

Understanding TVDI as an index that expresses soil moisture

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Received 12 May 2017; accepted 4 August 2017

Abstract

Given the need to search for robust indicators capable of representing the surface water condition in the various agricultural production regions in the state of Rio Grande do Sul, the objective of this study was to analyze the influence of different types of vegetation cover on the definition of Temperature Vegetation Dryness Index (TVDI) as an indicator of soil moisture in agricultural areas on a local scale. A Landsat 8-OLI image of February 7, 2015, and its Normalized Difference Vegetation Index (NDVI) product was used. The image was classified by the maximum likelihood method. The surface temperature (T_s) was obtained by the split-window algorithm and later the normalization of the TVDI model with the triangular characteristic dispersion was performed. With the data of TVDI, the different types of vegetation cover mapped were identified. Histograms of TVDI frequencies were also made for each of the targets. The scatter plots between TVDI and NDVI and between TVDI and T_s were made. The results showed that it was possible to differentiate the different types of soil use and cover, through the natural water condition of each target. With the scatter plots of the targets, it was possible to locate them with a certain overlap; the strong correlation between the index and T_s was observed. TVDI has been shown to be effective for monitoring the variation of the water condition and can be used for monitoring and sustainable management purposes.

Keywords: Landsat 8-OLI, supervised classification, split-window.

1. Introduction

At the state of Rio Grande do Sul (RS) it is usual the occurrence of crop frustration due to the hydric restrictions (Matzenauer et al., 2002; Sentelhas et al., 2015; Zanon et al., 2016), existing, therefore, the necessity of researching for reliable indicators that are able to represent the hydric conditions of the surface in diverse farming production regions, tillage or pasture.

The ideal index is the one that generates precise information, that is able to represent adequately the spatial variability of the humidity, which is easy to be obtained and preferably costing low. TVDI (Temperature-Vegetation

Dryness Index), proposed by Sandholt et al. (2002) fits in this demand, and it can constitute a very viable and robust monitoring tool. The index of soil humidity is obtained from the orbital remote sensor, through NDVI relation (Normalized Difference Vegetation Index) and the surface temperature (T_s) (Gao et al., 2011; Son et al., 2012). When there is a hydric restriction, there is also plants temperature elevation due to the limitation of the evapotranspiration (Gao et al., 2011; Son et al., 2012). So, in TVDI, the T_s is an indicator of the occurrence of hydric restrictions while NDVI indicates the quantity and the green biomass state.

Due to the scarcity of studies with TVDI in the state of Rio Grande do Sul, there is the necessity of deepening the understanding of this research. Starting from this premise, the aim of the study was analyzing the influence of different kinds of green coverage in TVDI definition as humidity indicator in agricultural areas in local scale.

2. Materials and methodology

The study was made in the Pampa biome of in the state of Rio Grande do Sul (Figure 1). This region is characterized by intensive agriculture featuring the cultivation of soybean and rice and the extensive livestock in grassland areas with herbaceous vegetation which is a characteristic of this biome.

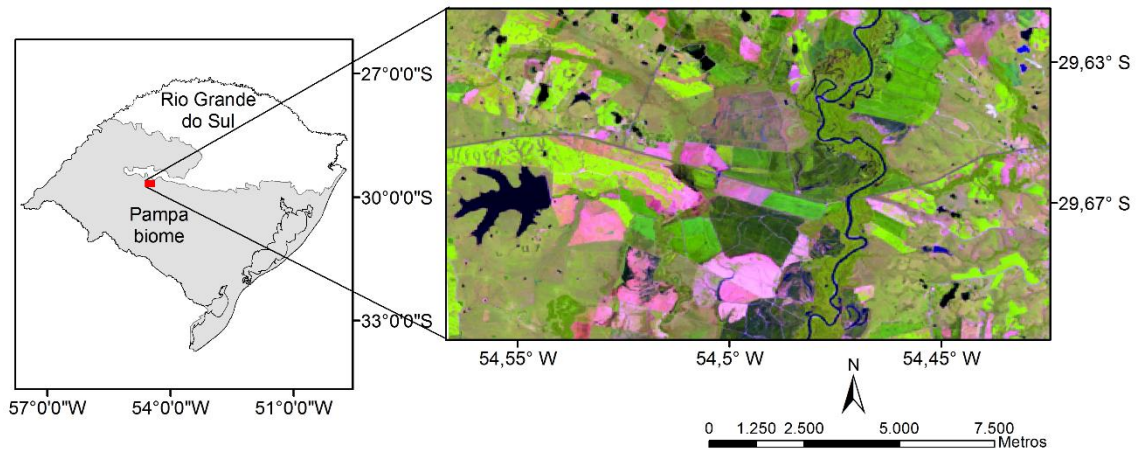


Figure 1 – Image Landsat-OLI, composition 6, 5, 4, RGB of 02/07/2015 (path/row – 223/81), showing the location of the study area in the Pampa biome in the state of Rio Grande do Sul.

It was used an image Landsat 8–OLI (orbit/point - 223/81) from 02/07/2015 obtained from the data base of USGS/ESPA (United States Geological Survey/Center Science Processing Architecture) (<https://espa.cr.usgs.gov>). The bands 1 to 7 were used to obtain thematic bands. The supervised classification was made by the maximum likelihood to the extraction of thematic information. The classification uses the statistic method, of classification pixel by pixel, in which the spectral distribution of categories in soil use is considered Gaussian or usual, that means, objects that belong to the same class will have spectral response approximated to the average of values to that category. To train the classifier GPS data collected in May 2015 were used.

To obtain TVDI have used images of NDVI and T_s according to the Equation 1.

$$TVDI = (T_s - T_{Smin}) / (a + b \text{NDVI} - T_{Smin}) \quad (1)$$

where: T_s is the radiative surface temperature observed in a given pixel (K); T_{Smin} is the minimum surface temperature (K), corresponding to the wet edge of the evaporative triangle; “a” and “b” are the linear and angular

coefficients of the straight line representing the dry edge.

NDVI was derived straightly from the product of USGS/ESPA. T_s was estimated through the application of the algorithm split-window, using bands 10 and 11 from the satellite Landsat 8-OLI, through the use of Equation 2 proposed by Jiménez-Muñoz et al. (2014).

$$T_s = T_{10} + 1,378(T_{10} - T_{11}) + 0,183(T_{10} - T_{11})^2 - 0,268 + (54,3 - 2,238)(1 - \epsilon) + (-129,2 + 16,4w)\Delta\epsilon \quad (2)$$

where: T_{10} and T_{11} the temperature in Kelvin in parts 10 and 11 of thermal, w is the content of water steam in the atmosphere in g cm^{-2} ; ϵ is the average emissivity in the thermal bands ($\Delta\epsilon = \epsilon_{10} + \epsilon_{11}$).

To the emissivity calculation in bands, 10 and 11 were used Equation 3 proposed by Sobrino et al. (2002).

$$\epsilon_{10} = \epsilon_{Vn}P_V + \epsilon_{Sn}(1 - P_V) \quad (3)$$

where: ϵ_{Vn} the emissivity of vegetation to each one of the thermal parts; ϵ_{Sn} the

emissivity of soil for each one of the thermal bands; P_V is the vegetation percentage.

The values of emissivity in bands 10 and 11 related to the vegetation and soil, according to Yu et al. (2014), are respectively $\varepsilon_{V10} = 0,9863$ and $\varepsilon_{V11} = 0,9896$; $\varepsilon_{S10} = 0,9668$ and $\varepsilon_{S11} = 0,9747$. To calculate the PV it was used the Equation 4 proposed by Schirmbeck and Rivas (2007):

$$P_V = 3,333NDVI - 1 \quad (4)$$

When NDVI is put in the interval (0 to 0,3) it is considered bare soil ($P_V = 0$); when the NDVI is in the range of (0,3 to 0,6) it responds to the linear function of two components: soil and vegetation, and when the NDVI is bigger or equal 0,6 ($P_V = 1$) it is considered vegetation.

After NDVI and T_S data collect the TVDI model normalization was made using the characteristic scatter plot triangular form (Price, 1990). In this scatter plot, the average T_{Smin} from the image delimits the humid limit of the evaporative triangle. The dry limit is where the biggest average temperature is found, referencing to the accurate data applying the parameters a and b, that are, respectively, the linear and angular coefficients from the adjusted straight line. The composition of average maximum and minimum temperature was obtained from different bands in the values

of vegetation index.

Having all the TVDI data, the different kinds of vegetal coverage mapped on the classified image were identified in the triangular dispersion that is characteristic of the index to be evaluated. It was also determined the histograms of index frequency to each aim, as well as the scatter plots between the TVDI and NDVI and between TVDI and T_S were made.

3. Results and discussion

The digital classification of image Landsat 8-OLI from 02/07/2015 (Figure 2) showed the occurrence in the study region of six thematic categories, which were: soybean, rice, grassland, bare soil, gallery forest, water and the other unclassified. The class water was not analyzed because the focus of the study was the vegetation. The thematic categories obtained represent the more frequent category of occupation in the whole half of the south of Rio Grande do Sul. So, the obtained results in this work will be able to subsidize the broader analyzes in the state.

The average values and the spatial distribution of NDVI values and of T_S , necessary parameters to determine TVDI, are showed in Table 1 and Figure 3 and 4.

Table 1 – Average data and pattern deviation (DP) of pixels from NDVI, of the surface temperature (T_S) and of TVDI to the five thematic classes in this study.

Category	NDVI		T_S (K)		TVDI	
	<i>average</i>	<i>DP</i>	<i>average</i>	<i>DP</i>	<i>average</i>	<i>DP</i>
Grassland	0,77	0,03	306	0,99	0,75	0,14
Soybean	0,90	0,05	303	1,03	0,34	0,18
Rice	0,83	0,05	301	1,09	0,09	0,12
Bare soil	0,53	0,10	311	2,46	0,82	0,15
Gallery forest	0,86	0,05	301	0,84	0,10	0,13

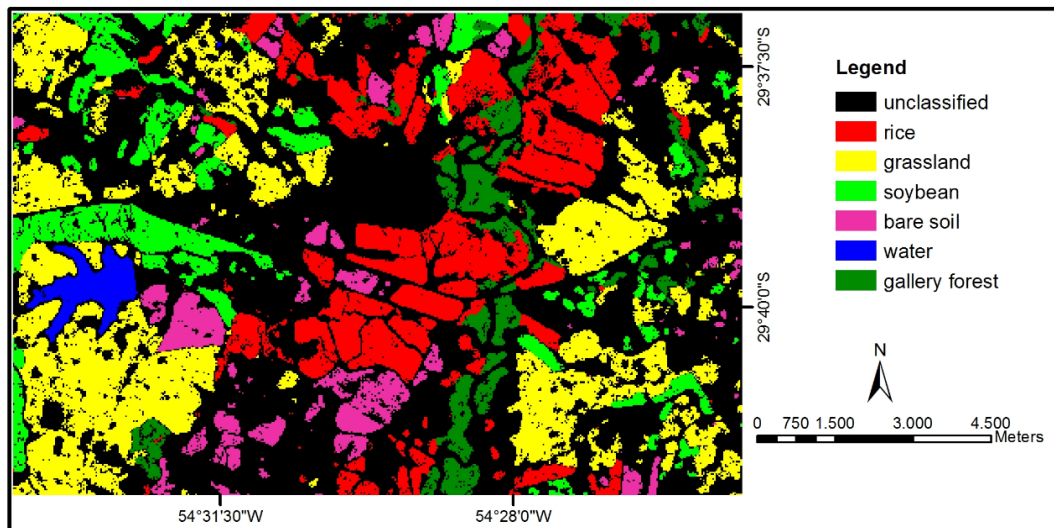


Figure 2 – Classified image by the supervised method of maximum likelihood, image Landsat 8-OLI (path/row – 223/81) from 02/07/2015 the Rio Grande do Sul.

High values of NDVI are associated to the annual cultivations; it happens because the period of image acquisition coincided with the great development vegetative period. In soybean, the average NDVI was 0,90 higher than the one obtained to the rice, with 0,83. Lower values in rice farming are expected due to the kind of plant (gramineous) and to the cultivation system (irrigated) (Jensen, 2009). The gallery forest also presented high values of NDVI, similar to the one observed in the rice farming.

NDVI intermediate values are in the

grassland areas (0,77) which are characterized by presenting herbaceous vegetation, a bit more undergrowth. In the bare soil, NDVI show lowest values comparing to the vegetation cover use, it was expected.. The average value of 0,53, can be considered more elevated than it would be expected to this application, which demonstrates the occurrence of spectral mixture resulting from the size of the Landsat pixel, of 30 x 30 m, being the pattern deviation of 0,1 superior to the other categories that present the values of 0,03 to 0,05.

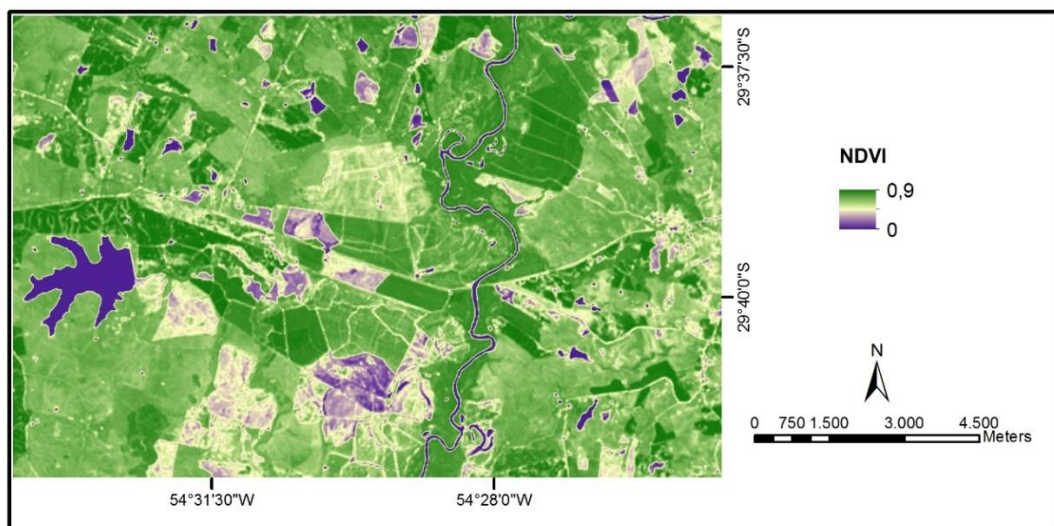


Figure 3 – Spatial distribution of NDVI to the study area, image Landsat 8-OLI (path/row – 223/81) from 02/07/2015, Rio Grande do Sul.

The higher temperature and the higher pattern deviation occurred in the bare soil area, what is expected because there is no vegetation to control the temperature variation. It is known

that if there is the scarce presence of vegetation in the soil/plant system, consequently there is less evapotranspiration and higher temperature (Wang et al., 2006). In these areas, the

temperature average value was 311 K (Table 1). The opposite happened in the areas occupied with rice, which irrigation is made by inundation. The high water availability, associated with the high tax of evapotranspiration, resulted in a reduction of temperature at about 10 K. Gallery forest presented on its temperature, the resemblance of what was observed in NDVI, the same value in rice areas and it happens because of water proximity. In soybean farming, the temperature average value was intermediate (303 K), what is the consequence of an intermediate hydric

condition. As soybean cultivation also occupies lea areas in the rotation with rice cultivation (Mengue and Fontana, 2016) the availability of water, in general, is superior to the grassland in terrains more distant from the water bodies, even when the cultivation is not irrigated. It is highlighted that, in this period, the crop is considered critical to the grains production and, frequently the evaporative demand of atmosphere is usually superior to the water necessary to the crop. In the grasslands, the values were higher with an average of 306 K.

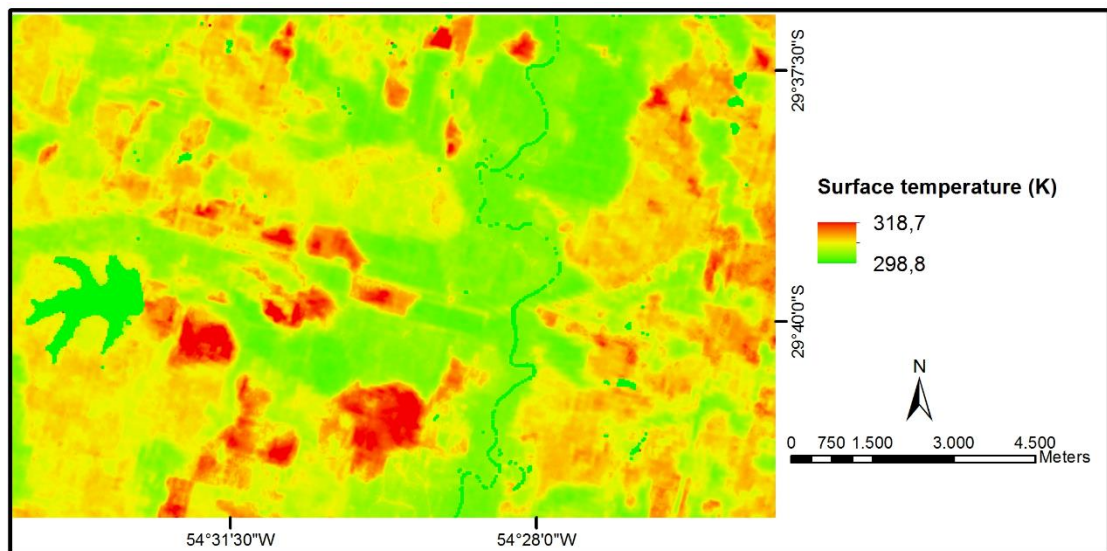


Figure 4 – Spatial distribution of Surface Temperature (T_s) to the area of study, image Landsat 8-OLI (path/row – 223/81) from 02/07/2015, Rio Grande do Sul.

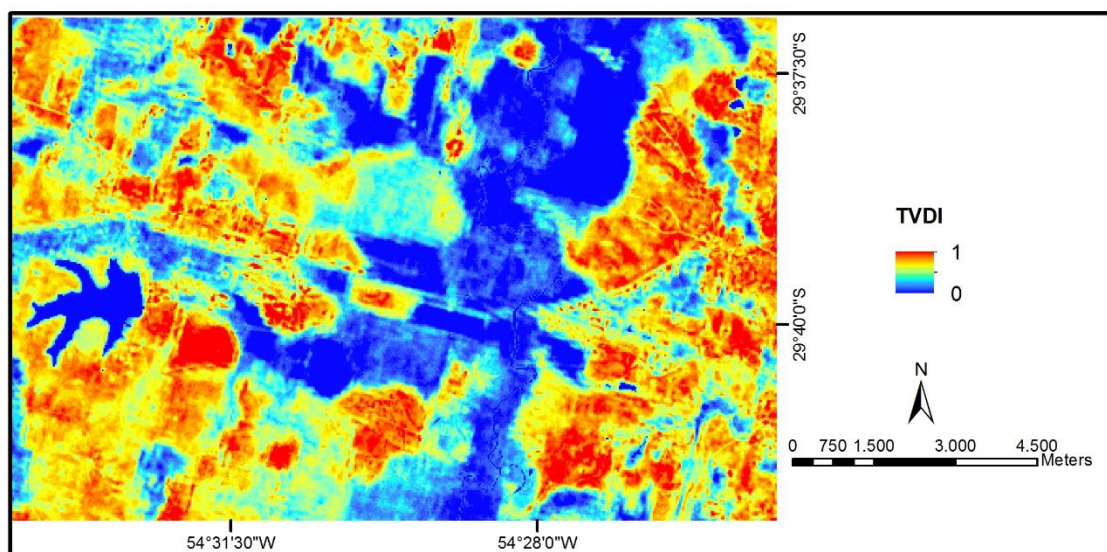


Figure 5 – Spatial distribution of TVDI to the area of study, image Landsat 8-OLI (path/row – 223/81) from 02/07/2015, Rio Grande do Sul.

TVDI spatial distribution to the region of study is presented in Figure 5, in which we observe the high association with temperature spatial distribution (Figure 4), corroborating Liang et al. (2014). There was the big amplitude of variation of TVDI values in the study area. Shallow values occur due to the presence of water and high accumulation of green biomass. The most significant average value was found in the bare soil of 0,82, while the lower occurred in rice areas, with average TVDI of 0,09, and of 0,10 in the gallery forest (Table 1). Again, soybean presented intermediate values in the index (0,35), since the farming in this period had the presence of abundant vegetation in vegetative high strength, however with some lack of water in some farming. Grassland areas presented high indexes according to what was expected by the presence of undergrowth vegetation and also by the practice of grazing without control that compacts the soil causing harm on infiltration (Nabinger et al., 2009). All TVDI values had a similar pattern deviation varying from 0,12 to 0,18.

Scatter plot of T_s and NDVI are presented in Figure 6 to all the image pixels, it was evidenced with different colors each one of the aims. In these scatter plots it is possible to identify the region in what pixels of different categories are concentrated, allowing the understanding of the obtained value to the TVDI index. As some superposition occurs, it is also showed the classes separately in this Figure.

The category bare soil (Figure 6b) had the image pixels concentrated in high temperatures and with a low index of vegetation, having many pixels making part of the dry limit of TVDI.

The inverse pattern was observed to the gallery forest (Figure 6) in what the pixels had a high concentration in NDVI high values and a big part of themselves making part of the humid limit, where TVDI is practically zero. It is highlighted in the straight line of the wet border is where the minimum temperature occurred in this image are concentrated.

Categorized pixels like rice (Figure 6c) again approximate themselves from the gallery forest observed the pattern. In rice farming, as it was previously described, there are low temperatures because of the use of energy to

evapotranspiration the available water, since there is irrigation by inundation and, in this cycle period, the cultivation was found in vegetative high strength, high NDVI.

Soybean (Figure 6c) showed an intermediate pattern between grassland and rice. Some pixels were situated next to or even on the straight line of dry limit highlighting the hydric deficit during the cultivation. There were also pixels on the humid straight line limit, associated with a favorable hydric condition to the crop. As in the image date, the crop presented a high proportion of green biomass because it is in a vegetative state of grain filling, all the pixels are located to the right of the triangle, with high values of NDVI.

Some pixels from the image (Figure 6a) in gray are not categorized, those usually represent the irregular surface, are concentrated at the edge of water course as it was already described by Carlson (2007).

To contribute to the interpretation of results, histograms of every one of the mapped categories can be analyzed by cuts of TVDI of 0,1 (Figure 7), which allows verifying where the majority of the population of the class is concentrated. Rice (Figure 7a) and gallery forest (Figure 7e) presented a distribution with big asymmetry to the left, with the most significant repetitions occurring in shallow values of TVDI (0,2). It is also with the asymmetry to the left, but with more significant scatter plot, with values between 0,2 and 0,5, we could find the pixels on the soybean farming. About the bare soil, (Figure 7a) and grasslands (Figure 7d) more recurring repetitions were bigger in TVDI values.

Analyzing the scatter plot of TVDI and NDVI (Figure 8 a, c, e, g, i) it is observed that the dispersion is significant, that means that the correlation between two variables is very small. The inverse is observed in the scatter plot of TVDI and T_s (Figure 8 b, d, f, h, j), with less dispersion and high coefficients of determination. That indicates that TVDI presents a high dependence of T_s , which has an immediate and faster answer to the situations of hydric restriction (Wang et al., 2006). NDVI presents more conservative and slower response to the biomass alteration facing the poor hydric restriction conditions.

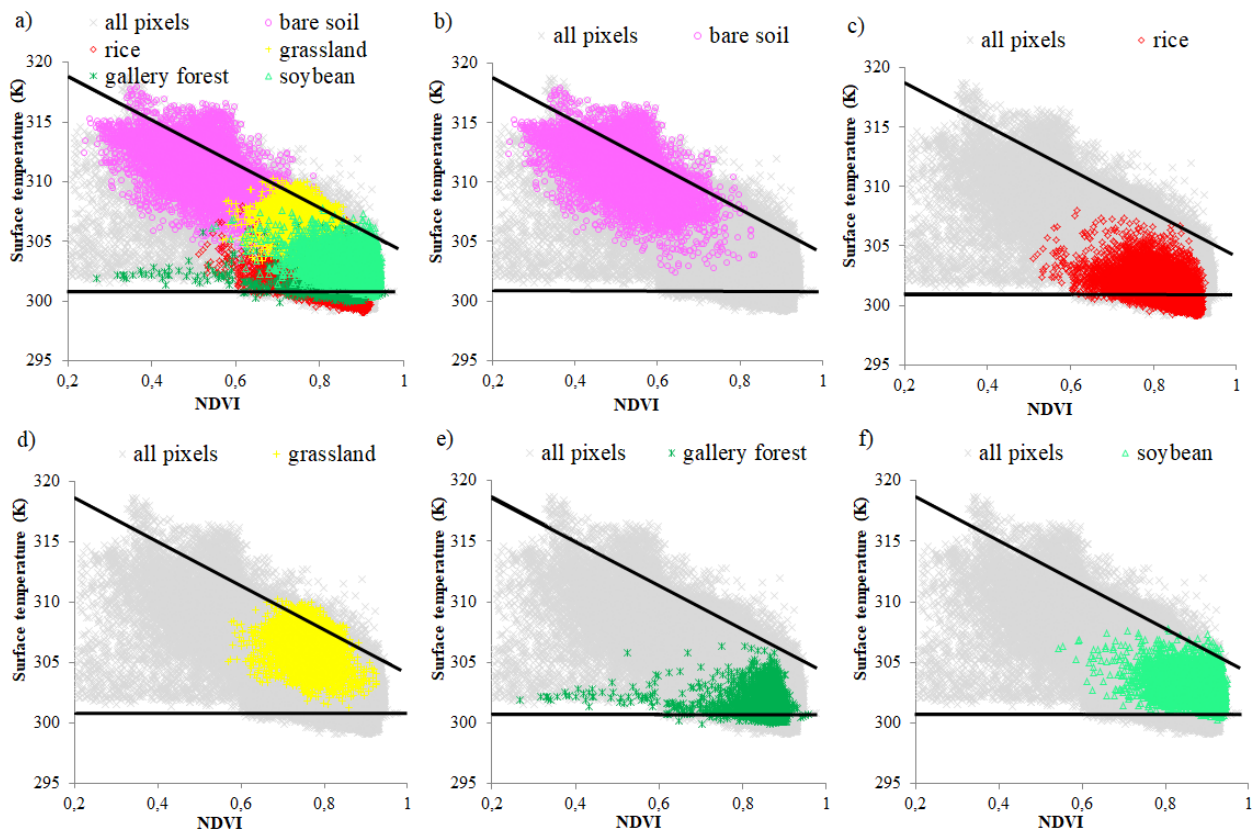


Figure 6 – Scatter plots of Surface Temperature (T_s) and NDVI to all the pixels from the image, bare soil, rice, grassland, gallery forest, and soybean.

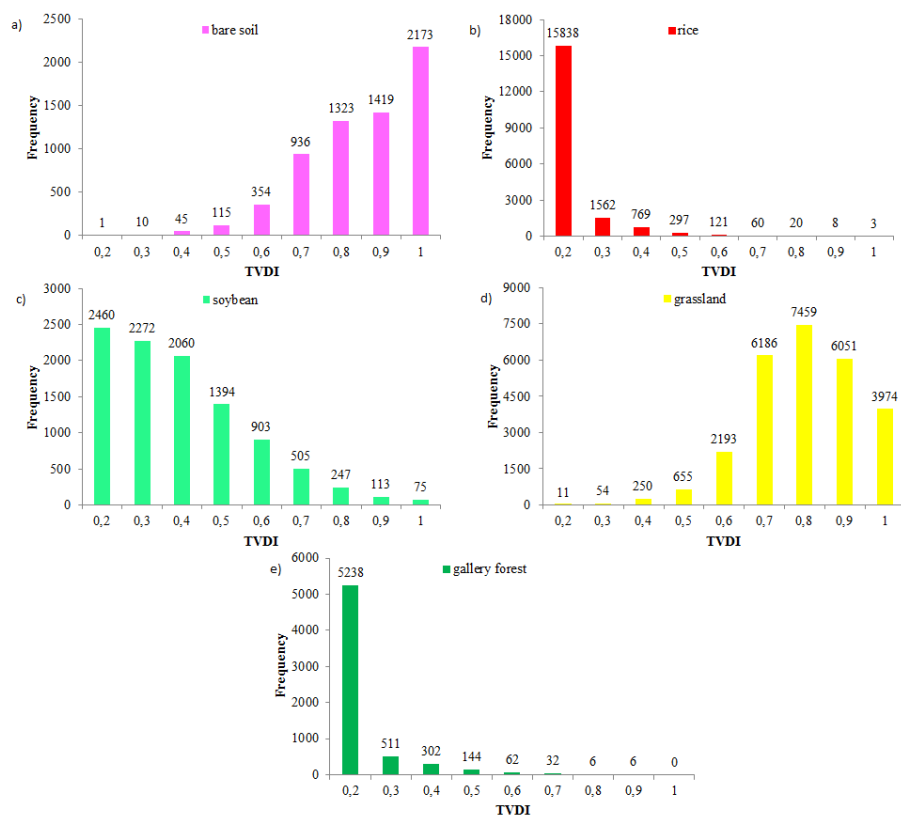


Figure 7 – Histograms to the aims of bare soil, rice, grassland, gallery forest, and soybean.

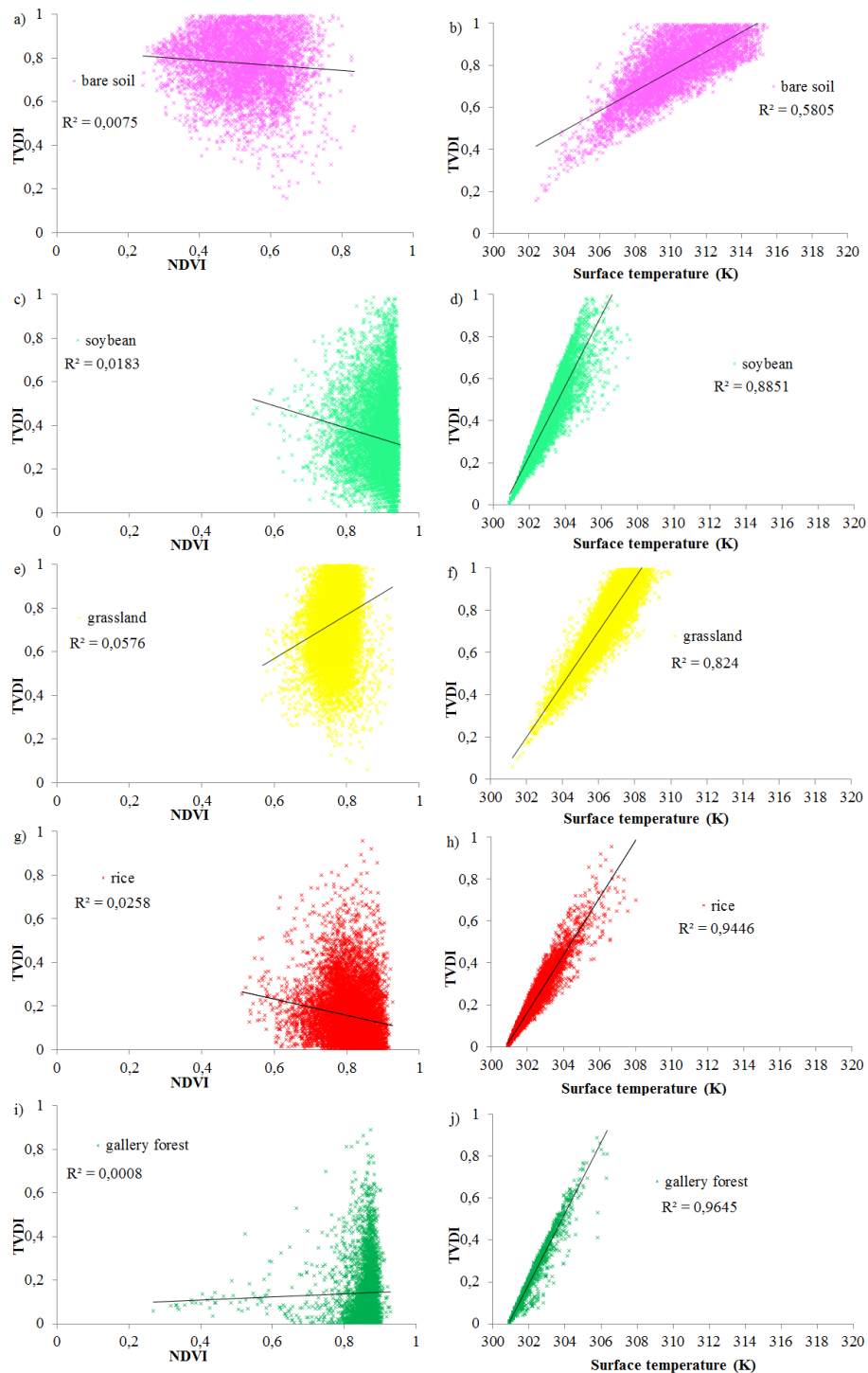


Figure 8 - Scatter plots of TVDI and NDVI (a, c, e, g, i), and TVDI and T_s (b, d, f, h, j) to bare soil, soybean, grassland, rice and gallery forest.

4. Conclusions

TVDI index, when it was obtained from a bi dimensional space defined by the proportion of green biomass and the surface temperature, shows a consistent theorist base that allows locating the aims in this area, promoting the understanding of their hydric condition.

The TVDI can, therefore, be used for monitoring purposes and sustainable management of Pampa biome.

Acknowledgments

To CNPq for the financial support to the research, project 456.585/2014-1 and to CAPES for the grant provided.

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