Article AR2411a

DOI: HTTPS://DOI.ORG/10.23910/1.2021.2411a

International Journal of Bio-resource and Stress Management

Crossref

August 2021

Print ISSN 0976-3988

Online ISSN 0976-4038

IJBSM 2021, 12(4):319-331

Research Article

Natural Resource Management

Assessing the Maize (*Zea mays* L.) Crop Performance Using Spectral Indices under Different Sowing Dates and Irrigations Schedules

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Open Access

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Citation: Pallavi et al., 2021. Assessing the Maize (*Zea mays* L.) Crop Performance using Spectral Indices under different Sowing Dates and Irrigations Schedules. International Journal of Bio-resource and Stress Management 2021, 12(4), 319-331. HTTPS://DOI.ORG/10.23910/1.2021.2411a.

Data Availability Statement: Legal restrictions are imposed on the public sharing of raw data. However, authors have full right to transfer or share the data in raw form upon request subject to either meeting the conditions of the original consents and the original research study. Further, access of data needs to meet whether the user complies with the ethical and legal obligations as data controllers to allow for secondary use of the data outside of the original study.

Conflict of interests: The authors have declared that no conflict of interest exists.

Acknowledgement: We thank Dr. M.V.R. Seshasai, Deputy Director, Earth & Climate Sciences Area (ECSA), Dr. C.S.K. Murthy, Group Director (AS&AG), National Remote Sensing Centre, Balanagar, Hyderabad for their inspiring guidance and encouragement. Authors are grateful to University for financial assistance to carry out the experiment and analysis of the related samples

Article History

RECEIVED on 09th June 2021 RECEIVED in revised form on 16th August 2021 ACCEPTED in final form on 25th August 2021

Abstract

Field experiment was conducted at ARI, PJTSAU, Hyderabad with four dates of sowing (18th June, 04th July, 19th July and 03rd August in *Kharif*, 2016 and 01st November, 18th November, 01st December and 17th December in *rabi*, 2016–17) as main plots and four irrigations regimes (Control, 0.4 IW/CPE, 0.6 IW/CPE and 0.8 IW/CPE in *kharif* and 0.4 IW/CPE, 0.6 IW/CPE, 0.8 IW/CPE and 1.0 IW/CPE in *rabi*) as sub-plots in split plot design replicated thrice. Scheduling irrigation at unstressed conditions, 0.8 IW/CPE (I_3) and 1.0 IW/CPE (I_4) of maize resulted in low reflectance in visible region (400 to 700 nm) and mid infrared (MIR) region (1350–2500 nm) and high in near infrared (NIR) region (700 to 1350 nm) during *kharif* and *rabi* respectively. While, under stressed condition, the reflectance was high in visible and MIR region and low in NIR region in rainfed and 0.4 IW/CPE (I_0) respectively in *kharif* and *rabi*. Significantly higher drymatter, LAI and grain yield was observed in 04th July (D_2) and 01st November (D_1) sown crop in *kharif* and *rabi* respectively. However, spectral indices (SR, PRI, NDWI at 1240, 1640 and 2130 nm, NDII, NMDI, WBI and SWRI) was attained by 18th June (D_1) and 01st November (D_1) during *kharif* and *rabi* respectively. Higher drymatter, LAI, grain yield and spectral indices was recorded with I_3 (0.8 IW/CPE) and I_4 (1.0 IW/CPE) in *kharif* and *rabi* respectively. All the spectral vegetation indices correlated positively with LAI, drymatter and grain yield.

Keywords: Maize, remote sensing, spectral indices, stress, water, yield

1. Introduction

Cereal grains are important staple foods providing substantial amounts of energy, protein and micronutrients for much of the world's population (Murdia et al., 2016). In cereals, maize (*Zea mays* L.) is grown throughout the year mainly due to photo-thermo-insensitive character, hence called 'queen of cereal' (Verma et al., 2012). Maize is one of the most versatile cereal crops having wider adaptability under varied agro-climatic conditions (Ramachandiran et al., 2016). Maize is the third most important cereal crop in India after rice and wheat (Singh et al., 2012). Its importance lies in the fact that it is not only used for human food and animal feed but at the same time it is also widely used for corn starch industry, corn oil production, baby corns etc (Parihar et al., 2011). It accounts for 9% of total food grain production in the country (Kumar et al., 2013). In India, maize is cultivated in an area of 9.02 mha with a production of 27.7 mt and productivity of 3.07 t ha^{-1} in 2019 (Anonymous, 2020). Maize crop growth is affected by different stresses viz., water, pest, weed, nutrients, etc., which reduce the productivity (Szeles et al., 2012). Stresses come from a range of factors that limit the potential growth of canopies (Prakash and Singh, 2020). Evaluation of the stress level to which plants are subjected to is therefore vital information required both for the quantification of consequences on production and for taking action for their mitigation (Ma et al., 2020). Plant physiology is significantly affected by abiotic/climatic stresses. It is well known that climate change and environmental extremes induce and enhance the impact of abiotic stresses (particularly drought) on plant fitness and performance (Kaushal and Wani, 2016).

Remote sensing is a better method to detect and quantify the impact of plant stress compared to visual techniques because a vegetative unit can be repeatedly, objectively, and nondestructively examined in a fast, robust, accurate, and inexpensive way (Mirik et al., 2012). Earlier research on applications of remote sensing in agriculture focused on the visible and near-infrared regions of the spectrum. The launch of new hyperspectral remote sensing satellites, the focus of current research has been shifted to investigate the possibilities of hyper spectral remote sensing in crop monitoring. Hyper spectral remote sensing techniques allow the early detection of vegetation stress, before the appearance of visible symptoms (Panigada et al., 2010). Hyperspectral technology can sometimes be considered as a part of spectroscopy. The electromagnetic spectrum ranges of hyperspectral sensors mainly concentrate on VIS–NIR (400–1000 nm) and sometimes contain a short wave infrared range (SWIR, 1000–2500 nm). These sensors could acquire spectral information from hundreds of narrow spectral bands (Ghamisi et al., 2017). Using that absorption and spectral reflection characteristics of vegetation researchers has defined many vegetation indices for monitoring vegetation parameters. Thus, imaging-based and RS techniques have attracted considerable attention because they can provide accurate geographic information (Ali et al., 2019).

Spectral vegetation indices were designed to evaluate vegetation condition, foliage, cover, phenology and processes in addition to be used for land cover classification, climate and land use detection, drought monitoring and habitat loss (Padilla et al., 2011). More recently, spectral vegetation indices are mathematical expressions involving reflectance values from different part of the electromagnetic spectrum, aimed to optimize information and normalize measurements made across varied environmental conditions (Mirik et al., 2012). The advent of spectral mapping and identification of vegetation by remote sensing methods, it assumes importance to study crop stress using remote sensing techniques in maize under different water stress conditions. Keeping these in view an experiment was planned for determination of water stress with hyper spectral reflectance and vegetation indices on maize.

2. Materials and Methods

2.1. Site description

The field experiment was conducted at Agricultural Research Institute, Professor Jayashankar Telangana State Agricultural University, Rajendranagar, Hyderabad having 17.019’ N Latitude, 78.023’ E Longitude and 542.3 m above mean sea level. The soil of the experimental site was sandy loam in texture, neutral in reaction, low in available nitrogen, phosphorus and high in available potassium, during *Kharif*, 2016 and *rabi*, 2016–17 with four dates of sowing (18^{th} June, 04^{th} July, 19^{th} July and 03^{rd} August in *Kharif*, 2016 and 01^{st} November, 18^{th} November, 01^{st} December and 17^{th} December in *rabi* 2016–17) as main plots and four Irrigations regimes (Control (Rainfed), 0.4 IW/CPE, 0.6 IW/CPE and 0.8 IW/CPE in *Kharif*, 2016 and 0.4 IW/CPE, 0.6 IW/CPE and 0.8 IW/CPE and 1.0 IW/CPE in *rabi*, 2016–17) as sub-plots in split plot design replicated thrice. During the crop period rainfall of 834.9 mm was received in 45 rainy days in *kharif,* 2016 and 11.8 mm in 2 rainy days in *rabi,* 2016–17, respectively. A uniform dose of 60 kg ha^{-1} P_2O_5 as single super phosphate, potassium @ 60 kg ha^{-1} as muriate of potash and $ZnSO_4$ @ 50 kg ha^{-1} was applied to all the treatments. The entire P_2O_5, $ZnSO_4$ and half of K_2O were applied at sowing. Nitrogen was applied as per the treatments (wherever it was required) in the form of urea (46% N) in three equal splits ($1/3^{rd}$ each at basal, at knee-high and tasseling). Similarly, the remaining potassium was applied along with urea during second top dressing at tasseling.

Leaf area was estimated on two plants in each plot at silking and the area of total leaves was measured with digital leaf area meter (LI-3100) and expressed in cm. Leaf area index was calculated by using the formula as proposed by Watson (1952). Two successive plants from the sampling row were uprooted at silking and were shade dried followed by oven dried at 65°C±5°C till constant weight obtained. The kernels from the air-dried cobs from each net plot were separated, cleaned and dried to obtain at least 13% moisture. Weight of grains of each plot was recorded separately and expressed as grain yield in kg ha^{-1}.

2.2. Description of spectroradiometer

Hyper spectral data were collected by using FieldSpec® 3 Spectroradiometer. The Field Spec® 3 Spectrometer is a general purpose spectrometer useful in application area requiring the measurement of reflectance, transmittance, radiance or irradiance. It is specifically designed for field environment remote sensing to acquire visible near infrared (VNIR) and short-wave infrared (SWIR) spectra. The Analytical Spectral Device (ASD) covers the spectral range between 350 to 2500 nm. The sampling interval over the 350–1000 nm range is 1.4 nm with a resolution of 3 nm (band width of half maximum). Over the 1000 -2500 nm range, the sampling interval is about 2 nm and the spectral resolution is between 10 and 12 nm. The results are then interpolated by the ASD software to produce readings at every 1 nm. A 1.2 m long fiber optic cable with a 25^0 field of view was used for the measurements. Spectral reflectance was derived as the ratio of reflected radiance to incident radiance estimated by a calibrated white reference (Spectralon).

2.3. Measurement of canopy reflectance

The canopy reflectance were measured in the spectral range of 350-2500 nm at sampling interval 1.4 nm @ 350-1000 nm and 2 nm @ 1000-2500 nm with the help of ASD FieldSpec® 3 Spectroradiometer (Analytical Spectral Devices Inc., Boulder, CO, USA). The reflectance measurements were made on sunny days between 11.00 and 13.00 hours in all plots. The FOV was 25^0 and the distance between the optical head of the spectroradiometer and the top of the plant was kept at 1 m for all observations. For optimization of ASD instrument, a Spectralon (Labsphere, Inc., Sutton, NH, USA) white reference panel was used to obtain reference signal prior to each canopy reflectance measurement.

The canopy reflectance was obtained after calibration with the white reference panel. Vegetation radiance measurement was taken by averaging 10 scans at an optimized integration time, with a dark current correction at every spectral measurement. The spectral readings were taken from each plot at silking of maize crop during both *kharif*, 2016 and *rabi,* 2016–17.

2.4. Processing of spectral responses

The spectral data was processed and exported to MS excel through ASD View Spec Pro (Version 6.2) software. Therefore, following narrow band and hyperspectral growth (i-iii) and canopy water status (iv-xi) indices were calculated using the following formulae (Table 1).

Table 1: Computation of indices

Sl. No.	Index	Abbreviation	Formula	Reference
i.	Simple ratio	SR	R900 / R680	Penuelas et al., 1997
ii.	Photochemical reflectance index	PRI	(R550-R530) / (R550+R530)	Gamon et al., 1992
iii.	Hyperspectral normalized difference vegetation index	hNDVI	(R900-R685) / (R900+R685)	Penuelas et al., 1997, Sims and Gamon, 2003
iv.	Normalized difference water index	NDWI1240	(R860-R1240) / (R860+R1240)	Gao, 1996
v.	Normalized difference water index	NDWI1640	(R860-R1640) / (R860+R1640)	Chen et al., 2005
vi.	Normalized difference water index	NDWI2130	(R860-R2130) / (R860+R2130)	Chen et al., 2005
vii.	Normalized difference infrared index	NDII	(R820-R1600) / (R820+R1600)	Hardisky et al., 1983
viii.	Normalized multi-band drought index	NMDI	R860-(R1640-R2130) / R860+(R1640+R2130)	Wang and Qu, 2007
ix.	Moisture stress index	MSI	R1600 / R820	Hunt et al., 1989
x.	Water band index	WBI	R900 / R970	Penuelas et al., 1993
xi.	Simple ratio water index	SRWI	R860 / R1240	Zarco-Tejada et al., 2003

2.5. Statistical analysis

The data were analyzed statistically applying analysis of variance technique for split plot design. The significance was tested by 'F' test (Snedecor and Cochron, 1967). Critical difference for examining treatment means for their significance was calculated at 5% level of probability (p=0.05). The influence of spectral indices was studied by comparing each date of sowing at optimum irrigation regimes (1.0 IW/

CPE), thus constituting four treatment combinations. Hence, maize crop growth period was divided into five phenophases *viz.,* P_1=Emergence to kneehigh stage; P_2=Kneehigh to tasseling stage; P_3=Knee high to silking stage; P_4=Silking to dough stage and P_5=Dough to physiological maturity stage. Means of all spectral indices that prevailed over different phenophases were calculated. The correlation coefficients were also worked out between spectral indices during different phenophases, dry matter, RWC, CTD, LAI, Yield attributes and grain yield of maize. Step wise regression (Draper and Smith, 1996) was carried out considering those spectral indices, which had significant influence on crop growth, yield and yield attributes.

3. Results and Discussion

3.1. Spectral signature in maize

In visible region (350-700 nm), the reflectance was higher (0.109 and 0.105) in 19th July (D_3) and 10 August (D_4) sown crop at silking stage compared to 18th June (D_1) and 04th July (D_2) sowings (0.072 and 0.069) during *kharif,* 2016. Reflectance was recorded higher (0.514) in 18th June (D_1) at silking during *kharif*, 2016 followed by 04th July (D_2) and 19th July (D_3) while, lowest reflectance (0.371) was observed with 10 August (D_4) sown crop (Figure 1) at NIR region (700 to 1350 nm). While, mid infrared (MIR) region (1350-2500 nm), the reflectance was higher (0.245) in 10 August (D_4) sown crop at silking stage followed by 18th June (D_1) (0.225), 19th July (D_3) (0.219) and 04th July (D_2) (0.195) sown crop.

During *rabi*, 2016–17 in visible region (350–700 nm), the reflectance was higher in 01st December (D_3) (0.133) sown crop at silking stage followed by 17th November (D_2) (0.115), 01st November (D_1) (0.081 and 0.081) and 18th December (D_4) (0.080 and 0.052) sown crop. Higher reflectance (0.568) was observed in 17th November (D_2) followed by 01st November (D_1), 01st December (D_3) and 18th December (D_4) sown crop at silking at NIR region (700 to 1350 nm). While, mid infrared (MIR) region (1350-2500 nm), the reflectance was higher (0.328) in 17th November (D_2) sown crop at silking stage followed by 01st December (D_3) (0.281), 18th December (D_4) (0.215) and 01st November (D_1) (0.212) sown crop. As crop advanced from knee high to silking, the leaf area and crop

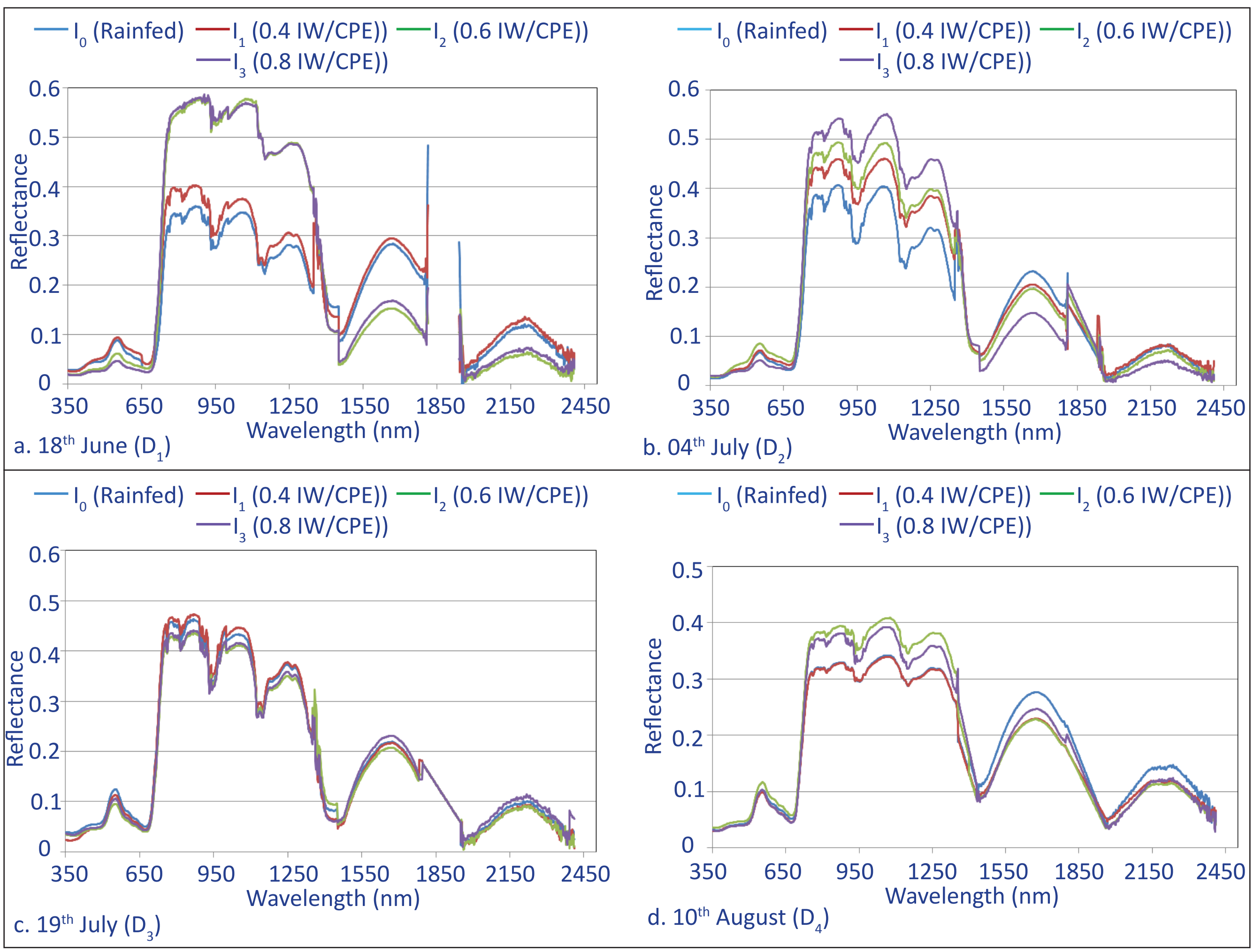

Figure 1: Hyperspectral reflectance of maize at silking stage as influenced by irrigation schedules and dates of sowing (a, b, c and d) during *kharif*, 2016

drymatter increased. The increased chlorophyll with the advancement of crop stage caused decreased reflectance in visible regions due to strong absorption by pigments whereas increase in canopy coverage resulted in increased reflectance in NIR region. As plant senescence from dough to maturity stage, reflectance increased in visible region and decreased in NIR region probably due to decrease in pigments and mobilization of N from leaves to grains (Rani et al., 2016).

It has been reported in literature that five absorption bands centered 950–970, 1150–1260, 1450, 1950 and 2250 are related to water absorption. Reflectance at these wavelengths show sensitivity to absorption to water and therefore has promising potential in estimating canopy water content. Since, the reflectance data at 2500 nm show a lot of noise due to presence of atmospheric water vapour content, 2250 nm wavelength was selected instead of 2500 nm. In visible region (350–700 nm), the reflectance was higher (0.118) in rainfed (I_0) at silking compared to 0.4 IW/CPE (I_1), 0.6 IW/CPE (I_2) and 0.8 IW/CPE (I_3) during *kharif,* 2016. While, in *rabi*, 2016-17 the reflectance was higher (0.109) in 0.4 IW/CPE (I_1) at silking respectively followed by 0.8 IW/CPE (I_3), 0.6 IW/CPE (I_2) and 0.4 IW/CPE (I_1). Higher reflectance (0.493) was observed in 0.8 IW/CPE (I_3) followed by 0.6 IW/CPE (I_2), 0.4 IW/CPE (I_1) at silking during *kharif,* 2016 (Figure 1) at NIR region. During *rabi*, 2016-17 higher reflectance (0.514) was observed in 1.0 IW/CPE (I_4) followed by 0.8 IW/CPE (I_3), 0.6 IW/CPE (I_2) at silking (Figure 2). Whereas, lowest reflectance was observed with Rainfed (I_0) and 0.4 IW/CPE (I_1) during *kharif*, 2016 and *rabi,* 2016-17 respectively at NIR regions (740-1350 nm). Maize reflectance at mid infrared (MIR) region (1350-2500 nm), the reflectance was higher (0.255) was observed in rainfed (I_0) at silking and dough stage respectively over 0.4 IW/CPE (I_1), 0.6 IW/CPE (I_2) and 0.8 IW/CPE (I_3) during *kharif,* 2016. While, in *rabi*, 2016-17 the reflectance was higher (0.289) in 0.4 IW/CPE (I_1) at silking followed by 0.8 IW/CPE (I_3), 0.6 IW/CPE (I_2) and 0.4 IW/CPE (I_1).

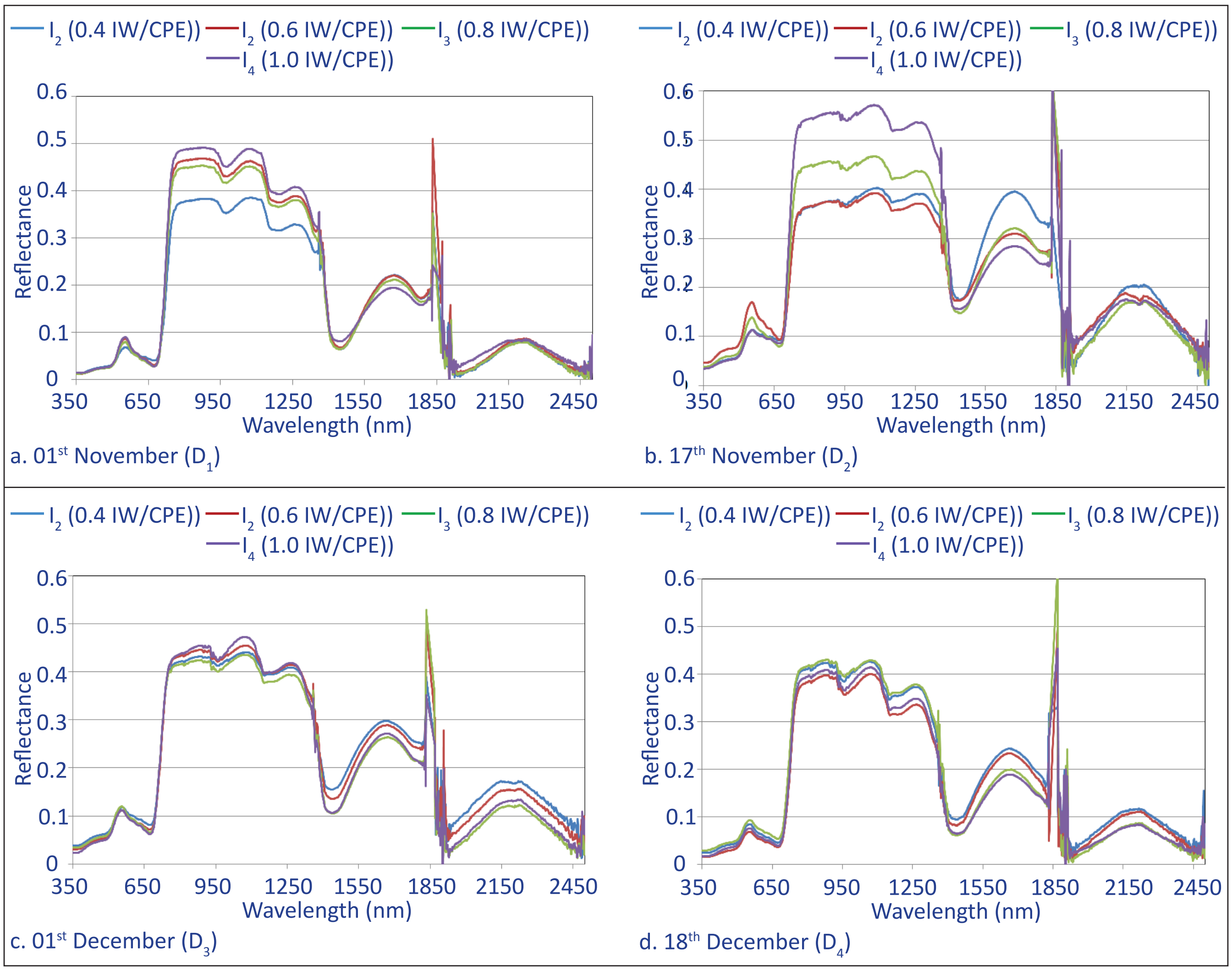

Figure 2: Hyperspectral reflectance of maize at silking stage as influenced by irrigation schedules and dates of sowing (a, b, c and d) during *rabi*, 2016-17

Scheduling irrigation at unstressed conditions, 0.8 IW/CPE (I_3) and 1.0 IW/CPE (I_4) of maize resulted in low reflectance in visible region (400 to 700 nm), high in near infrared (NIR) region (700 to 1350 nm) and low in mid infrared (MIR) region (1350–2500 nm) during *kharif*, 2016 and *rabi,* 2016-17 respectively. Under stressed condition, the reflectance was high in visible region and low in NIR region and high in MIR in rainfed and 0.4 IW/CPE (I_0) respectively in *kharif*, 2016 and *rabi,* 2016–17 compare to unstressed maize. The spectral data indicated that in the ultra-violet visible region (350-710 nm), the spectral reflectances were almost same and did not change with increasing water stress whereas, in NIR regions (740-1350 nm) the reflectance tended to increase with decreasing water stress, resulting in higher differential response at NIR than in visible regions. At higher wavelengths, in MIR (1350–2500 nm) is dominated by soil and leaf water absorption, particularly at 1400 and 1900 nm with reflectance increasing when leaf liquid water content decreases but their response to varying water stress was low compared to that in NIR region (Huete, 2004; Genc et al., 2013). This scattering occurred deep within the leaf tissue, and hence percentage light reflected in the NIR region provided details on the physiological condition of plant under stress (Nilsson, 1995; Hatfield and Pinter, 1993). The decline in reflectance was due to the reduced turgidity of spongy - mesophyll layer in water stressed compared to the turgidity levels of the crop received more irrigation (Jayasree et al., 2013).

3.2. Spectral vegetation indices

Spectral vegetation indices are mathematical expressions involving reflectance values from different part of the electromagnetic spectrum, aimed to optimize information and normalize measurements made across varied environmental conditions. The reflectance data were transformed in to vegetation indices viz., Simple Ratio (SR), Photochemical Reflectance Index (PRI), Hyperspectral Normalized Difference Vegetation Index (hNDVI), Normalized Difference Water Index ($NDWI_{1240}$), ($NDWI_{1640}$), ($NDWI_{2130}$), Normalized Difference Infrared Index (NDII), Normalized Multi-band Drought Index (NMDI), Moisture Stress Index (MSI), Water Band Index (WBI), Simple Ratio Water Index (SRWI) were used to distinguish water stress severity in maize at silking during *kharif*, 2016 and *rabi,* 2016–17 (Table 2).

Simple ratio is one of the most important ratio indices to represent plant health and dry matter production. Highest value of SR, PRI, NDWI at 1240, 1640 and 2130 nm, NDII, NMDI, WBI and SWRI was attained by 18th June (D_1) sowing followed by 04th July (D_2), 19th July (D_3) and 10th August (D_4) while, 01st November (D_1) followed by 17th November (D_2), 01st December (D_3) and 18 December (D_4) during *kharif*, 2016 and *rabi,* 2016-17 respectively at all the growth stages. The data revealed that highest SR, PRI, NDWI at 1240, 1640 and 2130 nm, NDII, NMDI, WBI and SWRI values were recorded with 0.8 IW/CPE (I_3), 0.6 IW/CPE (I_2), 0.4 IW/CPE (I_1) and rainfed (I_0) during *kharif*, 2016 however, 1.0 IW/CPE (I_4), 0.8 IW/CPE (I_3), 0.6 IW/CPE (I_2) and 0.4 IW/CPE (I_1) during *rabi,* 2016-17 respectively.

Similar results in wheat for different spectral indices (Prasad et al., 2007). PRI index as a measure of light use efficiency by wheat crop (Wu et al., 2008). Combination of SWIR and NIR is necessary to improve the accuracy in estimating vegetation water content at the leaf level from optical observations (Ceccato et al., 2002). The response of the $NDWI_{1240}$ index was ten times as strong for the stress group as for the control in the early stages of the stress (Bayat et al., 2016). This index is a measure of liquid water molecules in vegetation canopies that interacted with the incoming solar radiation. The NDWI was proposed by Gao (1996) as a tool to assess water stress and was used to estimate vegetative water content (Jackson et al., 2004). $NDWI_{1940}$ water indices may have special sensitivity to severe drought conditions given its high sensitivity to low EWT (Ranjan et al., 2015). It was observed that at booting stage, EWT and RLWC were significantly correlated with most of the hyperspectral indices whereas correlation of VWCd was significant with only WBI (Ranjan et al., 2015). The hyperspectral indices which have been identified in this study as good estimators of crop water status include reflectance at 860 nm wavelength in their formulae (Jacquemoud and Baret, 1990).

NDVI values increased with advancement of vegetative phase and reach highest level silking stage which also coincide with maximum leaf area index. Thereafter, NDVI values decreased as the crop progressed towards physiological maturity. Among the sowing environments, NDVI was higher under early sown crop at all growth stages followed by timely and late sown crop in both the seasons. Under incremental irrigation scheduling, hNDVI values were highest when irrigation scheduled at 0.8 IW/CPE (I_3) and 1.0 IW/CPE (I_4) during *kharif*, 2016 and *rabi,* 2016-17 respectively at all growth stages. NDVI values increased till production of maximum LAI by wheat crop and thereafter decreased towards maturity due to decrease in LAI. This index behaved closely with leaf area production by the crop. So, early sown crop showed greater NDVI values as compared to other sowing dates in 2010–12 (Verma et al., 2010). Unlike other ratio indices, MSI followed just the opposite trend. First sowing date recorded the lowest value of MSI, followed by remaining sowing dates during both the seasons. The lowest MSI value was noticed when irrigation scheduled at 0.8 IW/CPE (I_3) and 1.0 IW/CPE (I_4) during and *kharif*, 2016 and *rabi,* 2016–17 respectively at all growth stages.

3.3. Growth parameters and grain yield of maize

3.3.1. Growth parameters

In *kharif*, 2016 significantly higher DM accumulation and LAI was observed at silking (93.1 g plant^{-1}, 2.993), in 04th July (D_2) sown crop and significantly superior to 19th July (D_3), 18th June

Table 2: Spectral indices during silking stage of maize as influenced by dates of sowing and irrigation schedules

Kharif	*Rabi*	*Kharif*	*Rabi*	*Kharif*	*Rabi*	*Kharif*	*Rabi*	*Kharif*	*Rabi*	*Kharif*	*Rabi*	*Kharif*	*Rabi*
18-Jun (D_1)	01-Nov (D_1)	12.14	14.59	0.087	0.089	0.807	0.846	0.807	0.093	0.314	0.371	0.794	0.725
04-Jul (D_2)	17-Nov(D_2)	9.93	12.30	0.079	0.080	0.796	0.779	0.796	0.067	0.350	0.307	0.699	0.638
19-Jul (D_3)	01-Dec (D_3)	9.88	11.42	0.078	0.079	0.776	0.808	0.776	0.087	0.309	0.342	0.723	0.680
10-Aug (D_4)	18-Dec (D_4)	9.69	10.70	0.068	0.083	0.720	0.759	0.720	0.060	0.243	0.290	0.660	0.600
Irrigation levels (I)													
Kharif	*Rabi*												
Control (Rainfed) (I_0)	0.4 IW/CPE (I_1)	7.86	8.82	0.075	0.080	0.732	0.748	0.083	0.060	0.270	0.284	0.635	0.594
0.4 IW/CPE (I_1)	0.6 IW/CPE (I_2)	9.93	11.90	0.077	0.083	0.764	0.792	0.097	0.074	0.293	0.316	0.706	0.642
0.6 IW/CPE (I_2)	0.8 IW/CPE (I_3)	10.78	13.01	0.078	0.083	0.786	0.813	0.098	0.080	0.301	0.337	0.736	0.686
0.8 IW/CPE (I_3)	1.0 IW/CPE (I_4)	13.06	15.28	0.081	0.085	0.817	0.839	0.120	0.092	0.351	0.372	0.799	0.719

Date of sowing (D)		NDII		NMDI		MSI		WBI		SRWI	
Kharif	*Rabi*	*Kharif*	*Rabi*	*Kharif*	*Rabi*	*Kharif*	*Rabi*	*Kharif*	*Rabi*	*Kharif*	*Rabi*
18-Jun (D_1)	01-Nov (D_1)	0.474	0.410	0.399	0.434	0.347	0.422	1.104	1.085	1.151	1.206
04-Jul (D_2)	17-Nov(D_2)	0.367	0.339	0.420	0.398	0.465	0.506	1.044	1.063	1.230	1.148
19-Jul (D_3)	01-Dec (D_3)	0.407	0.372	0.400	0.419	0.424	0.466	1.077	1.069	1.159	1.193
10-Aug (D_4)	18-Dec (D_4)	0.371	0.321	0.368	0.395	0.477	0.537	1.075	1.060	1.094	1.135
Irrigation levels (I)											
Kharif	*Rabi*										
Control (Rainfed) (I_0)	0.4 IW/CPE (I_1)	0.348	0.312	0.379	0.387	0.491	0.536	1.068	1.064	1.133	1.131
0.4 IW/CPE (I_1)	0.6 IW/CPE (I_2)	0.393	0.349	0.393	0.406	0.438	0.498	1.071	1.066	1.154	1.166
0.6 IW/CPE (I_2)	0.8 IW/CPE (I_3)	0.406	0.373	0.390	0.413	0.426	0.467	1.070	1.067	1.157	1.178
0.8 IW/CPE (I_3)	1.0 IW/CPE (I_4)	0.473	0.409	0.424	0.438	0.357	0.429	1.091	1.079	1.191	1.207

(D_1) and 10th August (D_4) sown crops respectively. However, 19th July (D_3) was comparable with 18th June (D_1) (Table 3). Lowest DM accumulation and LAI at silking (79.9 g plant^{-1}, 2.457) was observed in 10th August (D_4) sown crop. In *rabi*, 2016-17 01st November (D_1) sown crop showed maximum DM accumulation and LAI at silking (109.7 g plant^{-1}, 2.769) and significantly superior to 17th November (D_2), 01st December (D_3) and 18th December sown crops respectively while, 17th November (D_2) dry matter production was comparable with 01st December (D_3) sown crop. The lowest DM accumulation and LAI was observed at silking (130.4 g plant^{-1}, 2.170) with 18th December (D_4) sown crops respectively. Crop sown on 10th August (D_4) and 18th December (D_4) recorded low DM production by 33% and 19% over 04th July (D_2) and 01st November (D_1) sown crops in *kharif*, 2016 and *rabi*, 2016–17 respectively. The reduction in maximum LAI in 10th August and 18th December, at silking stage was by 21% and 23% over 04th July and 01st November sown crop in *kharif*, 2016 and *rabi*, 2016–17 respectively.

The observed difference in DM accumulation during development may result from differences in climate, differential absorption of PAR due to variation in plant population and LAI, or differences in the efficiency of converting absorbed photosynthetic active radiation (APAR) into DM (Tollenaar and Agui-lera, 1992). Higher temperature during vegetative growth stage hastened growth rate in early sown crop (Van Dobben, 1962), whereas, in delayed sowings, minimum temperatures reduced growth rate resulting in lower DM production. Early sowing date of in spring and fall resulted in high biomass because of greater solar radiation

Table 3: Drymatter (g plant^{-1}) production, LAI (%) and grain yield (kg ha^{-1}) of maize at silking as influenced by dates of sowing and irrigation schedules

Treatments		Drymatter		LAI		*Grain yield*	
Date of sowing (D)		Silking stage		Silking stage		Silking stage	
Kharif	*Rabi*	*Kharif*	*Rabi*	*Kharif*	*Rabi*	*Kharif*	*Rabi*
18-Jun (D_1)	01-Nov (D_1)	87.8	109.7	2.867	2.769	5600	5396
04-Jul (D_2)	17-Nov(D_2)	93.1	101.3	2.993	2.662	6963	4777
19-Jul (D_3)	01-Dec (D_3)	87.2	98.1	2.870	2.656	5961	4775
10-Aug (D_4)	18-Dec (D_4)	79.9	83.1	2.457	2.170	3011	4047
SEm±		1.2	1.5	2.5	0.019	0.028	105
CD (p=0.05)		4.3	5.3	8.5	0.067	0.097	364
Irrigation schedules (I)							
Kharif	*Rabi*						
Control (Rainfed) (I_0)	0.4 IW/CPE (I_1)	73.7	85.0	2.451	1.921	4108	2464
0.4 IW/CPE (I_1)	0.6 IW/CPE (I_2)	85.2	94.5	2.698	2.562	5333	3837
0.6 IW/CPE (I_2)	0.8 IW/CPE (I_3)	89.7	101.3	2.887	2.805	5725	5588
0.8 IW/CPE (I_3)	1.0 IW/CPE (I_4)	99.4	111.4	3.149	2.969	6369	7105
SEm±		2.6	2.9	3.5	0.066	0.048	186
CD (p=0.05)		7.5	8.4	10.2	0.193	0.142	544
Interaction (D×I)							
SEm±		4.6	5.8	0.133	0.097	373	334
CD (p=0.05)a		NS	NS	NS	NS	NS	NS
SEm±		5.0	5.2	0.116	0.089	339	306
CD (p=0.05)b		NS	NS	NS	NS	NS	NS

a: Difference of two Irrigations at same levels of dates of sowing; b: Difference of two dates of sowing at same or different levels of irrigations; NS: Not significant at p=0.05

interception and thus resulted in higher RUE. Because, total biomass is depended on light interception and RUE (Abbas et al., 2020). Warmer temperatures speed up crop development rate, consequential shorter phases and less affective grain filling phase resulted in lesser partitioning of biomass toward grains in rabi (Rani et al., 2013).

Relatively higher DM accumulation was recorded with I_3 (0.8 IW/CPE) and I_4 (1.0 IW/CPE) at silking (99.4 and 111.4 g plant^{-1}) stage in *kharif*, 2016 and *rabi*, 2016–17 respectively. Which was however, significantly superior to I_2 (0.6 IW/CPE), I_1 (0.4 IW/CPE) and I_0 (rainfed) during *kharif*, 2016 and I_3 (0.8 IW/CPE), I_2 (0.6 IW/CPE) and I_1 (0.4 IW/CPE) during *rabi*, 2016–17 (Table 3). DM production during *kharif*, I_2 (0.6 IW/CPE) was comparable with I_1 (0.4 IW/CPE). LAI reached to a maximum value (3.149) at silking in the 0.8 IW/CPE (I_3) which was significantly superior to I_2 (0.6 IW/CPE), I_1 (0.4 IW/CPE) and rainfed (I_0) in *kharif,* 2016. However, I_2 (0.6 IW/CPE) was comparable with I_1 (0.4 IW/CPE) during *kharif,* 2016. Higher LAI (2.969) was observed with I_4 (1.0 IW/CPE) and significantly superior over I_3 (0.8 IW/CPE), I_2 (0.6 IW/CPE) and I_1 (0.4 IW/CPE) during *rabi*, 2016–17. The control rainfed plot in *kharif*, 2016 and 0.4 IW/CPE in *rabi*, 2016–17 recorded the significantly lower LAI (2.451 and 1.921) over other treatments at silking. The rate of increase in LAI due to increase of number of irrigations (0 to 3 and 3 to 8) at silking varied from 22 to 30% and 28 to 35% during *kharif*, 2016 and *rabi*, 2016–17 respectively.

The dry matter accumulation in maize is associated with plant height, number of leaves and leaf growth and its persistence during vegetative phase and a combination of cobs, grains cob^{-1} and grain weight with concurrent shifts in leaf and stem mass during reproductive period (Payero et al., 2009). Higher leaf number, expansion and duration of leaf area coupled with higher vegetative growth period caused 28–32% loss of final dry matter weight (Cakir, 2004).

3.3.2. Grain yield

During *kharif*, 2016–17 grain yield of maize was highest (6963 kg ha^{-1}) in 04th July (D_2) sown crop, which was significantly superior to 19th July (D_3), 18th June (D_1) and 10th August (D_4)

sown crops, however, 19th July (D_3) was on par with 18th June (D_1). Lowest grain yield (3011 kg ha^{-1}) was recorded with 10th August (D_4). In *rabi*, 01st November (D_1) sown crop recorded the highest (5396 kg ha^{-1}) grain yield, which was significantly superior over 17th November (D_2), 01st December (D_3) and 18 December (D_4) however, 17th November (D_2) sown crop, in turn comparable with 01st December (D_3) sown crop. Significantly the lowest grain yield was observed in 18th December (D_4) sown crop (4047 kg ha^{-1}) across all other sowing dates. Sowing on 10th August (D_4) and 18th December (D_4) reduced the grain yield by 57% and 25% over 04th July (D_2) and 01st November (D_1) in *kharif*, 2016 and *rabi*, 2016–17 respectively. Late sowing affected grain yield by decreasing kernel number per unit area (Table 3). Yield increased with optimum planting date probably due to improved physiological conditions during the silking period for optimum kernel set (Barbieri et al., 2000). Late sowing of maize manifested significant reduction in grain yield. Low growth rate in the late sown crop could be mainly due to unfavourable environmental effects encountered during the reproductive phase and due to the low net assimilation rate (Rani et al., 2016). Optimum planting date for maize was 15th July in the Peshawar region. Variation in biomass yield across sowing dates was associated more with differences in the amount of radiation intercepted than differences in radiation use efficiency (Ahmad et al., 2001).

During *kharif*, 2016 grain yield of maize was highest (6369 kg ha^{-1}) in 0.8 IW/CPE (I_3), which was significantly superior to I_2 (0.6 IW/CPE), I_1 (0.4 IW/CPE) and I_0 (rainfed). However, I_2 (0.6 IW/CPE) was comparable with I_1 (0.4 IW/CPE) and lowest grain yield (4108 kg ha^{-1}) was recorded with control (I_0). During *rabi*, 2016-17 significantly highest grain yield (7105 kg ha^{-1}) was obtained with I_4 (1.0 IW/CPE) over I_3 (0.8 IW/CPE), I_2 (0.6 IW/CPE) and I_1 (0.4 IW/CPE). The lowest grain yield was obtained (2464 kg ha^{-1}) with irrigation scheduling of 0.4 IW/CPE (I_1). The increase in grain yield with irrigation scheduling of 0.8 IW/CPE (I_3) over control (I_0) and 1.0 IW/CPE (I_4) over 0.4 IW/CPE (I_1) was 36% and 65%, respectively in *kharif*, 2016 and *rabi,* 2016-17 respectively. Results of the study showed that the yield and yield components were limited by soil moisture content and low temperature stress in the delayed sowing date. This reduction in water use is accompanied by decrease in plant water content affecting the crop growth and development of the plants resulting in reduced crop yields (Kumar et al., 2013).

3.4. Relationship between spectral vegetation indices and growth parameters

Correlation coefficients between spectral vegetation indices (SR, PRI, hNDVI, $NDWI_{1240}$, $NDWI_{1640}$, $NDWI_{2130}$, NDII, NMDI, MSI, WBI, SRWI) and biophysical and growth parameters of maize crop at different phenophases during *kharif*, 2016 and *rabi*, 2016−17 are presented in Table 4. The results indicate that at knee high stage PRI was positively associated with drymatter (0.56). SR (-0.37), $NDWI_{1240}$ (-0.41), $NDWI_{1640}$ (-0.37), NDII (-0.33) and NDMI (-0.44) and SRWI (-0.40) were significantly and negatively associated with LAI except with PRI (0.53) which is positively correlated. At silking stage, superior and positive correlation was observed with drymatter and SR (0.72), PRI (0.54), hNDVI (0.51), $NDWI_{1640}$ (0.41), NMDI (0.43) and WBI (0.38). LAI was positively associated with SR (0.50), PRI (0.37), $NDWI_{1240}$ (0.57), $NDWI_{2130}$ (0.67), NDII (0.71) and WBI (0.65) while negatively correlated with MSI (-0.68). At dough stage, all the spectral indices were positively correlated with drymatter and LAI except PRI and MSI which are negatively associated. At physiological maturity, drymatter was positively correlated with SR (0.62), $NDWI_{1640}$ (0.55), $NDWI_{2130}$ (0.74), NMDI (0.36), SRWI (0.66) while, PRI (-0.37) and MSI (-0.58) were negatively correlated. LAI was positively correlated with SR (0.47), $NDWI_{2130}$ (0.74), NMDI (0.50), WBI (0.36) and SRWI (0.50) while, negatively associated with MSI (-0.53).

However, the relationship between NDVI and LAI for pooled data over the two years, the overall best fit was exponential with a coefficient of determination (R^2 =0.85) (Jayasree et al., 2013). An exponential relationship between LAI and NDVI was observed for soybean, beans, peas, corn and wheat (Haboudane et al., 2004). hyperspectral indices hNDVI and PRI for better ABM prediction. PRI is the best index for chlorophyll content prediction by an exponential model in wheat crop (Zhao et al., 2007). All the hyperspectral indices based on SWIR reflectances which are identified as the best estimator of crop water stress include 1640 nm in their formulae. Similarly, the exponential relation of broadband NDVI with LAI (Vina et al., 2011) with RMSE 1.18 was improved to an exponential 44 relationship when hNDVI was related with LAI, which showed much lower RMSE of 0.30. Linear relationship between SR and LAI (R^2=0.87), exponential relationship NDVI and PRI with LAI (R^2=0.91 and 0.87, respectively) of wheat (Aparicio et al., 2000). This study also supported the similar type of relationship when hNDVI was used as an estimator for LAI.

The results indicate that grain yield were significantly and positively associated with SR, hNDVI, $NDWI_{1240}$, $NDWI_{1640}$, $NDWI_{2130}$, NDII, NMDI, WBI and SRWI at knee high, silking, dough and physiological maturity. Yield was negatively and significantly correlated with MSI and PRI at all phenophases. Superior correlation was observed at dough and silking stages of maize crop as compared to knee high and physiological maturity stage. Highest values at the booting stage may be due to the highest amount of green leaf area. Decreasing trend from booting to maturity can be attributed to reduced reflectance in the NIR region and increased reflectance in visible region. This is due to damage of green tissue from booting to harvesting stage of crop growth in wheat (Prasad et al., 2007; Pradhan et al., 2012; Ramachandiran et al., 2016).

3.5. Regression analysis

Stepwise regression analysis was performed to find out the critical spectral indices responsible for higher maize drymatter, grain yield at various phenophases. The regression models obtained were presented in the Table 5.

Table 4: Correlation coefficients for relationships between spectral vegetation indices at different phenophases and growth parameters of maize

Biophysical/ growth parameter	SR	PRI	hNDVI	$NDWI_{1240}$	$NDWI_{1640}$	$NDWI_{2130}$	NDII	NMDI	MSI	WBI	SRWI
Knee high stage											
DM	0.08	0.56^{**}	0.35	0.01	0.03	0.11	-0.01	-0.10	-0.08	0.01	0.02
LAI	-0.37^{*}	0.53^{**}	-0.14	-0.41^{*}	-0.37^{*}	-0.33	-0.41^{*}	-0.44^{*}	0.35	-0.34	-0.40^{*}
Grain yield	0.33	0.26	0.40^{*}	0.31	0.28	0.31	0.29	0.23	-0.33	0.30	0.29
Silking stage											
DM	0.72^{**}	0.54^{**}	0.51^{**}	0.15	0.41^{*}	0.31	0.35	0.43^{*}	-0.31	0.38^{*}	0.25
LAI	0.50^{**}	0.37^{*}	0.31	0.57^{**}	0.21	0.67^{**}	0.71^{**}	0.22	-0.68^{**}	0.65^{**}	0.09
Grain yield	0.62^{**}	0.44^{*}	0.31	0.38^{*}	0.18	0.54^{**}	0.57^{**}	0.20	-0.53^{**}	0.54^{**}	0.02
Dough stage											
DM	0.06^{**}	-0.37^{*}	0.56^{**}	0.49^{**}	0.57^{**}	0.48^{**}	0.48^{**}	0.55^{**}	-0.46^{**}	0.32	0.57^{**}
LAI	0.35^{*}	-0.63^{**}	0.47^{**}	0.67^{**}	0.72^{**}	0.69^{**}	0.70^{**}	0.73^{**}	-0.67^{**}	0.52^{**}	0.68^{**}
Grain yield	0.75^{**}	-0.42^{*}	0.78^{**}	0.71^{**}	0.75^{**}	0.71^{**}	0.70^{**}	0.72^{**}	-0.69^{**}	0.59^{**}	0.77^{**}
Physiological maturity											
DM	0.62^{**}	-0.37^{*}	0.32	0.18	0.55^{**}	0.74^{**}	0.15	0.36^{*}	-0.58^{**}	0.12	0.66^{**}
LAI	0.47^{**}	-0.11	0.14	0.05	0.30	0.74^{**}	0.16	0.50^{**}	-0.53^{**}	0.36^{*}	0.50^{**}
Grain yield	0.46^{**}	-0.18	0.20	0.23	0.47^{**}	0.67^{**}	0.14	0.32	-0.44^{*}	0.20	0.58^{**}

**: Significant at the (*p*=0.01) level; *: Significant at the (*p*=0.05) level

Note: Simple Ratio (SR), Photochemical Reflectance Index (PRI), Hyperspectral Normalized Difference Vegetation Index (hNDVI), Normalized Difference Water Index ($NDWI_{1240}$), ($NDWI_{1640}$), ($NDWI_{2130}$), Normalized Difference Infrared Index (NDII), Normalized Multi-band Drought Index (NMDI), Moisture Stress Index (MSI), Water Band Index (WBI), Simple Ratio Water Index (SRWI), Drymatter (g plant^{-1}) (DM), Leaf Area Index (LAI), Relative Water content (%) (RWC), Canopy Temperature Difference (°C) (CTD)

Table 5: Stepwise regression models relating LAI, drymatter, CTD, yield attributes and yield with spectral indices

Models	Stage	Regression model	R^2
Model I	Drymatter at silking	$Y=55.4^{**}+3.6^{**}P_3SR$	0.52
Model II	Drymatter at dough	$Y=365.8^{**}+203.9^{**}P_4SRWI+2.9^{**}P3SR–465.1^{**}P4WBI$	0.57
Model III	Drymatter at PM	$Y=82.8+240.6^{**}\ P_5NDWI_{2130}+147.8^{**}\ P_3NDWI_{2130}+96.5^{**}P_5SRWI–95.5^{**}\ P_5hNDVI–1223.3^{*}\ P_1PRI$	0.84
Model IV	LAI at silking	$Y=-8.8^{**}+17.7^{**}\ P_3NDII+11.7^{**}\ P_3MSI–1.9^{**}\ P_3NDWI_{1640}$	0.67
Model V	LAI at dough	$Y=0.3+3.2^{**}\ P_4NMDI–1.1^{**}\ P_3NDWI_{2130}$	0.60
Model VI	LAI at PM	$Y=1.0+2.9^{**}\ P_5NDWI_{2130}+1.4^{*}\ P_4hNDVI–1.0^{**}\ P_5hNDVI–8.0^{**}\ P_4PRI$	0.77
Model VII	Grain yield	$Y=-17647^{**}+11004^{**}\ P_5NDWI_{1640}+395^{**}\ P_3SR+59539^{**}\ P_4SRWI–130158^{**}\ P_4NDWI_{1240}–4113^{**}\ P_3WBI+2384^{**}\ P_5hNDVI+21154^{*}\ P_3NDWI_{1240}$	0.95

**: Significant at the (*p*=0.01) level; *: Significant at the (*p*=0.05) level; Y: Predicted value

Note: Simple Ratio (SR), Photochemical Reflectance Index (PRI), Hyperspectral Normalized Difference Vegetation Index (hNDVI), Normalized Difference Water Index ($NDWI_{1240}$), ($NDWI_{1640}$), ($NDWI_{2130}$), Normalized Difference Infrared Index (NDII), Normalized Multi-band Drought Index (NMDI), Moisture Stress Index (MSI), Water Band Index (WBI), Simple Ratio Water Index (SRWI), Knee high stage (P_1), Silking stage (P_3), Dough stage (P_4), Physiological maturity (P_5), Leaf Area Index (LAI), Drymatter (DM), Canopy Temperature Difference (CTD), Relative Water Content (RWC), Physiological maturity (PM)

3.5.1. Regression models for prediction of drymatter

Model I: Drymatter at silking

The SR prevailed during P_3 stage (knee high to silking stage) of the crop growth, accounted for 52% variation in DMP at silking stage.

Model II: Drymatter at dough

During the growing season, DMP at dough was influenced by SR at silking, SRWI and WBI at dough during crop growth. These spectral indices accounted for 57% of variation in DMP at dough stage.

Model III: Drymatter at physiological maturity

The PRI prevailed during emergence to knee high stage, $NDWI_{2130}$ prevailed during P_3 stage (knee high to silking stage) of the crop growth, $NDWI_{2130}$, SRWI and hNDVI during physiological maturity accounted for 84% variation in DMP at physiological maturity.

3.5.2. Regression models for prediction of leaf area index

Model IV: Leaf area index at silking

The leaf area index (LAI) at P_3 (Silking) was influenced by NDII, MSI and $NDWI_{1640}$ at silking and which accounted for 67% of variation in leaf area index in maize.

Model V: Leaf area index at dough

During the growing season, leaf area index at dough stage was influenced by $NDWI_{2130}$ at silking and NMDI at dough stage. These spectral indices prevailed at P_3 and P_4 stage (Silking and dough stage) accounted for 60% of variation in LAI at dough stage.

Model VI: Leaf area index at physiological maturity

Hyperspectral normalized difference vegetation index prevailed at dough and physiological maturity, photochemical reflectance index at dough and normalized difference water index at 2130 nm at PM influenced the LAI at physiological maturity stage and which accounted for 77% of total variation in LAI at physiological maturity.

In rainfed conditions, integration of either NDVI, SR, or PRI from heading to maturity explained 52, 59, and 39% of the variability in yield within genotypes in rainfed conditions and 39, 28, and 26% under irrigation. The usefulness of the SR and NDVI for calculating green area and grain yield was limited to LAI values <3 (Aparicio et al., 2000; Babar et al., 2006).

3.5.3. Regression models for prediction of grain yield

Model VII: Grain yield

During the growing season, grain yield was influenced by SR, WBI and $NDWI_{1240}$ at silking, $NDWI_{1240}$ and SRWI at dough, $NDWI_{1640}$ and hNDVI at physiological maturity which accounted for 95% variation in grain yield of maize crop. Prediction of crop yield improved by individually combining NDVI and CV (Arnall et al., 2006). NDVI obtained from midseason spectral reflectance data of crop might prove a better indicator and could be used to predict yield (Raun et al., 2001). The relationship of NDVI with grain and biomass yields was stronger at the heading stage (r=0.98 and R^2=0.93) in irrigated wheat. Similar relationship of grain and biomass yields was also observed for NDWI (Chandel et al., 2019).

4. Conclusion

To assess the combined effect of dates of sowing and water stress in maize, hyperspectral reflectance value were transformed into spectral vegetation indices. All the spectral vegetation indices *viz.,* SR, PRI, hNDVI, $NDWI_{1240}$, $NDWI_{1640}$, $NDWI_{2130}$, NDII, NMDI, MSI, WBI and SRWI were positively correlated with LAI, dry matter and grain yield. This result indicates the ability of spectral vegetation indices to quantify effect of water stress on maize through remote sensing.

5. Acknowledgement

We thank Dr. M.V.R. Seshasai, Deputy Director, Earth & Climate Sciences Area (ECSA), Dr. C.S.K. Murthy, Group Director (AS&AG), National Remote Sensing Centre, Balanagar, Hyderabad for their inspiring guidance and encouragement. Authors are grateful to University for financial assistance to carry out the experiment and analysis of the related samples.

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