Estimation of maize properties and differentiating moisture and nitrogen deficiency stress via ground – based remotely sensed data

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Abstract

Moisture and nitrogen deficiency are major determinant factors for cereal production in arid and semi - arid environments. The ability to detect crop stress at early growth stages is crucially important if significant reductions in yield are to be averted. In this context, remotely sensed data offers the possibility of providing a rapid and accurate tool for site - specific management in cereal crop production. This research examined the potential of hyperspectral and broadband remote sensing for predicting maize properties under nitrogen and moisture stress conditions during 2015 and 2016 seasons. Spectra were collected from drip irrigated maize subjected to various rates of irrigation regimes and nitrogen fertilization across two test seasons. A total of 60 spectral vegetation indices were derived and examined to predict maize yield and other plant canopy properties (chlorophyll, and water content). Highly significant correlations between maize crop properties and various vegetation indices were identified including; Ratio Vegetation Index (RVI) and Normalized Difference Vegetation Index (NDVI) sensitive to maize grain yield. $C_{red\ edge}$ demonstrated the strongest significant correlation with maize yield. The correlations with grain yield were found to be strongest at the flowering stage. Penalized linear discriminant analysis (PLDA) showed the possibility to distinguish between moisture and nitrogen stress spectrally. The implications of this work for the use of satellite based remote sensing in arid zone precision agriculture are discussed.

Keywords: crop stress, properties, chlorophyll, water content, spectra, grain yield

1. Introduction

Maize (*Zea mays L.*) is among the most important grain and forage crop in irrigated agriculture (Shaddad et al., 2011) that provides a staple source of food in many countries worldwide (Namara et al., 2010). It is known as a sensitive crop to water stress (Saruhan et al., 2012) and therefore monitoring maize at different growth stages efficiently is important to enhance crop growth and productivity. In arid and semi arid environments, water induced stress is considered the main limiting factor to plant growth and productivity of maize more than any other environmental factors (Hao et al., 2016) especially at the flowering and grain filling stages. In another maize experiment, Oyekunle and Badu-Apraku, (2014) concluded that adverse effects from water stress can occur at any maize growth stage. It is evident that water deficiency induces different changes in physio – biochemical properties of crops causing inhibitory effects on crop growth and productivity (Ashraf, 2010). Mansouri-Far et al., (2010) noticed a reduction in maize yield with increased deficit irrigation conditions.

Nitrogen is an essential crop nutrient that is important for plant growth and development and thus it is important to develop an appropriate water and nitrogen fertilization management strategy in order to enhance their application efficiency (Ajdary et al., 2007). Wang and Xing, (2016) showed that maize yield could be maximized with optimum irrigation and nitrogen management. Nilahyane et al. (2018) pointed out that water and nitrogen combination could lead to massive maize yield reduction in case of water shortage. Markovic et al. (2017) also concluded that maize yield is fundamentally influenced by the amount of available water and N and added that both factors significantly affected maize yield in a two-year maize experiment.

Monitoring agricultural crop production in areas suffering from moisture and nitrogen deficiency is traditionally based on point-sampling techniques, an approach that is laborious, costly and tends to be spatially unrepresentative. Reliable and rapid techniques for spotting stress in agricultural crops are consequently required to improve current farming practices, especially in developing countries where existing agricultural systems hardly cope with the high demands of rapid population growth.

The content of photosynthetic pigments within plant leaves tends to be the first parts of plants to respond to stress. This is especially the case for leaf pigments such as xanthophylls, chlorophylls, and carotenoids. These pigments are highly absorbent to light in the photosynthetically active portion of the electromagnetic spectrum (Prasad *et al.*, 2007) and can be measured in spectral characteristics of crop canopies and leaves (Araus *et al.*, 2001). Thus the spectra of plant canopy and leaves could be employed to assess foliar pigment content and thereby obtain a better understanding of crop growth. Previous studies have documented the role of vegetation indices calculated from remotely sensed data to detect stress in vegetation. These include for example, the determination of grain yield (weber et al., 2012: Kawamura et al., 2018; El-Hendawy et al., 2019); chlorophyll *a* concentration (Jin et al., 2012; Elmetwalli, 2013; Schlemmer et al., 2013; Martinez and Ramos, 2015); pest injuries and plant diseases (Genc *et al.*, 2008 Ashourloo et al. 2014), nitrogen deficiency (Feng et al., 2014; Thorp et al., 2017); aerial plant biomass (Elmetwalli, 2008, Fu et al., 2014; Kanke et al., 2016) and water stress (Dejonge et al., 2016).

Remote sensing can therefore be a robust tool for site-specific crop management, particularly for water and nitrogen fertilization management. In agricultural crops, leaf chlorophyll is highly related to nitrogen status in plants. The ability to identify spatial variability in canopy chlorophyll concentration via remotely sensed data resulted in rapid quantification of crop N status across large field systems (Rodriguez and Miller, 2000). Other studies have shown the possibility of remote sensing to predict crop grain yield (Babar *et al*., 2006; Padilla et al., 2012). The potential of remote sensing to monitor crop health status has been demonstrated, but published work has focused on detecting moisture and nitrogen deficiency stress at the leaf scale. Therefore this research demonstrated the potential of using remote sensing to detect both nitrogen and moisture stress at both leaf and canopy scale. Measurements at the canopy scale are arguably important to evaluate the potential successful implementation of airborne or satellite remote sensing in precision agriculture. The overall aim of this research was to assess the potential role of remotely sensed data to detect and distinguish sources of stress spectrally.

2. Materials and methods

2.1 Experimental design

Two field experiments of maize were performed at Albasatin Research Station, Elbohaira Province, Egypt (latitude of 30°55`2.9``, longitude of 29°57`25.2``) over the summer seasons of 2015 and 2016. Three random soil samples were collected and analyzed showing low organic matter (0.13%), a pH of 7.4 and an Electrical Conductivity (EC) of 1.21 dS m^{-1}. The soil of the experimental site was loamy in texture with typical particle size distribution of 68.2% sand, 22.5% silt and 9.3% clay with an average bulk density of 1.53 g cm^{-3}. The experimental design was laid out as a split plot with three replicates. Irrigation regimes were assigned for the main plots while nitrogen rates were assigned for the sub-main plots. Maize plants were subjected to twelve different treatments of moisture and nitrogen deficiency stress; using the combinations of four levels of irrigation regimes at 1.25, 1.0, 0.8 and 0.6 Evapotranspiration (ETc) and three rates of nitrogen fertilization at 120, 180 and 240 kg N ha^{-1}. Maize seeds were sown on May 15th and 24th and harvested on September 5th and 22nd of 2015 and 2016 seasons respectively. Potassium in the form of potassium sulphate and phosphorus were applied to the soil during land preparation at rates of 120 and 60 kg ha^{-1} respectively.

The amount of irrigation water applied (Table 1) for each treatment via drip irrigation was quantified using the following equation

$$Wa = \frac{I.ETc}{Ea} + LR$$

Where I is the empirical irrigation rate (1.25, 1.0, 0.8, and 0.6 ETc); Ea is the irrigation efficiency of drip irrigation system assumed at 80% and LR is the leaching requirements assumed at 20% of the estimated irrigation water, and crop evapotranspiration was calculated according to Allen et al. (1998) as follows:

$$ETc = ETo * kc,$$

Where ETo is the reference evapotranspiration and kc is the coefficient of crop and its values were recommended by Allen et al. (1998) and ETo was calculated using the following formula:

$$ETo = Ep\ kp$$

Where Ep is the cumulative evaporation amount of water; and kp is the evaporation pan coefficient assumed at 0.75 for the study area. Evaporation data were collected from a class A pan at Albasatin Research Station. Irrigation time was identified as follows:

$$T = \frac{Wa * A}{q}$$

Where T is the irrigation time (h); Wa is the depth of irrigation water applied (mm); A is the wetted area by each emitter in m^2 and q is the emitter discharge rate (L h^{-1})

2.2 Reflectance measurements

Spectra were collected from crop canopies and leaves using an ASD FieldSpec spectroradiometer with a 3.5° field of view foropic. The instrument was fixed at the end of a telescopic pole at a constant height of 2 m from the soil surface to have larger scanning area. Spectra (350 -1050 nm) of the crop canopy were collected regularly under solar radiation on cloud-free days from 11:00 to 15:00 h GMT. Spectra collection was started at early growth stages prior applying various moisture and nitrogen deficiency stress treatments. Collection was repeated periodically throughout the growing season until harvest time. A white spectralon was used to calibrate reflectance acquired by the spectroradiometer. Spectra were then pre-processed using the dedicated ASD software and then used to calculate different broadband and hyperspectral vegetation indices, of which the more successful are listed in Le Maire et al. (2004). Among these used indices Normalized Difference Vegetation index (NDVI), Ratio Vegetation Index (RVI), Simple Ratio (SR), Soil Adjusted Vegetation Index (SAVI). Table 2 details examples of commonly used vegetation indices showing the equations to calculate them.

The spectra collected from each treatment were averaged and the overall mean spectrum was tested in principal component analysis (PCA) to initially notice differences in the spectral signature captured from healthy and stressed treatments. Thereafter penalized linear discriminant analysis (PLDA) (Hastie et al., 1995) was performed on the whole set of spectra captured from each treatment at the flowering time to notice if spectral response of maize could be used to identify the source of stress and its level (low , medium or high). The mda package in R software was employed to perform PLDA; the R package 'from the software R statistics v 3.0.2 (R foundation for statistical computing 2013).

2.3 Determination of maize yield, leaf chlorophyll content, and canopy water content

At harvest time, an area of 5 m^2 from each treatment was sampled to calculate total maize grain yield. Cobs were weighed for the whole sample and then converted into Mg ha^{-1}. Leaf chlorophyll content was measured at different growth stages immediately following the spectra measurements. A portable SPAD chlorophyll meter (Konica-Minolta, Osaka, Japan) was employed to measure leaf chlorophyll content which gives measures of chlorophyll as SPAV values. Twenty Apical leaves were sampled from each treatment and for all experimental plots. Thereafter, a representative subsample was placed in an oven at 70°C for 24 h until a constant weight. Samples were weighed before and after drying to determine leaf water content as follows:

$$WC = \frac{FW - DW}{FW} 100$$

Where FW is the fresh weight of plant sample and DW is the dry weight of the plant sample.

2.4 Statistical analysis

SPSS (SPSS Inc., Chicago, II, USA) was run to perform one and two-way analysis of variance (ANOVA) to establish significant differences in maize crop responses to moisture and nitrogen stress. Nitrogen, moisture and nitrogen/moisture combinations were used as predictor variables, and yield records as the response variable. Data were tested for normality using Anderson-Darling method with 95% significance level. The Pearson Product Moment coefficient of correlation was employed to assess the relationship between different vegetation indices and crop properties and hence to identify optimum vegetation indices for predicting maize yield and properties. Simple linear and multivariate regression analyses were performed to derive regression equations to retrieve grain yield from collected spectra. The collected spectra including all wavelengths from various treatments were then used in principal component analysis (PCA) (Minitab v.14; Minitab Inc., State college, PA, USA) to discover differences and differentiate between spectral responses of healthy and stressed maize plants. The mda package in R software was employed to perform PLDA to distinguish between moisture and nitrogen deficiency stresses.

3. Results

3.1 Effects of moisture and nitrogen stress on maize grain yield

The ANOVA was run to assess the effects of both moisture and nitrogen on maize grain yield. The results are summarised in Table 3. It is evident that both moisture and nitrogen significantly affected maize grain yield in both seasons. The interaction between moisture and N showed significant effect on total grain yield in 2016 season only. Moisture stress strongly reduced grain yield in the 2015 and 2016 growing season ($p < 0.005$). The highest grain yields of 8.41 and 9.42 Mg ha^{-1} were recorded with the combination 1.25 ETc and 240 kg N ha^{-1} in 2015 and 2016 seasons (Table 4). Nitrogen fertilization also significantly influenced maize grain yield in both seasons. Significant decreases in maize yield were observed with increased nitrogen deficiency levels. Averaged over two seasons, the grain yields fell to about 54.1 and 25.3% of the maximum value when plants were subjected to the lowest irrigation regime and the highest nitrogen deficiency level respectively compared with the greatest records.

The regression analysis showed a significant linear relationship between maize grain yield and moisture regime in both seasons (Table 5). This indicates that yield reductions were highest in the combinations with the lowest watering regimes (0.6 ETc). A further significant linear relationship was found between maize grain yield and nitrogen deficiency levels showing that maize yield reductions were greater at the highest nitrogen deficiency level (120 kg N ha^{-1}).

3.2 Effects of moisture and nitrogen stress on leaf chlorophyll content of maize

The chlorophyll content of maize plants was significantly affected by both rates of moisture regime and N fertilization rates since in the combination of water stress and N deficiency treatments, the chlorophyll content decreased relative to full application of water and N treatments in both investigated seasons. The greatest chlorophyll content of 51.7 and 50.9 (SPAD values) was recorded with plots having full irrigation regime with 240 kg N ha^{-1} in 2015 and 2016 respectively (Table 6). In non-stressed plots, all N fertilization rates enhanced leaf chlorophyll content.

3.3 Correlation between vegetation indices and maize grain yield, water content and chlorophyll content

Some vegetation indices correlated strongly with the measured maize grain yield. From individual measuring dates, it is evident that at early growth stages (seedling) all vegetation indices produced non-significant correlations with the measured grain yield which may have been a result of the interference between vegetation and soil background. Due to inconsistent performance of different indices over the growing season, the correlation coefficient values at different growth stages were averaged, and then ranked to identify the optimum index to predict maize properties. The coefficient of correlation increased gradually to reach the peak at the flowering stage in both seasons. The $C_{red\ edge}$ was identified as the optimum index to predict maize yield in 2015 and 2016 seasons. Figures 1 and 2 show the relationship between $C_{red\ edge}$, NDVI, RVI and maize grain yield at the flowering stage in both seasons (R^2 >

0.83). Although RVI and NDVI produced higher correlations at the flowering stage compared with the $C_{red\ edge}$, their correlations were less from flowering onwards. The results further demonstrated that the collected spectra at the canopy scale (until filling stage) produced higher correlations in comparison to those collected at the leaf scale. The maximum correlation values were recorded just before the flowering stage.

The results of plant water content (WC), showed that the PSNDb and NDVI produced the greatest average correlations with WC with the coefficient of correlation over 0.86 as seen in Figures 1 and 2. The optimum vegetation indices sensitive to chlorophyll content were OSAVI and R_{675}/R_{700} in 2015 and RVI and R_{800}-R_{550} in 2016. It is obvious that the red edge region of the electromagnetic spectrum seems to be sensitive to chlorophyll content in particular the 675 to 800 nm range.

3.4 Distinguishing between moisture and nitrogen deficiency stresses

The principal component analysis (PCA) was run on full spectra acquired at different growth stages over the growing season to distinguish between moisture and N deficiency stresses and revealed that at the flowering time, there was a possible of some variability between both sources of stress. The score plot of PCA showed a certain trend for nitrogen deficiency and moisture stress to plot in separate quarters especially fully irrigated and fertilized treatments (Fig. 3). The PCA score plots suggested that spectra in the VIS and NIR parts of the electromagnetic spectrum were strongly correlated with the level of stress; however, there was a need to have a clear distinguishing between both types of stress. As a result the PLDA was performed on spectra collected at different growth stages over the growing season. The results demonstrated that the spectra collected at the canopy scale showed better distinction between moisture and N stressors which are in broad agreement with previous findings of Wang et al. (2002) and Elmetwalli et al., (2012). Table 8 presents the results of the PDLA for the spectra acquired at the flowering stage. The training misclassification value was 0.11 whilst the prediction misclassification was 0.24. The user's accuracy reached 100% in five treatments out of twelve and over 65% in four other treatments. Also, the producer's accuracy reached over 70% in eight treatments five of those a 100%. The PLDA therefore demonstrated the possibility to distinguish most differences between N deficiency and moisture stresses. It is therefore evident that remotely sensed data have the potential to distinguish sources of stress which ultimately helpful to take the right decisions to avoid crop reductions.

4. Discussion

Quantifying crop productivity in cereals is considered a priority for agricultural research programmes (Steinmetz *et al*., 1990) in response to the demands of rapid population growth (Rudorff *et al*., 1996). Increased efforts are therefore needed to detect the effects of moisture and nitrogen deficiency stresses in maize. There was no specific index to predict crop yield over the growing season. The correlation coefficient of the relationship between different vegetation indices and crop properties at different growth stages was averaged and ranked to come up with the optimum index to predict maize yield. The $C_{red\ edge}$ seems to be the optimum vegetation index to predict maize yield. The results further showed that the band ratios RVI and NDVI are efficient and could also be used to predict maize yield. Moreover, these indices were ranked among the best five indices for predicting maize yield in both seasons.

Our results demonstrated the potential of remotely sensed data to predict maize yield subjected to moisture and N deficiency stress conditions. These results confirm the previous findings of Babar et al. (2006) and Prasad et al. (2007) who demonstrated that crop yield can be predicted before the plant maturation stage is reached. Whilst hyperspectral data revealed a potential to differentiate between moisture and N deficiency stresses. Hyperspectral data provided no significant advantage over the broadband spectral indices for predicting maize yield. With respect to time, Babar *et al*. (2006) concluded that measuring reflectance at the heading and the grain filling stages appears to be the most suitable time for selecting different genotypes for optimum wheat yield. They also found that RNDVI, GNDVI and SR showed significant positive correlations with grain yield at the heading and the grain filling stages. However, the present study showed that the measurements at the canopy scale have shown that the flowering stage seems to be the optimum stage for predicting maize yield and other properties.

The present study revealed that moisture stress induced by irrigation deficiency resulted serious impairment of growth – related properties in terms of chlorophyll. Anjum et al. (2011) considered chlorophyll concentration as a symptom of water stress due to photo-oxidation. When plants are subjected to water stress, chlorophyll concentration decreases and hence photosynthesis causes reductions in plant growth and productivity. Under deficit irrigation conditions, the decrease in chlorophyll a content is more pronounced. The chlorophyll content was significantly declined with increased levels of water stress which was supported by the results obtained by Mafakheri et al. (2010).

To distinguish sources of stress, the PCA analysis was performed using spectra captured at different growth stages and the results showed minor differentiation at early growth stages which can be related to the interference between spectra of vegetation and others of soil background. It was noticed that at the canopy scale the spectra collected from stressed maize plants was influenced by high moisture and N deficiency stresses. The PCA score plots at the flowering stage showed some differences between moisture and nitrogen deficiency stressed plants and high levels of stress. Our results therefore showed that the feasibility of determining spectral end members derived from new generation of hyperspectral imagery which can be employed to assess the degree and source of stress. Broadly, the PLDA run on spectra acquired at the canopy scale demonstrated the possibility to predict the source of stress in maize plants and even differentiate between low, medium and high level of moisture and nitrogen deficiency stresses. Systematic changes were observed in the spectra collected from maize canopies that were subjected to stress. It is recommended that when this technique is conducted at a large scale (local or regional scale) using satellite-based platforms, the stochastic effects produced from small-scale heterogeneity might be much reduced. In conclusion, the work presented here has shown the novel possibility of predicting spectral end members resulted from either moisture or nitrogen deficiency stress in one of the main strategic agricultural crops.

The results therefore importantly suggested that remote sensing could provide a robust approach to predict crop properties at relatively early stages of plant growth; enabling appropriate management practices to be implemented to limit crop reductions and enhance crop productivity. Moreover, existing remote sensing satellites with broad band but high spatial resolution (2 m resolution) such as GeoEye1 and Worldview2 or medium resolution such as ESA Sentienel 2 (10-20m resolution) have the ability to provide regional and field scale information for farmers to improve crop yield in semi-arid and arid environments. The resulting spatial perspective would also provide a valuable basis from which to offer a cost benefit analysis between improving water and soil resources, irrigation technologies and increasing crop yield.

5. Conclusion

The effectiveness of hyperspectral and broadband remote sensing data for the prediction of maize yield in response to moisture and nitrogen deficiency stresses at both leaf and canopy scales. The results indicated that the flowering stage was the optimum to predict maize yield through remotely sensed data. There was no significant advantage in using hyperspectral indices over broadband vegetation indices. The $C_{red\ edge}$ provided the optimum index for predicting maize yield. Hyperspectral data provided no advantage in such predictions. The NDVI and PSNDb have shown importance in the prediction of plant water content. The 675 to 800 nm range seems to be feasible to predict leaf chlorophyll content. Consequently broadband satellite based remote sensing platforms with high spatial resolution capabilities would be well suited to predict grain yield in semi arid and arid environments. Further work is required at different sites and environments as well as different crops to validate the results obtained in this research. Moreover, statistical approaches such as partial least square regression (PLSR) may be of interest to improve the prediction of crop traits combining spectral measurements of various growth stages and seasons to identify the optimum vegetation indices.

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Table 1 Total irrigation water applied (mm) to different treatments in 2015 and 2016 growing seasons

Season	Growth stage	Total irrigation water applied, mm			
		1.25 ETc	1.00 ETc	0.80 ETc	0.60 ETc
2015	Initial	84.0	67.2	53.8	40.3
	Development	244.4	195.5	156.4	117.3
	Mid-season	235.5	188.4	150.7	113.0
	Maturation	38.0	30.4	24.3	18.2
	Total	601.9	481.5	385.2	288.8
2016	Initial	82.3	65.8	52.6	39.5
	Development	234.8	187.8	150.2	112.7
	Mid-season	226.6	181.3	145.0	108.8
	Maturation	36.1	28.9	23.1	17.3
	Total	579.8	463.8	371.0	278.3

Table 2 Examples of commonly used spectral vegetation indices

Notation	Formulae	Reference
SLAVI	NIR/(Red+NIR)	Lymburner *et al*., 2000
RVI	NIR/Red	Pearson & Miller, 1972
VI1	NIR/(green-1)	Vina, 2003
$GNDVI_{br}$	(NIR-green)/ (NIR+green)	Osborne *et al*., 2004
DVI	NIR-Red	Tucker, 1979
SI	Red/NIR	Jiang *et al*., 2003
OSAVI	[(NIR-Red)/(NIR+Red+L)]*(1+L), L = 0.16	Rondeaux *et al*., 1996
NDVI	(NIR-Red)/(NIR+Red)	Rouse *et al*., 1974
IPVI	NIR/(NIR+Red)	Crippen, 1990
RDVI	$\sqrt{NDVI \times DVI}$	Reujean & Breon, 1995
$R_{shoulder}$	Mean $R_{750\text{-}850}$	Strachan *et al*., 2002
SR	NIR/Red	Jiang *et al*., 2003
$C_{rededge}$	$(R_{800}/R_{700} - 1)$	Elmetwalli, 2008
R_{695}/R_{760}	R_{695}/R_{760}	Carter, 1994
R_{605}/R_{760}	R_{605}/R_{760}	Carter, 1994
R_{710}/R_{760}	R_{710}/R_{760}	Carter, 1994
R_{695}/R_{670}	R_{695}/R_{670}	Carter, 1994
R_{750}/R_{550}	R_{750}/R_{550}	Gitelson & Merzlyak, 1994
R_{750}/R_{700}	R_{750}/R_{700}	Gitelson & Merzlyak, 1994
R_{725}/R_{675}	R_{725}/R_{675}	Gitelson & Merzlyak, 1994

NDVI, Normalized Difference Vegetation Index; RVI, Ratio Vegetation Index; $GNDVI_{br}$, Green Normalized Difference Vegetation Index; DVI, Difference Vegetation Index; SR, Simple Ratio; SLAVI, Specific Leaf Area Vegetation Index; OSAVI, Optimized Soil Adjusted Vegetation Index; VI1, Vegetation Index One; RDVI, Renormalized Difference Vegetation Index; SI, Stress Index; IPVI, Infra-Red Percentage Vegetation Index

Table 3 Analysis of variance for the experimental variables on maize productivity. MS- Mean Square; DF-Degrees of Freedom; NS-Non Significant and **-highly significant at 0.01 probability level.

Source	2015		2016	
	D.F	MS	D.F	MS
Replicates	2	0.07	2	0.19
Water regime (A)	3	32.09**	3	34.38**
Residual	6	0.034	6	0.12
N rates (B)	2	5.42**	2	15.94**
A*B	6	NS	6	0.79**
Error	16	0.14	16	0.16

Table 4. Effect of irrigation regime and N fertilization rate on maize yield (Mg ha^{-1}) in both investigated seasons. Least significant Difference (LSD) values are listed and values with different letters are statistically significant.

Season	Irrigation regime	N Fertilization, kg ha^{-1}			Mean	LSD
		120	180	240		
2015	1.25 ETc	6.79	7.65	8.41	7.62a	0.32
	1.00 ETc	6.37	7.14	8.16	7.22b	
	0.80 ETc	5.35	5.62	6.55	5.84c	
	0.60 ETc	3.11	3.36	3.85	3.44d	
Mean LSD=0.44		5.41c	5.94b	6.74a		
2016	1.25 ETc	6.33	8.46	9.42	8.07a	0.59
	1.00 ETc	6.26	7.82	9.09	7.72a	
	0.80 ETc	5.16	6.93	7.36	6.48b	
	0.60 ETc	3.26	3.83	4.19	3.76c	
Mean LSD=0.47		5.25c	6.76b	7.52a		

Table 5 Simple regression results for predicting maize grain yield as a function of evapotranspiration rate (ETc) and Nitrogen fertilization rate (N) in 2015 and 2016 growing seasons. Regression equations and determination coefficient (R^2) are listed.

Growing season	Crop parameter	Equation	R^2
2015	Yield (Y), Mg ha^{-1}	Y = 6.96 ETc – 0.39	0.83
		Y = 0.014 N – 5.19	0.88
2016	Yield (Y), Mg ha^{-1}	Y = 7.93 ETc – 0.28	0.82
		Y = 0.026 N – 3.43	0.87

Table 6 Effect of irrigation regime and N fertilization rate on chlorophyll content (SPAD values) of maize of various treatments in 2015 and 2016 growing seasons. Least significant Difference (LSD) values are listed and values with different letters are statistically significant.

Season	Irrigation regime	N Fertilization, kg ha^{-1}			Mean	LSD
		120	180	240		
2015	1.25 ETc	41.0	48.6	51.7	47.10a	1.31
	1.00 ETc	39.9	45.4	48.9	44.73b	
	0.80 ETc	39.6	42.6	43.2	41.80c	
	0.60 ETc	38.6	40.5	41.4	40.17d	
Mean LSD=0.99		39.78c	44.28b	46.3a		
2016	1.25 ETc	40.1	43.6	50.9	44.87a	0.56
	1.00 ETc	38.3	41.4	44.6	41.43b	
	0.80 ETc	37.5	40.9	41.7	40.03c	
	0.60 ETc	36.6	37.9	38.3	37.60d	
Mean LSD=0.79		38.13c	40.95b	43.88a		

Table 7 Coefficient of correlation for the relationship between vegetation indices and maize grain yield at different growth stages in the 2015 and 2016 summer growing seasons. Values with ** are highly significant at 0.01 probability level.

Season	Vegetation Index	Growth stage					
		seedlings	jointing	flowering	filling	maturation	Mean
2015	RVI	0.22	0.71**	0.94**	0.60**	0.49**	0.586**
	NDVI	0.27	0.62**	0.90**	0.65**	0.57**	0.602**
	SR	0.16	0.70**	0.92**	0.65**	0.49**	0.584**
	RDVI	0.14	0.65**	0.94**	0.69**	0.49**	0.582**
	$GNDVI_{hy}$	0.23	0.61**	0.94**	0.64**	0.59**	0.602**
	$PSND_b$	0.19	0.58**	0.94**	0.73**	0.50**	0.588**
	R_{695}/R_{760}	-0.25	-0.52**	-0.92**	-0.74**	-0.49**	-0.584**
	R_{750}/R_{550}	0.27	0.64**	0.93**	0.61**	0.60**	0.610**
	R_{750}/R_{700}	0.20	0.70**	0.93**	0.71**	0.53**	0.614**
	$C_{red\ edge}$	0.18	0.71**	0.93**	0.74**	0.54**	0.620**
2016	RVI	0.24	0.62*	0.91**	0.75**	0.52*	0.608**
	NDVI	0.31	0.60**	0.93**	0.67**	0.62**	0.626**
	SR	0.24	0.63**	0.92**	0.76**	0.53**	0.616**
	RDVI	0.19	0.49**	0.88**	0.69**	0.39	0.528*
	$GNDVI_{hy}$	0.33	0.55**	0.89**	0.69**	0.65**	0.622**
	$PSND_b$	0.28	0.52**	0.81**	0.70**	0.57**	0.576**
	R_{695}/R_{760}	-0.30	-0.46**	-0.88**	-0.65**	-0.51*	-0.560**
	R_{750}/R_{550}	0.33	-0.60**	0.92**	-0.72**	-0.64**	-0.642**
	R_{750}/R_{700}	0.23	0.63**	0.89**	0.76**	0.63**	0.628**
	$C_{red\ edge}$	0.25	0.65**	0.92**	0.78**	0.65**	0.650**

Table 8. Confusion matrix for PLDA performed on spectra measurements collected from maize canopies subjected to moisture and nitrogen deficiency stresses. Labels: T1-I_1F_1; T2- I_1F_2; T3-I_1F_3; T4-I_2F_1; T5- I_2F_2; T6-I_2F_3; T7-I_3F_1; T8- I_3F_2; T9-I_3F_3; T10-I_4F_1; T11-I_4F_2; T12-I_4F_3. I_1, I_2, I_3 and I_4 are 1.25, 1.0, 0.80 and 0.60 ETc and F_1, F_2 and F_3 are 240, 180 and 120 kg N respectively.

PDLA	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	Total	User's accuracy
T1	5	0	0	0	4	0	0	0	0	0	0	0	9	0.55
T2	0	7	0	0	0	5	0	0	0	0	0	0	12	0.58
T3	0	0	8	0	0	0	0	0	0	0	1	0	9	0.89
T4	0	0	3	6	0	0	0	0	0	0	0	0	9	0. 67
T5	2	0	0	0	3	0	0	0	0	4	0	0	9	0.33
T6	0	0	0	0	0	5	0	0	0	0	0	0	5	1.00
T7	0	0	0	0	0	1	7	0	0	0	0	2	10	0.70
T8	0	0	0	0	0	0	0	4	0	0	3	0	7	1.00
T9	0	0	0	0	0	0	0	0	6	0	0	0	6	1.00
T10	0	0	0	0	0	0	0	0	0	4	1	0	5	0.80
T11	0	0	0	0	0	0	0	0	0	0	7	0	7	1.00
T12	0	0	0	0	0	0	0	0	0	0	0	5	5	1.00
Total	7	7	11	6	7	11	7	4	6	8	12	7	78	
Producer's accuracy	0.71	1.00	0.72	1.00	0.43	0.45	1.00	1.00	1.00	0.50	0.58	0.71		

Training misclassification rate	**Prediction misclassification rate**
0.11	**0.24**

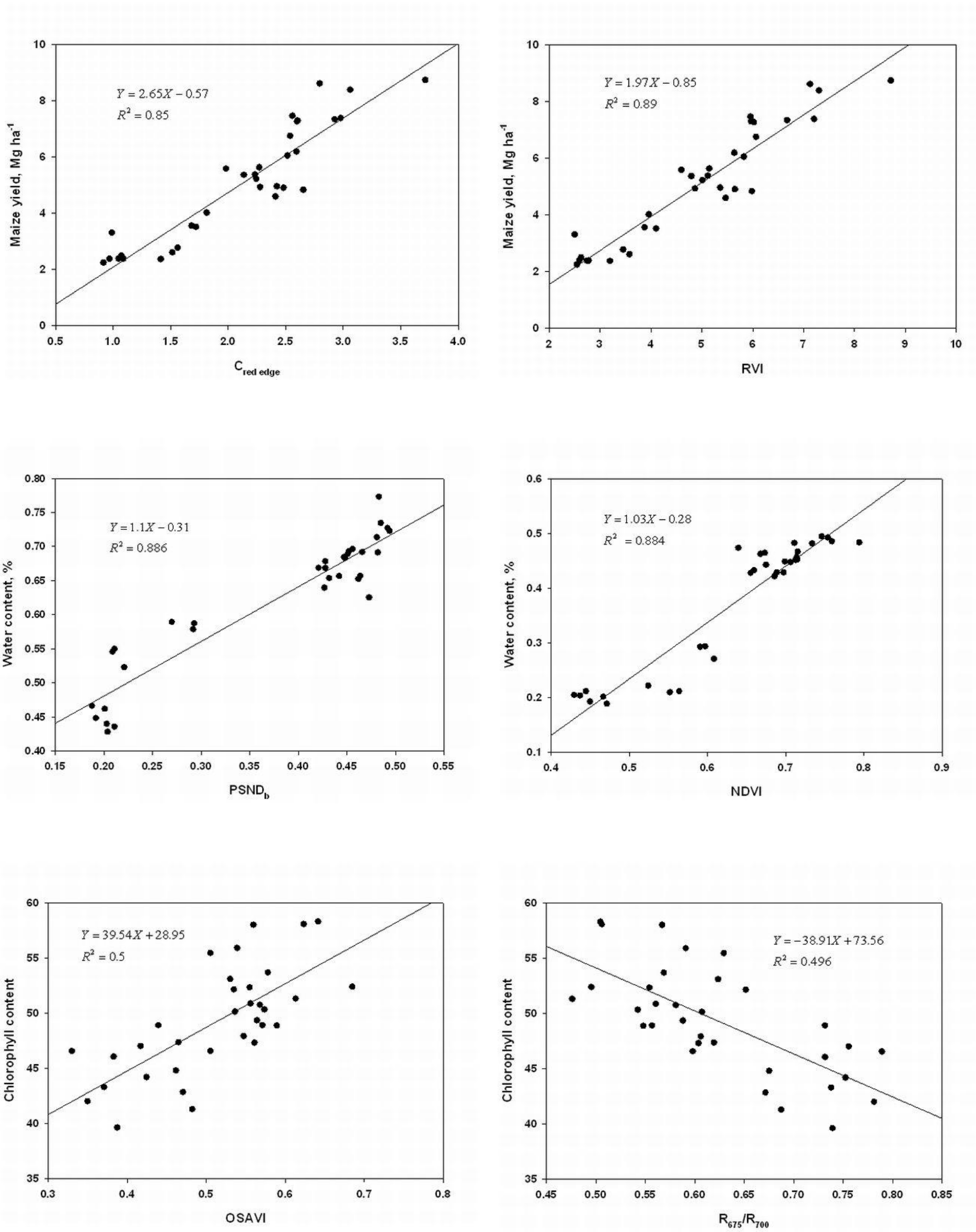

Fig. 1. The relationship between different vegetation indices derived from spectra obtained using solar illumination and maize yield, water content and chlorophyll content at the flowering stage in 2015 summer season

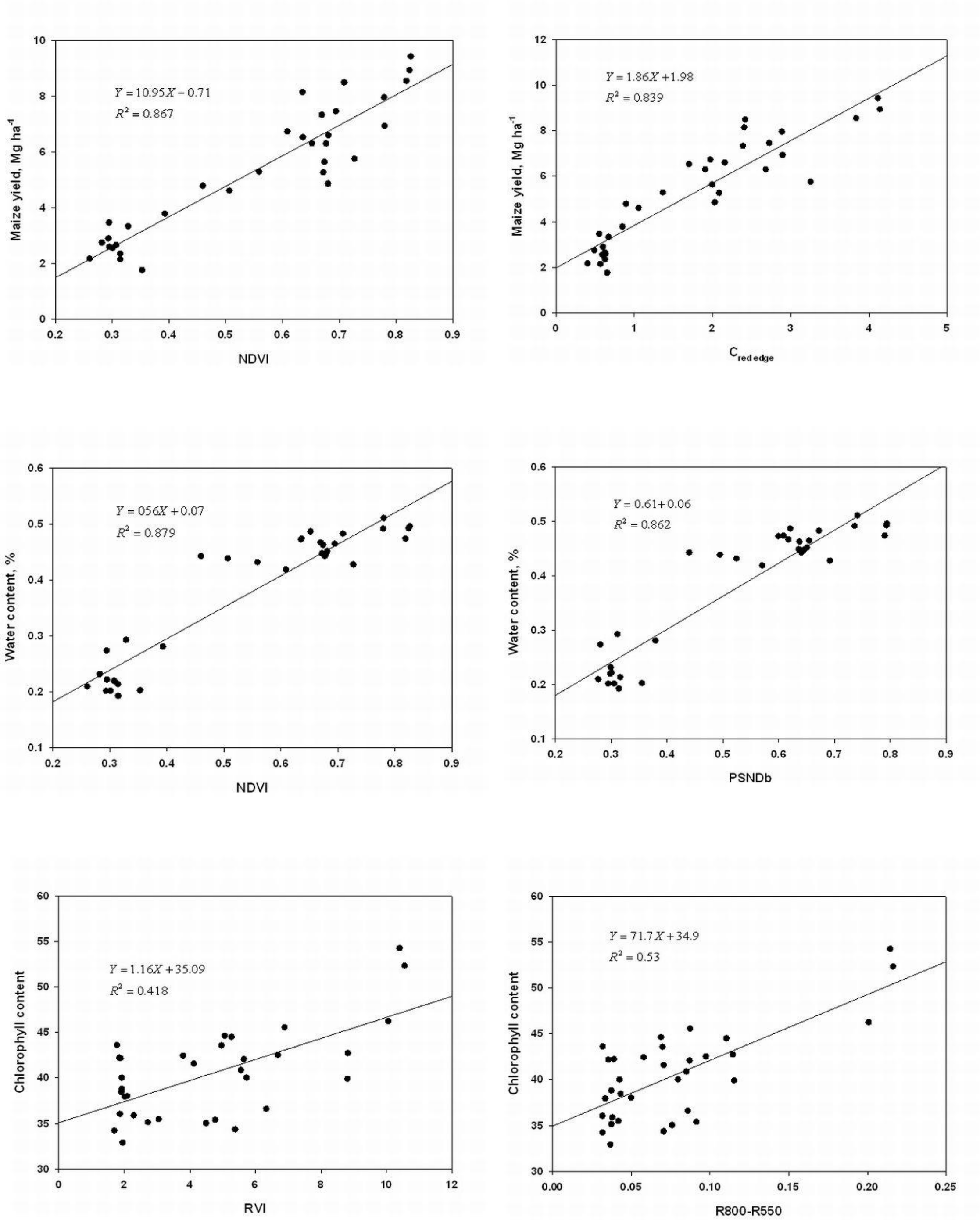

Fig. 2. The relationship between different vegetation indices derived from spectra obtained using solar illumination and maize yield, water content and chlorophyll content at the flowering stage in 2016 summer season.

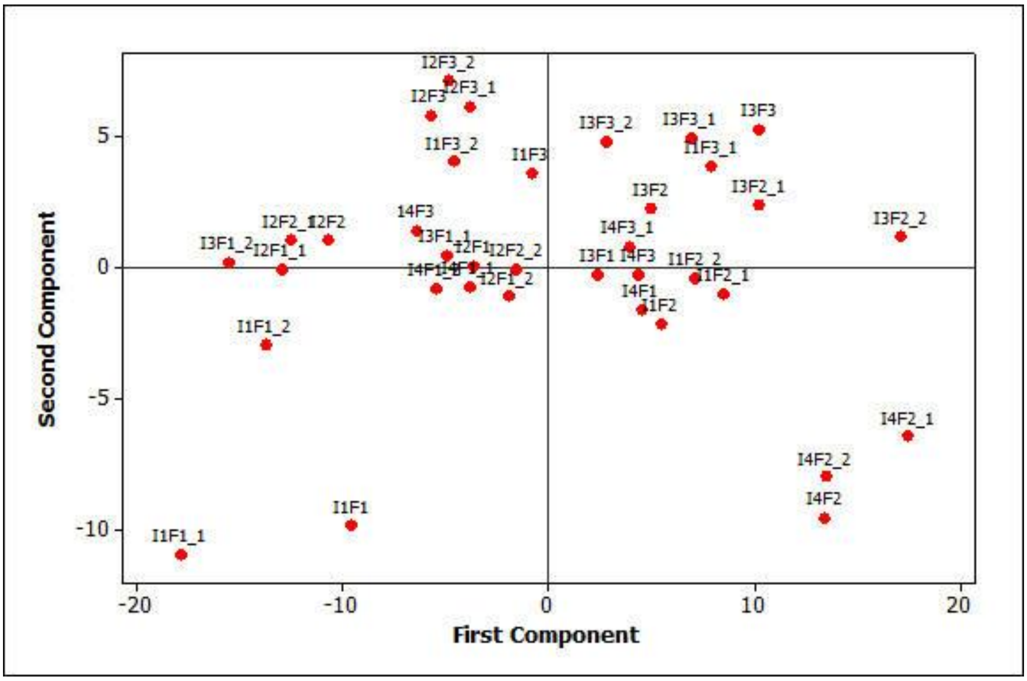

Fig. 3. PCA score plot for the whole dataset of spectra collected from various treatments of moisture and nitrogen deficiency induced stressed maize canopies at the flowering stage in 2015 growing season. Labels: T1-I_1F_1; T2- I_1F_2; T3-I_1F_3; T4-I_2F_1; T5- I_2F_2; T6-I_2F_3; T7-I_3F_1; T8- I_3F_2; T9-I_3F_3; T10-I_4F_1; T11-I_4F_2; T12-I_4F_3. I_1, I_2, I_3 and I_4 are 1.25, 1.0, 0.80 and 0.60 ETc and F_1, F_2 and F_3 are 240, 180 and 120 kg N respectively.