Journal of Agriculture and Ecology Research International
8(3): 1-10, 2016; Article no.JAERI.20623
ISSN: 2394-1073

SCIENCEDOMAIN *international*
www.sciencedomain.org

Applicability of Monitoring Peanut Reflectance Using Hyperspectral Data for Precision Agriculture in East Nile Delta, Egypt

M. M. El-Sharkawy[1*], E. Farg[2], S. M. Arafat[2] and M. S. Abd El-Wahed[3]

[1]Department of Soil and Water, Faculty of Agriculture, Beni-Suef University, Egypt.
[2]Department of Agriculture Applications, National Authority for Remote Sensing and Space Sciences (NARSS), Egypt.
[3]Department of Soil, Faculty of Agriculture, Ain Shams University, Egypt.

Authors' contributions

This work was carried out in collaboration between all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/JAERI/2016/20623
Editor(s):
(1) Daniele De Wrachien, Department of Agricultural and Environmental Sciences of the State University of Milan, Italy.
Reviewers:
(1) Shin Nagai, Japan Agency for Marine-Earth Science and Technology (JAMSTEC), Japan.
(2) Artemi Cerda, University of Valencia, Spain.
Complete Peer review History: http://sciencedomain.org/review-history/15203

Short Research Article

Received 1st August 2015
Accepted 23rd February 2016
Published 28th June 2016

ABSTRACT

Hyperspectral ground measurements can be used for giving timely information about crops in specific areas and thereby providing valuable data for decision makers. In the current study, ASD field Spec4 spectroradiometer were used to monitor the variation and differences of the summer crop vegetation cover reflectance. Furthermore, two hyperspectral vegetation indices calculated from the data represented by Normalized Difference Vegetation Index $NDVI_{HS}$ and Soil Adjusted Vegetation Index $SAVI_{HS}$ in east Nile Delta, Egypt. The results obtained showed that the mid-season stage had the highest values of calculated VI's that return to the high reflection from the plant canopy at the near infrared and high absorption at the red wavelength, also the initial growth stage VI's values lower than the mid- season stage and higher than the late season. In addition, the analysis of spectral signatures differences showed the late growth stage was the highest reflection overall the visible range (blue, green and red). Results of Tukey's HSD showed that blue,

**Corresponding author: E-mail: mohamed200802@yahoo.com;*

Red and NIR spectral zones are more sufficient in the monitoring differences between peanut growth stages than green, SWIR-1 and SWIR-2 spectral zones.

Keywords: Peanut reflectance; hyperspectral indices; arid land.

1. INTRODUCTION

Food security is the backbone of the developing countries. Egypt still one of the most importing food production in the entire world, to solve this problem we have to increase crop yield. High yields achievement requires an understanding of main factors that affect yield, such as improving soil quality, managing irrigation water and nitrogen fertilizers application [1]. Farming system is included numerous components, however the varieties that exist inside of a field can be abridged in three classes of variety; namely natural variations like soil variation and topography; random variations such as rainfall variation and managed variations such as the seed or fertilizer application [2]. Peanut (*Arachis hypogaea* L.) is an important food crop in summer season. Egypt is a major peanut exporting country with planted area at 0.6 million hectares and estimated production about 0.2 million tons for 2015/2016 production year [3]. One of the most important retrieved information from remote sensing is vegetation indices, many studies were applied for monitoring reflectance of strategic summer and winter crops; however few reviews were applied in peanut reflectance. Quantitative estimations of plant biochemical and biophysical variables can be accomplished by the estimation of reflected radiation from plant leaves and canopies [4,5,6,7]. [8] suggested a new 12 hyperspectral narrow-wavebands for predicting some of the plant biophysical components based on ground level reflectivity measurements of soybeans, potato, cotton, corn, and sunflower gathered using a field spectroradiometer having 490 hyperspectral narrow-wavebands between 350 and 1050 nanometers. The waveband centers and the waveband widths are: $\lambda_1 = 0.495\ \mu m$ ($\Delta\lambda_1 = 0.030\ \mu m$), $\lambda_2 = 0.525\ \mu m$ ($\Delta\lambda_2 = 0.020\ \mu m$), $\lambda_3 = 0.550\ \mu m$ ($\Delta\lambda_3 = 0.020\ \mu m$), $\lambda_4 = 0.568\ \mu m$ ($\Delta\lambda_4 = 0.010\ \mu m$), $\lambda_5 = 0.668\ \mu m$ ($\Delta\lambda_5 = 0.004\ \mu m$), $\lambda_6 = 0.682\ \mu m$ ($\Delta\lambda_6 = 0.004\ \mu m$), $\lambda_7 = 0.696\ \mu m$ ($\Delta\lambda_7 = 0.004\ \mu m$), $\lambda_8 = 0.720\ \mu m$ ($\Delta\lambda_8 = 0.010\ \mu m$), $\lambda_9 = 0.845\ \mu m$ ($\Delta\lambda_9 = 0.070\ \mu m$), $\lambda_{10} = 0.920\ \mu m$ ($\Delta\lambda_{10} = 0.020\ \mu m$), $\lambda_{11} = 0.982\ \mu m$ ($\Delta\lambda_{11} = 0.030\ \mu m$), and $\lambda_{12} = 1.025\ \mu m$ ($\Delta\lambda_{12} = 0.010\ \mu m$).

The principle behind NDVI is that red band where chlorophyll causes considerable absorption of incoming sunlight, whereas the near infrared (NIR) band where a plant's spongy-mesophyll leaf structure creates considerable reflectance. NDVI values vary according to the growth stage [9,10], also according to [11] the Soil-Adjusted Vegetation Index (SAVI) is the best index utilized to describe the arid areas or parched vegetation areas, knowing the sparse distribution of vegetation between bared soil patches. Soil is a complex system that is relevant for the Earth System functioning besides its major role in food production [12-19]. Hyperspectral remote sensing is a precision agricultural tool which can be utilized to enhance the crop production [20]. In terms of associating with plant biochemical information hyperspectral indices or narrow-band indices were appeared to be more exact than broad band indices, due to small physiological changes are usually detectable at particular wavelengths [21]. Also when the soil is damaged the recovery is very expensive, and precision agriculture can help to avoid this mismanagement [22-27]. Remote sensing imagery with soil data analyses allowed for the identification of spatial pattern of crop growth variability [28]. Utilizing vegetation indices calculated from remote sensing data such as the Normalized Deference Vegetation Index (NDVI), has been examined to estimate crop coefficients within the field and also examined for regional scales [29 and 30]. [31] Indicated that using the soil suitability model and a sufficient numerous of field observations within each strata or class, an acceptable accuracy and good spatial distribution of the suitability classification was achieved. Furthermore, using automated variable rate sprayers combined with site-specific management for herbs infection areas are greatly responsible for lowering cost of herbicides and decreasing environmental impact, through applying the least amount of herbicides necessary. According to [32] physiological spectral indices of growth stages have significant correlations between varied classes productivity and similarity of spectral measures, referring to similarity between the samples' spectra decreases as the pigments concentration in the plant leaves increases, which offer as a precision agriculture tool to manage crop variations within fields that can affect crop yield. [32] also indicated that in the range of 350–1000 nm, the red-edge (705-750 nm) is the most sensitive spectral region for assessing vegetation healthy, for peanut spectral. However, the degree of significance is dictated by the particular band arrangement formation of the hyperspectral sensor as well as the crop and the results of Tukey's HSD showed that blue, green and NIR spectral zones are more sufficient in the discrimination between peanut growth stages than red, SWIR-1 and SWIR-2 spectral zones. Furthermore, electromagnetic peanut crop mapping was successfully employed to simulate vegetation healthy effect on canopy structure and final yield.

Many previous studies have tested similarity between the seasonal trend of different vegetation indices and annual crops transpiration [33-39]. This study will focus on highlighting the variation and differences in one of the major summer crop vegetation cover reflectance using hyperspectral ground measurements of ASD field Spec4 spetroradiometer.

2. MATERIALS AND METHODS

2.1 Study Area

The study area is located in Ismailia governorate in east Nile Delta, Egypt. The area is bounded by 30^{o} 29′ 00″ N and 30^{o} 30′ 00″ N latitude and 31^{o} 56′ 00″ E and 31^{o} 57′ 00″ E longitude. The study area located in arid land and the region climate is arid Mediterranean type with an average annual precipitation of about 20 mm and temperature 18 c^{o}. The whole area of the current study represented by one pivot within area about 67 hectares, cultivated with peanut crop and irrigated using Ismailia canal branched from Nile River with Total Dissolved Salts (TDS) of 544 $mg.L^{-1}$. The investigation was applied on 63 hectares, shown in Fig. 1. Generally the soil in the study area is sandy clay loam, relatively moderate permeable.

2.2 Field Data

The data collected for 8 samples systematic randomly distributed to cover the variation of crop overall the investigated area. Samples collected with interval of 30 days starting from 60 days after plantation representing initial growth stage, 90 days after plantation representing the mid-season growth stage and 120 days after plantation represents the late season growth stage.

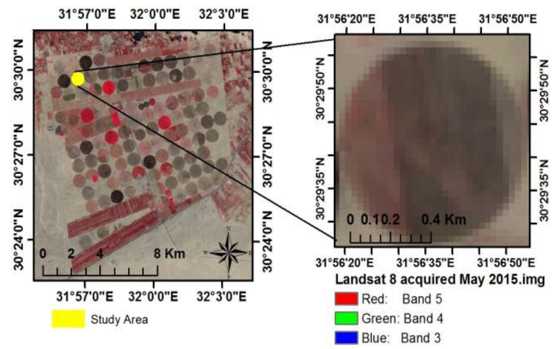

Fig. 1. Location of study area Landsat 8 image in false color composition

Analytical Spectrum Device (ASD Field Spec) is hyper-spectral sensor used to measure the reflection of different terrestrial targets such as peanut or other plants in a wide optical spectral range (Visible range– Near Infrared range – Short Wave Infrared range) starting from 350 nm to 2500 nm with one nanometer (nm) sampling interval output spectral data. The sampling interval is different at 350-1050 nm and 1000-2500 nm 1.4 nm and 2 nm respectively. These are the intervals which the device is capturing the reflectance the device itself making an interpolation for the data automatically and gives the final data output with 1 nm interval for the all spectrum range 350-2500 nm. Hyperspectral data of handheld spectroradiometer reflectance measurements Both of NDVI developed by [7] Equation 1 as the most known and widely used vegetation index. On the other hand, to account for changes in the soil and detecting the land optical characteristics, soil adjusted indices minimizing the background influence had developed. The leading index in such improvement is the SAVI [11] which includes a canopy background adjustment factor L using narrow bands, SAVI Equation 2.

$$NDVI = \frac{(\rho_{800} - \rho_{670})}{(\rho_{800} + \rho_{670})} \qquad (1)$$

$$SAVI = (1 + L) * \frac{(\rho_{800} - \rho_{670})}{(\rho_{800} + \rho_{670} + L)} \qquad (2)$$

2.3 Comparing Standard Deviations from Several Populations

Analysis of variance (ANOVA) methods are for comparing means from several populations or processes. While similar methods are occasionally used for comparing several standard deviations (sd), usually by using the natural logarithm of sample variances as the response variable. When using ANOVA models with collected data from designed experiments for statistical analysis, an important assessment is given by the F-max test of the assumption of constant standard deviations (sd) across the combinations of k factor-level. The F-max test is utilized to test the theories [40] Equation 3.

$$F_{\max} = \left(\frac{\max(s_i)}{\min(s_i)}\right)^2 \quad (3)$$

2.4 Multiple Comparisons

Multiple comparisons of means frequently involve preselected comparisons that address specific questions. For example, an researcher has interest in the existence of overall experimental effects; consequently, the summaries provided by an ANOVA table are of secondary interest, perhaps only to provide an estimate of the experimental error variance. In contrast, researchers in many experimental settings do not know which factor effects may turn out to be measurably or statistically noteworthy. If so, the *F*-statistics in an ANOVA table produce the main information source on statistically noteworthy factor or significant variable impacts. Although, after an *F*-test in an ANOVA table has shown significance, an experimenter usually wishes to conduct further examinations to figure out which sets of means or which groups of means are significantly different from one another [40]. Tukey's significant difference procedure (TSD) is a similar technique to Fisher's LSD procedure. It differs mainly in the range of the *k* averages, furthermore the critical point calculated from the range statistic distribution, not obtained from the *t*-distribution [40]. Moreover, if there are a set of means (A, B, C, D), which can be ranked in the order A > B > C > D, basically not the whole possible comparisons between the groups of means need be examined using Tukey's test.

3. RESULTS

Fig. 2 show the results of the collected hyperspectral data measurements at 30 cm height above plant canopy at each growth stage. The means of spectral measurements, of Peanut crop, through three stage growth, were processed to illustrate the peanut spectral behavior through three stage growth. Moreover, the calculation of the averaged spectra of peanut crop samples enabled to compare the spectral behavior through the different growth stages and test the significance of spectral variation, through spectrum of 350- 2500, of peanut's different growth stages. The graphical presentation of the spectral means indicated that there are significant differences at certain spectrum wavelength and similar at other one.

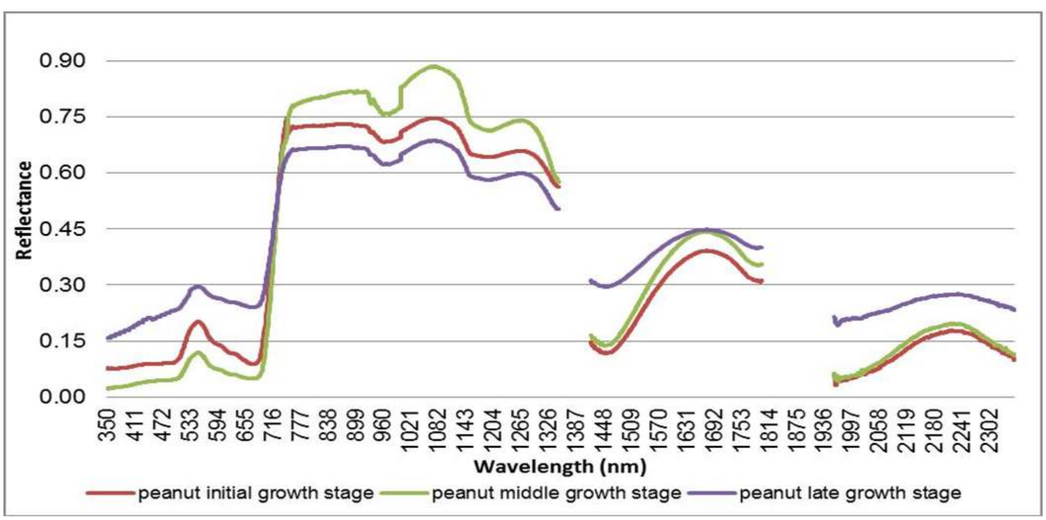

Fig. 2. Mean hyper-spectral signature of peanut crop for each growth stages 2015 season

The data revealed as shown in Tables 1, 2, 3 and 4 as well as Figs. 3, 4 and 5 show that the differences between all growth stages reflectance in visible wavelength 350-450 nm, 450-550 nm and 550-700 nm that represent blue, green and red respectively were significantly different. The cause of high reflectance values of the late season growth stage along the visible range of the spectrum is the peanut crop leaves turning from the green to yellow color.

Moreover, for both of mid-season and initial growth stages were follow the same trend, while the initial growth stage reflectance values were higher than mid- season that is return to the influence of the soil background, where soil is reflect higher at the visible range than the vegetation, mean reflectance. Our results agreed with [41] stated that absorption is essentially a function of changes in the spin and angular momentum of electrons, where visible range spectral response affected by chlorophylls a and b, carotenoids, brown pigments, and other accessory pigments.

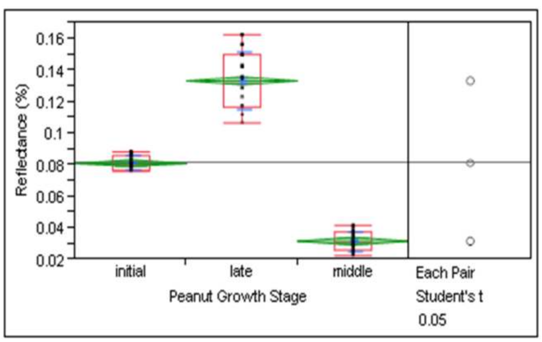

Fig. 3. One-way ANOVA analysis Tukey's HSD test for blue range

Meanwhile, Table 4 and Fig. 6 illustrate the differences between all growth stages reflectance at the near- infrared NIR range 700-1000 nm, where the mid-season growth stage was the highest reflectance, where it is highest vegetative stage. The initial growth stage was lower as result of low vegetation cover and plant leaves still in the developing phase that result less reflection at the NIR range. Furthermore, the reflectance of the late season growth stage at the NIR range was the lowest because of changes in leaves structure. That agreed with [24] who stated that internal structure of the leaves of the plant manage the spectral reflectance and the transmission on the whole spectrum, but this appears more clearly where the absorption is low, especially in the near infrared domain.

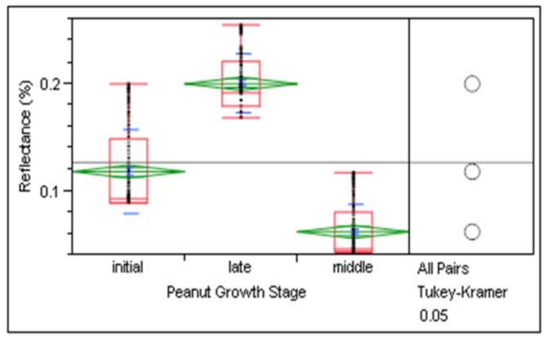

Fig. 4. One-way ANOVA analysis Tukey's HSD test for green rage

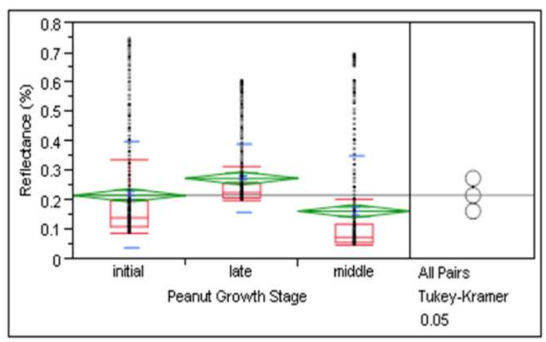

Fig. 5. One-way ANOVA analysis Tukey's HSD test for red range

Table 1. Significance of difference between peanut growth stages according to Tukey's for blue range

G. stages	Mean reflectance				Summary of fit for means comparisons for all pairs	
Initial	C			0.07	Adj Rsquare	0.93
Middle		B		0.03		
Late			A	0.13	Observations	300

*Levels not connected by same letter are significantly different

Table 2. Significance of difference between peanut growth stages according to Tukey's for green range

G. stages	Mean reflectance				Summary of fit for means comparisons for all pairs	
Initial	C			0.12	Adj Rsquare	0.76
Middle		B		0.06		
Late			A	0.20	Observations	300
*Levels not connected by same letter are significantly different						

Table 3. Significance of difference between peanut growth stages according to Tukey's for red range

G. stages	Mean reflectance				Summary of fit for means comparisons for all pairs	
Initial	B			0.22	Adj Rsquare	0.07
Middle		C		0.16		
Late			A	0.28	Observations	600
*Levels not connected by same letter are significantly different						

Table 4. Significance of difference between peanut growth stages according to Tukey's for NIR range

G. stages	Mean reflectance				Summary of fit for means comparisons for all pairs	
Initial	B			0.79	Adj Rsquare	0.94
Middle		A		0.72		
Late			C	0.62	Observations	750
*Levels not connected by same letter are significantly different						

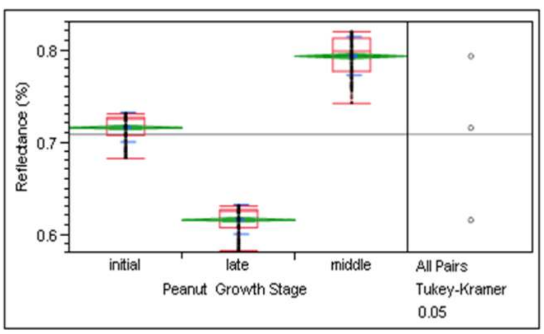

Fig. 6. The results of one-way ANOVA analysis Tukey's HSD test for near infrared range

Moreover, the results show in Tables 5 and 6 also illustrated in Figs. 7 and 8 that difference between growth stages reflectance along the shortwave infrared (1000-1800 nm) and (1800-2500 nm) represent SWIR1 and SWIR2, respectively. The reflectance values at SWIR1 in the different growth stages were similar and almost had the same trend. On the other hand, the reflectance varies along SWIR2 depending on the plant water content and the water stress.

The comparison of reflectance value of the different spectrum's regions generally indicated that the plant leaf typically has a low reflectance in the visible spectral region because of strong absorption by chlorophylls, a relatively high reflectance in the near-infrared because of internal leaf scattering and a relatively low reflectance in the shortwave ranges because of strong absorption by water. The Spectral indices of growth stages of difference peanut growth stages are shown in Table 7.

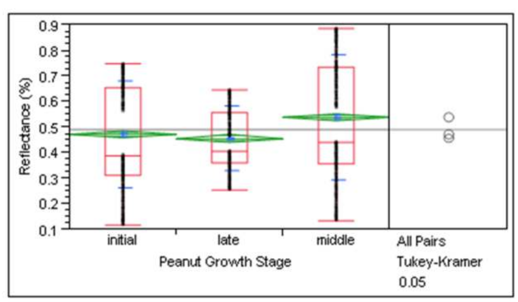

Fig. 7. Results of one-way ANOVA analysis Tukey's HSD test for first Short Wave Infra-Red SWIR range

Tables 8 and 9 represent the differences between $NDVI_{HS}$ and $SAVI_{HS}$ values for each growth stage. The interpretations of the calculated vegetation indices from hyper-spectral data show that NDVI and SAVI values were lowest at initial growth stage and ascending increased to reach optimum values at mid-season growth stage, while these values decreased at the late season growth stage. This may be attributed to the development of peanut crop growth, whereas peanut plants start to convert the entire nutrients uptake into peanut nuts during the late growth stage at the end of the growth season.

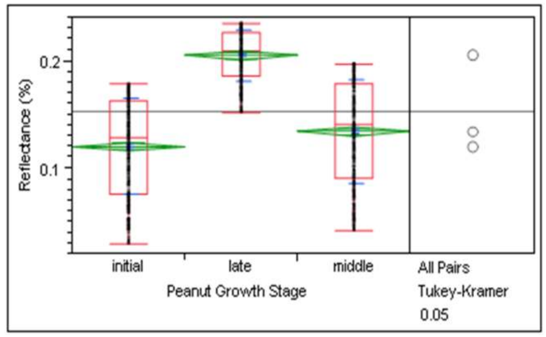

Fig. 8. Results of one-way ANOVA analysis Tukey's HSD test for second Short Wave Infra-Red SWIR range

Table 5. Significance of difference between peanut growth stages according to Tukey's for SWIR1 range

G. stages	Mean reflectance				Summary of fit for means comparisons for all pairs	
Initial	C			0.54	Adj Rsquare	0.03
Middle		B		0.47		
Late			A	0.46	Observations	2184

*Levels not connected by same letter are significantly different

Table 6. Significance of difference between peanut growth stages according to Tukey's for SWIR2 range

G. stages	Mean reflectance				Summary of fit for means comparisons for all pairs	
Initial	C			0.21	Adj Rsquare	0.46
Middle		B		0.13		
Late			A	0.12	Observations	1197

*Levels not connected by same letter are significantly different

Table 7. Spectral indices of growth stages of difference peanut growth stages

	Wavelength (nm)					
Range (nm)	**446-450**	**450-455**	**640-655**	**660-670**	**1115-1125**	**2160-2200**
Center (nm)	449	452	645.6	662.6	1120	2180
Spectral indices	β-Cryptoxanthin	β-Carotene	Chlorophyll b	Chlorophyll a	Lignin	Nitrogen
References	**Rodriguez-Amaya & Kimura 2004**		**Lichtenthaler H.K. & Wellburn A.R., 1983**		**Murray et al. 2008 Huang et al. 2004**	
Initial G. stage	0.0887	0.0889	0.1059	0.0921	0.7234	0.1654
Midlle G. stage	0.0421	0.0424	0.0549	0.0493	0.8549	0.1835
Late G. stage	0.1627	0.1681	0.2084	0.2023	0.6234	0.2304

Table 8. Descriptive statistics (minimum, maximum, average values and standard deviation for $NDVI_{HS}$)

Variables stage	Minimum	Maximum	Mean	Standard error	Standard deviation	Count
Initial	0.03	0.27	0.14	0.01	0.07	52
Middle	0.2	0.57	0.39	0.01	0.11	65
Late	0.1	0.69	0.47	0.01	0.13	78

Table 9. Descriptive statistics (minimum, maximum, average values and standard deviation for $SAVI_{HS}$)

Variables stage	Minimum	Maximum	Mean	Standard error	Standard deviation	Count
Initial	0.02	0.25	0.12	0.01	0.07	52
Middle	0.15	0.59	0.38	0.02	0.13	65
Late	0.1	0.61	0.47	0.01	0.13	78

4. CONCLUSION

The results showed that the spectral signatures of the initial mid-season, late season stage were different at certain ranges and similar at another. The differences appear clearly at visible, near infrared and second shortwave ranges. At the first shortwave range both of mid-season and initial season growth stages were similar to each other. Also the results of the calculated VI's show mid- season stage had the highest values of calculated VI's that return to the high reflection from the plant canopy at the near infrared and high absorption at the red wavelength. That is the cause of mid- season growth stage being the highest vegetative stage. Where differences of spectral signatures showed that late growth stage was the highest reflection overall the visible range (blue, green and red). On the other hand, the initial growth stage VI's values lower than the mid- season stage and higher than the late season.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Hatfield JL, Prueger JH. Increasing nitrogen use efficiency of corn in Midwestern cropping systems. Proceedings of the 2nd International Nitrogen Conference on Science and Policy. The Scientific World. 2001; 1(S2):682-690.
2. Hatfield JL, Sauer TJ, Prueger JH. Managing soils for greater water use efficiency: A review. Agronomy Journal. 2001;93:271-280.
3. USDA. World Agricultural Production, Foreign Agricultural Service / Office of Global Analysis, International Production Assessment Division (IPAD / PECAD), South Building, Washington, DC 20250-1051; 2015.

   Available: http://www.pecad.fas.usda.gov/
4. Carrol MW, Glaser JA, Hellmich RL, Hunt TE, Sappington TW, Calvin D, Copenhaver K, Fridgen J. Use of spectral vegetation indices derived from airborne hyperspectral imagery for detection of European corn borer infestation in Iowa corn plots. Journal of Economic Entomology. 2008;101:1614–1623.
5. Carter GA, Knapp AK. Leaf optical properties in higher plants: linking spectral characteristics to stress and chlorophyll concentration. American Journal of Botany. 2001;88:677–684.
6. Carter GA, Miller RL. Early detection of plant stress by digital imaging with narrow stress-sensitive wavebands. Remote Sensing of Environment. 1994;50:295–302.
7. Daughtry CST, Walthall CL, Kim MS, Brown de Colstoun E, Mc Murtrey JE. Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. Remote Sensing of Environment. 2000;74:229–239.
8. Prasad S. Thenkabail, Ronald B. Smith, Eddy De Pauw. Hyperspectral vegetation indices for determining agricultural crop characteristics. Center for Earth Observation (CEO), Yale University; 2001.

9. Rouse JW, Haas RH, Schell JA, Deering DW, Harlan JC. Monitoring the vernal advancement and retrogradation of natural vegetation. NASA/GSFC, Type III, Final Re-port, Greenbelt, MD. 1974;1–371.
10. Tucker CJ, Dregne HE, Newcomb WW. Expansion and contraction of the sahara desert from 1980 to 1990. Science, New Series. 1991;253(5017):299-300.
11. Huete A. A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment. 1988;25:295–309.
12. Berendse F, van Ruijven J, Jongejans E, Keesstra SD. Loss of plant species diversity reduces soil erosion resistance of embankments that are crucial for the safety of human societies in low-lying areas. Ecosystems. 2015;18:881-888. DOI: http://dx.doi.org/10.1007/s10021-015-9869-6
13. Keesstra SD, Geissen V, van Schaik L, Mosse K, Piiranen S. Soil as a filter for groundwater quality. Current Opinions in Environmental Sustainability. 2012;4:507-516.
DOI:http://dx.doi.org/10.1016/j.cosust.2012.10.007
14. Brevik EC, Cerdà A, Mataix-Solera J, Pereg L, Quinton JN, Six J, Van Oost K. The interdisciplinary nature of SOIL. SOIL. 2015;1:117-129.
DOI:http://dx.doi.org/10.5194/soil-1-117-2015
15. Parras-Alcántara L, Martín-Carrillo M, Lozano-García B. Impacts of land use change in soil carbon and nitrogen in a Mediterranean agricultural area (Southern Spain). Solid Earth. 2013;4(1):167-177. DOI:http://dx.doi.org/10.5194/se-4-167-2013
16. Paz-Ferreiro J, Lu H, Fu S, Méndez A, Gascó G. Use of phytoremediation and biochar to remediate heavy metal polluted soils: A review. Solid Earth. 2014;5(1):65-75.
DOI:http://dx.doi.org/10.5194/se-5-65-2014
17. Novara A, Gristina L, Guaitoli F, Santoro A, Cerdà A. Managing soil nitrate with cover crops and buffer strips in Sicilian vineyards. Solid Earth. 2013;4(2): 255-262. DOI:http://dx.doi.org/10.5194/se-4-255-2013
18. Zhao G, Mu X, Wen Z, Wang F, Gao P. Soil erosion, conservation, and eco-environment changes in the loess plateau of china. Land Degradation and Development. 2013;24(5):499-510.
DOI: http://dx.doi.org/10.1002/ldr.2246
19. De Souza Braz AM, Fernandes AR, Alleoni LRF. Soil attributes after the conversion from forest to pasture in Amazon. Land Degradation and Development. 2013; 24(1):33-38.
(Cited 10 times)
DOI: http://dx.doi.org/10.1002/ldr.1100
20. Mekuria W, Aynekulu E. Exclosure land management for restoration of the soils in degraded communal grazing lands in northern Ethiopia. Land Degradation and Development. 2013;24(6):528-538.
(Cited 6 times)
DOI: http://dx.doi.org/10.1002/ldr.114
21. Sovoe S. Mapping irrigated area fragments for crop water use assessment using handheld spectroradiometer. International Journal of Agronomy. 2011;2011:1-8.
22. Giménez Morera A, Ruiz Sinoga JD, Cerdà A. The impact of cotton geotex-tiles on soil and water losses in Mediterranean rainfed agricultural land. Land Degradation and Development. 2010;210-217.
DOI: http://dx.doi.org/10.1002/ldr.971
23. Mekonnen M, Keesstra SD, Stroosnijder L, Baartman JEM, Maroulis J. Soil conservation through sediment trapping: A review. Land Degradation and Development; 2015.
DOI: http://dx.doi.org/10.1002/ldr.2308
24. Mekonnen M, Keesstra SD, Baartman JE, Ritsema CJ, Melesse AM. Evaluating sediment storage dams: Structural off-site sediment trapping measures in northwest Ethiopia. Cuadernos de Investigación Geográfica. 2015;41(1):7-22.
DOI: http://dx.doi.org/10.18172/cig.2643
25. Bai XY, Wang SJ, Xiong KN. Assessing spatial-temporal evolution processes of Karst Rocky Desertification Land: Indications For Restoration Strategies. Land De-gradation and Development. 2013;24(1):47-56.
DOI: http://dx.doi.org/10.1002/ldr.1102
26. Tejada M, Benítez C. Effects of crushed maize straw residues on soil biological properties and soil restoration. Land Degradation and Development. 2014; 25(5):501-509.
DOI: http://dx.doi.org/10.1002/ldr.2316
27. Roa-Fuentes LL, Martínez-Garza C, Etchevers J, Campo J. Recovery of soil C and N in a tropical pasture: Passive and active restoration. Land Degradation and Development. 2015;26(3):201-210.
DOI: http://dx.doi.org/10.1002/ldr.2197

28. El-Sharkawy MM, Sheta AS, Abd El-Wahed MS, Arafat SM, El Behiery OM. Precision agriculture using remote sensing and GIS for peanut crop production in arid land. International Journal of Plant & Soil Science. 2016;10(3):1-9.
DOI: 10.9734/IJPSS/2016/20539
29. Peñuelas J, Baret F, Filella I. Semiempirical indices to assess carotenoids/chlorophyll a ratio from leaf spectral reflectance. Photosynthetica. 1995;31: 221–230.
30. Rouse JW, Haas RH, Schell JA, Deering DW. Monitoring vegetation systems in the great plains with ERTS. Third ERTS Symposium, NASA SP-351 I: 309-317; 1974.
31. El-Sharkawy MM, Abd El-Hady AM, Arafat SM, Aggag AM. Precision farming using remote sensing and GIS to improve soil and potato crop management. Journal of Agriculture and Environmental Science. 2013;21(1):8-16.
32. El-Sharkawy MM, Sheta AS, Arafat SM, Abd El-Wahed MS. Precision agriculture using advanced remote sensing techniques for peanut crop in arid land. Journal of Hyperspectral Remote Sensing. 2016;6(1):72-81.
DOI: 10.5935/2237-2202.20160007
33. Jackson RD, Idso SB, Reginato RJ, Pinter PJ. Remotely sensed crop temperatures and reflectance as inputs to irrigation scheduling. In Irrigation and Drainage: Today's Challenges; ASCE: New York, NY, USA. 1980;390-397.
34. Bausch WC. Soil background effects on reflectance-based crop coefficients for corn. Remote Sensing of Environment. 1993; 46:213-222.
35. Bausch WC. Remote sensing of crop coefficients for improving the irrigation scheduling of corn. Agriculture Water Management. 1995;27:55-68.
36. Hunsaker DJ, Pinter PJ Jr., Barnes EM, Kimball BA. Estimating cotton evapotranspiration crop coefficients with a multispectral vegetation index. Irrigation Science. 2003;22:95-104.
37. Hunsaker DJ, Pinter PJ Jr., Kimball BA. Wheat basal crop coefficients deter-mined by normalized difference vegetation index. Irrigation Science. 2005;24:1-14.
38. Duchemin B, Hadria R, Er-Raki S, Boulet G, Maisongrande P, Chehbouni A, Escadafal R, Ezzahar J, Hoedjes J, Karrou H, Khabba S, Mougenot B, Olioso A, Rodriguez JC, Simonneaux V. Monitoring wheat phenology and irrigation in Central Morocco: On the use of relationship between evapotranspiration, crops coefficients, leaf area index and remotely-sensed vegetation indices. Agriculture Water Management. 2006;79:1-27.
39. Er-Raki S, Chehbouni A, Guemouria N, Duchemin B, Ezzahar J, Hadria R. Combining FAO-56 model and ground-based remote sensing to estimate water consump-tions of wheat crops in a semi-arid region. Agriculture Water Management. 2007;87:41-54.
40. Mason Robert L, Gunst Richard F, Hess James L. Statistical design and analysis of experiments with applications of engineering and science, 2nd edition. John Willey and Sons Hoboken, New Jersey, USA; 2003.
41. Jacquemoud S, Baret F. Prospect: A model of leaf optical properties spectra. Remote Sensing of Environment. 1990;34: 75-91.

Peer-review history:
The peer review history for this paper can be accessed here:
http://sciencedomain.org/review-history/15203