetation index (EVI) (Huete et al., 2002). Additionally, the relationship between VIs, leaf area index (LAI) and chlorophyll content (Chl) can be considered in studies involving Bio estimation because these parameters are also an important factor that influences APAR (Qin et al., 2018).

Chl, for example, can be considered a good indicator of the ability of vegetation to photosynthesize; if a plant has a higher chlorophyll content it will have a greater photosynthesis ability as well as a higher APAR. The green chlorophyll index (CI_{green}) developed by Gitelson et al. (2005) is an excellent example for estimating Chl in maize. The same logic applies to leaf area (i.e., higher LAI = increased light uptake = greater photosynthesis = greater APAR), and the soil-adjusted vegetation index (SAVI) (Huete, 1988) is one of the most suitable indices for LAI estimation according to Hatfield and Prueger (2010). In this context, several VIs can be proposed to estimate APAR, LAI and Chl and, consequently, green/dry Bio; however, an ideal VI should be highly sensitive to biophysical parameters while being relatively insensitive to noise caused by canopy background and atmospheric effects (Huemmrich, 1996; Ji and Peters, 2007). Therefore, it is always very important to evaluate these VIs while considering the influence of these aspects and to improve the relationship with APAR, LAI and Chl.

A simple and interesting approach to analyze the efficiency of the use of VIs to estimate corn green Bio uses the relationship with the photosynthetic vegetation sub-pixel fraction (fPV) for the following reasons: First, the fPV is a pure spectrum of green biomass because it is chosen based on the pixel distribution in the “Near infrared (NIR)-RED” 2D space (Plaza et al., 2002; Wang et al., 2014b, where the pixel with the highest NIR and lowest RED values is the PV endmember, as is expected for the pixel (area) with the highest amount of green biomass. Second, the fPV when compared with VIs is less subject to variations in scene lighting conditions and atmospheric variations (Shimabukuro et al., 1998). Third, the fPV is the fraction of live vegetation (Tarazona et al., 2018) or green vegetation (Guerschman et al., 2015; Ji et al., 2020), that is, photosynthesizing vegetation (Dennison et al., 2019; Gutman and Ignatov, 1998), which directly relates to the fraction of APAR (fAPAR) according to De Jong (2012). Additionally, the fAPAR in maize crops rapidly increases during the vegetative stage, remains relatively stable at

the stage of reproduction, and finally slowly decreases during the senescence stage (Zhang et al., 2013), as normally occurs with the fPV over the seasons. These aspects make the fPV a suitable parameter to indirectly evaluate VIs.

The fPV can be estimated using spectral mixture analysis (SMA) (Adams et al., 1986), a well-established and effective technique to address this mixture issue (Somers et al., 2011). The SMA model is based on the assumption that the spectra of materials in an instrumental instantaneous field of view (IFOV) combine linearly, with proportions given by their relative abundances (Adams et al., 1995, 1986; Roberts et al., 1998; Shimabukuro and Smith, 1991). The SMA model is widely employed (Ferreira et al., 2007; Somers et al., 2011), especially in areas with low spectral variability and low variation in the number and the type of end-member classes contained from pixel to pixel (Sun et al., 2017), such as irrigated corn fields. These fields normally contain (i) photosynthetic vegetation (healthy corn plants), (ii) soil and (iii) shade. In addition to the fPV, the application of the SMA model also generates the shade fraction (fSh), which may be interesting additional information because shade leads to either the reduction or total loss of information in an image, which can potentially lead to corruption of biophysical parameters derived from pixel values such as VIs (Wu et al., 2015; Xu et al., 2019).

In this context, the aims of this study were to analyze the potential of using the spectral vegetation indices for estimating corn green biomass based on their relationship with the photosynthetic vegetation sub-pixel fraction derived from the spectral mixture analysis and to define the three best VIs. Additionally, considering that corn Bio is directly related to grain yield using the harvest index approach, this study also aimed to assess the best interval of VI accumulation (days) for corn grain yield estimation using the three best classified indices.

2. Materials and methods

2.1. Study areas and ground data

The study areas belong to two commercial farms in the western region of Bahia state, Brazil. The primary study area (A1) was a center pivot field (13°13'50.32"S, 43°42'35.83"W and 458 m above mean sea

Fig. 1. Location of study areas in Brazil.

level) in the municipality of Serra do Ramalho (Fig. 1b). The field has approximately 90 ha of cropped area, with soils classified as Yellow Latosol (Santos et al., 2011). The second area (A2) involved six center pivots in the municipality of São Desidério and is inserted in the rectangle bounded by the coordinate pairs $12^{\circ}28'08''\text{S}$ - $45^{\circ}45'12''\text{W}$ and $12^{\circ}25'40''\text{S}$ - $45^{\circ}34'55''\text{W}$, with an average altitude of 750 m above sea level (Fig. 1c). As in the first area of study, the predominant soil type in A2 is Yellow Latosol (Santos et al., 2011). These two farms have a flat relief and, according to Köppen's climatic classification (Alvares et al., 2013), the climate of the region is tropical, with a rainy season in the summer and a dry winter.

A1 was used in the first part of the study, which involved the investigation of the performance of nine vegetation indices (VIs) for green Bio estimation based on their relationship with the photosynthetic vegetation sub-pixel fraction (fPV) images derived from spectral mixture analysis (SMA). A2 was used in the second study of corn grain yield estimation based on cumulative vegetation indices over different periods of

Table 1 Sowing date (SD), harvest date (HD), cultivated hybrid varieties (Hybrid), Area (A) and yield for each center pivot (CP) analyzed.

CP	SD	HD	Hybrid	A (ha)	Yield (Mg ha ⁻¹)
A1					
11	05/05/2015	09/22/2015	DBK 390 Pro 2	90	7.03
A2					
01B	04/12/2018	09/18/2018	Status Viptera 3	115	10.81
02B	04/13/2018	09/18/2018	Status Viptera 3	80	11.37
06A	04/16/2018	09/08/2018	DuPont Pioneer 30F35	80	10.23
07A	04/17/2018	09/09/2018	DuPont Pioneer 30F35	80	10.34
08A	04/18/2018	09/10/2018	DuPont Pioneer 30F35	80	10.96
17	04/20/2018	09/20/2018	Supremo Viptera 3	260	12.01

the growing season. The corn crop (*Zea mays* L.) data are presented in Table 1.

Figure 2 provides the overall processes followed in this study. A detailed description is subsequently provided.

2.2. Satellite data and data pre-processing

The present study used shortwave surface reflectance (SR) images of the operational land imager (OLI) sensor - Landsat 8 and images of the MultiSpectral Instrument (MSI) - sensor Sentinel 2A and B. Landsat OLI has a spatial resolution of 30 m, a temporal resolution of 16 days and spectral bands such as 1-Coastal blue (0.435-0.451 μm), 2-Blue (0.452-0.512 μm), 3-Green (0.533-0.590 μm), 4-Red (0.636-0.673 μm), 5-near infrared (0.851-0.879 μm), 6-shortwave infrared-1 (1.566-1.651 μm) and 7-shortwave infrared-2 (2.107-2.294 μm) (Roy et al., 2014; USGS (United States Geological Survey), 2016). OLI sensor images (path: 219 and row: 069) were downloaded from the United States Geological Survey (USGS) EarthExplore (<https://earthexplorer.usgs.gov/>).

Sentinel 2 is a mission composed of twin satellites named Sentinel- 2A and Sentinel-2B in the same orbit, phased at 180° to each other, which reduces the revisit time from 10 days to 5 days. The satellites acquire images in 13 bands positioned in the visible (VIS), red-edge, near infrared (NIR) and shortwave infrared (SWIR) spectral regions, with spatial resolutions ranging from 10 to 60 m (European Space Agency, 2015;

Fig. 2. Step-by-step flowchart to assess the performance of nine VIs used for corn green biomass production estimation based on their relationship with the fraction of photosynthetic vegetation estimated from spectral mixture analysis (a) and for corn grain yield estimation from the cumulative VIs (b).

Navarro et al., 2017). The present study used the bands of red, green, blue and NIR, which have 10-m spatial resolution. The spectral width of these bands (in μm) for the 2A and 2B satellites are blue (0.458-0.523 and 0.443-0.541), green (0.543-0.578 and 0.536- 0.582), red (0.650-0680 and 0.646-0.685) and NIR (0.785-0.900 and 0.767-0.900). SR images were obtained by the Dark-Object Subtraction (DOS1) atmospheric correction method (Chavez, 1996, 1988).

A total of seven cloud-free OLI sensor images that covered A1 (Fig. 1b) were acquired during the irrigated corn growing season of 2015. A total of 23 cloud-free MSI sensor images that covered A2 (Fig. 1c) were

downloaded. The number of MSI sensor images used for corn grain yield estimation changed between the six center pivots, based on different sowing and harvest dates for the fields (see Table 1).

2.3. Vegetation spectral indices

Table 2 shows the nine spectral vegetation indices related to APAR, LAI and Chl used in this work. For each biophysical parameter (i.e., APAR, LAI and Chl), three VIs that have very good relationships with them were selected based on their physical meaning and previous studies. However, note that all these VIs somehow relate to other biophysical vegetation parameters. These VIs use a combination of visible and near-infrared bands.

2.4. Spectral mixture analysis (SMA)

From a mathematical point of view, any mixed pixel of a corn plantation area in a no-till system can be denoted as a linear combination of spectral endmembers such as (i) photosynthetic vegetation (i.e., healthy corn plants), (ii) soil, and (iii) shade. Therefore, the SMA model aims to separate each mixed pixel of the components and its respective proportion in the interest area (Adams et al., 1995, 1986; Roberts et al., 1998; Shimabukuro and Smith, 1991). Note that the spectral behavior of non-photosynthetic vegetation (fNPV) is very similar to that of soil, especially dark soils (Adams et al., 1995; Xiao and Moody, 2005), and it was thus modeled as a soil in the SMA application.

The application of the SMA model basically consists of the following five steps: (i) endmember selection, (ii) development of a spectral library, (iii) establishment of constraints, (iv) mathematical resolution of the SMA model, and (v) evaluation of results. SMA decomposition was accomplished by means of an open-source plug-in for the ENVI (Exelis Visual Information Solutions, Boulder, Colorado) software named Visualization and Image Processing for Environmental Research (VIPER) Tools, version 1.5 (Roberts et al., 2007), available at <https://sites.google.com/site/ucsbvipperlabor/viper-tools>.

Endmember selection is the most important step in SMA (Fernández-Manso et al., 2012). Endmembers are spectral signatures of constituent materials in an image scene (Yin et al., 2019), and selecting endmembers

Table 2 Vegetative indices evaluated in this study

<i>Name</i>	<i>Equation</i>	<i>References</i>
SR ¹	$SR = \rho_{NIR} / \rho_{red}$	Jordan (1969)
NDVI ¹	$NDVI = (\rho_{NIR} - \rho_{red}) / (\rho_{NIR} + \rho_{red})$	Rouse et al. (1973)
gNDVI ¹	$gNDVI = (\rho_{NIR} - \rho_{green}) / (\rho_{NIR} + \rho_{green})$	Gitelson et al. (1996)
EVI ²	$EVI = 2.5 \frac{\rho_{NIR} - \rho_{red}}{(\rho_{NIR} + 6 \times \rho_{red} - 7.5 \times \rho_{blue} + 1)}$	Huete et al. (2002)
SAVI ²	$SAVI = \frac{\rho_{NIR} - \rho_{red}}{(\rho_{NIR} + \rho_{red} + L)} \times (1 + L)$	Huete (1988)
OSAVI ²	$OSAVI = \frac{\rho_{NIR} - \rho_{red}}{(\rho_{NIR} + \rho_{red} + 0.16)}$	Rondeaux et al. (1996)
CVI ³	$CVI = \frac{\rho_{NIR}}{\rho_{green}} \times \frac{\rho_{red}}{\rho_{green}}$	Vincini et al. (2008)
CI _{green} ³	$CI_{green} = (\rho_{NIR} / \rho_{green}) - 1$	Gitelson et al. (2005)
NAVI ³	$NAVI = 1 - \rho_{red} / \rho_{NIR}$	Carmona et al. (2015)

SR = simple ratio; NDVI = normalized difference vegetative index; gNDVI = green normalized difference vegetative index; EVI = enhanced vegetation index; SAVI = soil-adjusted vegetation index; OSAVI = optimized soil-adjusted vegetation index; CVI = chlorophyll vegetation index; CI_{green} = green chlorophyll index and NAVI = normalized area vegetation index. ρ_{NIR} , ρ_{red} , ρ_{green} , ρ_{blue} refer to the reflectances of near-infrared, red, green, and blue spectral bands, respectively, and L is the soil brightness correction factor (0.5 was used).

Regarding the number superscript next to an index name, ¹ means that the VI is more indicated for APAR estimation; ² means that the VI is more indicated for LAI estimation and ³ means that the VI is more indicated for Chl estimation.

involves identifying both the numbers and types of endmembers and their corresponding spectral signatures (Shrivastava et al., 2016). In this work, the OLI sensor multispectral bands 1 to 7 were used as input to find the endmembers, after layer stack creation with these bands.

The endmembers (i.e., photosynthetic vegetation and soil/nonphotosynthetic vegetation) were obtained from the image of May 18, 2015 and were used for the SMA model application in all seven images. They were selected from the image based on the distribution of the pixels in the red-infrared sample space (i.e., 2D scatter plot) and considering the

Fig. 3. Endmember spectra used for spectral mixture analysis of the OLI images. NIR = near infrared, and SWIR = shortwave Infrared.

simplex theory (Bajjouk et al., 1998), where the purest pixels are at the vertices of the distribution. The NIR and red bands were able to better produce straight and distinct triangles, as previously described in similar works (Baig et al., 2014; Kao et al., 2014). The endmember spectra used for spectral mixture analysis of the OLI images can be seen in Figure 3.

The SMA model in VIPER tools was run using the single spectral library and adopted the minimum allowable endmember fraction, maximum allowable endmember fraction, maximum allowable shade fraction and a maximum allowable RMSE with values of 0.05, 1.05, and 0.8 and 0.025, respectively. These values are the standards for the Viper Tools software, which was used to derive the fractions of the three endmembers (photosynthetic vegetation, soil and shade). Note that VIPER Tools allows the shade component to be computed from the difference between the user-defined summation and the values of the other components, removing the need for the user to select endmembers for this component (Roberts et al., 2007).

2.5. Vegetation spectral indices performance evaluation

To rank the three best VIs to be used in the estimation of green Bio considering their relationship to the fPV, the Pearson's correlation coefficients between these VIs and the fPV were analyzed. Previous studies have been performed using linear correlation to verify the relationship between these remote sensing variables (Jiménez-Muñoz et al., 2009; Rundquist, 2002). It was considered that their better performance was all the greater because of the higher positive correlation of VIs with the fPV (reference). The reasons that the fPV is a suitable parameter to evaluate the VIs (reference) were discussed in the introduction.

Regarding the fraction of shade (fSh), its influence on VIs is not easily analyzed. Studies with this focus commonly involve the use of specific equipment, such as field imaging spectrometer systems (Wu et al., 2015) or push-broom scanning sensors (Zhou et al., 2017). Therefore, the fSh was considered as additional information, and the following approach was taken: the VIs with better performance, in general, where those that had no correlation (close to 0) or higher negative correlation (close to -1) to the fSh. This criterion was established based on the premises of Zhang and Huang (2015). These authors note that shadows can lead to either a reduction or total loss of information in an image, which can potentially lead to the corruption of biophysical parameters derived from pixel values, such as VIs.

In addition, the performance of VIs was also assessed by comparison with fPV values by means of the root mean square error (RMSE) and Willmott's index of agreement (d) (Willmott, 1982). The fPV and VIs were normalized to a range from 0 to 1 to enable comparisons between them. These analyses used data of the center pivot number 11 in the year 2015, located in A1 (Fig. 1b), and the information was extracted from 904 regularly spaced pixels inside the field (Fig. 4).

Fig. 4. Regular point grid spacing resulting in 904 pixels within the center pivot field after a -30 m buffer from the original vector layer (white line) was used to avoid a border effect.

2.6. Corn grain yield estimation based on cumulative VIs

Based on dry Bio, corn grain yield can be assessed using a harvest index (HI) (Caviglia et al., 2014; Djaman et al., 2013; Hütsch and Schubert, 2018). Therefore, the VIs used to assess corn green or dry biomass are also useful for grain estimation, as shown in previous studies (Bertolin et al., 2017; Campos et al., 2018; Fang et al., 2011; Tagarakis and Ketterings, 2017; Venancio et al., 2019). The three VIs classified as the best were used to estimate corn grain yield based on VIs accumulated in different intervals over the corn growth season.

Cumulative VIs or time-integrated VIs (Reed et al., 1994) represent the integrated area under the curve and were calculated in this current work using numerical integration by means of trapezoidal rules developed by Kross et al. (2015). The VI time-series were then used during the active growing months (April to October). The cumulative VIs were computed based on the periods presented in Table 3. Origin Pro 2017 software (OriginLab Corporation, Northampton, MA, USA) was used in the procedure. For this purpose, the corn grain yield measured in the 2018 growing season and MSI sensor images were used. The used intervals, taking into account important corn phenological stages and defined based on days after sowing (DAS), are presented in Table 3.

The choice of the best interval among the six analyzed was based on the r^2 value. No independent validation of the results was performed. Only the best interval for corn grain yield estimation was evaluated. Note

Table 3 Time interval number (Interval), initial (DAS_i) and final (DAS_f) days after sowing (DAS) of VI accumulation and the respective description of intervals.

Interval	DAS _i	DAS _f	Interval description
1	0	77	From sowing to flowering/pollination
2	0	120	From sowing to physiological maturity
3	7	77	From emergence to flowering/pollination
4	7	120	From emergence to physiological maturity
5	14	77	From beginning of photosynthetic processes to flowering/pollination
6	14	120	From beginning of photosynthetic processes to physiological maturity

These DAS values represent the average values because these events can change according to climatic conditions, hybrids, and crop management, among others.

that the lack of images near the sowing and harvesting dates is disadvantageous for the VI curves and, consequently, for the estimation of the cumulative VI, and it was necessary to use mean values for these dates. The values were obtained from center pivot fields that had approximately four days difference between sowing date and image acquisition date. The criterion for the harvesting date was the use of images coinciding with this date or up to three days before.

3. Results and Discussion

3.1. SMA model application

Fig. 5 presents the sub-pixel fractions of photosynthetic vegetation (fPV), soil (fS) and shade (fSh) that resulted from SMA model application, along with an RGB image. The light areas in these images indicate the highest proportion of the components (fPV, fS and fSh) in the pixels. As a function of corn crop development, the fPV and fS had an antagonistic behavior, and the fSh had the lowest variation among the fractions. After 13 DAS, the fPV represents only 4.5% of the image; most of it is formed by the fS, at 75.4% (Fig. 5).

At 61 DAS, the corn crop showed the highest values of the fPV among the seven images, and this value is probably close to the maximum value since the maximum leaf area index (LAI) is observed between 60 and 70 DAS (Bergamaschi et al., 2006; Kross et al., 2015; Lizaso et al., 2005; Lukeba et al., 2013; Soleymani, 2018; Soufizadeh et al., 2018; Wolschick et al., 2003). At 77 DAS, the fPV tends to decrease because the plants reach their maximum height (Lizaso et al., 2005; Lukeba et al., 2013); the reproductive phase begins from this moment (Hanway, 1966). The fS proportion is automatically linked to the fPV; as the fPV increases, there is a decrease in the fS, and the opposite is also true (Fig. 5).

The highest values of the fSh were observed during the initial stage, 20.2% and 22.2% at 13 and 29 DAS, respectively (Fig. 5). This behavior results from the shadow generated by the corn plant, which is projected on the ground and then measured by the imager sensor. As the crop develops, the fSh would tend to increase but the sensor cannot measure it as at the initial stage, when corn leaves are at the top of the surface (i.e., the element to be captured). Due to these facts, the fSh had

Fig. 5. RGB composite image, photosynthetic vegetation (fPV), soil (fS) and shade (fSh) sub-pixel fractions as a function of the days after sowing (DAS).

the lowest value at 61 DAS (9.5%), when the LAI tended to be maximum, as previously discussed.

3.2. Corn development access by means of VIs and the fPV

Fig. 6 shows the spatial and temporal distribution of the fPV and VIs over the corn growing season after the normalization for the 0 to 1 interval. The spatial and temporal distributions of corn growth of the nine VIs are well correlated with the fPV. It can be seen from Fig. 6 that, at 13 DAS, all VIs had low values, which indicates the start of corn growth, when corn emergence normally occurs in a period less than eight days under normal air temperatures (20 to 30 °C) (Schneider and Gupta, 1985). By 13 DAS, only two leaves have normally fully emerged (Hanway, 1966). By 29 DAS, corn plants have six leaves fully formed (Hanway, 1966), which

Fig. 6. Spatial and temporal distribution of vegetation indices (VI) as a function of the days after sowing (DAS).

provides good soil cover, from 40 to 50%, taking the fPV into account (Fig. 6). This soil cover is reflected in a considerable increase of the VI value compared with the 13 DAS case.

At 61 DAS, the maximum values were observed for the majority of the VIs, which reflects the maximum LAI, also observed around this period, as previously discussed. Despite the high values in this period, the differences between 45 and 77 DAS are very low (Fig. 6) due to the establishment of the plant stand, covering all the soil surface, and few physical canopy changes.

From 77 DAS, VI values begin to decrease until harvesting time, when the values are similar to those at the beginning of the cycle but slightly higher. These decreases are related to the beginning of the reproductive phase, which normally starts at ± 77 DAS (Hanway, 1966). Then, once the plant reaches maximum height, photoassimilates will be exclusively used for pollination, fertilization, and dry matter accumulation in the grains, as shown by Bender et al. (2013). As a consequence, the plants lose vegetative vigor, which is reflected in the VI values. Due to the sensitivity to corn crop changes, VIs have been widely used in a number of studies

involving this crop, such as in the determination of dry biomass (Campos et al., 2018; Kross et al., 2015), leaf area index (Kross et al., 2015) and plant nitrogen content (Maresma et al., 2016).

3.3. Vegetation indices performance

Fig. 7 shows the first performance evaluation, a visual comparison of the temporal pattern between the fPV and VIs after their normalization for the 0 to 1 interval. Both the VIs and the fPV rapidly increased from 13 to 61 DAS, except for the SR, NDVI and NAVI, which reached their peaks earlier at 45 DAS (Fig. 7). Regarding the early season, it is possible to verify that the CVI, gNDVI and NAVI mainly do not agree well with the fPV but are overestimates. On the other hand, underestimates or overestimates are not the main problem; the limitation occurs when the VIs do not have a pattern of temporal variation similar to the fPV, as verified for the CVI (Fig. 7). This VI started the cycle with overestimates, stabilized during a period in which the fPV increased (29 to 45 DAS) and, in the late season, underestimated the fPV (Fig. 7).

Analyzing the final portion of the season (i.e., from 77 DAS), a poor agreement for SR and CI_{green} with the fPV can be clearly seen. However, the EVI, SAVI, OSAVI and NDVI exhibited behavior more similar to the fPV, especially the EVI, with great proximity between the temporal curves over the entire season (Fig. 7).

Fig. 7. Temporal pattern of VIs and the fPV as a function of the days after sowing, after their normalization for 0 to 1 interval.

Good and very good Pearson correlation coefficients (r) were observed between the fPV and the VIs, with the highest values observed for the EVI and SAVI (0.99), followed by the OSAVI (0.98), NDVI (0.96), NAVI (0.95) and gNDVI (0.94) (Fig. 8). However, a lower value was verified for the CVI (0.64), which was also not significant. Finally, SR and CI_{green} had good values, 0.86 and 0.88, respectively (Fig. 8). Guo et al. (2007) compared the NDVI and EVI with the levels of vegetation cover and verified that the correlation of the EVI was especially better than that of the NDVI at the higher levels of vegetation cover. Shafian et al. (2018), working with sorghum, verified that among the NDVI, EVI, gNDVI, and MTVI2, the first showed the highest correlation with the fraction of photosynthetic vegetation.

The high linear correlation between the fPV and some VIs verified for the majority of VIs occurs because both the fPV and VIs highlight the amount of green vegetation in the pixels (Li et al., 2015; Shimabukuro et al., 1998), and a greater or lower correlation is linked to factors such as the sensitivity of the VI to the biophysical parameters analyzed, the noise caused by canopy background and atmospheric effects.

For example, regarding noise problems, the EVI compared with the NDVI has reduced air and soil influence in the spectral canopy response (Huete et al., 2002). The same occurs with the SAVI, which overcomes the NDVI limitations related to soil background brightness (Huete, 1988). Therefore, the higher values for the SAVI and EVI compared with the NDVI may be the result of the advantages cited above. However, despite these positive points for the SAVI and EVI, the NDVI is the most widely used VI for the retrieval of vegetation canopy biophysical properties (Adole et al., 2016; Jiang et al., 2006; Matsushita et al., 2007).

The field observations are also very important in discussing VI performance (good results for some and poor for others). It is important to make clear that abiotic and biotic stresses were not verified in the corn plantations. Therefore, the discussion about the performance of the VIs based on field observations needs to be restricted to normal plant growth (Hanway, 1966). For example, the CVI had the worst correlation coefficient ($r = 0.64$) due to an overestimation during early stages (mainly 13 DAS), and it was verified in the field observations that the corn plant had only two leaf pairs at 13 DAS and that soil coverage by the corn plant was thus very low. Based on this fact, low values are expected for vegetation indices, although the CVI was very high, which

shows the low sensibility of these VIs when the plants presented low IAF. However, some VIs (e.g., the SAVI and EVI) had good accordance; because of their formulations, there are empirical coefficients to decrease the background brightness (Huete et al., 2002; Huete, 1988) and isolate the plant response.

At 45 DAS considerable soil coverage was observed in the field, with the full soil coverage reached at 61 DAS; this observation explains the date of the best concordance between the fPV and all VIs (Fig. 7) because at this period, the soil influence is eliminated and only the plant reflectance influences the VI levels.

Several studies have shown the positive influence of the use of both irrigation and fertilizers (nitrogen mainly) on maize plant vigor/ greenness, photosynthesis capacity and yield (Bassi et al., 2018; Ding et al., 2005; Fernandez et al., 2019; Kitonyo et al., 2018; Liu et al., 2019; Vos et al., 2005; Wang et al., 2019). Therefore, these practices will directly affect VI values, as will be discussed below. The main reason is that the majority of the VIs include in their formulation red, green and near-infrared wavelengths reflectances, which totally depend on chlorophyll content and leaf structure and are in turn strongly influenced by these practices.

For example, in healthy vegetation, reflectance in the red region is very low due to chlorophyll strongly absorbing light at this wavelength, whereas it is high in green wavelengths due to chlorophyll reflecting strongly the light at this wavelength (Huete, 2004; Jensen, 2007; Roy, 1989). Therefore, a plant well managed in terms of irrigation and fertilization will have higher chlorophyll content and low reflectance in red wavelengths and high reflectance in green wavelengths. The NIR reflectance is directly related to the internal structure of plant leaves (Huete, 2004; Jensen, 2007; Roy, 1989). As fertilization and water stress cause changes in the inner leaf structure, they will lead to changes in the spectral response in NIR wavelengths. Maresma et al. (2016) analyzed the NDVI among other VIs to determine nitrogen application and yield prediction in corn and verified low values for the NDVI in areas with no nitrogen application in comparison with areas where it was applied as a consequence of the red wavelength increase and NIR reflectance (decrease). Similar results were found by Shaver et al. (2011).

VI values were negatively correlated with the fraction of shade (fSh), according to Fig. 8, and the EVI had the highest negative value of the Pearson correlation coefficient, -0.78. The CVI had the lowest value ($r=-0.37$) and was not significant. According to the premise of Zhang and

Fig. 8. Correlation matrix between vegetation indices (SR, NDVI, gNDVI, EVI, SAVI, OSAVI, Cl_{green} , CVI and NAVI) and photosynthetic vegetation, soil and shade sub-pixel fractions. * indicates significance of regression at p -value <0.05 , ** indicates significance of regression at p -value <0.01 , and *** indicates significance of regression at p -value <0.001 .

Huang (2015) already discussed, the best indices are those that have no correlation (close to 0) or higher negative correlation (close to -1) with the fSh. Interesting results of the shadow effects on VIs can be seen in the work of Zhou et al. (2017) with rice; these authors investigated the spectral properties of sunlit and shaded components in rice canopies with near-ground imaging spectroscopy data.

Table 4 shows the root mean square error (RMSE) and Willmott's index of agreement (d) values between VIs and the fPV. Considering the quantitative accuracy assessment based on the RMSE, it can be seen that the EVI has the best agreement with the fPV, with an average RMSE value of 6.5%. With an RMSE of 9.8%, the SAVI was the second best VI based on the statistical parameters, closely followed by the CI_{green} and OSAVI, with 11.5% and 11.8%, respectively. The NDVI had an intermediate RMSE (13%), the fifth highest value (Table 4). The highest RMSE values were observed for RS (23.6%) and the CVI (21.1%).

SR and the CI_{green} had higher RMSE values in the late season, which stood out from the rest (Table 4). Near-infrared reflectance (750-1350 nm) is determined by the inner structural features of leaves, the structural organization of the spongy mesophyll, and the ratio of cells to air spaces within this tissue (Gates et al., 1965; Knipling, 1970; Pinto et al., 2017). However, reflectance in the visible region (400-700 nm) is mostly determined by photosynthetic pigments (Gates et al., 1965). Therefore,

Table 4 Root mean square error (RMSE) and Willmott's index of agreement (d) with average value (μ) referring to the comparison of the vegetation indices with the fraction of photosynthetic vegetation (fPV) as a function of the days after sowing after their normalization to the 0 to 1 interval

DAS	SR	NDVI	$gNDVI$	EVI	SAVI	OSAVI	CI_{green}	CVI	NAVI
Root mean square error – RMSE (%)									
13	4.7	28.1	53.7	17.1	23.2	25.7	12.9	50.7	43.6
29	21.1	31.8	36.9	13.4	20.8	26.6	1.7	24.8	39.1
45	10.7	11.8	12.3	6.8	8.4	10.8	2.8	11.0	13.0
61	21.6	2.4	3.5	1.7	2.3	2.8	2.8	11.0	3.3
77	22.9	5.4	6.6	3.1	4.4	5.6	5.6	12.0	7.1
93	37.4	5.2	5.5	1.5	4.4	5.4	22.2	21.1	8.7
109	47.1	6.6	8.9	2.0	4.8	6.2	32.2	16.9	14.8
μ	23.6	13.0	18.2	6.5	9.8	11.9	11.5	21.1	18.5
Willmott's index of agreement – d									
13	0.984	0.594	0.250	0.808	0.685	0.637	0.884	0.278	0.352
29	0.801	0.521	0.433	0.879	0.739	0.621	0.998	0.654	0.400
45	0.934	0.902	0.893	0.966	0.949	0.917	0.995	0.929	0.881
61	0.785	0.996	0.991	0.998	0.996	0.994	0.994	0.930	0.992
77	0.771	0.978	0.968	0.993	0.985	0.977	0.979	0.917	0.963
93	0.588	0.980	0.977	0.998	0.986	0.978	0.780	0.795	0.944
109	0.502	0.968	0.941	0.997	0.983	0.971	0.654	0.854	0.849
μ	0.766	0.848	0.779	0.948	0.903	0.871	0.898	0.765	0.769

with leaf senescence, there is a disorganization in the structural features, which reduces reflectance in the near-infrared region, and an increase in the red region due to the decrease of photosynthetic pigment absorption (Gates et al., 1965; Knipling, 1970), which leads to an abrupt reduction in SR value (see Eq. 5) in the late season. The decreases of the normalized vegetation indices tend to be subtler.

The analysis is similar for the CI_{green} , but the green band is used in its formulation instead of the red band. Therefore, at the senescence stage, the reflectance in the green wavelength, which is relatively high when the plant has a high vigor, decreases. This decrease at the first moment may lead to an increase in CI_{green} value; however, the near infrared reflectance decreases in a much greater proportion, which culminates in a rapid VI decrease.

With respect to the RMSE values during the early season, as observed, the gNDVI, CVI and NAVI had the highest RMSE values (Table 4). On the other hand, SR, the EVI and the CI_{green} had the lowest values. Additionally, the NDVI, SAVI and OSAVI had intermediate average RMSE values (Table 4). Comparing the most well-known VIs (i.e., the NDVI, SAVI and EVI), the NDVI showed higher RMSE values in all seven images. An important detail involving the NDVI is that after 61 DAS, RMSE values for the SAVI and NDVI were very close, 2.3 and 2.4, respectively. However, after 77 DAS, when corn reaches its maximum height (Lizaso et al., 2005; Lukeba et al., 2013) and consequently a dense biomass, the difference between them increased, with values of 4.4 and 5.4 for the SAVI and NDVI, respectively. These values suggest a saturation of the NDVI at high biomass values and consequently show different values of the fPV. Previous studies have demonstrated problems with NDVI saturation in corn fields (Chen et al., 2006; Hatfield and Prueger, 2010; Wang et al., 2013, 2016). Summarizing the RMSE analysis and considering the average values, the EVI was the best VI, followed by the SAVI, CI_{green} and OSVAI.

The results of Willmott's index of agreement (d) are presented in Table 4. The CVI had the worst result ($d=0.765$), which was very close to those of SR, the NAVI and the gNDVI (Table 4). The NDVI and OSAVI had intermediate values considering all nine indices, 0.848 and 0.871, respectively. The best results were observed for the EVI ($d = 0.948$), SAVI ($d=0.903$) and CI_{green} ($d=0.903$). The difference between these three VIs was the equilibrium in the "d" values over the season, which always remained high, unlike the others, which had a greater amplitude. For

Fig. 9. Scatter plot of the EVI and the fPV using data of 904 pixels extracted from the center pivot area for the different days after sowing (DAS) and a graph showing all seven images.

example, for the EVI, the lowest “d” value was 0.808 at 13 DAS, with the majority of the values above 0.94. (Table 4). Generally, and considering all the VIs examined, the best “d” values were verified from 45 to 93 DAS, when the soil cover by the plants was very high.

A scatter plot of the EVI and the fPV was added (Fig. 9) to make the relationship between VIs and the fPV clear. The excellent agreement between the EVI and the fPV can be verified, especially for DAS values of 45, 61, 77, 93 and 109. As discussed previously, this is a result of the full soil cover highlighting the plant response. On the other hand, a low concordance is verified for 13 DAS, which shows that VIs tend to have low efficiencies for crop monitoring during the first weeks after planting. Finally, excellent results can be seen when all images were grouped ($R^2 = 0.978$).

The three best VIs to be used in corn green biomass estimation were ranked considering their relationship with the fraction of photosynthetic vegetation (fPV). The EVI and SAVI showed the best results for the statistical parameters analyzed (i.e., Pearson correlation coefficient, root mean square error and Willmott’s index of agreement) in addition to the good agreement of the visual analysis. The CI_{green} showed slightly higher results for RMSE and Willmott’s index of agreement in comparison to the OSAVI but could not obtain a much higher Pearson correlation coefficient

(0.98 versus 0.88). Moreover, according to Fig. 7, the OSAVI showed a more similar behavior to the fPV than did the CI_{green} during the entire corn season. Therefore, the OSAVI was considered the third best VI.

The final rank of the three best VIs potentially evaluated for green Bio estimation considering the close relationship between Bio-APAR and APAR-VI was, from best to worst: the EVI, SAVI and OSAVI. However, it is important to highlight that this work does not replace studies that aim to directly find the best vegetation indices for assessing vegetation biophysical parameters. The results presented here need to be seen as complementary information that will help in choosing the VIs with the highest potential for biomass estimation.

Corn is considered the third most important crop in the region of the study area, the first being soybeans (AIBA (Association of Farmers and Irrigators of Bahia), 2019), cropped in very similar conditions in the area of the present study. Therefore, the results of this study can be tested in wide areas planted with this crop. Another point is that the study areas are located close to the largest sugarcane producing region in the world (southeastern Brazil), which presents similar edaphoclimatic characteristics. Therefore, the results of this study can be easily represented and used for the cultivation of sugar cane in other parts of Brazil and in various parts of the world.

3.4. Corn grain yield estimation based on cumulative VIs

The EVI, SAVI and OSAVI were used for corn yield estimation once these indices showed the best performance, as already described. Table 5 shows the mean values for the EVI, SAVI, and OSAVI relative to the sowing and harvesting dates in study area 2 (Fig. 1c) during the 2018 season. For the EVI and SAVI, the values referring to sowing date (SD) remained at approximately 0.09, whereas for the OSAVI they remained at

Table 5 Mean values with standard deviation for the EVI, SAVI, and OSAVI for sowing date (SD) and harvesting date (HD) in the 2018 season.

<i>Vegetation indices</i>	<i>SD</i>	<i>HD</i>
EVI	0.0926±0.0048	0.1394±0.0101
SAVI	0.0992±0.0075	0.1588±0.0106
OSAVI	0.1135±0.0085	0.1819±0.0126

Fig. 10. Relationships between the accumulated EVI and corn grain yield. * indicates significance at p -value < 0.05. The dotted lines represent the 1:1 line, and the solid black lines represent the linear regressions.

approximately 0.1135. For harvesting date (HD), VI values were higher than those for SD, with a greater difference between the SAVI and EVI regarding sowing date.

Fig. 10 shows the relationship between the accumulated EVI and measured grain yield. Among the six time intervals of accumulation, the intervals that extended until 120 DAS obtained the best results, with the highest r^2 value verified in the interval of 7-120 DAS (Fig. 10d), followed by 14-120 DAS (Fig. 10f). On the other hand, when the interval was limited between 0 and 77 DAS (Fig. 10a), r^2 reached its lowest value (0.756), which was very close to 7-77 DAS, with $r^2 = 0.758$ (Fig. 10c).

The relationships between the SAVI accumulated in different intervals over the season and measured grain yield are presented in Fig. 11. The results are similar to the EVI, with the highest r^2 value occurring in the interval 14-120 DAS (Fig. 11f). This interval showed a slightly higher r^2 than the 7-120 interval (Fig. 11d). Only 77 days of accumulation (0-77 DAS) led to the worst results of estimation, with an r^2 equal to 0.756 (Fig. 11a).

Fig. 11. Relationships between the accumulated SAVI and corn grain yield. * indicates significance at p -value < 0.05. The dotted lines represent the 1:1 line, and the solid black lines represent the linear regressions.

Fig. 12 shows the relationship between six different intervals of the OSAVI and measured grain yield. As observed for the EVI and SAVI, when accumulated between 14 and 120 DAS, the OSAVI performed best for yield estimation, with an r^2 of 0.79 (Fig. 12f). However, the difference from the 7-120 DAS interval is very low. The worst interval again was 0-77 DAS (Fig. 11a), which was also found previously with the EVI and SAVI.

Regarding the three vegetation indices examined (the EVI, SAVI and OSAVI), the interval of 14-120 DAS was the best for grain yield estimation, showing the highest r^2 values. However, the differences from the 7-120 DAS interval were very subtle, especially for the EVI and SAVI. These results can be explained based on the physiological behavior of corn plants. At 14 DAS, corn plants normally have two leaves fully emerged (Hanway, 1966) and are then already able to photosynthesize (Fancelli and Dourado Neto, 2000). Therefore, defining the beginning of VI accumulation at 14 days after sowing prevents biomass accumulation before the start of the photosynthetic process (i.e., starting with

Fig. 12. Relationships between the accumulated OSAVI and corn grain yield. * indicates significance at p -value < 0.05 . The dotted lines represent the 1:1 line, and the solid black lines represent the linear regressions.

0 DAS) and consequently overestimates grain yield. The study of Gava et al. (2010) showed that dry biomass accumulation in corn plants has a sigmoidal pattern and begins approximately 10 days after emergence.

When corn plants reach 120 DAS, they are very close to physiological maturity, and the grain requires no more moisture or nutrient input (Angel et al., 2017). Therefore, extending the accumulation further is not justified. Biomass accumulation until 77 DAS is important because it would have very early yield results, which would facilitate the planning of harvesting, storage, etc. Additionally, although the r^2 is higher for intervals with 120 DAS, there is a great risk of not being able to get cloudless images in this period, and the risk is lower at 14-77 DAS, with a slightly decreasing r^2 . On the other hand, with only 77 DAS, all the reproductive phases are omitted because the vegetative stages are normally finished at this time (Hanway, 1966). Therefore, many factors that may occur in these stages and affect grain production would not be considered, such as water stress, pests and diseases, and nutritional stress.

4. Conclusions and remarks

Nine vegetation indices (SR, NDVI, gNDVI, EVI, SAVI, OSAVI, C_Igreen, CVI and NAVI) were calculated for an irrigated commercial corn field by center pivot and were potentially evaluated based on their relationship with the fraction of photosynthetic vegetation (fPV) estimated by spectral mixture analysis (SMA). Additional information to infer the performance of vegetation indices (VIs) is very useful because these remote sensing variables are usually used without previous knowledge of their efficiency for biomass and yield estimation, being commonly chosen empirically.

Among the nine VIs potentially analyzed, the EVI had the best performance based on its relationship with the fPV, with a Pearson correlation coefficient, RMSE and Willmott's index of agreement of 0.99, 6.5%, and 0.948, respectively. The final ranking of the three best VIs were the EVI, the SAVI and the OSAVI.

Corn yield estimation from accumulated VIs is a very interesting application of remote sensing data because it involves practicality (i.e., in the VIs obtained) and efficiency (i.e., VIs can accurately estimate grain yield). Six intervals of accumulation were tested over the season using the three best ranked vegetation indices in the primary objective. The intervals that extended up to 120 days after sowing produced the best results. Future investigations with a larger sample number and an independent validation for grain yield estimates based on VI accumulation are important to validate the conclusions that can be drawn from this study.

Competing Interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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