DEVELOPMENT AND EVALUATION OF REMOTE SENSING TECHNIQUES FOR ASSESSING WINTER WHEAT GROWTH AND YIELD

A Dissertation

by

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ABSTRACT

Wheat (*Triticum aestivum* L.) production can be enhanced through the development of improved cultivars with wider genetic background, capable of producing higher yield under various agro-climatic conditions, biotic and abiotic stresses. Early growth stages in wheat can be influenced by many factors, such as planting date, type of cultivar, and water management, among others. It is essential to monitor the crop performance early by taking accurate measurements of crop growth parameters. Monitoring wheat performance during the growing season will provide information on productivity and prospects for realizing yield potential. However, monitoring conventional methods are time-consuming, labor-intensive and can cause large sampling errors. Remote sensing tools have provided easy and quick measurements of ground cover and aboveground biomass, without destructive sampling. The central objective of this research is to evaluate the performance of wheat genotypes using remote sensors on a ground-based plant sensing system, Greenseeker®, and manned aircraft system, under rainfed and irrigated conditions. Field experiments were conducted in the Texas A&M AgriLife Research Experiment Station at Bushland, Texas, in 2011-2012, 2012-2013, 2014-2015 and 2015-2016 winter wheat growing seasons. Yield as the major desirable trait for plant breeders was associated with biomass at anthesis and maturity, harvest index, spikes m^{-2}, seeds m^{-2}, seeds $spike^{-1}$ and TKW. Spectral data from the remote sensors were taken during tillering, jointing, and heading stage, and used to compute eleven spectral vegetation indices. Results showed that significant variation exists among the genotypes using the indices at different growth stages. Field data included aboveground biomass, percent ground cover (%GC), and yield. The field data and vegetation indices had a significant relationship (R^2 = 0.30-0.99, $P<0.05$) with the %GC, aboveground biomass, and yield. %GC had the best estimation

among the field data with a single index (R^2 = 0.84; training and R^2 = 0.94; validation, P<.0001). Results indicate that the indices could be used as an indirect selection tool for screening a large number of early-generation lines and advanced wheat genotypes. Overall, this study illustrated the potential use of remote sensing techniques by wheat breeders for high-throughput phenotyping to screen for drought tolerant and high-yielding genotypes.

DEDICATION

To my Heavenly Father

for the strength, wisdom and life

given me to complete my program.

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All work for the dissertation was completed by the student, under the advisement of the committee.

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NOMENCLATURE

ABM	Aboveground biomass
ANOVA	Analysis of variance
AN	Anthesis
CT	Canopy temperature
CTD	Canopy temperature depression
GCV	Genotypic coefficient of variation
GLM	General Linear Model
HTPPs	High throughput phenotyping platforms
JT	Jointing
MA	Maturity
MSS	Multispectral scanner
NDVI	Normalized Difference Vegetation index
NIR	Near infrared
PCV	Phenotypic coefficient of variation
PVI	Perpendicular Vegetation index
RVI	Ratio vegetation index
SRI	Spectral reflectance indices
SVI	Spectral vegetation indices
TKW	Thousand kernel weight
VIS	Visible

TABLE OF CONTENTS

LIST OF FIGURES

Page

LIST OF TABLES

Page

CHAPTER I

INTRODUCTION AND LITERATURE REVIEW

Wheat (*Triticum aestivum* L.) is one of the world's most important cereals and staple foods, and there is increasing demand for its production. Wheat is a major crop in the U.S. Southern Great Plains, including the Texas High Plains (Howell et al., 1995; Musick et al., 1994). The U.S. Southern Great Plains accounts for approximately 30% of total U.S. wheat production (Lollato et al., 2017). Wheat cultivation under optimum management technique requires growing the best-adapted cultivars in the most suitable environmental condition. Due to the nature of the semi-arid environment, wheat production in the area is primarily limited by drought stress during the growing season. In addition, other abiotic and biotic stresses such as heat, disease, insects, and weeds frequently hamper yield and end-use quality.

Drought is responsible for severe food shortages and famine in developing countries where irrigation facilities are not well developed to meet the transpiration needs of the crop. The Ogallala aquifer is the major water source for irrigation in the Texas High Plains. Based on the limited amount of freshwater resources available for irrigation (Botterill and Fisher, 2003), it is essential to develop production systems with limited irrigation while simultaneously improving water use efficiency. Water-use efficiency (WUE) is the amount of yield produced per unit of water lost through evapotranspiration. WUE is a physiological trait that depends on the drought tolerance of the crop defined as the ability of the plants to temporarily maintain its processes (such as photosynthesis, respiration, nutrition uptake, plant hormone functions) at low water levels. Drought tolerance is a quantitative trait with a complex phenotype affected by the plant phenology. Generally, plants tend to reduce water use under drought stress. Since crop productivity is a function of water use, plant breeders are faced with the challenge of improving WUE among other traits (Blum, 2005).

Over the decades, wheat breeding has played an important role in increasing yield by developing cultivars with better drought tolerance traits. Breeding efforts for improved drought tolerance over the past few decades have revolved around the exploitation of high yield potential or selection of genotypes for morphological and physiological characters responsible for drought tolerance under various field conditions. This can be achieved partly by developing new drought-tolerant, water-efficient (Orr et al., 1998) and high yielding crop varieties. Drought tolerance is a target trait for breeding approaches to crop improvement. Over 80 years of breeding activities for major crops have led to low to moderate increase in yield under drought. Reasonable effort has been made to understand the physiological and molecular responses of plants to water deficits (Cattivelli et al., 2008). According to Nakhforoosh et al. (2016), the developments in genotyping and sequencing in the last decade have resulted in a tangible increase in genomic data. However, the genetic basis of tolerance is known to be polygenic (Ravi et al., 2011), and this brings about the major uncertainty as regards the choice of measured traits and the difficult task of ensuring an appropriate growing environment. Genotypic information must be complemented with the related plant phenotypical traits. Drought tolerance is regulated by genetic and environmental factors and by cultivation methods or crop management. To improve drought tolerance traits there is need to analyze the possible mechanisms and physiological characteristics of various wheat genotypes.

Wheat breeding for drought tolerance has been constrained by the absence of effective tools for the precise phenotyping of drought-related traits. The spectral reflectance methods that integrate the whole canopy for the yield assessment of many genotypes in a short time are highly desirable because field evaluation of genotypes for several years across locations is expensive and time-consuming (Reynolds et al., 1999). The advancement in remote sensing technology has recently led to the development of high-throughput phenotyping platforms (HTPPs) to overcome limitations in phenotypic data collection using conventional methods (Passioura, 2012). There is the need to implement non-destructive, easy, quick and practical tools that can evaluate large numbers of genotypes in a relatively short time. This can be done using remote sensing tools with the canopy spectral reflectance indices (SRIs) technique. This technique is based on the amount of light reflected from the canopy at a specific wavelength, due to the biochemical, physiological and structural properties of the canopy, showing spectral information to assess canopy chlorophyll content, photosynthetic efficiency, plant vigor, chlorophyll content, aboveground biomass, leaf area index, grain yield, and plant water status (Ajayi et al., 2016; El-Hendawy et al., 2015; Gutierrez et al., 2010; Prasad et al., 2007).

The crop canopy reflectance is the fraction of incoming light reflected by the crop canopy. Chlorophyll present in leaves absorbs light in the visible (VIS) light wavelengths (450-700 nanometers (nm)), with more blue (450-520 nm) and red (630-680 nm) light being absorbed than green light (520-600 nm). This results in higher reflectance in the green band, and is the reason that plants appear green to the human eyes. Compared to visible light, plants absorb much less near-infrared (NIR) light. That is, plants reflect more light in NIR wavelengths of 700-1400 nm, with percent NIR reflectance increasing as crop biomass increases. The shortwave infrared wavelengths of 1400-2500 nm are characteristic of the water content in the leaves of the plant canopy. These reflectance characteristics for visible, NIR and SWIR light of crop canopies are the basis for the development of numerous vegetative indices (Araus et al., 2001).

Vegetation indices (VI) are mathematical equations of spectral bands of the electromagnetic spectrum, mainly in the VIS and NIR regions. The ratio indices were originally described by Birth and McVey (1968). Ratio indices of reflected and transmitted radiation have been used since the late 1960s to estimate plant growth. Jordan (1969) first published on the use of the simple ratio vegetation index (RVI), in which he used the ratio of transmitted radiation at 800 nm to 675 nm to estimate the leaf area index (LAI). Several band combinations have been used to define spectral vegetation indices since then, but the most common are in the strong chlorophyll absorption region (around 670 nm) and in the NIR region (750 - 900 nm), where vegetation reflects highly due to leaf cellular structure. Vegetation indices attempt to maximize the spectral contribution from green vegetation and minimize the effects of the soil background, atmosphere, and sun-target-sensor geometry. In addition, because the index is constructed as a ratio, problems of variable illumination due to topography are minimized. However, the index is susceptible to division by zero errors and the resulting measurement scale is not linear. A study regarding its efficiency has been published by Vaiopoulos et al. (2004). Since vegetation has high NIR reflectance but low red reflectance, RVI is sensitive when vegetation increases than when vegetation is low. Its sensitivity is enhanced by the Normalized Difference Vegetation Index (NDVI).

The NDVI was introduced by Rouse et al. (1974) in order to produce a spectral VI that separates green vegetation from its background soil brightness using Landsat

Multispectral Scanner (MSS) data. It is expressed as the difference between the NIR and red bands normalized by the sum of those bands. It is based on the contrast between the maximum absorption in the red due to chlorophyll pigments and the maximum reflection in the infrared caused by leaf cellular structure. It is the most commonly used VI as it retains the ability to minimize topographic effects while producing a linear measurement scale. In addition, division by zero errors is significantly reduced. Furthermore, the measurement scale has the desirable property of ranging from -1 to +1, with 0 representing no vegetation, negative values representing non-vegetated surfaces and positive values representing vegetation density. Light reflected from the soil can have a significant effect on NDVI values; the greater the radiance reflected from the soil, the lower the NDVI values are. NDVI is more sensitive to sparse vegetation densities and less sensitive to high vegetation densities. Other researchers have used a variation of NDVI, called green or blue NDVI (GNDVI or BNDVI), to account for variations in the green or blue band instead of a red band, which is good for estimating LAI and detecting water stress on plants (Gitelson et al., 1996; Wang et al., 2007). NDVI and RVI are the most common vegetation indices used in spectral reflectance studies today.

There exists a challenge to develop remote sensing systems that are targeted specifically to the trait of interest. Ghanem et al. (2015) noted that current HTPP systems using imaging are unable to observe plant characteristics that are targeted quantitative traits. Measurements such as plant height and leaf number, which are readily measured can indicate early plant vigor and leaf area development. These measurements seem more appropriate for the initial screening in the field. There is also an uncertainty of the choice of traits to be measured and the difficulty of ensuring an ideal and controllable experimental growing environment. Morphophysiological measurements such as LAI, and the total dry weight per plant (TDW), canopy temperature (CT), leaf relative water content (RWC), leaf water potential, and water content of the aboveground biomass demonstrated strong relationships with SRIs (Barakat et al., 2016; El-Hendawy et al., 2015). The recent study showed the potential of spectral reflectance indices to detect the water status of the wheat plants and detect differences in green biomass, green leaf area, and grain yield effectively under water shortage conditions (El-Hendawy et al., 2015). The spectral reflectance indices and morphophysiological traits that are used as reliable selection criteria should have higher genetic variation and heritability (El-Hendawy et al., 2015). El-Hendawy et al. (2017) considered the performance of wheat genotypes under different water regimes and tested the relationships between SRIs and drought tolerance indices with grain yield. Their results show that selection based on the drought tolerance indices has the possibility to identify wheat genotypes that produce desirable yields in both normal and stress conditions. The use of either vegetation or water SRI to predict grain yield is also dependent on the phenological growth stage. The response of the plant due to water stress can be observed in the production of photo assimilates, and their further transformation into grain yield.

Infrared thermography involves low-cost CT measurements for high-throughput field phenotyping. The CT is an indicator of crop water stress. Canopy temperature depression (CTD) is the difference between air temperature and CT; it gives indirect estimate of stomatal conductance, leaf chlorophyll, leaf water potential and grain yield. A cooler canopy (higher CTD) may be one of the reasons for higher wheat yield under dryland conditions (Pradhan et al., 2014). Bellundagi et al. (2013) supported their findings with additional field data such as ground cover, flag leaf area, and leaf relative water content.

Another approach is the use of thermal infrared (TIR) detectors to measure plant temperature which may vary due to partial stomatal closure. That is, the soil water being conserved by the plant may be due to partial stomatal closure under high atmospheric vapor pressure deficit, leading to yield increase. TIR can be useful also as an early indirect selection to eliminate those lines that under high vapor pressure deficit conditions exhibit low temperatures (Ghanem et al., 2015). Wheat breeders can improve on these characteristics which may have a significant effect on grain yield.

Overall, the factors to be considered for water use efficiency and drought tolerance are those that are responsible for wheat cultivars to perform optimally under drought stress. These include i) ability to capture more soil water; ii) ability to optimize the available water for efficient use; and iii) partitioning assimilates for reproductive growth under stress (Aparicio et al., 2002b; Lorens et al., 1987; Reynolds et al., 2005). All these can be monitored and assessed throughout the growing season and under water-stressed condition using remote sensing tools as indirect selection criteria for drought tolerance and water use efficiency. The progress of wheat breeding requires accurate physiological phenotyping of the desirable traits. However, it is difficult and complex to phenotype for traits that are not visible to the naked eyes. A well-planned step by step physiological phenotyping approach will assist to effectively address the challenge of integrating phenotyping in a breeding program. For improved breeding and phenotyping effort in identifying drought tolerance and water use efficient genotypes, the following steps can be noted. This include: i) selecting traits that are evidently going to improve the crop productivity; ii) having basic knowledge of the trait to direct the indirect selection approach; and iii) developing several phenotypic and genotypic screening for insight on the trait expression at various growth stages (also across years and location) in the breeding process (Ghanem et al., 2015; Glazier et al., 2002; Miflin, 2000).

This dissertation focuses on the evaluation of aboveground biomass, yield and its components, assessment of remote sensors both ground-based and aerial systems, under rainfed and irrigated conditions. Chapter II covers the evaluation of wheat genotypes for their yield potential and dry matter accumulation and their relation to yield component traits to identify sources of germplasm for breeding drought tolerance. Chapter III, IV, and V reflect on the use of ground-based and aerial remote sensors to assess the growth, performance and yield of winter wheat genotypes. Development of stress tolerant cultivars is always a major objective of many breeding programs. However, success has been limited by inadequate screening techniques in identifying genotypes that show clear differences in response to various environmental stresses during the growing season. The overall objective of this study was to develop and evaluate remote sensing techniques for assessing phenotypic traits of winter wheat genotypes in the Texas High Plains.

CHAPTER II

GENETIC VARIABILITY AND TRAIT ASSOCIATION WITH YIELD IN WINTER WHEAT (*Triticum aestivum* L.) UNDER IRRIGATED AND RAINFED CONDITIONS

INTRODUCTION

In most wheat (*Triticum aestivum* L.) breeding programs, yield is the major selection criterion influenced directly and indirectly by several environmental, morphological, physiological, biochemical, and metabolic plant processes, where their genetics and relationships are unclearly known (Jackson et al., 1996; Orr et al., 1998). Yield is a quantitative trait that may be influenced by the following morpho-physiological and yield component traits: canopy temperature (CT), leaf relative water content, leaf water potential, water content of the aboveground biomass, photosynthetic efficiency, plant vigor, chlorophyll content, leaf area index, plant height, harvest index (HI), number of spikes/m^2, seeds/spike, and 1000-kernel weight (TKW). Wheat yields are reduced when the plant is water-stressed as a result of the physiological and biochemical processes being altered (Lascano et al., 2001). Hence, the life cycle of the plant is shortened by reducing the size of organs such as leaves, tillers, spikes, the number of spikelets, and the ratio of spike dry weight to total dry weight. Yield components are determined throughout the development and growth during wheat growing season. The three yield components include spikes per unit area, seeds per spike and seed weight. The product of these components is yield, when measured without error and expressed in the appropriate unit.

The development of high-yielding genotypes through identifying drought tolerant mechanisms is important for increasing yield potential under both rainfed and irrigated conditions. The quantitative variation in a plant population is based on the phenotypic, genotypic and environmental variation. The phenotypic variance includes genetic variance, genotype x environment interaction and error variance (Acquaah, 2012). Wheat breeders improve large populations by selecting genotypes based on their phenotypes. The genetic component of variation is important as a result of being transferred to the next generation (Hamdi, 1992). Genetic variability among wheat genotypes can be estimated based on qualitative and quantitative traits. Heritability in broad sense, it is the ratio of genotypic variation to the phenotypic variance, which is the proportion of phenotypic variance due to solely genetic differences i.e. heritable. Heritability varies from zero to one; from no genetic contribution (instead all environment) to all genetic contribution, respectively (Acquaah, 2012).

Yield selection under drought stress conditions is difficult as a result of its low heritability due to variations in the magnitude of the stress conditions on the field (Ludlow and Muchow, 1990; Yağdi and Sozen, 2009). In all studies that are dedicated to drought tolerance the crucial aspect is the assessment of the degree of drought tolerance in different genotypes. In many studies the identification of tolerant and susceptible genotypes is based on few plant traits related to drought response such as stomatal conductance, photosynthetic capacity, rooting depth, osmotic adjustment (Araus et al., 2002; Cattivelli et al., 2008). Selection for drought tolerant wheat genotypes may be more efficient under well-watered conditions than under water-stressed conditions, with identifying genotypes with higher yield potential than others (Rajaram, 2001; Rajaram et al., 1996). Grain yield selection is a conventional approach when measuring yield itself, whereas it is a logical approach when considering indirect traits (Richards, 1996). Kashif and Khaliq (2004) suggested that indirect selection for yield using its components, might be more effective than direct selection. This is because of low heritability for yield, also when the component has a higher heritability than yield and the genetic correlation between the two traits is high. The difficulty in identifying a physiological parameter as a reliable indicator of yield in dry conditions has suggested that yield performance over a range of environments should be used as the main indicator for drought tolerance (Voltas et al., 2005). The selection for drought tolerant genotypes should be based on important morpho-physiological and yield component traits, not only on yield. In order to make good use of the genetic variability among the large population, there is need to have information about the mutual association between yield and yield components. That is, the correlation coefficients of various component traits with yield and among themselves (Mary and Gopalan, 2006).

The ability to discriminate among performance of different genotypes depends on the information on the environment (E) where the plant are growing so as to separate genotypic effects (G) from the total phenotype (P) where (P=G+E+G*E). Also one can evaluate and relate the response of similar genotypes in different environment or vice-versa (Orr et al., 1998). The genotype by environment interaction (G*E or GEI) is the interaction of genotype with the factors (either environmental or physiological) that can affect the expression of a trait. According to Reynolds et al. (2001), traits which have less G*E have their genotypes classified based on these traits and despite their trait expression, will mostly maintain their classification across different environments. These traits are highly heritable with limited environmental effect on their expression, hence these traits will be effectively selected across locations and years. Generally, there is a greater probability of obtaining significant G*E when the genetic complexity of a trait is greater (Alberts, 2004; Reynolds et al., 2001).

The size of genetic variability in a population and the extent of heritability of the desirable traits, determine the rate of genetic gain for yield in a breeding program. The objective of this study was to investigate plant traits that contribute to yield under different two water regimes – rainfed and irrigated, and to what extent these traits may be considered as specific selection criteria for tolerance to drought stress conditions in the Southern Great Plains (SGP). These objectives was achieved by estimating genetic variability, identifying traits that impact drought tolerance, estimate the extent of genotypic and phenotypic variability (heritability) and evaluate association among the yield and yield components among the 20 wheat genotypes.

MATERIALS AND METHODS

Description of Study Area

Field experiment was conducted at the Texas A&M AgriLife Research Experiment Station, Bushland, Texas (Lat. 35º11'N, Long. 102º06'W; elevation 1170m above the mean sea level) during the 2011-2012 (Year 1) and 2015-2016 (Year 2) growing seasons. The soil type was Pullman clay loam (fine, mixed, thermic Torrertic Paleustoll: USDA classification) described by Unger and Pringle (1981). The climatic condition was semi-arid with erratic precipitation and high evaporative demands. Weather data (Table 1) was downloaded for the Bushland station for Year 1 and Year 2 from the Texas High Plains Evapotranspiration (TXHPET) Network (http://txhighplainset.tamu.edu) and US Climate Data Network (http://usclimatedata.com), respectively. Precipitation was significantly and generally lower for year 1 than year 2, especially at the earlier and later growth stages, that is pre-emergence and anthesis, respectively. The total precipitation during the growing season was 166 mm and 310 mm (Year 1 and 2), and the average maximum and minimum temperature during the growing season was 18.4 ºC and 1.8 ºC, respectively, in 2011-2012, and 21.6 ºC and 4.5 ºC, respectively, in 2015-2016. Although the temperature in year 2 was generally higher, it can be explained by the increased precipitation. Overall, year 1 had wheat plants more water stressed throughout the entire growing season.

Experimental Design

Twenty winter wheat genotypes were grown under two water regimes – rainfed and irrigated, during 2011-2012 and 2015-2016. Ten of these genotypes were developed by the Texas A&M wheat breeding program, while the other ten were developed by wheat breeding programs from Kansas, Colorado, Oklahoma and Nebraska. As seen in Table 2, these genotypes consist of wide genetic background based on their pedigree. In the irrigated treatment, irrigation was applied several times during the wheat growing season to supplement seasonal rainfall. The experimental design was a randomized complete block design (RCBD) with three replications. The seeding rate for irrigated and rainfed fields, was 100 kg/ha and 67 kg/ha, respectively. The plot size for irrigated plots was 1.52 m x 3.05m (4.64 m^2) and 1.52 m x 4.27 m (7.0 m^2) for rainfed plots, while the row spacing for all plots was 18 cm.

Table 1 Mean maximum (Max) and minimum (Min) temperatures, and total monthly precipitation from October to June for the 2011-2012 (Year 1) and 2015-2016 (Year 2) in Bushland, TX.

	Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	Apr.	May	June
Mean temperature (°C)									
Year 1									
Max	17.8	15.9	5.3	13.6	10.9	21.2	24.8	27.8	30.7
Min	2.3	0.4	-4.8	-3.9	-3.8	2.7	7.3	10.7	15.4
Year 2									
Max	21.8	15.6	11.5	10.1	15.1	19.4	21.1	24.1	32.2
Min	9.0	-0.2	-3.5	-4.9	-2.7	0.5	4.3	8.2	16.3
Total precipitation (mm)									
Year 1									
	10.7	6.6	31.5	2.3	2.5	34	16.3	29.0	33.0
Year 2									
	128.3	23.9	10.9	5.6	3.8	4.6	72.6	31.5	29.2

Table 2 Wheat genotypes used in this study and their pedigrees.

Name	Year of release	Pedigree
TAM W-101	1971	KS56761/Bison (=TX65A1682) (CI 15324)
TAM 105	1979	Short wheat/Sturdy composite bulk selection
TAM 110†	1996	TXGH12588-105=(TAM 105*4/Amigo*4//Largo)
TAM 111	2003	TAM 107/TX78V3620/CTK78/3/TX87V1233
TAM 112†	2005	105*4/Amigo*4//Largo)
TAM 304	2007	TX01D3232=TX92U3060/TX91D6564 (=X95U104-P66)
TAM 113	2010	TX02A0252=TX90V6313//TX94V3724(TAM-200 BC41254-1-8-1-1/TX86V1405
TX99A0153-1†	Not released	Ogallala/TAM-202
TX86A5606†	Not released	TAM 105*4/ Amigo*4//Largo
TX86A8072†	Not released	TAM 105*4/ Amigo*4//Largo
TAM 114	2014	TX07A001505=T107//TX98V3620/Ctk78/3/TX87V1233/4/N87V106//TX86V1540/T200
TX11Vsyn0101	Not released	TAM 111*2/CIMMYT E95Syn4152-5
PlainsGoldByrd	Not released	CO06424=TAM 112/CO970547-7
Iba	2013	OK07209=OK93P656-(RMH 3299)/OK99621 F4:10
AMPSY068	Not released	TAM 111*2/CIMMYT E951yn4152-37
AMPSY588	Not released	TAM 112/CIMMYT E951yn4152-46//TAM 112
Dumas	2000	WI90-425/WI89-483
Jagalene	2001	Abilene/Jagger
Hatcher	2005	Yumar/PI372129//TAM-200/3/4*Yumar/4/KS91H184/Vista
BillBrown	2007	Yumar/Arlin
Winterhawk	2007	474S10-1/X87897-26//HBK0736-3
Endurance	2004	HBY756A/´Siouxland`//´2180`
Duster	2006	OK93P656H3299-2C04=WO405D/HGF112//W7469C/HCF012
Billings	2009	OK03522=N566/OK94P597 F4:14
Jagger	1994	KS82W418/Stephens (=KS84063-9-39-3) (PI 593688)
Fuller	2006	KS00F5-14-7=BULK SELN

†The genotype has 1AL.1RS rye translocation.

Data collection

Aboveground biomass was collected at anthesis and at maturity; 50 cm of one row was cut at ground level from each plot. For each sample, the stems (including leaves and leaf sheaths) and heads were separated and counted. To determine the dry biomass, the stems and heads were dried at 60°C for 72 hours.

Yields were obtained by machine-harvesting with a Wintersteiger plot combine. The yield based on about 10 % moisture content was expressed on a kilogram per hectare basis. To calculate the harvest index (grain yield divided by aboveground biomass), grain yield or seed weight was obtained from 50 cm of one row at maturity. The four yield components (spikes per square meter, seeds per spike, thousand-kernel weight (TKW), and seeds per square meter) were determined. The threshed seeds were weighed after dried to 0% moisture at 130°C for 19 h (ASAE, 1998). Then, the TKW was calculated by weighing 250 seeds and multiplied by four. Seeds per spike and seeds per square meter were determined by dividing the total number of seeds by the number of spikes per sample and then dividing by sample area.

Data Analysis

Statistical analysis carried out in this study was done using the SAS version 9.3 (Statistical Analysis System Institute, Cary, NC, USA), META-R (Multi Environment Trial Analysis with R) macro (Alvarado et al., 2015) and XLSTAT developed by Addinsoft (2010) for Microsoft Excel. Analysis of variance (ANOVA) was performed using the General Linear Model procedure. Individual water regime data were subjected to ANOVA to determine the significance of genotypic component in each environment. Analysis of variance was performed using the following equation to determine if there was a significant effect of genotype, year, and environment, genotype x environment, and genotype x year interactions on the traits:

$$Y_{ijkl} = \mu + E_i + B_{ji} + G_k + GE_{ik} + \varepsilon_{ijkl}$$

where Y_{ijkl} is the measurement of genotype k on plot l in block j, and environment i; μ is the overall mean of all plots in all environments; E_i is the effect of environment i; B_{ji} is the effect of block j within environment i using replication; G_k is the effect of genotype k; GE_{ik} is the interaction of genotype i with experiment k; ε_{ijkl} is the plot residual.

Means of the individual environment data was subjected to ANOVA to determine the significance of genotypic component in each environment. Significant means were compared using least significant difference (LSD) multiple means comparison technique at Probability value ≤ 0.05. The statistical model used for individual environment analysis was as follows:

$$Y_{ik} = \mu + R_k + G_i + \varepsilon_{ik}$$

Where Y_{ik} is the observed phenotypic value of the ith genotype in kth replicate, μ is the overall mean, R_k is the replication effect, G_i is the genetic effect of ith genotype and ε_{ik} is the residual.

Using the META-R, heritability in a broad sense was estimated from the result of variance analysis according to the formula used by Burton and Devane (1953), also computing phenotypic and environmental variance. Genotypic and phenotypic correlations were worked out according to the method given by Burton (1952) and Kwon and Torrie (1964). Phenotypic (δ^2p) and genotypic (δ^2g) variances were obtained according to Baye (2002) as $\delta^2g = MS_p - (MS_e/r)$, and $\delta^2p = MS_g/r$, where MS_p and MS_g are mean squares of phenotypes and genotypes, respectively; r was number of replication. The mean values were used for genetic analyses to determine phenotypic coefficient of variation (PCV) and genotypic coefficient of variation (GCV) using the variances (δ^2) and mean (x), according to Singh and Chaudhary (1979) as:

$$GCV (\%) = \sqrt{(\delta^2 g)}/x * 100$$

$$PCV (\%) = \sqrt{(\delta^2 p)}/x * 100$$

Broad-sense heritability (h^2) or repeatability estimate of each trait was computed as:

$$Heritability (h^2) = \delta^2 g/ \delta^2 p$$

Principal component analysis for GGE (i.e., G = genotype and GE = genotype by environment and/or trait interaction) was performed to visualize relationships among genotypes and environment and/or traits by using the genotypic means of each environment in the XLSTAT software.

RESULTS

Analysis of variance and mean performance

The analysis of variance indicated the existence of highly significant variability for all the traits studied (Table 3). For year 1, the mean sum of squares due to genotype x environment interaction was high for only spikes/m^2, TKW, and yield. There was no genotype x environment interaction for year 2. Environmental (water regime) variance for all traits appeared significant for both years, except spikes/m^2 and seeds per spike for year 2. For year 1, the mean sum of squares due to genotypes was high for all the traits except aboveground biomass at anthesis. Year 2 recorded all traits with high mean sum of squares due to genotypes except aboveground biomass at maturity and anthesis.

Table 3 Mean sum of square for analysis of variance of 20 wheat genotypes across rainfed and irrigated environments for the growing seasons 2011-2012 (Year 1) and 2015-2016 (Year 2).

Traits	**Genotype (G)**	**Environment (E)**	**G x E**
	Year 1		
Biomass at MA	50861.64*	31549138.32***	31285.21
Harvest index	0.006**	0.06***	0.002
Spikes/m^2	48797.71*	13035001.06***	46060.61*
Seeds/spike	25.42**	32.12*	9.37
Seeds/m^2	19322982**	3944076122***	9042614
Biomass at AN	28727.22	12607509.58***	23290.52
Yield	9283.99**	3620502.06***	8394.99***
TKW	19.43*	1488.54***	16.55*
	Year 2		
Biomass at MA	66460.37	932489.49**	116657.21
Harvest index	0.005*	0.13***	0.003
Spikes/m^2	113719.81***	51405.25	53892.04
Seeds/spike	23.35***	6.62	4.54
Seeds/m^2	32338913.1**	279129908***	18565758
Biomass at AN	48101.65	5500586.74***	49470.53
Yield	6009.93*	1069523.69***	3687.49
TKW	38.22***	263.70***	3.03

*, **, and *** Significant at 0.05, 0.01 and <.0001, respectively

Similar genotypes (14 total) that were planted in both year 1 and 2 were selected to perform analysis of variance for year and genotype x year interaction (Table 4). Significant interaction exists among the 14 genotypes and years only with spikes/m^2, seeds per spike and TKW. The year effect was highly significant for all the traits, so also the genotypes for all traits except seeds/m^2, aboveground biomass at maturity and anthesis.

Table 4 Mean sum of square for analysis of variance of 14 genotypes across rainfed and irrigated environments for both growing seasons.

Source	**Genotype (G)**	**Year (Y)**	**G x Y**
Trait/df	13	3	39
Biomass at MA	78929.29	13200034.99***	67169.98
Harvest index	0.005*	0.07***	0.003
Spikes/m^2	109525.62***	3602351.25***	59236.19**
Seeds/spike	23.41***	77.62***	9.36*
Seeds/m^2	23726362	1061609004***	14305562
Biomass at AN	21305.37	4300849.08***	37862.08
Yield	11278.48**	1372253.89***	5959.45
TKW	32.08***	1820.77***	8.28*

*, **, and *** Significant at 0.05, 0.01 and <.0001, respectively

There was considerable variability in the mean values of aboveground biomass, yield and yield component traits in each individual environment for each of the two years (Tables 5 and 6). Significant variation was found among the 20 genotypes for only TKW for year 1 under rainfed condition. Under irrigated condition, all traits were significantly different among the 20 wheat genotypes except aboveground biomass, harvest, and TKW. The study in Year 2 under rainfed condition showed significant differences in spikes/m^2 and TKW among the 20 wheat genotypes. Under irrigated condition, all traits appeared significantly different among the genotypes except aboveground biomass at anthesis and maturity.

According to the means of three replications for year 1 (Table 5), the aboveground biomass at maturity was between 364 and 592 g/m^2 (average of 458 g/m^2) and, 1241 and 1787 g/m^2 (average of 1484 g/m^2) under rainfed and irrigated conditions, respectively. TAM 105, Fuller, TX86A5606, TAM 110 had the lowest aboveground biomass while

Jagger was the highest followed by TX99A0153-1, Billings, Winterhawk, Endurance, TAM 111, Hatcher, TAM 112, and TAM 113 under rainfed condition in year 1. Under irrigated condition for year 1, Hatcher had the highest aboveground biomass at maturity, followed by Winterhawk, Duster, TX99A0153-1, and TAM 113, while the lowest was found with TAM 110, and Dumas. For year 2 (Table 6), the aboveground biomass at maturity was determined between 1178 and 2000 g/m^2 (average of 1519 g/m^2) and, 1434 and 2020 g/m^2 (average of 1696 g/m^2) under rainfed and irrigated conditions, respectively. Under rainfed condition, TAM 105 had the highest aboveground biomass at maturity, the lowest was TX99A0153-1, and Iba, while TAM 304 had the highest under irrigated condition and the lowest was Dumas and TAM 110. Aboveground biomass at anthesis for year 1 under rainfed condition ranged from 345 to 583 g/m^2 with TAM 113 and TX99A0153-1 as the minimum and maximum, respectively. Values under irrigated condition ranged from 887 to 1261 g/m^2 with TAM 110 and Jagger as the minimum and maximum, respectively.

Harvest index values were generally within 0.18 and 0.38 under rainfed condition and within 0.27 and 0.41 under irrigated condition for both years. Endurance (0.38), TAM 110, TX99A0153-1, TX86A5606 and Duster (0.36), and Jagalene (0.35) had the highest harvest index value under rainfed condition for year 1, while year 2 recorded TAM 112 (0.33), TAM 111 and Winterhawk (0.31), TAM 105 (0.29), TAM 113 (0.28), TAM 304 and Hatcher (0.27) as the highest. Lowest under year 1 was TAM W-101 (0.22), and under year 2 was TX11Vsyn0101 and TAM 114 (0.18), and TX99A0153-1 (0.19).

TAM 112 (652) and BillBrown (529) had the highest spikes/m^2, the lowest was Fuller (334) and TAM 105 (337) under rainfed condition in year 1. Year 2 had TAM 105

(1537) has the significantly highest spikes/m^2 value and TX99A0153-1 (731) as the significantly lowest value. Under irrigated condition in year 1, the value was between 772 and 1339 with TAM 111 and Duster as the minimum and maximum, respectively. Spikes/m^2 in year 2 under irrigated condition ranged from 709 to 1244, with AMPSY 068 and Iba as the significantly lowest and highest, respectively.

For year 1, seeds per spike values ranged from approximately 10 to 20 with TAM W-101 and Endurance as the minimum and maximum, respectively under rainfed condition. Seeds per spike values ranged from 12 to 24 under irrigated condition, with TAM W-101 and TAM 304 as the minimum and maximum, respectively. Seeds/m^2 values were between 3800 and 10538 for TAM W-101 and Jagger respectively, under rainfed condition, while under irrigated condition the values were significantly higher and was between 13133 and 24020 for TAM W-101 and Duster respectively, for year 1. Year 2 under rainfed condition had seeds/m^2 values ranged from 6926 and 19451 for TX99A0153-1 and TAM 105, respectively. Under irrigated condition, seeds/m^2 values were between 12131 and 20956 for Hatcher and TAM 304, respectively.

Thousand-kernel weight (TKW) ranged from 14 g to 26 g under rainfed condition in year 1 with BillBrown and TAM W-101 as the lowest and highest, respectively and year 2 it ranged from 27 to 40 g with Duster and AMPSY 068 as the minimum and maximum, respectively. For year 1 under irrigated condition, TKW ranged from 24 g in BillBrown to 33 g in Billings. In year 2, TKW ranged from 31 to 40 g with Plains Gold Byrd, TAM 105, and Duster as the lowest (31 g) and AMPSY 068 and Billings as the highest (approximately 40 g).

Yield values under rainfed condition for year 1 was determined between 66 and 105 g/m^2 with TAM W-101 and TAM 112 as the minimum and maximum, respectively. Year 2 was found between 249 and 411 g/m^2 with TAM 114 and Plains Gold Byrd as lowest and highest, respectively. Irrigated condition for year 1 recorded yield values that ranged from 414 to 649 g/m^2 with TAM W-101 and Winterhawk as the minimum and maximum, respectively. Yield values for year 2 was between 433 and 549 g/m^2 with TAM 105 and Plains Gold Byrd as the minimum and maximum, respectively. Generally, TAM genotypes showed more similar values for yield, and yield component traits compared to the other genotypes.

Table 5 Mean performance of aboveground biomass at anthesis and maturity, harvest index, yield and yield components for 20 genotypes across rainfed and irrigated environments for the growing season 2011-2012 (Year 1).

Genotype	**Biomass at MA**	**HI**	**Spikes**	**Seeds/ spike**	**Seeds**	**Biomass at AN**	**Yield**	**TKW**
	g/m^2		**no./m^2**		**no./m^2**	**g/m^2**	**g/m^2**	**g**
Rainfed								
TAM W-101	439.93	0.22	401.20	9.63	3800.38	415.67	66.23	26.20
TAM 105	364.42	0.30	337.46	16.69	5392.12	470.87	86.16	23.10
TAM 110	388.11	0.36	412.45	17.12	7021.69	359.77	86.47	19.90
TAM 111	477.05	0.32	397.45	16.18	6415.67	454.22	87.59	23.40
TAM 112	474.43	0.28	652.42	13.00	7651.11	483.16	104.97	17.80
TAM 304	429.77	0.31	431.20	17.67	7787.49	377.02	78.50	17.10
TAM 113	472.97	0.29	419.95	14.22	6200.27	344.73	99.76	22.70
TX99A0153-1	531.23	0.36	487.44	17.34	8641.72	582.86	103.95	21.90
TX86A5606	386.99	0.36	408.70	16.32	6689.52	351.74	83.51	21.40
TX86A8072	436.22	0.30	419.95	14.64	6146.94	425.42	78.91	21.60
Dumas	460.55	0.26	442.44	14.29	6310.28	461.12	77.48	19.40
Jagalene	457.93	0.35	464.94	16.01	7421.64	428.20	99.96	21.80
Hatcher	476.12	0.24	408.70	14.31	5843.65	400.34	86.16	20.00
BillBrown	448.52	0.26	528.68	16.10	8491.31	461.98	78.09	14.30
Winterhawk	500.79	0.34	386.20	17.66	6812.25	447.99	98.02	24.90
Endurance	482.41	0.38	457.44	19.66	8955.62	383.31	100.17	20.40
Duster	447.54	0.36	438.70	17.78	7732.76	461.57	96.79	20.60
Billings	518.82	0.30	468.69	14.94	6935.65	395.58	95.87	21.80
Jagger	592.05	0.32	536.18	19.48	10538.4	414.96	101.19	18.20
Fuller	377.88	0.31	333.71	16.63	5644.35	483.05	90.97	20.70
Mean	458.19	0.31	441.69	15.98	7021.64	430.18	90.04	19.57
LSD (0.05)	NS	NS	NS	NS	NS	NS	NS	3.09

Table 5 Continued.

Genotype	Biomass at MA	HI	Spikes	Seeds/ spike	Seeds	Biomass at AN	Yield	TKW
	g/m^2		no./m^2		no./m^2	g/m^2	g/m^2	g
Irrigated								
TAM W-101	1311.06	0.31	1106.11	12.16	13132.75	986.43	413.65	31.50
TAM 105	1394.38	0.36	1106.11	16.68	18407.90	918.15	500.15	27.20
TAM 110	1241.21	0.39	1102.36	15.30	16861.66	886.73	478.85	28.40
TAM 111	1319.16	0.39	772.40	21.62	16471.74	1182.26	514.32	31.40
TAM 112	1425.95	0.37	1053.62	16.48	16973.35	1032.25	527.71	31.10
TAM 304	1481.59	0.41	869.89	23.97	20731.84	1117.36	603.49	29.10
TAM 113	1609.67	0.32	1267.34	16.17	20451.06	1108.44	526.13	25.40
TX99A0153-1	1631.50	0.34	1248.59	15.45	19389.51	1068.47	561.94	29.20
TX86A5606	1309.86	0.37	1064.87	15.68	16348.40	964.57	488.64	29.50
TX86A8072	1391.86	0.30	1031.12	14.20	14686.87	1308.06	419.65	28.30
Dumas	1269.48	0.34	847.39	17.60	15085.48	1155.42	425.50	28.40
Jagalene	1512.56	0.39	1267.34	17.20	21900.27	910.16	582.49	26.80
Hatcher	1787.74	0.32	1421.07	14.74	20713.59	992.31	571.62	28.00
BillBrown	1527.37	0.35	1109.86	16.63	18814.31	1116.54	532.77	24.40
Winterhawk	1723.02	0.38	1154.86	17.95	20503.62	1125.35	649.08	31.70
Endurance	1412.19	0.35	1042.37	16.43	17144.61	1168.84	489.39	28.80
Duster	1686.28	0.37	1338.58	17.81	24020.27	1000.30	622.31	25.90
Billings	1517.89	0.39	963.63	18.45	17732.25	1038.06	583.76	32.90
Jagger	1529.62	0.34	1181.10	17.70	20812.02	1261.15	524.63	25.70
Fuller	1591.26	0.35	1068.62	18.14	19571.36	1228.08	556.28	28.60
Mean	1483.68	0.36	1100.86	17.02	18487.64	1078.45	437.43	26.61
LSD (0.05)	NS	NS	309.89	3.56	5744.90	NS	151.72	NS

†LSD: Least significant difference; NS: not significant

Table 6 Mean performance of aboveground biomass at anthesis and harvest, harvest index, yield and yield components for 20 genotypes across rainfed and irrigated environments for the growing season 2015-2016 (Year 2).

Genotype	Biomass at MA	HI	Spikes	Seeds/ spike	Seeds	Biomass at AN	Yield	TKW
	g/m^2		$no./m^2$		$no./m^2$	g/m^2	g/m^2	g
Rainfed								
TAM 105	1999.70	0.29	1537.31	20.26	19451.35	654.26	368.49	29.23
TAM 110	1603.67	0.23	1199.85	16.44	11578.89	796.36	354.74	31.77
TAM 111	1529.36	0.31	854.89	19.97	13919.13	636.90	366.65	34.03
TAM 112	1695.46	0.33	1057.37	20.30	16785.42	612.37	329.21	33.10
TAM 113	1788.75	0.28	967.38	19.84	16269.75	662.43	362.21	32.20
TAM 114	1470.30	0.18	1023.62	18.16	10190.72	839.56	249.43	29.07
TAM 304	1479.30	0.27	952.38	20.05	13697.45	904.65	287.94	29.57
TX99A0153-1	1177.95	0.19	731.16	13.84	6926.44	729.17	288.48	33.45
Dumas	1367.90	0.22	806.15	18.02	9822.90	739.82	286.35	29.77
Jagalene	1439.33	0.29	926.13	21.00	12896.25	928.23	303.01	31.80
Hatcher	1463.74	0.27	971.13	18.81	11845.94	895.09	330.40	32.90
Plains Gold Byrd	1541.92	0.30	1012.37	21.45	15757.93	811.47	411.30	30.27
Winterhawk	1483.50	0.31	1117.36	19.92	14690.38	840.76	332.39	33.50
Iba	1237.50	0.25	1072.37	22.19	11267.26	785.30	379.58	28.73
Endurance	1531.55	0.23	933.63	19.69	13079.25	547.96	274.22	31.30
Duster	1537.53	0.25	1154.86	22.73	14821.31	629.32	334.77	27.23
Billings	1514.29	0.22	858.64	15.43	10102.05	528.20	271.42	33.50
AMPSY068	1369.78	0.24	693.66	15.61	8701.52	708.17	296.53	39.83
AMPSY588	1414.74	0.22	914.89	15.76	9681.18	776.98	293.08	35.80
TX11Vsyn0101	1546.74	0.18	849.27	14.25	9532.63	697.23	238.49	32.60
Mean	1518.44	0.26	986.28	18.84	12654.25	736.21	317.93	31.96
LSD (0.05)	NS	NS	NS	4.54	NS	NS	NS	2.03

Table 6 Continued.

Genotype	Biomass at MA	HI	Spikes	Seeds/ spike	Seeds	Biomass at AN	Yield	TKW
	g/m^2		no./m^2		no./m^2	g/m^2	g/m^2	g
Irrigated								
TAM 105	1505.77	0.27	941.13	17.78	12633.32	1108.85	433.03	31.67
TAM 110	1454.22	0.35	1038.62	19.72	14110.98	1013.21	462.68	35.67
TAM 111	1653.43	0.36	824.90	19.99	16371.41	1119.46	519.67	36.33
TAM 112	1773.30	0.35	997.38	19.23	17372.83	1136.86	509.35	36.33
TAM 113	1675.70	0.32	933.63	19.00	15226.37	1204.31	533.87	35.33
TAM 114	1630.75	0.29	978.63	19.68	13972.60	1456.51	494.97	33.67
TAM 304	2019.72	0.34	1031.12	21.51	20956.15	1258.33	528.99	32.33
TX99A0153-1	1885.86	0.28	1113.61	16.03	14980.30	1037.83	521.79	35.00
Dumas	1434.27	0.31	727.41	19.92	13746.17	1000.75	447.69	33.00
Jagalene	1714.85	0.33	937.38	18.92	15909.51	951.46	460.78	36.00
Hatcher	1553.54	0.28	869.89	17.95	12131.09	1240.45	535.48	36.33
Plains Gold Byrd	1943.61	0.33	1214.85	21.94	20874.93	1329.86	548.53	31.00
Winterhawk	1506.26	0.32	787.40	18.37	13437.51	1255.98	531.29	35.67
Iba	1998.16	0.33	1244.84	21.72	20061.33	1221.04	547.92	33.33
Endurance	1724.18	0.35	907.39	20.63	17341.74	1232.62	498.88	34.67
Duster	1846.08	0.32	1094.86	21.35	18446.79	1083.28	535.34	31.33
Billings	1814.59	0.32	802.40	16.50	15007.70	1418.67	513.65	39.00
AMPSY068	1539.18	0.33	708.66	16.88	12761.07	1369.33	512.40	39.67
AMPSY588	1646.53	0.33	963.63	18.11	14979.28	1136.03	504.58	37.00
TX11Vsyn0101	1602.29	0.29	731.16	18.08	12625.06	966.82	494.08	37.00
Mean	1696.12	0.32	942.45	19.17	15647.31	1179.33	506.75	35.02
LSD (0.05)	NS	0.05	229.28	1.66	4046.60	NS	59.18	2.64

†LSD: Least significant difference; NS: not significant

Variances, coefficient of variability and heritability for traits in the 20 wheat genotypes

The estimates of phenotypic variance, genotypic variance, environmental variance, broad sense heritability or repeatability, phenotypic and genotypic coefficient of variability (PCV and GCV) for year 1 and 2 are given in Tables 7 and 8. Generally, it was observed that the phenotypic variance was significantly greater than the genotypic and environmental variances for all traits under both water regimes and years. The environmental variance was greater than the genotypic variance for all the traits under both water regimes and years, with some exceptions such as; aboveground biomass at maturity under irrigated condition for year 1, seeds/spike and TKW under rainfed condition for year 2, spikes/m^2, seeds/spike, seeds/m^2, and TKW under irrigated condition for year 2. As seen in Table 8, environmental variance was greater than genotypic variance for all traits except TKW in year 2, and equal variance of 3.13 for seeds/spike.

Repeatability for all the traits under rainfed and irrigated condition ranged from 0.15 to 0.41, for year 1, while year 2 ranged from 0.24 to 0.81 (Table 7a-b). Broad-sense heritability estimated on the basis of genotypic and phenotypic variances for each year was between 2% and 25% for all traits in year 1, between 0.4% and 72% for all traits in year 2 (Table 8). Seeds/spike had the highest heritability estimates of 25% in year 1. Spike/m^2, aboveground biomass at anthesis, yield and TKW had the lowest heritability estimates in year 1. Seeds/spike and TKW had the highest heritability estimates of 50% and 72%, respectively, in year 2 only. The lowest heritability estimates was found with aboveground biomass at anthesis and maturity in year 2.

It was observed that seeds/m^2 showed the highest PCV under rainfed and irrigated condition for both years, while yield had the highest PCV under irrigated condition in year 1. The highest GCV was found also with seeds/m^2 under rainfed condition for year 1 and year 2, and under irrigated condition in year 2. Under irrigated condition for year 1, the highest PCV was found with yield, and lowest was harvest index, for year 2 the highest PCV was seeds/m^2 while lowest was yield and TKW. For year 1 under rainfed condition, the lowest GCV was TKW, for year 2, the lowest GCV was TKW.

Table 7 Variance components and repeatability for different traits of 20 wheat genotypes under rainfed and irrigated conditions during year 1 (a) and year 2 (b).

(a) Trait	Phenotypic Variance	Genotypic Variance	Environmental Variance	Repeatability	PCV (%)	GCV (%)
Rainfed						
Biomass at MA	13860.90	3029.02	10831.88	0.22	25.70	12.01
Harvest index	0.005	0.002	0.003	0.41	21.75	13.93
Spikes/m^2	17755.02	5148.00	12607.02	0.29	30.17	16.24
Seeds/spike	14.37	5.25	9.12	0.37	23.71	14.33
Seeds/m^2	6360506.90	2175359.20	4185147.70	0.34	35.92	21.01
Biomass at AN	15018.20	3179.53	11838.67	0.21	28.49	13.11
Yield	342.50	115.60	226.89	0.34	20.55	11.94
TKW	22.89	3.50	19.39	0.15	24.45	9.56
Irrigated						
Biomass at MA	24353.26	65011.24	40657.98	0.37	10.52	17.19
Harvest index	0.001	0.002	0.002	0.33	7.83	13.68
Spikes/m^2	26471.44	60393.71	33922.27	0.44	14.78	22.32
Seeds/spike	6.35	10.48	4.13	0.61	14.81	19.02
Seeds/m^2	7279839.17	17034637.77	9754798.60	0.43	14.59	22.32
Biomass at AN	14159.72	60975.99	46816.27	0.23	11.03	22.90
Yield	5777.39	14075.01	8297.62	0.41	17.38	27.12
TKW	5.53	20.11	14.58	0.28	8.84	16.85

Table 7 Continued.

(b) Trait	Phenotypic Variance	Genotypic Variance	Environmental Variance	Repeatability	PCV (%)	GCV (%)
Rainfed						
Biomass at MA	114557.56	29125.70	85431.86	0.25	22.29	11.24
Harvest index	0.01	0.002	0.004	0.34	27.93	16.17
Spikes/m^2	69093.29	32006.23	37087.06	0.46	26.65	18.14
Seeds/spike	11.41	6.14	5.28	0.54	17.93	13.15
Seeds/m^2	26660198.77	9138820.77	17521378.00	0.34	40.80	23.89
Biomass at AN	56674.06	13437.62	43236.45	0.24	32.34	15.75
Yield	4929.93	2140.96	2788.98	0.43	22.08	14.55
TKW	9.93	8.01	1.93	0.81	9.86	8.85
Irrigated						
Biomass at MA	87828.54	31521.81	56306.74	0.36	17.47	10.47
Harvest index	0.002	0.001	0.001	0.40	12.89	8.20
Spikes/m^2	43532.90	23666.96	19865.94	0.54	22.14	16.32
Seeds/spike	4.05	3.00	1.05	0.74	10.50	9.04
Seeds/m^2	13681522.80	7543487.90	6138034.90	0.55	23.64	17.55
Biomass at AN	78835.99	19979.71	58856.28	0.25	23.81	11.99
Yield	2251.55	1091.53	1160.02	0.48	9.36	6.52
TKW	8.43	5.76	2.67	0.68	8.29	6.85

Table 8 Variance components and heritability for different traits of 20 wheat genotypes under rainfed and irrigated conditions during year 1 and year 2.

Trait	Phenotypic Variance	Genotypic Variance	Environmental Variance	Heritability (%)	PCV (%)	GCV (%)
Year 1						
Biomass at MA	30996.26	3262.74	27733.52	0.11	18.13	5.88
Harvest index	0.003	0.001	0.002	0.19	16.00	7.04
Spikes/m^2	24327.37	456.18	23871.19	0.02	20.22	2.77
Seeds/spike	10.88	2.67	8.21	0.25	19.99	9.91
Seeds/m^2	10284381.67	1713394.67	8570987.00	0.17	25.14	10.26
Biomass at AN	32461.05	906.12	31554.93	0.03	23.89	3.99
Yield	4635.94	148.17	4487.78	0.03	25.82	4.62
TKW	9.80	0.48	9.32	0.05	13.56	3.00
Year 2						
Biomass at MA	76772.78	-8366.28	85139.06	-0.11	17.24	5.69
Harvest index	0.003	0.0004	0.003	0.14	19.04	7.04
Spikes/m^2	44120.64	9971.30	34149.35	0.23	21.78	10.35
Seeds/spike	6.27	3.13	3.13	0.50	13.17	9.32
Seeds/m^2	17092443.83	2295525.83	14796918.00	0.13	29.22	10.71
Biomass at AN	56220.54	-228.15	56448.69	-0.004	24.76	1.58
Yield	3317.77	387.08	2930.68	0.12	13.97	4.77
TKW	8.15	5.86	2.28	0.72	8.52	7.23

Association between pairs of traits for the 20 wheat genotypes

Correlation coefficients revealed a wide spectrum of relationship between the aboveground biomass, harvest index and yield component traits, and among themselves both at genotypic and phenotypic levels (Tables 9 and 10; year 1 and 2, respectively). For phenotypic correlations in year 1, biomass at maturity had positive and strong correlation to spikes/m^2, seeds/m^2, and yield, under rainfed conditions (0.54, 0.59 and 0.51, respectively), and under irrigated conditions (0.68, 0.78 and 0.78, respectively). Under rainfed conditions in year 2, biomass at maturity had a strong and positive relationship with harvest index, spikes/m^2, and seeds/m^2. Biomass at maturity under irrigated condition had a strong and positive relationship with yield, spikes/m^2, and seeds/m^2. The genotypic relationship was similar to the phenotypic relationship under irrigated condition but including harvest index and seeds/spike. For year 1 under rainfed conditions, biomass at anthesis showed weak correlation with all the traits, but under irrigated conditions biomass at anthesis showed weak and negative correlations with harvest index (-0.34), spikes/m^2 (-0.36), and seeds/spike (0.26), all these at the phenotypic level. Genotypic correlations were not computed by META-r for biomass at anthesis and maturity due to extremely small values, same also with TKW.

TKW had a significant phenotypic correlation with spikes/m^2 (0.57) and seeds/m^2 (-0.60), also highly significant genotypic correlations with same traits including seeds/spike (-0.60), under rainfed condition for year 1. Phenotypic correlation between TKW was with spikes/m^2 (-0.47) and seeds/m^2 (-0.48), while genotypic correlation was with biomass at maturity, spikes/m^2, seeds/m^2 and yield, under irrigated condition for year 1. This relationship was similar for year 2 also, but negative correlation of TKW with spikes/m^2 (-

0.55 and -0.61, under rainfed and irrigated conditions, respectively). Seeds per spike significantly correlated with harvest index, seed/m^2, and yield at both phenotypic and genotypic levels, and negatively correlated with TKW at only genotypic level under rainfed condition in year 1. Under irrigated condition, seeds per spike significantly correlated with harvest index (0.48 and 0.59), negatively correlated to spikes/m^2 at both phenotypic and genotypic levels (-0.51 and -0.64, respectively), also with yield positive phenotypic and negative genotypic correlation. In year 2, seeds per spike correlation was similar with year 1 under rainfed condition, including positive correlation with spikes/m^2. Irrigated condition gave similar correlations in year 2 excluding yield, and including seeds/m^2 (0.70 and 0.76), and biomass at maturity only with significant genotypic correlation (0.70). Under rainfed condition in year 1 at phenotypic and genotypic levels, harvest index presented a significant association with yield (0.56 and 0.99), seeds/m^2 (0.51 and 0.48), and seeds/spike (0.77 and 0.89). Irrigated condition had harvest index correlated with seeds/spike (0.71 and 0.99) at both levels, while negatively with spikes/m^2 and yield only at genotypic level. In year 2 under rainfed condition, harvest index was associated with similar traits as in year 1, while under irrigated condition harvest index significantly associated with seeds/spike and seeds/m^2.

Overall under rainfed conditions in year 1, yield correlated with biomass at maturity (0.51) at phenotypic level, harvest index (0.56 and 0.99), seeds/m^2 (0.57 and 0.99) and seeds per spike (0.46 and 0.99) at both levels (phenotypic and genotypic levels, respectively), while with spikes/m^2 (0.83) only at genotypic level. Similarly, under irrigated condition, yield associated significantly with biomass at maturity (0.78 and 0.86), and seeds per spike (0.51 and -0.48) at both levels (phenotypic and genotypic levels, respectively), seeds/m^2 (0.85) at phenotypic level, while with harvest index (-0.83), and spikes/m^2 (0.56) at only genotypic level. In year 2 under rainfed conditions, yield was positively and significantly correlated with harvest index (0.70 and 0.90), seeds/spike (0.61 and 0.78), seeds/m^2 (0.62 and 0.84) and spikes/m^2 (0.50 and 0.47) at both levels (phenotypic and genotypic levels, respectively). Whereas under irrigated condition, yield correlated positively and significantly with biomass at maturity (0.61 and 0.99) and seeds/m^2 (0.49 and 0.58) at both levels (phenotypic and genotypic levels, respectively), also with biomass at anthesis only at phenotypic level.

Table 9 Phenotypic (r_p) and genotypic (r_g) correlation coefficient for traits in 20 wheat genotypes under rainfed and irrigated conditions during year 1.

Rainfed		HI	Spikes/m^2	Seeds per spike	Seeds/m^2	Biomass at AN	Yield	TKW
Biomass at MA	r_p	0.02	0.54*	0.17	0.59**	0.17	0.51*	-0.06
	r_g	-	-	-	-	-	-	-
HI	r_p		-0.06	0.77***	0.51*	-0.01	0.56*	0.06
	r_g		-0.41	0.89***	0.48*	-	0.99***	-0.17
Spikes/m^2	r_p			-0.04	0.63**	0.19	0.40	-0.57*
	r_g			0.32	0.65**	-	0.83***	-0.99***
Seeds per spike	r_p				0.72**	0.03	0.46*	-0.30
	r_g				0.93***	-	0.99***	-0.60**
Seeds/m^2	r_p					0.11	0.57**	-0.60**
	r_g					-	0.99***	-0.99***
Biomass at AN	r_p						0.22	-0.003
	r_g							-
Yield	r_p							-0.02
	r_g							0.15

*, **, and *** Significant at 0.05, 0.01 and <.0001, respectively

Table 9 Continued.

Irrigated		HI	Spikes/m^2	Seeds per spike	Seeds/m^2	Biomass at AN	Yield	TKW
Biomass at MA	r_p	-0.10	0.68**	0.07	0.78***	0.08	0.78***	-0.23
	r_g	-0.15	0.62**	0.05	0.75***	-	0.86***	-0.99***
HI	r_p		-0.34	0.71**	0.30	-0.34	0.54	0.27
	r_g		-0.56*	0.99***	0.41	-	-0.83***	-0.23
Spikes/m^2	r_p			-0.51*	0.59**	-0.36	0.35	-0.47*
	r_g			-0.64**	0.46	-	0.56**	-0.82***
Seeds per spike	r_p				0.38	0.26	0.51*	0.10
	r_g				0.38	-	-0.48*	-0.11
Seeds/m^2	r_p					-0.11	0.85***	-0.48*
	r_g						0.08	-0.99***
Biomass at AN	r_p						-0.13	-0.04
	r_g							-
Yield	r_p							-0.01
	r_g							0.54*

*, **, and *** Significant at 0.05, 0.01 and <.0001, respectively

Table 10 Phenotypic (r_p) and genotypic (r_g) correlation coefficient for traits in 20 wheat genotypes under rainfed and irrigated conditions during year 2.

Rainfed		HI	Spikes/m^2	Seeds per spike	Seeds/m^2	Biomass at AN	Yield	TKW
Biomass at MA	r_p	0.43*	0.68**	0.28	0.80***	-0.33	0.31	-0.19
	r_g	-	-	-	-	-	-	-
HI	r_p		0.37	0.69**	0.79***	0.06	0.70**	-0.002
	r_g		0.35	0.63**	0.70**	-	0.99***	-
Spikes/m^2	r_p			0.51*	0.73**	0.02	0.50*	-0.55**
	r_g			0.61**	0.71**	-	0.47*	-
Seeds per spike	r_p				0.74**	0.12	0.61**	-0.59**
	r_g				0.88***	-	0.78***	-
Seeds/m^2	r_p					-0.14	0.62**	-0.38
	r_g						0.84***	-
Biomass at AN	r_p						0.06	-0.10
	r_g							-
Yield	r_p							-0.19

*, **, and *** Significant at 0.05, 0.01 and <.0001, respectively

Table 10 Continued.

Irrigated		HI	Spikes/m^2	Seeds per spike	Seeds/m^2	Biomass at AN	Yield	TKW
Biomass at MA	r_p	0.22	0.70***	0.41	0.86***	0.22	0.61**	-0.33
	r_g	0.61**	0.63**	0.70***	0.96***	-	0.99***	-
HI	r_p		0.10	0.48*	0.54*	0.03	0.19	0.15
	r_g		0.24	0.59**	0.66**	-	0.18	-
Spikes/m^2	r_p			0.52*	0.71**	0.02	0.35	-0.61**
	r_g			0.65**	0.70**	-	0.38	-
Seeds per spike	r_p				0.76***	0.02	0.23	-0.69**
	r_g				0.88***	-	0.26	-
Seeds/m^2	r_p					0.14	0.49*	-0.51*
	r_g					-	0.58**	-
Biomass at AN	r_p						0.47*	0.10
	r_g							-
Yield	r_p							0.01

*, **, and *** Significant at 0.05, 0.01 and <.0001, respectively

Genotype by Trait Biplots for Trait Relations and Genotype Comparisons

This analysis was performed for each year, where the first two principal components (PC1 and PC2) were used to display a two-dimensional GGE biplot so as to explain the maximum amount of cumulative variability (Table A1). All the 8 PCs, where the first three generally appear significant with eigenvalues greater than 1. It is clear that the variability decreases as the PC progresses. The first three PCs present the cumulative variability of 80.10% and 83.77%, under rainfed condition for year 1 and year 2, respectively, while 87.56% and 82.85%, under irrigated condition for year 1 and year 2, respectively. The factor loadings for all the variables presented the number of seed/m^2 as the followed by yield for year 1 under both conditions (Table A2). Seed/m^2 also had the highest loading in year 2 followed by other variables in PC1, up until PC3. These imply their similarity in their trend of change in variability at the significant PCs where negative values show negative association with other variables in the PC. These are clearly seen in the biplots with PC1 and PC2.

The biplot is constructed by plotting the primary effects scores of each genotype with twenty in total represented by blue dots and each against their respective secondary effect score eight traits is represented in red color. A vector is drawn from the biplot origin to each dot of the traits to aid visualization of the relationships between and among the traits. A genotype by trait (GT) biplot is constructed by plotting the PC1 scores against the PC2 scores for each genotype and each trait. The biplot analysis of genotype by trait as a two-way factor for each year is presented in figures 1A – 1D.

The GT biplot for each of the two years, explained 64.60 to 70.99 % variation of the total dataset. For both years, the largest variation explained by the biplots came consistently from aboveground biomass at maturity under rainfed condition, seeds per spike, and spikes/m^2. The most important relations revealed by these biplots are: (i) a strong negative association between TKW and spikes/m^2 (fig. 1A), TKW and spikes/m^2 (fig. 1B), between aboveground biomass at anthesis and biomass at maturity (fig. 1C), TKW and seeds/spike, TKW and spikes/m^2 (fig. 1D) as indicated by the large obtuse angles between their vectors, (ii) a near zero correlation between harvest index and aboveground biomass both anthesis and at maturity (fig. 1A), seeds/spike and aboveground biomass at maturity, harvest index and aboveground biomass at maturity (fig. 1B), seeds/spike and seeds/m^2 (fig. 1C), aboveground biomass at anthesis and seeds/m^2, yield and spikes/m^2 (fig. 1D) as indicated by the near perpendicular vectors, (iii) a positive association between seeds/spike and seeds/m^2 both being correlated with yield (fig. 1A), yield and aboveground biomass at maturity both correlated with seeds/m^2 (fig. 1B), yield and spikes/m^2 both correlated with harvest index (fig. 1C), harvest index and seeds/m^2 both correlated with aboveground biomass at maturity (fig. 1D), as indicated by the acute angles.

The length of the vectors for all the traits and genotypes indicate their stability; the closest to the origin (PC1 and PC2 axis) imply more stable genotypes for that particular trait. Generally, under rainfed condition, the twenty genotypes are more stable in their performance for all the traits especially yield (fig. 1A and fig. 1B), harvest index, spikes/m^2, and seed/m^2 (fig. 1C). Under irrigated condition, the twenty genotypes appeared mostly less stable with few clustered near the origin, aboveground biomass at anthesis (fig. 1B) and harvest index (fig. 1D) were most stable among the other traits.

In Fig. 1A, Endurance (16), Jagger (19), and TX99A0153-1 (8) appeared to have greater value in harvest index, seeds/spike, yield, and seed/m^2, compared to TAM 112 (5) which had the best value in spikes/m^2 and aboveground biomass at maturity. TAM 105 (2), TAM 110 (3) and TX86A5606 (9) were best in TKW but slightly better than Winterhawk (15) and Endurance (16) in harvest index and seeds/spike. Genotypes 1, 10, 11, and 13 were of lowest value in all the traits. Figure 1B showed Duster (17), Winterhawk (15), and Jagalene had the better value in yield, seeds/m^2, and aboveground biomass at maturity compared with Hatcher (13) and TAM 113 (7) which had the best value in spike/m^2. TAM 304 (6) had better value in harvest index and seed/spike than all other genotypes. TAM 111 (4) and Billings (18) were slightly better than TAM 304 in spikes/m^2, harvest index and seeds/spike. TAM 111 (4) and Dumas (11) had higher values of TKW and aboveground biomass than all other traits. Genotypes 1, 2, 10, and 16 had the lowest value on all the traits. In figure 1C, TAM 105 (1) was good in most of the traits (except TKW) and better than Billings (17). While TAM 114 (6), TX99A0153-1 (8) and Dumas (9) were slightly better than Iba (14) and most genotypes in aboveground biomass at anthesis. Besides TAM 105 (1) as the best, TAM 112 (4), Plains Gold Byrd (12), and Iba (14), were best in seeds/spike, yield, harvest index, spikes/m^2, seeds/m^2 and aboveground biomass at maturity. The following genotypes had lower values in all other traits but highest values in TKW; 15, 17, 18, 19, and 20. Figure 1D indicates that TAM 304 (7), Plains Gold Byrd (12), Iba (14), Duster (16) were better in all traits except TKW. Billings (17) and AMPSY068 (18) were slightly better than all genotypes in TKW. Genotypes 1, 2, 8, 9, 10, and 20 were of lowest value for all the traits.

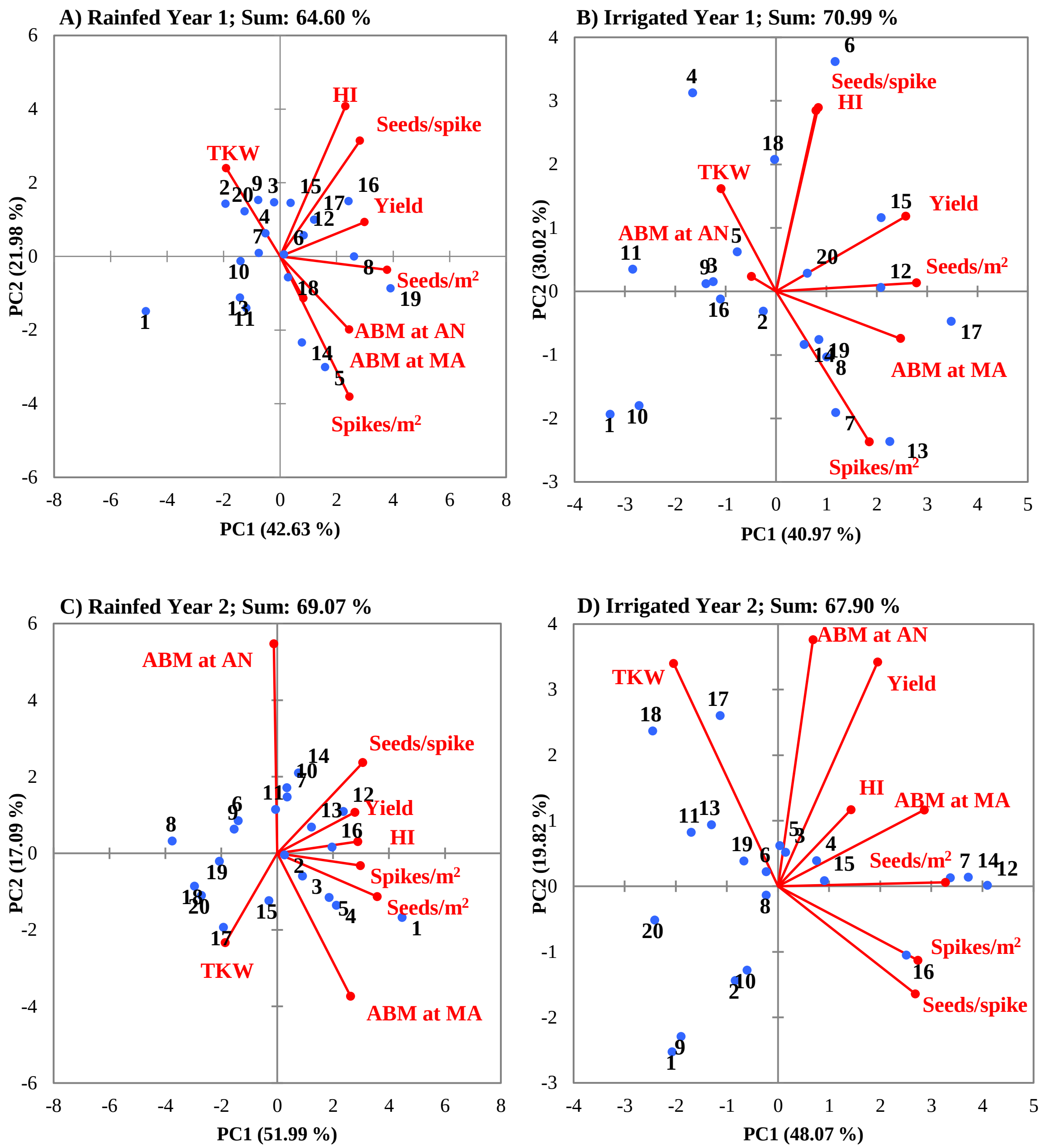

Figure 1. Biplot based on the twenty wheat genotypes (blue color), two water regimes (Rainfed and Irrigated) and eight traits (red color) for two years.

The numbers are different genotypes in Year 1; 1=TAM W101, 2=TAM 105, 3=TAM 110, 4=TAM 111, 5=TAM 112, 6=TAM 304, 7=TAM 113, 8=TX99A0153-1, 9=TX86A5606, 10=TX86A8072, 11=Dumas, 12=Jagalene, 13=Hatcher, 14=BillBrown, 15=Winterhawk, 16=Endurance, 17=Duster, 18=Billings, 19=Jagger, 20=Fuller.The numbers are different genotypes in year 2; 1=TAM 105, 2=TAM 110, 3=TAM 111, 4=TAM 112, 5=TAM 113, 6=TAM 114, 7=TAM 304, 8=TX99A0153-1, 9=Dumas, 10=Jagalene, 11= Hatcher, 12=Plains Gold Byrd, 13=Winterhawk, 14=Iba, 15=Endurance, 16=Duster, 17=Billings, 18=AMPSY068, 9=AMPSY588, 20=TX11Vsyn0101.

DISCUSSION

According to Allard (1960) genotypic variability represents the extent of the effects of heritability and genetic variation. Selection can be applied successfully within a population with significantly high genotypic variance. The significant genotypic variability in biomass at maturity, harvest index, spikes/m^2, seeds/m^2, seeds/spike, yield and TKW indicates that selection may be conducted with respect to these traits. Rajaram et al. (1996) noted that these traits as they are drought related, determines crop productivity under water stress conditions. Since yield is the combined effect of heads per unit area, seeds per spike and grain/seed weight, any change in seed number and weight due to moisture stress will ultimately affect yield (Foulkes et al., 2004; Rajaram et al., 1996; Reynolds et al., 2001). Seed number is much more influenced by factors affecting growth, but the influence of water stress is more important, because water stress for few days before spike emergence in wheat reduces seed number (Reynolds et al., 2005; Sharma and Bhargava, 1996).

The differences among the traits have provided the opportunity to discriminate among the wheat genotypes under different water regimes for drought tolerance assessment. Generally, TAM genotypes showed similar values in many variables compared to the other genotypes. In agreement with Xue et al. (2014), the more recently released genotypes such as TAM 112 had higher yields, spikes/m^2 and harvest index than older genotypes such as TAM W-101 mostly under rainfed condition. The wheat genotypes under rainfed conditions generally had reduced yield especially in year 1, due to reduction in spikes per unit area and fewer seeds per spike. These results are also indicative that through proper selection procedures these traits can be fixed in genotypes especially for water-limited situations. As seen in this study that harvest index declined with increase in water stress. Trethowan et al. (2002) observed that the reduction in harvest index suggests that grain yield is more sensitive to water stress than aboveground biomass because the reduced grain yield was produced by fewer heads or spikes per unit area, few seeds per spike and lighter seeds.

Environmental variance was found significant for all the traits except spikes/m^2. This implies that these traits were intensely affected by the contrasting environmental conditions of water regimes. The genotype x environment variance component was determined to be significant for spikes/m^2, tillers/m^2, yield for year 1 only. This interaction variance indicates that selection should be carried out over a sample of environments and breed different genotypes for every specific environment (Voltas et al., 2005) and every year, since the weather conditions are not constant. Due to these results, it is recommended to develop different genotypes for different water regimes with respect to important yield component traits and yield which is generally considered as major target in wheat breeding program.

Ansari et al. (2004) concluded that high heritability percentage reflects the large heritable variance which may offer the possibility of improvement through selection. The repeatability and heritability values estimated at quite low levels of 0.4% - 44% for most of the traits varying for each year and water regime, can be explained by the increased phenotypical variance due to the effect of genotype x environment. Budak (2000) stated that broad-sense heritability of grain yield was 67%. The same researchers suggested that the yield seem to be controlled by genotypes more than environment. Novoselovic et al. (2004) estimated heritability of 21 % - 78% for seed yield in wheat. The heritability estimated in this study was well within the range of these results.

According to Mundiyara et al. (2014) and Tsegaye et al. (2012) the higher PCV and GCV values for most of the traits could be evidence for the existence of a wide range of variation for such traits. Generally, the PCV values for most traits were closer than the corresponding GCV values showing little environment effect on the expression of these traits. Based on the phenotypic expression, selection may be effective for the genetic improvement of such traits. Under rainfed condition, the differences between GCV and PCV was the highest for grain yield indicating more environmental influences. PCVs were slightly higher than GCVs for all traits indicating presence of environmental influence on the expression of traits in agreement with Ali et al. (2008), Sharma and Garg (2002) and Kumar et al. (2003).

The genetic correlation provided information on how likely the traits share the same genes. The phenotypic correlation is the observed correlation between two traits. Positive significant associations were determined under rainfed conditions between yield and the following traits; biomass at maturity, harvest index, seeds/m^2, seeds per spike, and spikes/m^2. This result is similar to the findings of Kara and Akman (2007), indicating that wheat yield can be improved by selecting genotypes having higher performances for the above traits especially under water-stressed conditions. Negative significant correlations such as yield with spikes/m^2, TKW with spikes/m^2, spikes/m^2 with harvest index and seeds per spike shows that important yield component traits are generally inversely correlated with each other and harvest index (Khanna, 1990; Luo et al., 2015; Reynolds et al., 2001).

The genotype by trait biplot analysis presented between 64 and 71 % total variation of the data, which reflects the complexity of the relationships among the eight traits. The biplot may not accurately reflect the means as it did not explain all variation of the data but it displays the most important patterns of the data (Ilker et al., 2011; Yan and Tinker, 2006). In respective of this relatively low proportion the fundamental patterns among these traits are visible by the biplots. The correlation coefficients among the traits indicate that the GT biplots correctly displays relationships among the traits that had large scores on either PC1 or PC2. GT biplot results describe the interrelationships among all traits on the basis of overall pattern of the data compared to correlation coefficients that only describe the relationships between two traits. The interrelationships among these traits are most important to wheat breeding. The GT biplot was also used to compare genotypes based on the multiple traits and to identify genotypes that are particularly good in certain traits as candidates for parents in wheat breeding (Malik et al., 2014; Yan and Frégeau-Reid, 2008).

Traits that contribute to wheat yield were identified by variability, correlation and principal component analysis between yield and yield components. Based on this knowledge, the wheat breeder can begin a more educated attempt to introduce these specific traits into more widely adapted genotypes and thus meet a goal for developing cultivars better adapted to dryland conditions. But the final test for any wheat variety for areas subjected to limited moisture supply will be found in whether it has ability to yield optimally under relatively dry conditions over a period of years. Based on the findings, it can be concluded that selection will be effective in the traits used in this study as revealed by the significant variations among the genotypes. This study demonstrated that the GT biplot is an excellent tool for visualizing accession by trait data. Therefore, the genetic variability for these traits over different water regimes can be further exploited through improvement and selection programs in multiple locations.

CHAPTER III

ASSESSMENT OF TWO GROUND-BASED CROP CANOPY SENSORS IN WINTER WHEAT

INTRODUCTION

Wheat (*Triticum aestivum* L.) is a highly adapted crop across the world, however a particular variety hardly possess the potential to survive in various environmental conditions. An adapted variety is achieved by the interaction between the genetics and the environment. Drought is one of the most common environmental stresses that affect growth and development of wheat (Araus et al., 2002). Crop adaption to drought stress is crucial to develop newly improved methods for increasing stress tolerant plants (Hasanuzzaman et al., 2017). The response of plant to drought stress depends on several factors such as plant genotype, growth stage, stress duration, physiological growth, and environmental conditions (Chaves et al., 2003; Kilic and Yagbasanlar, 2010; McDonald and Davies, 1996).

In wheat breeding programs, increased yield potential has been the target in improving drought tolerance of wheat. It is however important to characterize physiological parameters related to drought tolerant genotypes before success can be achieved (Bogale et al., 2011; Veesar et al., 2007). The stages of crop growth and development can be affected by water stress conditions in varying magnitude, also drought tolerant genotypes may be identified at any stage from vegetative to reproductive phase. Drought stress before anthesis can reduce number of heads and number of seeds per head (Denčić et al., 2000; Guttieri et al., 2001). While drought stress imposed during later stages might additionally result in reduction of seeds per head and seed weight (Gupta et al., 2001). There is the need to connect phenotype to genotype with high efficiency in order for crop improvement efforts to attain increased crop yield potential in the future. The plant phenotype includes complex plant traits such as growth, development, tolerance, canopy architecture, physiology, and yield. Plant phenotyping involves comprehensive assessment of these complex traits through direct measurements such as biomass, leaf characteristics, yield related traits, and stress response (Andrade-Sanchez et al., 2014; Fiorani and Schurr, 2013; Xue et al., 2006). It is quite a laborious, and time-consuming process to collect field measurements for screening large number of genotypes required in traditional breeding programs. It often involves destructive measurements taken from a subsection of the experimental plot, which may not accurately represent the entire plot and can be subject to individual sampling error. Field-based high throughput phenotyping methods using remote sensing techniques have been implored in monitoring traits associated with biomass development and yield (Araus and Cairns, 2014; White et al., 2012).

Remote sensing techniques involve the characterization of the crop canopy based on its spectral reflectance (Aparicio et al., 2000; Reynolds et al., 1999). The crop canopy reflectance is the fraction of incoming light reflected by the crop canopy. The leaf pigments present absorbs light in the visible wavelengths (450-700 nanometers (nm)), with more blue (450-520 nm) and red (630-680 nm) light being absorbed than green light (520-600 nm). This results in higher reflectance in the green band, and is the reason plants appear green to the human eye. Compared to visible light, plants absorb much less near-infrared (NIR) light. That is, plants reflect more light in NIR wavelengths of 700-1400 nm, with percent NIR reflectance increasing as crop biomass increases. These reflectance characteristics for visible and NIR light of crop canopies are the basis for the development of numerous vegetative indices or spectral reflectance indices (SRI) to estimate diverse physiological traits (Araus et al., 2001). One such index is the NDVI - Normalized Difference Vegetation Index (Rouse et al., 1974) which is calculated using light reflectance of the red and NIR bands. The formula for calculating NDVI is as follows: NDVI = (NIR - Red) / (NIR + Red). Values for NDVI range from -1.0 to +1.0. In typical sensing operations output ranges from 0.1 to 0.9, with values ranging from 0.1 to 0.2 for soil surfaces and 0.2 to 1.0 for crop canopies (NDVI values increase as both crop biomass and greenness increase). Another is the Ratio Vegetation index (RVI) (Jordan, 1969), the reflectance at NIR wavelength divided by the red wavelength.

There are several approaches available for field phenotyping ranging from hand-held sensors, such as spectroradiometers (Ajayi et al., 2016; Gnyp et al., 2014), sensors mounted on field-fixed or mobile platforms (Pradhan et al., 2014; Rundquist et al., 2014; Sui and Thomasson, 2006; Sui et al., 2012; Thomasson et al., 2004), to sensors on unmanned aerial vehicles (UAVs), and manned aircraft (Chapman et al., 2014; Shi et al., 2016). The objective of this study is to evaluate the performance of two ground-based systems; namely hand-held and tractor mounted sensors, in estimating plant parameters.

MATERIALS AND METHODS

The field experiment was conducted at the Texas A&M AgriLife Research Experiment Station, Bushland, Texas (Lat. 35º11’N, Long. 102º06’W; elevation 1170m above the mean sea level) during the 2012-2016 growing season. The soil type was Pullman clay loam (fine, mixed, thermic Torrertic Paleustoll: USDA classification), the properties of which have been described by Unger and Pringle (1981). For this study, twenty winter wheat genotypes were planted under rainfed and irrigated conditions during three growing seasons 2012-2013, 2014-2015 and 2015-2016 in Bushland. The experiment was a randomized complete block design with three replications. The seeding rate was 67 kg/ha, plot size was 1.52 m x 4.27 m (6.50 m^2) while the row spacing for all plots was 18 cm. Weather data files (Fig. 2 a-b) were downloaded for the Bushland station for Year 1, Year 2 and Year 3 from the United States Department of Agriculture, Agricultural Research Service website (https://www.ars.usda.gov). The climate was semi-arid with erratic precipitation and high evaporative demands. The long-term precipitation accumulated during the growing season was 287 mm, and the average maximum and minimum temperature during the growing season was 41.1ºC and -6.7 ºC respectively.

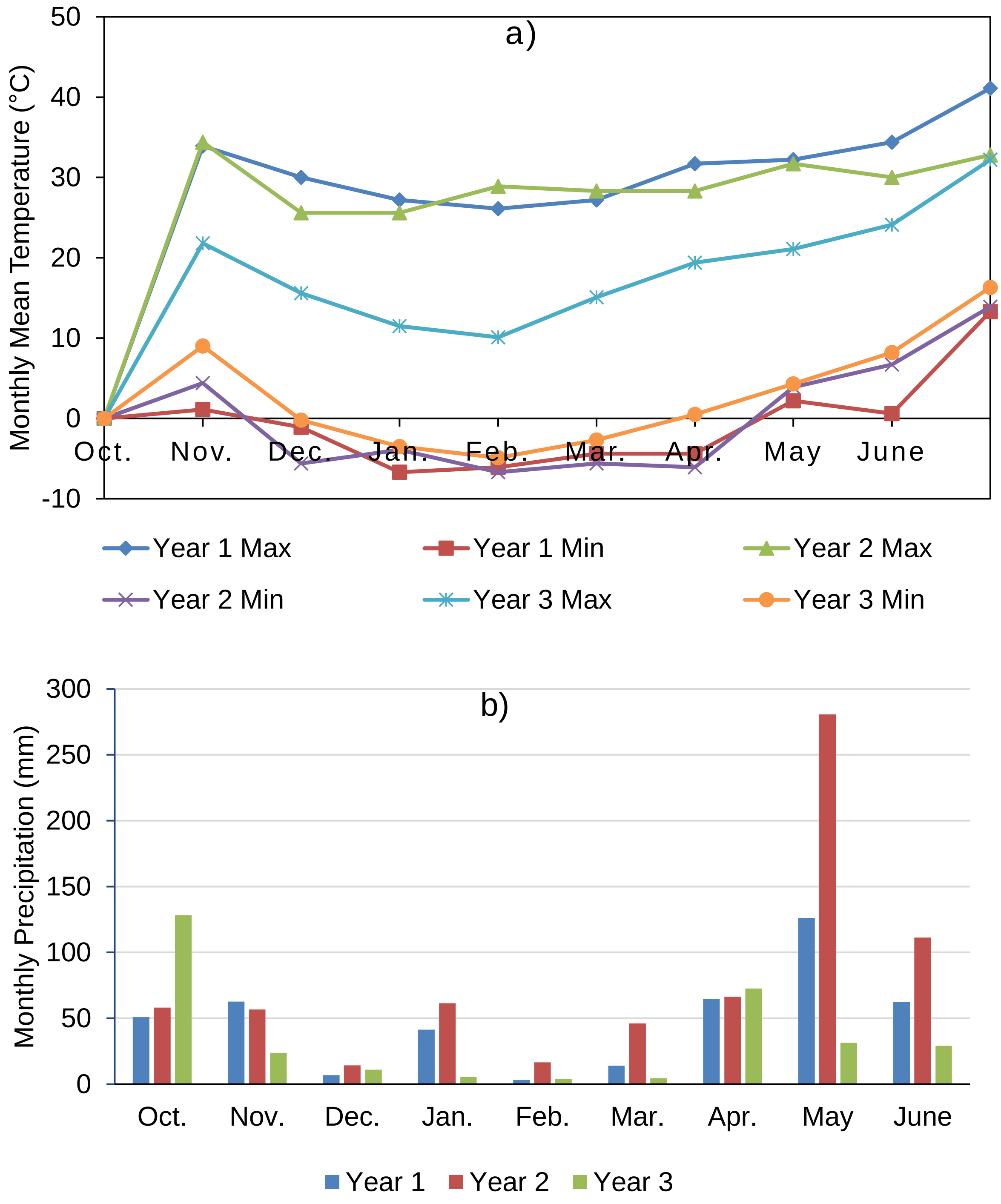

Figure 2 a) Mean maximum (Max) and minimum (Min) temperatures, and b) total monthly precipitation from October to June for the 2012-2013 (Year 1), 2014-2015 (Year 2) and 2015-2016 (Year 3) winter wheat-growing season in Bushland, TX.

Ground Based Sensors

Ground Based Plant Health Sensing System

The ground-based plant health sensing system (GBPHS) comprise of a multispectral optical sensor, an ultrasonic sensor and a global positioning system (GPS), and a data acquisition unit mounted on a tractor. The optical sensors consist of silicon photodiodes (PDB-C111, Photonic Detectors, Camarillo, California) used for light detection within the associated wavelength range of 400 to 1100 nm. This sensing system is used to map plant height and measure plant canopy reflectance. Plant height is measured using an ultrasonic sensor (model 607281, SensComp, Livonia, Michigan) to scan plant canopy while spatial information is collected by the system from a GPS receiver. The data acquisition unit includes a 206 MHz, 32-bit, low-power CPU, and Windows CE compatible peripherals suitable for embedded low-power and battery applications (R.L.C. Enterprises, Inc., Paso Robles, California). As a result of the sensor mounted on a tractor, measurements were carefully taken at the jointing (JT) and anthesis (AN) stage so as not to damage the plants when driving the tractor across the field plots, during the Year 1 (JT and AN) and Year 2 (JT only). In year 2, plant height data was not correctly accessible from the sensor.

Greenseeker® Handheld crop sensor

The Greenseeker® handheld crop sensor (Trimble Navigation Limited, Sunnyvale, California) is an active light source optical sensor that is used to measure plant biomass and display as NDVI (Normalized Difference Vegetation Index). The optical sensor emits a brief burst of radiation from red (Red; 660 nm) and near-infrared (NIR; 770 nm) light-emitting diodes (LEDs) to collect reflectance data that are independent of the solar conditions. The measurements are taken at a vertical viewing angle from a distance of 0.5-0.6 m above the crop to ensure accurate readings.

Field data collection

Aboveground biomass

Aboveground biomass was collected at anthesis; 1m of one row was cut at ground level from each plot. For each sample, the stems and heads were separated and counted. To determine the dry biomass, the stems and heads were dried at 60°C for 72 hours. The total weight in grams was expressed on per m^2 basis.

Plant height

Plant height was defined as the distance from the ground level to the tip of the tallest head using a ruler. For each plot, two measurements were taken from two middle rows at the ends of the plot, attempting to capture the average height for each plot. The two measurements were then averaged for a single value.

Leaf Chlorophyll

Leaf chlorophyll was measured using the same sampling method for both irrigated and rainfed conditions. The leaf chlorophyll was measured with a portable chlorophyll meter (SPAD- Soil Plant Analysis Development 502, Minolta Camera Co. Ltd., Japan). In each plot, readings were taken from four fully-expanded flag leaves and two readings (one at the center of the leaf blade, and another near the tip) were taken per leaf, all of which were averaged for a single value per plot.

Yield

Yields of both rainfed and irrigated plots were obtained by machine-harvesting with a Wintersteiger plot combine. The yield based on 10 % moisture content was expressed on a kilogram per hectare basis. The yield data was obtained only for Year 3, this is due to frost and hailstorm damage in Years 1 and 2.

Data analysis

Statistical analysis carried out in this study was done using the SAS version 9.3 (Statistical Analysis System Institute, Cary, NC, USA), and XLSTAT developed by Addinsoft (2010) for Microsoft Excel. Analysis of variance (ANOVA) was performed using the General Linear Model to compare differences in each of the plant parameters for irrigated and rainfed conditions. For both irrigated and rainfed conditions, statistical associations (using Pearson correlation) were developed between sensor data (ground-based plant health sensing system and Greenseeker®) and measured values of aboveground biomass and yield, and were plotted for visual analysis in scatter plots and biplot analysis. Based on the associations, multiple regression models were developed. The selection of the best statistical models based on R^2, adjusted R^2, root mean square error (RMSE) and confidence interval (95 %). The performance of the model was evaluated by comparing the R^2 and RMSE of prediction. The larger R^2 and the smaller RMSE reflect greater precision and the accuracy of the model, to predict aboveground biomass and yield.

RESULTS

Summary statistics of field data and sensor parameters

The range and means of aboveground biomass, yield, plant height and leaf chlorophyll are presented in Table 11. During the growing season in year 1under rainfed, aboveground biomass at jointing ranged from 271 to 600 g/m^2 with mean of 435 g/m^2. For year 2, the aboveground biomass was much lower than year 1 with mean of 334 g/m^2. At anthesis stage for the first year, aboveground biomass ranged from 313 to 559 g/m^2 with a mean of 416 g/m^2, while the second year had values from 556 to 1084 g/m^2 with a mean of 736 g/m^2 same as the third year though ranged from 528 to 928 g/m^2. Under irrigated fields for year 1 aboveground biomass was measured only at anthesis, the genotypes were significantly different with an overall mean of 945 g/m^2. In year 2 under irrigated fields, genotypes had aboveground biomass value at jointing lower than rainfed fields; it ranged from 110 to 330 g/m^2 with a mean of 205 g/m^2. At anthesis stage in year 2, aboveground biomass values on irrigated field, ranged from 749 to 1544 g/m^2 with a mean of 1166 g/m^2, year 3 had a mean of 1177 g/m^2.

Yield for the 20 wheat genotypes were recorded during the third growing season with the mean of 318 and 507 g/m^2 under rainfed and irrigated fields, respectively. Under rainfed field, the genotypes recorded plant height with mean of 30 and 40 cm for year 1 and 2, respectively. The genotypes under irrigated field had plant height mean of 42 and 92 cm for year 1 and 2, respectively. Leaf chlorophyll under rainfed field had mean of 54 for year 1 and 40 for year 2, while under irrigated field a mean of 43 for year 2 only.

As seen on Table 12, the range and mean of sensor parameters obtained from the ground-based plant health sensing system under rainfed and irrigated conditions. Generally, NDVI values for the 20 wheat genotypes were significantly different under both growth stages and field conditions. At jointing stage, rainfed fields for year 2 (0.44) recorded higher NDVI values than year 1 (0.60). At anthesis, significant NDVI values of 0.76 and 0.78 were recorded under rainfed and irrigated fields, respectively. At both growth stages on the rainfed field, the plant height from the sensor recorded the same value of 17cm, while 27 cm under irrigated field at anthesis only.

Figure 3 a-d displayed the NDVI values from the Greenseeker® sensor for years 2 and 3 at several growth stages during the season. Under dryland condition, the NDVI values for year 1 collected at four growth stages (post-emergence, tillering, jointing and heading) was between 0.30 and 0.80, while irrigated field was between 0.20 and 0.90. All stages were significant under rainfed field except at jointing, while all under irrigated field except at jointing and heading. In year 2 NDVI values were collected at several dates during the growing season to correspond with specific growth stages. Rainfed field ranged from 0.20 to 0.90 and irrigated field ranged from 0.60 to 0.90. The growth stage in year 2 was from post-emergence to maturity. Under rainfed field, the 20 wheat genotypes were distinguishable for all dates/stages except at tillering (2/17/2016) and the four dates around heading (04/21/2016) before maturity. There was significant difference among the genotypes for all stages except around jointing (3/11 and 4/9) and heading (5/13).

Table 11 Summary statistics of plant height, leaf chlorophyll, yield, and aboveground biomass (ABM) for the 20 genotypes.

		ABM g/m^2 (Jointing)			ABM g/m^2 (Anthesis)			Yield g/m^2		
Year	**Condition**	**Min**	**Max**	**Mean P>F**	**Max**	**Mean**	**Mean P>F**	**Min**	**Max**	**Mean P>F**
2012-2013	Rainfed	271	600	435 ***	313	559	416 ***		-	
	Irrigated		-		807	1147	945 ***		-	
2014-2015	Rainfed	255	454	334 *	556	1084	736 *		-	
	Irrigated	110	330	205 *	749	1544	1166 *		-	
2015-2016	Rainfed		-		528	928	736 NS	239	411	318 NS
	Irrigated		-		952	1457	1177 NS	433	549	507 *

		Plant height (cm)			Leaf chlorophyll		
Year	**Condition**	**Min**	**Max**	**Mean P>F**	**Min**	**Max**	**Mean P>F**
2012-2013	Rainfed	24	32	30 *	49	59	54 *
	Irrigated	37	47	42 *		-	
2014-2015	Rainfed	43	54	49 *	35	47	40 *
	Irrigated	87	94	92	37	48	43 *

[†] NS: No significance; *, **, and *** significant at 0.05, 0.01, and <.0001, respectively

Table 12 Summary statistics of NDVI and plant height values for the 20 wheat genotypes obtained from the Ground-based plant health sensing system under rainfed and irrigated conditions.

NDVI

		Jointing						**Pre-Anthesis/Anthesis**			
Year	**Condition**	**Min**	**Max**	**Mean**	**P>F**	**Year**	**Condition**	**Min**	**Max**	**Mean**	**P>F**
2012-2013	Rainfed	0.41	0.46	0.44	***	2012-2013	Rainfed	0.73	0.79	0.76	***
	Irrigated		-				Irrigated	0.71	0.86	0.78	***
2014-2015	Rainfed	0.43	0.67	0.60	***						
	Irrigated		-								

Plant Height (cm)

		Jointing						**Pre-Anthesis/Anthesis**			
Year	**Condition**	**Min**	**Max**	**Mean**	**P>F**	**Year**	**Condition**	**Min**	**Max**	**Mean**	**P>F**
2012-2013	Rainfed	16	19	17	***	2012-2013	Rainfed	16	18	17	***
	Irrigated		-				Irrigated	23	30	27	***
2014-2015	Rainfed		-								
	Irrigated		-								

† *, **, and *** significant at 0.05, 0.01, and <.0001, respectively

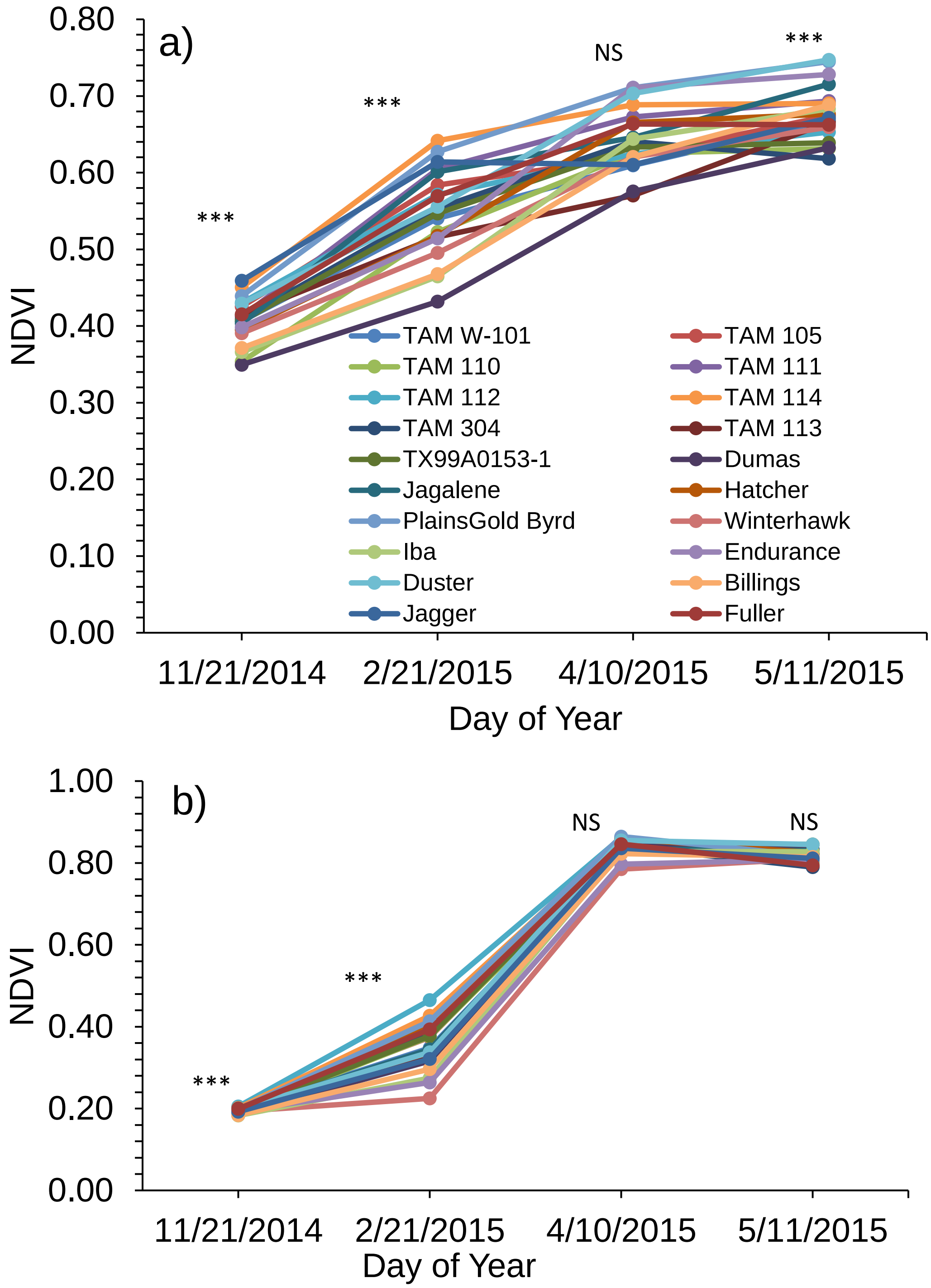

Figure 3 NDVI values obtained from the Greenseeker® sensor during the growing season in rainfed (a, c) and irrigated (b, d) fields.

[†] NS: No significance; *, **, and *** significant at 0.05, 0.01, and <.0001, respectively

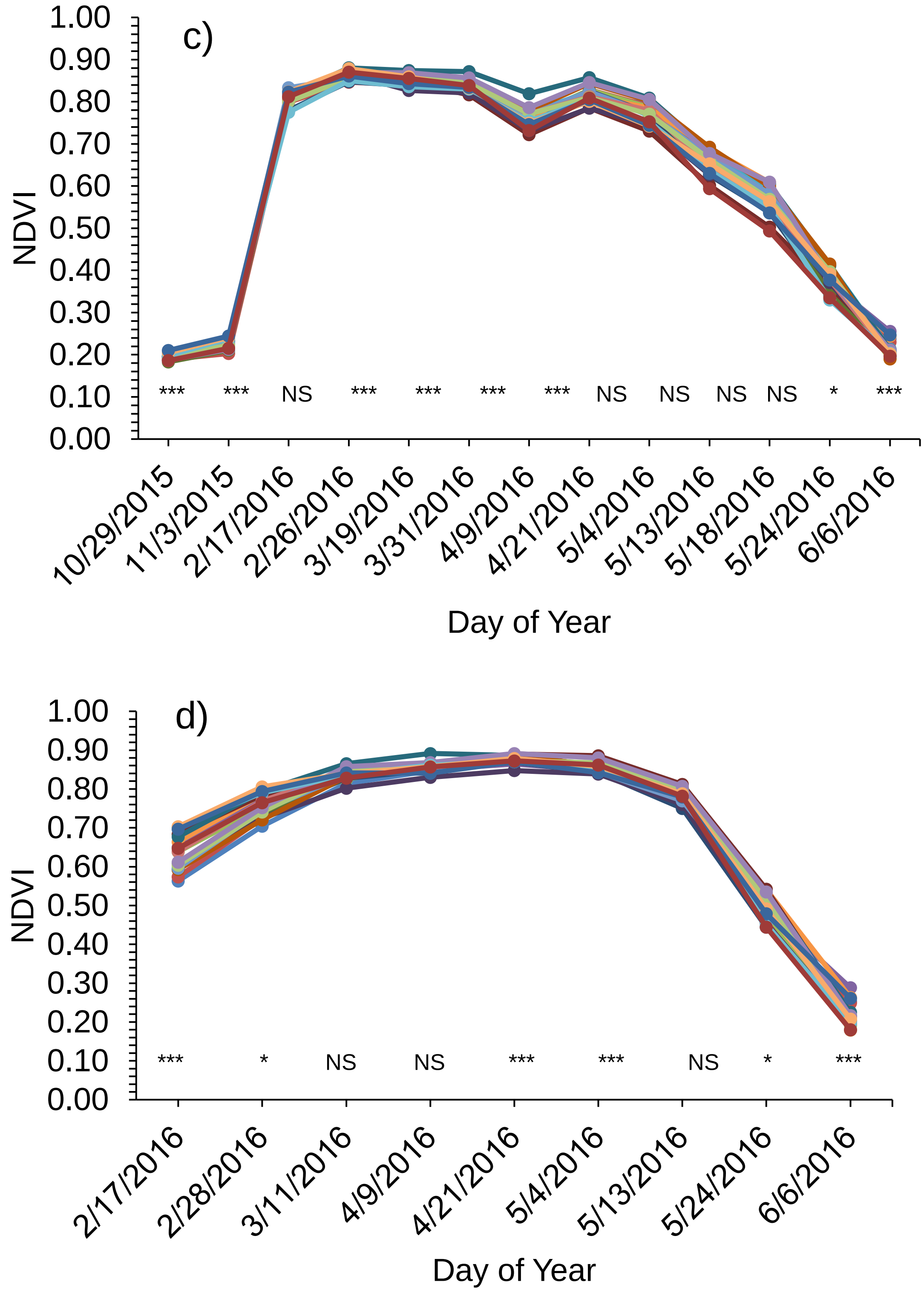

Figure 3 Continued

Correlation between field data and sensor parameters

The correlation coefficients (r) between field data and sensor parameters are presented in Tables 13 and 14. As seen in Table 13, aboveground biomass at jointing for rainfed field in year 1 had poor association with NDVI at anthesis, and with NDVI at jointing in year 2. However, aboveground biomass at jointing in year 1 had weak association with NDVI at jointing and positively strong association with plant height at jointing. Aboveground biomass at anthesis in year 1 had poor correlations with NDVI at jointing and anthesis, weak correlation with plant height at jointing and strong association with plant height at anthesis. In year 2, aboveground biomass at anthesis had weak correlation with NDVI at jointing. Leaf chlorophyll generally showed negative and poor correlations with all the parameters for both years. Under rainfed field, plant height measured manually showed poor correlation with NDVI at jointing for year 2, while weak correlation with sensor plant height at jointing and anthesis, and NDVI at anthesis, and significant correlation with NDVI at jointing for year 1. Under irrigated condition, aboveground biomass and manual plant height showed poor and negative correlations with the parameters.

Aboveground biomass at jointing showed poor correlation with NDVI at all stages in rainfed field in Table 14. Correlation was strong under irrigated condition for all stages except at heading. Aboveground biomass at anthesis for year 2 showed significant association with NDVI at tillering and jointing under rainfed condition, at all stages except at heading under irrigated condition. For year 2 correlation were not significant. In year 3 yield correlated best with NDVI at heading; r=0.63 and 0.48, in rainfed and irrigated fields, respectively. Leaf chlorophyll and manual plant height correlated best also with NDVI at heading under rainfed condition. There were no associations in similar case under irrigated condition.

Table 13 Correlation between the field data and sensor parameters from the ground-based plant health system.

	Rainfed				Irrigated	
2012-2013	ABM JT	ABM AN	Leaf chlorophyll	Plant height	ABM AN	Plant height
NDVI_JT	0.34	-0.06	-0.25	0.48*	-	-
NDVI_AN	0.07	0.07	0.07	0.35	0.07	-0.36
Plant height JT	0.60***	0.16	0.07	0.37	-	-
Plant height AN	0.29	0.50*	-0.25	0.14	0.03	-0.02
2014-2015						
NDVI_JT	0.07	0.23	-0.07	0.03	-	-

† JT: Jointing; AN: Anthesis; *, **, and *** significant at 0.05, 0.01, and <.0001, respectively

Table 14 Correlation between the field data and the NDVI values from the Greenseeker® sensor.

Year	DOY/Growth stages	ABM JT	ABM AN	Yield	Plant height	Leaf chlorophyll
2014-2015						
Rainfed	Pre-emergence	0.07	0.37	-	0.20	0.12
	Tillering	0.17	0.57*	-	0.29	0.07
	Jointing	0.05	0.53*	-	0.37	0.23
	Heading	-0.32	0.38	-	0.71**	0.50*
Irrigated	Pre-emergence	0.57*	0.44*	-	0.20	-0.09
	Tillering	0.87***	0.58*	-	0.09	-0.20
	Jointing	0.79***	0.55*	-	0.11	-0.25
	Heading	0.21	0.02	-	0.02	0.34
2015-2016						
Rainfed	Tillering	-	0.05	-0.20	-	-
	Jointing	-	0.17	0.31	-	-
	Heading	-	0.23	0.63**	-	-
Irrigated	Tillering	-	0.35	0.40	-	-
	Jointing	-	0.30	0.39	-	-
	Heading	-	0.14	0.48*	-	-

† JT: Jointing; AN: Anthesis; *, **, and *** significant at 0.05, 0.01, and <.0001, respectively

Evaluation of vegetation indices for the estimation of aboveground biomass and yield

The regression models and their accuracies are shown in Tables 15 and 16. In year 1, aboveground biomass at jointing and NDVI and plant height values from the ground-based plant health system (Table 15) showed significant relationship under rainfed with R^2 of 0.44 and RMSE of 65.67 g/m^2. NDVI alone did not show any relationship. Aboveground biomass at anthesis showed significant R^2 of 0.31 and lowest RMSE of 59.83 g/m^2 with sensor plant height. Under irrigated condition, aboveground biomass presented no relationship with the sensor parameters. In year 2 under rainfed condition, there also was no relationship.

Table 16 showed the regression models selected for aboveground biomass and yield from the Greenseeker® sensor. In year 2 under rainfed condition, aboveground biomass showed poor relationship with the NDVI values, while aboveground biomass at anthesis had a significant 46% coefficient of determination with NDVI values at all the four growth stages. A high R^2 (0.75 - 0.88) was recorded under irrigated condition for aboveground biomass at jointing, while at anthesis a low R^2 of 0.35. Year 3 did not show better results compared to year 2, aboveground biomass at anthesis in year 3 showed no relationship. Yield showed the significant coefficient of determination of 0.28 and 0.33 in rainfed and irrigated fields, respectively with NDVI values at jointing and heading for rainfed field then tillering and heading for irrigated field.

Table 15 The Regression models and statistics from the sensor parameters obtained from the ground-based plant health system.

		Model	RMSE	Adjusted R^2	R^2	Predictors
<u>2012-2013</u>						
Rainfed	ABM JT	1	77.49	0.06	0.12	NDVI^{1}
		2	65.80	0.33	0.36**	HT^{1}
		3	65.18	0.34	0.41**	NDVI^{1} & HT^{1}
		4	65.67	0.33	0.44*	NDVI^{1} & HT^{1,2}
		5	67.82	0.29	0.44*	NDVI^{1,2} & HT^{1,2}
	ABM AN	6	69.83	-0.05	0.0045	NDVI^{2}
		7	60.50	0.21	0.25*	HT^{2}
		8	59.83	0.23	0.31*	HT^{1,2}
		9	62.24	0.17	0.25	NDVI^{2} & HT^{2}
		10	62.99	0.14	0.32	NDVI^{1,2} & HT^{1,2}
Irrigated	ABM AN	16	99.73	-0.05	0.005	HT^{2}
		17	99.95	-0.05	0.0009	NDVI^{2}
		18	102.61	-0.11	0.005	NDVI^{2} & HT^{2}
<u>2014-2015</u>						
Rainfed	ABM JT	22	52.70	-0.05	0.005	NDVI^{1}
	ABM AN	23	131.86	-0.0006	0.05	NDVI^{2}

† ABM: aboveground biomass; RMSE: root mean square error; R^2: coefficient of determination; JT, ^{1}: Jointing; AN, ^{2}: Anthesis; HT: Plant height; *, **, and *** significant at 0.05, 0.01, and <.0001, respectively

Table 16 The Regression models and statistics from the sensor parameters obtained from the Greenseeker® sensor.

		Model	RMSE	Adjusted R^2	R^2	Predictors
2014-2015						
Rainfed	ABM JT	1	49.97	0.06	0.11	$NDVI^{4}$
		2	46.66	0.18	0.26	$NDVI^{3, 4}$
		3	47.06	0.16	0.29	$NDVI^{2,3, 4}$
	ABM AN	4	111.07	0.29	0.33**	$NDVI^{2}$
		5	106.12	0.35	0.42**	$NDVI^{2, 3}$
		6	105.69	0.36	0.46*	$NDVI^{1, 2, 3}$
		7	108.94	0.32	0.46*	$NDVI^{1, 2, 3, 4}$
Irrigated	ABM JT	8	27.11	0.74	0.75***	$NDVI^{2}$
		9	21.56	0.83	0.85***	$NDVI^{2, 4}$
		10	20.59	0.85	0.87***	$NDVI^{2, 3, 4}$
		11	20.83	0.85	0.88***	$NDVI^{1, 2, 3, 4}$
	ABM AN	12	161.13	0.30	0.34**	$NDVI^{2}$
		13	164.72	0.27	0.35*	$NDVI^{2, 3}$
2015-2016						
Rainfed	ABM AN	14	116.51	-0.01	0.04	$NDVI^{2}$
		15	119.56	-0.06	0.05	$NDVI^{2, 4}$
		16	122.80	-0.12	0.06	$NDVI^{2, 3, 4}$
	Yield	17	40.49	0.23	0.27*	$NDVI^{4}$
		18	41.44	0.20	0.28*	$NDVI^{3, 4}$
		19	42.42	0.15	0.29	$NDVI^{2, 3, 4}$
Irrigated	ABM AN	20	141.47	0.07	0.13	$NDVI^{2}$
		21	141.35	0.07	0.18	$NDVI^{2, 3}$
		22	145.11	0.03	0.18	$NDVI^{2, 3, 4}$
	Yield	23	29.87	0.18	0.23*	$NDVI^{4}$
		24	28.70	0.25	0.33*	$NDVI^{2, 4}$
		25	29.42	0.21	0.33	$NDVI^{2, 3, 4}$

† ABM: aboveground biomass; RMSE: root mean square error; R squared: coefficient of determination; $NDVI^{1, 2, 3, 4}$ - 1: Pre-emergence, 2: Tillering, 3 or JT: Jointing, 4: Heading; AN: Anthesis; *, **, and *** significant at 0.05, 0.01, and <.0001, respectively

Analysis of variance of the mean of the aboveground biomass at jointing and anthesis is depicted in Table 17. It is showed that aboveground biomass at jointing in the first two years are significantly interacted with the wheat genotypes and water regimes, which imply there is a three-way interaction. The jointing stage, is critical in wheat development hence at this stage aboveground biomass is affected by the environmental condition; stress condition and the genotype. Also, the first two years showed significant interaction with the water regimes, since the amount of precipitation varied per year. Above ground biomass at anthesis across the three years showed no three-way interaction, but a significant two-way interaction with the year and water regimes.

Table 17 Combined analyses of variance of the aboveground biomass (ABM) at jointing (JT) and anthesis (AN) across three years, two water regimes and twenty wheat genotypes.

Source	ABM at JT	ABM at AN
Year	1845637***	978
Genotype	31189*	19451
Water regimes	45437621***	1860350***
Rep	12092	71045*
Rep (Year)	45553	5170
Year x Genotype	22288	16736
Year x Water regimes	3559917***	2772828***
Genotype x Water regimes	19311	18814
Year x Genotype x Water regimes	36197*	11808

Relationship between observed and predicted values of aboveground biomass and yield

Figure 4 presented the linear relationship between aboveground biomass and NDVI values obtained from the ground-based plant health sensor combined at jointing and anthesis. This relationship combined the data from rainfed and irrigated fields on one plotted graph. A significant coefficient of determination of 0.76 was computed showing the proportion of aboveground biomass explained by NDVI at jointing and anthesis combined for year 1 and year 2. The RMSE of 116.62 g/m^2 recorded was better overall compared to individual modeled RMSE from both the plant health sensor and Greenseeker® sensor.

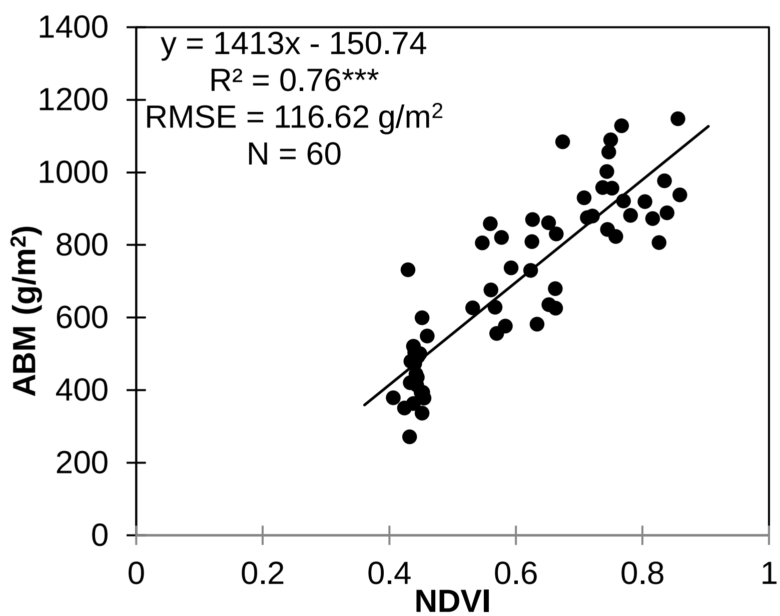

Figure 4 Relationship between aboveground biomass (ABM) and NDVI at jointing and anthesis under rainfed and irrigated fields using the NDVI values from the ground-based plant health sensing system. Lines correspond to best fit functions.

Combined growth stages relationship using Greenseeker® sensor data did not show better relationship than individual growth stages when plotted. The genotypes were randomly selected into two groups for training and validation sets (n = 10 for each set). Both sets are plotted on figure 5 and 6.

Figure 5 a-d showed the scatter plots for the relationship between observed and predicted values of aboveground biomass in year 2 using the NDVI values from the Greenseeker® sensor. Under rainfed field (fig. 4 a, c), the predictability of the training set was 55% and 59% at jointing and anthesis, respectively. The validation set for aboveground biomass at jointing was poor, while at anthesis 44% predictability was recorded. The irrigated field recorded better R^2 of 91% and 13%, at jointing and anthesis, respectively. Irrigated field recorded 90% and 67% validated predictability of aboveground biomass at jointing and anthesis, respectively.

Figure 6 a-d showed the scatter plots for aboveground biomass using the NDVI values from the Greenseeker® sensor in year 3. Results from year 2 were better than year 3; rainfed field had the R^2 of 36% and 43%, for aboveground biomass at anthesis and yield, respectively. Under irrigated field, the relationship between observed and predicted aboveground biomass and yield was an R^2 of 12% and 30%, respectively. Generally, the RMSE for the validation was mostly greater than the training set.

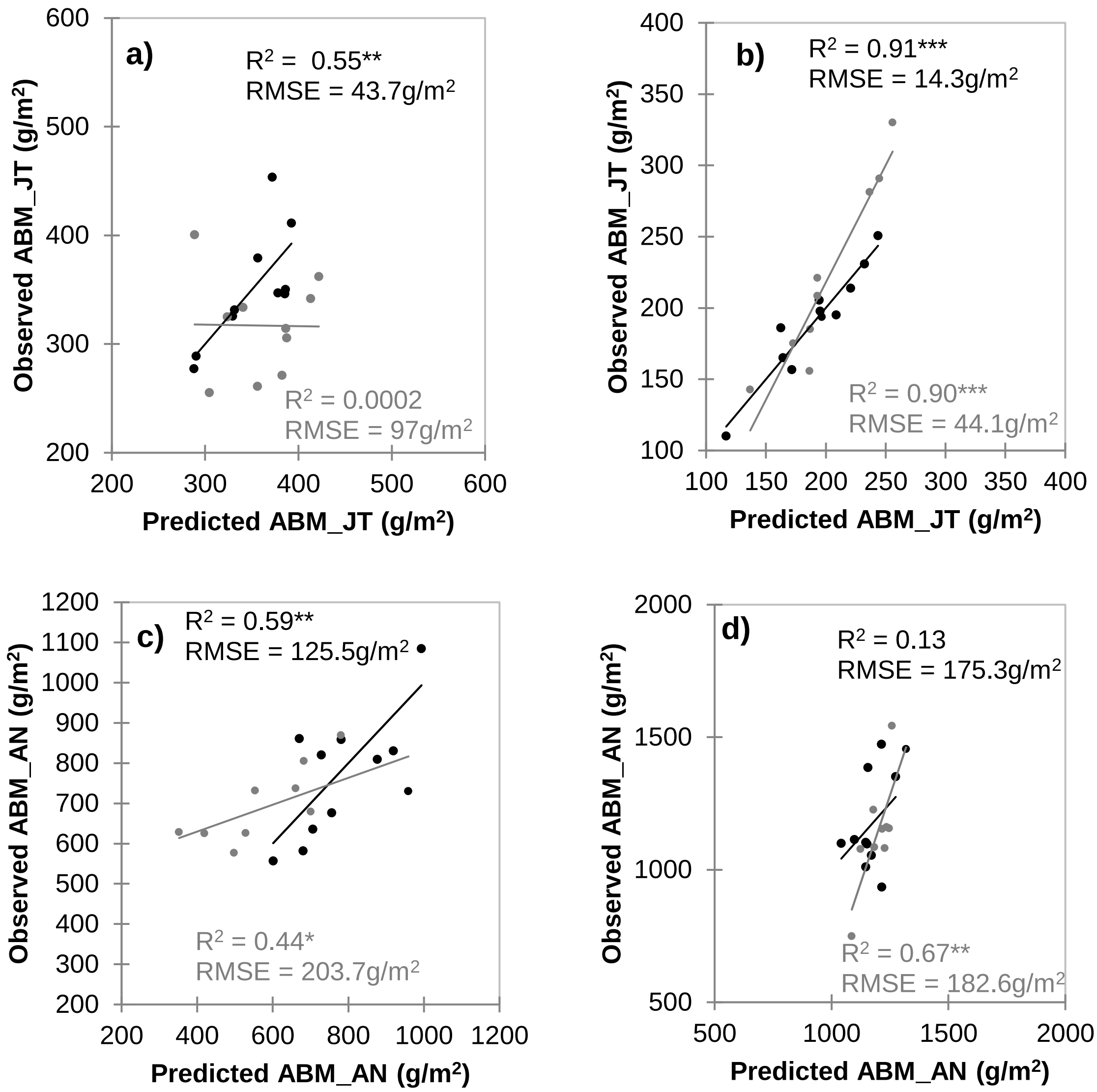

Figure 5 Scatter plots showing training (black) and validation (grey) sets between observed and predicted aboveground biomass (ABM) under rainfed (a, c) and irrigated (b, d) fields at jointing (JT) and anthesis (AN) using the NDVI values from the Greenseeker® sensor in 2014-2015 growing season (Year 2).
*, **, and *** significant at 0.05, 0.01, and <.0001, respectively.

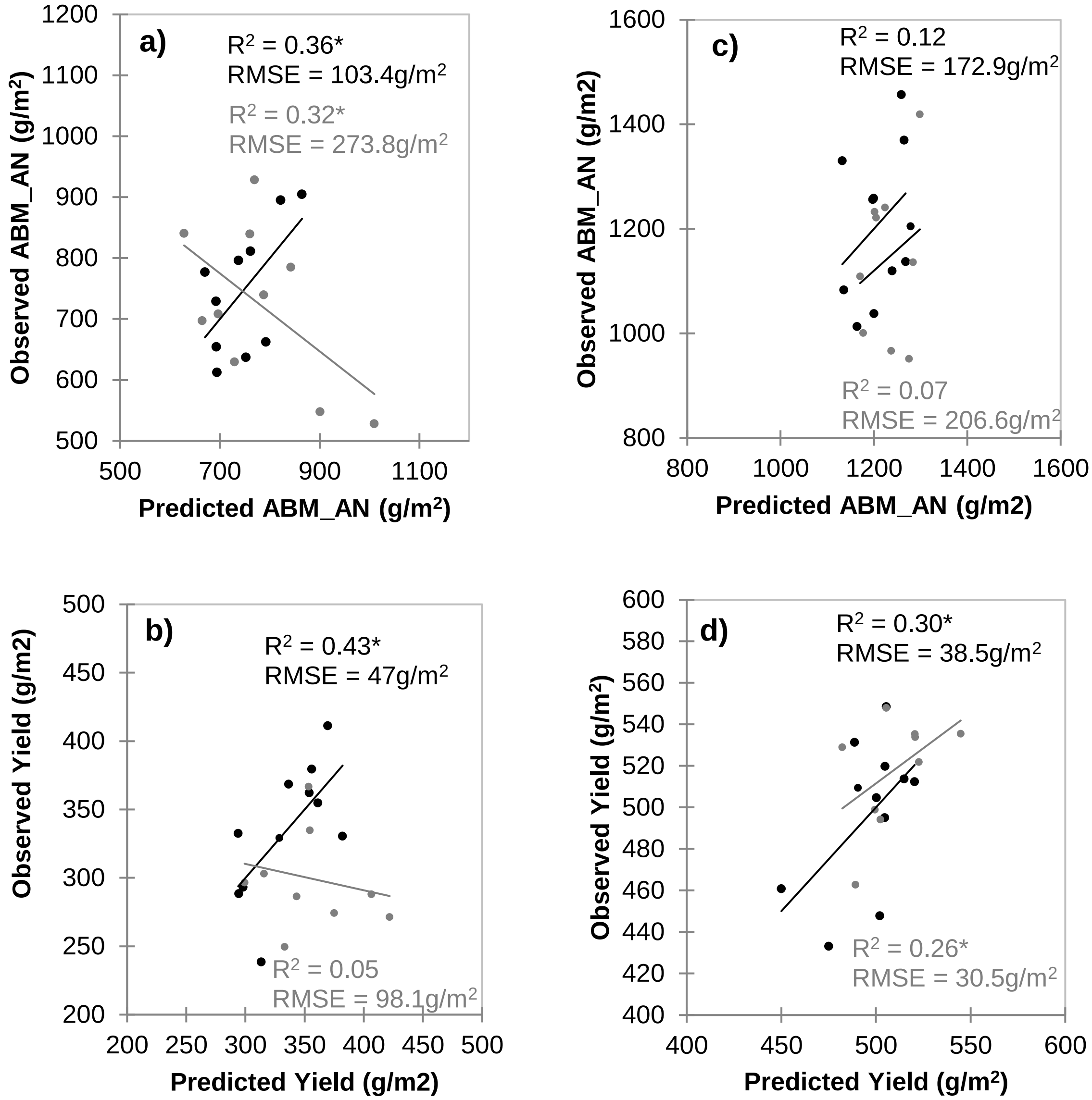

Figure 6 Scatter plots showing training (black) and validation (grey) sets between observed and predicted aboveground biomass (ABM), and yield under rainfed (a, c) and irrigated (b, d) fields at jointing (JT) and anthesis (AN) using the NDVI values from the Greenseeker® sensor under rainfed and irrigated fields in 2015-2016 growing season (Year 3). *, **, and *** significant at 0.05, 0.01, and <.0001, respectively.

Biplot analysis showing the performance of the twenty wheat genotypes and overall associations

The results of the biplot analysis can be used to select genotypes based on their performance and stability as seen in figures 7 and 8. The data from year 1 was presented in figure 6. The genotypes that performed high yielding or adaptable to aboveground biomass at jointing and NDVI with sensor plant height at jointing are located at the lower right axes of the plot. Under rainfed condition (fig. 7a), these include: TAM W-101, TAM 113, TAM 110, Billings, Winterhawk and TX99A0153-1, while with aboveground biomass and sensor plant height at anthesis - TAM 112, BillBrown, Duster, Dumas and Hatcher, the latter two genotypes are most stable. Other genotypes at the left side of the axes were unstable and non-adaptable or low yielding especially TX86A8072, Fuller and Endurance. The irrigated condition (fig. 7b) recorded NDVI and sensor plant height with TAM 111, Billings, TAM 113, TX99A0153-1, Jagger and Duster as high yielding, Jagger, Duster and TAM 111 as most stable. TAM W-101 and BillBrown were better than TAM 110, Dumas, Winterhawk and TAM 105 in aboveground biomass at anthesis.

Figure 8 a-b displayed the biplot analysis with the Greenseeker® sensor (GS) in years 2 and 3, and the plant health sensor (PHS) in year 2. The rainfed field in year 2 (Fig. 8a) showed TAM 114, TAM 105, Jagger, Fuller, TAM 112, TAM 111, and TX99A0153-1 as high yielding in all the parameters except in NDVI values from the Greenseeker® sensor at jointing and heading. TAM 105, TAM 114, Jagger, Fuller, TAM 112, and TAM 111 were most stable in aboveground biomass at jointing and anthesis, NDVI at post-emergence and tillering (GS), and NDVI at jointing (PHS). In year 2, TAM 113, TAM 110, TAM 304, Hatcher, Dumas, Winterhawk, TAM W-101, Iba and Billings were not as yielding as the genotypes listed above, although stable. Overall in year 2 under rainfed field, the genotypes were clustered together in their parameters, the same cannot be said under irrigated field. Irrigated field showed TAM 105, TAM 112 and PlainsGoldByrd as most stable and high yielding in aboveground biomass at anthesis, NDVI at post-emergence and tillering, compared to Fuller and TAM 304. TAM 114 and Hatcher were most stable in aboveground biomass and NDVI at jointing. TX99A0153-1 and Duster were best with NDVI at heading. Other genotypes were less stable in these parameters especially Winterhawk, Endurance, Dumas and Iba.

The biplot analysis for year 3 was shown in figure 8 c-d. Under rainfed condition (fig. 8c), the yield, NDVI at jointing and heading had high yielding and stable genotypes with PlainsGoldByrd, Duster, TAM 113, TAM 111, TAM 110, and TAM 112, while Hatcher and Iba not as much. Winterhawk showed best with aboveground biomass at anthesis and NDVI at tillering, followed by Jagalene, AMPSY588, TAM 114, AMPSY068, TX99A0153-1, TX11Vsyn0101 and Dumas. Other genotypes were not as high yielding in the parameters especially Billings. Irrigated field (fig. 7c) showed better clusters with the genotypes than rainfed field for year 3. Yield, aboveground biomass at anthesis and NDVI at tillering had genotypes TAM 113, AMPSY068, Billings, Iba, TAM 114, and Winterhawk as their best and most stable with Winterhawk and Iba. TAM 111, Endurance, PlainsGoldByrd, TX99A0153-1, Hatcher and Duster were stable and best in NDVI at jointing and heading, followed by Dumas, TAM 110, TAM 105 and TX11Vsyn0101. Jagalene, AMPSY588, TAM 112 and TAM 304 had low in yield, NDVI and aboveground biomass.

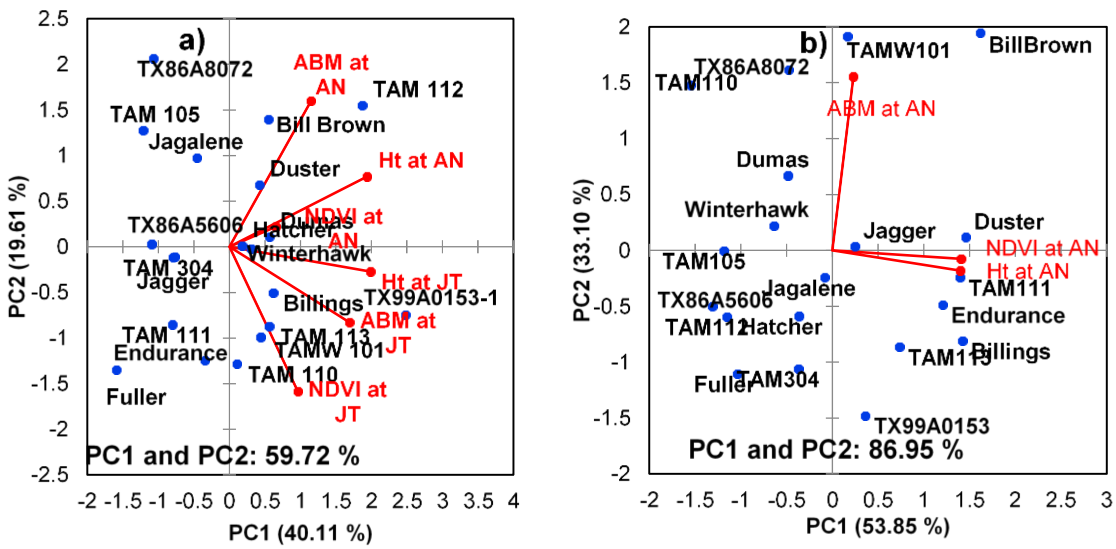

Figure 7 Biplot showing the twenty genotypes and field parameters from the ground-based plant health sensor under rainfed (a) and irrigated (b) fields in year 1.

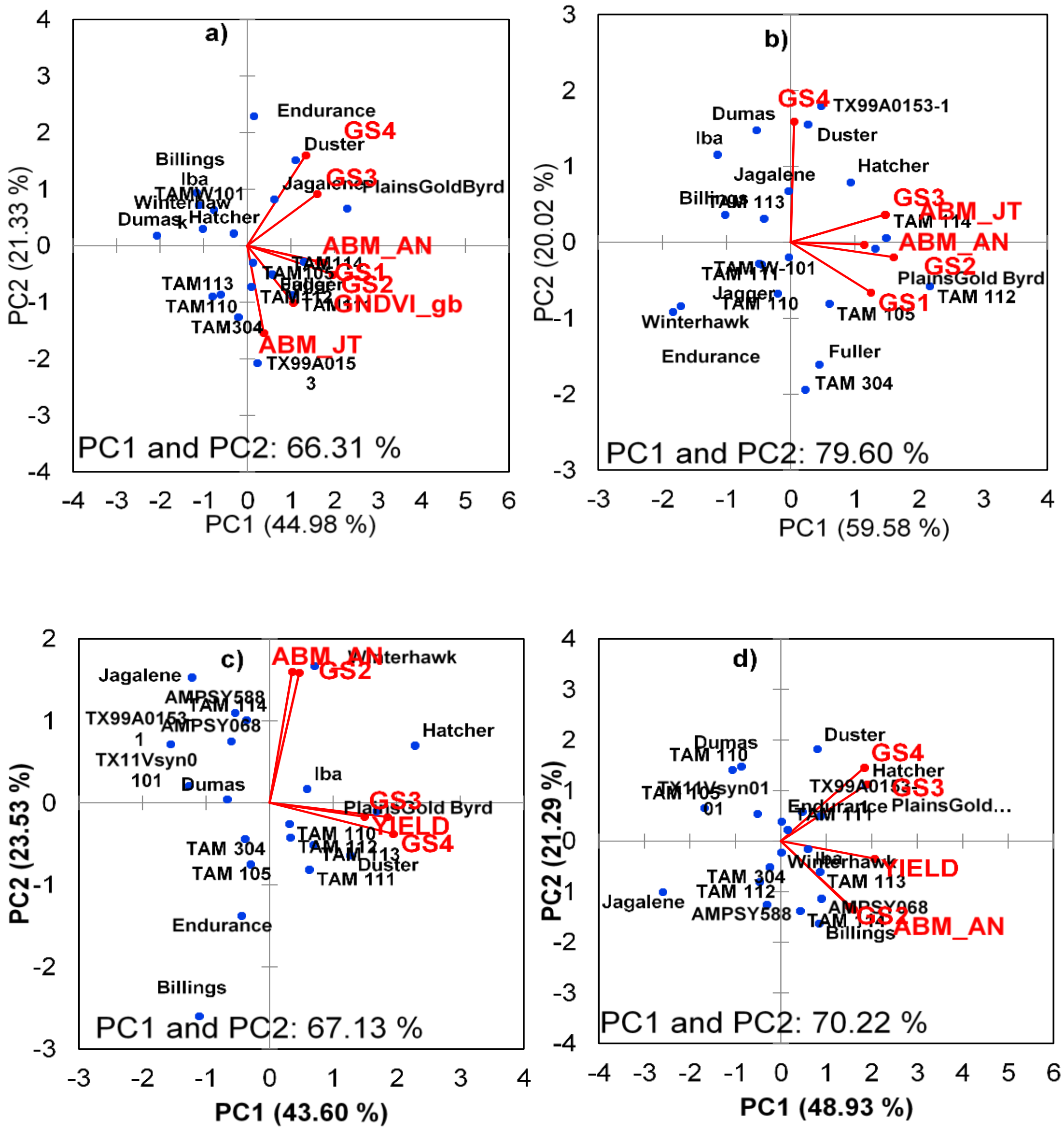

Figure 8 Biplot showing the twenty genotypes and field parameters from the Greenseeker® sensor under rainfed (a) and irrigated (b) fields in year 2; rainfed (c) and irrigated (d) fields in year 3.
Greenseeker® sensor: GS; 1-4 implies the post-emergence to heading; gb: ground-based plant health sensor.

DISCUSSION

Genotypic variation of plant and sensor parameters across growth stages

The summary statistics with significant genotypic variation generally showed that the genotypes can be discriminated in their aboveground biomass at jointing and anthesis, and yield at maturity, also the sensor parameters at different growth stages (Tables 1 and 2). This study involves wheat genotypes with wide genetic background commonly grown in the Southern Great Plains of the USA. The NDVI was the only vegetation index explored from the sensors used, and variation have been found among the genotypes. Aparicio et al. (2000) and Royo et al. (2003) also had genotypic variation in NDVI of wheat across growth stages under rainfed and irrigated conditions.

The trend from emergence to maturity is increasing to early grain filling and then decrease to near maturity, as seen with the Greenseeker data in years 1 and 2. This is because of the reduced reflected radiation or reflectance mainly in the Near infrared and also the visible regions of the electromagnetic spectrum due to loss of green tissue as growth stage moves on after emergence to maturity (Aparicio et al., 2000; Sims and Gamon, 2002). In year 2 under rainfed condition (Fig. 3a), the genotypes showed no variation in NDVI at jointing stage, it may be as a result of the low precipitation with high and low temperature during this month (Fig. 1) which could have caused water deficit stress. Billings dropped slightly in performance as regards vegetation health based on the NDVI values at jointing (0.6143), and picked up at heading (0.6103) with the highest precipitation (281 mm) throughout the growing season. Other genotypes increased in their performance past jointing until the heading stage. TAM 304 and Fuller decreased slightly at heading stage. Whereas under irrigated field (Fig. 3b), the genotypes were homogenous in NDVI values at jointing and heading stages. This supports studies that found the best growth stages to estimate plant parameters from spectral reflectance measurements were within jointing and heading stages (Ahlrichs and Bauer, 1983; Xavier et al., 2006). More growth stages were presented in Year 3 under both field conditions. Under rainfed field, the deep trough seen during tillering can be as a result of prolonged water stress deficit (fig. 1).

Correlation between NDVI and aboveground biomass with yield

Strong correlations recorded has been between sensor parameters and field data were found at the same growth stage, as seen with sensor plant height and aboveground biomass in Table 3. Hence, according to Prasad et al. (2007) the relationship will be stronger as the growth stage proceeds. In year 3, selected dates corresponded to critical growth stages during the growing season. Poor correlation among the parameters are noticed which may be due to inconsistent dates of sampling. Aboveground biomass at anthesis generally showed better correlations with NDVI under both water regimes and at all growth stages except at heading. Leaf chlorophyll and plant height had poor correlations mostly except at heading. Also yield data correlated best with NDVI at heading. These correlations provide information about the growth stages that are best to estimate the related field data. Although this can change over years and environmental conditions or water regime. Therefore, repeated measurement of spectral data at different growth stages are important to monitor the overall vegetation health and performance of the wheat genotypes. Babar et al. (2006) noted that most associations were stronger at later growth stages than at early growth stages.

Interaction effect of genotypes, environmental conditions and years.

Significant interaction was observed between the twenty genotypes, environmental conditions and years (Table 7). This imply that the year and environmental conditions are important to estimate the aboveground biomass of the wheat genotypes at jointing but not at anthesis stages. At both jointing and anthesis, the year by environment was significant meaning that rainfed and irrigated field are variable each year. Hence, estimation to be made on the field data needs to be for each year and field condition type unless supplementary data is included that can provide additional explanation to the field data estimated. Since the jointing stages was significantly interacted with the genotype, year and environment, it is recommended to take measurements around jointing growth stage, before anthesis – at heading (Babar et al., 2006; Prasad et al., 2007).

Relationship between field data and sensor parameters

Aboveground biomass and yield are important traits that wheat breeders look for in selecting best genotype. Since better correlations were found between aboveground biomass and yield with NDVI values, the field data used for regression model are these two only (Tables 5 and 6). The relationship developed with NDVI values from the plant health sensor was not better than NDVI values from the Greenseeker based on their R^2 (0.44 vs 0.88), RMSE (67.82 vs 20.83) and significance (5% vs 0.01%). This may be based on the level of accuracy in data sampling. Year 2 showed better relationship than year 3 and irrigated field generally had better relationship than rainfed field, these may be due to the favorable weather conditions in year 2 than year 3.

The relationship between NDVI and aboveground biomass with yield was linear (Figures 4-6). Figure 4 with data from the plant health sensor has the combination of growth stages at jointing and anthesis for both water regimes. This improved the coefficient of determination from 0.44 to 0.76. It was recommended by Prasad et al. (2007) that reflectance measurements at heading and at grain-filling be taken, and combine the information from the two readings. The combination of growth stages of SRI information was more predictive and had stronger relationship than individual growth stages as noted by Gutierrez et al. (2010). Figures 5 and 6 displayed the relationship between observed and predicted aboveground biomass at jointing and anthesis, and yield. The linear trends between observed and predicted values in this study indicate that information about vegetation health or greenness only provides a point of reference for estimating aboveground biomass at a given time during the growing season. For overall better accuracy, aboveground biomass needs to be sampled during the same time as the sensor parameters. The estimation or predictability of the field data was weakened when field data measured does not have consistency with the sensor parameters, except for yield data.

Selection of genotypes

The biplot analysis provided an overview of association among the twenty genotypes with respect to the sensor parameters and field data. A visual analysis of the genotypes showed variability, and high yielding ones such as TAM (Texas A&M) genotypes.

NDVI provides a simple estimate of vegetation health and a means of monitoring changes in vegetation over time. It remains the most commonly known and used vegetation index to detect live green plant canopies in multispectral remote sensing data. Ground-based plant health sensor can be valuable when multiple dates are captured but there lies the task of safely and accurately maneuvering around the field with the tractor-mounted sensor. Greenseeker sensor as a handheld sensing tool may have less sampling error due to mobility compared to the plant health sensor. Overall, the use of ground-based sensors has shown some value by reason of the proportion of predictability of the field data – aboveground biomass and yield.

CHAPTER IV

NON-DESTRUCTIVE SAMPLING FOR MONITORING GROWTH, PERFORMANCE AND YIELD OF WINTER WHEAT GENOTYPES

INTRODUCTION

In a typical wheat breeding program, large number of advanced lines are evaluated for high yield potential with methods that involves field evaluation for multiple years and locations (Royo et al., 2003; Trethowan et al., 2003). An adequate breeding strategy requires a better understanding of the factors responsible for growth and development because grain yield in a given environment is directly and indirectly influenced by genetic, morphological, physiological, and environmental factors (Richards, 1996). Wheat breeding around the world for yield improvement has been based primarily on the practical selection criteria of yield mainly; however, yield has demonstrated low heritability and a high genotype-environment interaction (Jackson et al., 1996; Trethowan et al., 2003). According to Royo et al. (2003) high yielding genotypes can be identified before physiological maturity when the crop is harvested. An easy, quick, nondestructive, and objective selection tool is needed for breeder to reduce the laborious and time consuming process of high yield and drought tolerant genotype selection when screening large number of genotypes (Reynolds et al., 1999). It is important that this selection tool have high heritability and a strong association with yield and other plant parameters to detect high yielding and drought tolerant genotypes rapidly and efficiently from a large number of early generation lines and for advanced genotypes.

Spectral reflectance indices or vegetation indices (SRI or SVI) are a potential technique selection tool that could assess yield at the genotypic level without destructive sampling. These indices are based on canopy spectral reflectance measured in the visible [400-700 nm], near-infrared [700-1200 nm], and mid-infrared [>1200 nm] regions, which are easy to use (Araus et al., 2001; Reynolds et al., 1999). Canopy reflectance properties are based mainly on the absorption of light at specific wavelengths associated with plant characteristics (Araus et al., 2002). In the visible region, reflectance is relatively low because the light is absorbed by leaf pigments (chlorophyll, carotenoid and anthocyanins). In contrast, the reflectance in the NIR wavelengths is high because the radiation is scattered by plant tissue structures in the canopy.

Several spectral reflectance indices have been established for estimating physiological traits and for predicting yield by repeated measurements of reflectance during the plant developmental stages. The most commonly known index for analyzing vegetation is the normalized difference vegetation index (NDVI). Araus et al. (2001) used as an indirect assessment of canopy biomass, leaf area index, and potential photosynthetic capacity. Reynolds et al. (1999) found an association between NDVI and yield and biomass (R^2=0.36-0.44) in bread wheat genotypes in an irrigated environment. The red NDVI (RNDVI) and the green NDVI (GNDVI) have been established for estimating canopy photosynthetic area for predicting grain yield and biomass in wheat and corn under water stressed environments (Gutiérrez-Rodríguez et al., 2004; Osborne et al., 2002). The simple ratio (SR) also known as ratio vegetation index (RVI) is also used as an indicator of canopy photosynthetic active area (Aparicio et al., 2000). Other studies in durum wheat genotypes have demonstrated a strong association (R^2>0.80) between several SVI (i.e., NDVI, SR) and grain yield and biomass under rainfed and irrigated conditions (Aparicio et al., 2002b; Royo et al., 2003).

However, these indices are affected by changes in the water regimes and soil background. Under rainfed conditions, there is a limitation in the application of these indices due to low sensitivity to low vegetation cover. Error can occur in the indication of crop health condition due to high relative humidity in the atmosphere which may hamper detection of plant stress. Also, soil background in the spectral readings may give an inaccurate idea of the crop health (Nayak, 2005). The Normalized Difference Water Index (NDWI) follows the same rationale as NDVI, it employs the near infrared band and a band in the short-wave infrared (SWIR) (Gao, 1996). NDWI has been used to detect and monitor the moisture condition of vegetation canopies of corn and soybeans (Jackson et al., 2004).

The Perpendicular Vegetation Index (PVI) used the red and near-infrared bands to calculate the perpendicular distance between the vegetation spot on the NIR-Red scatterplot and the soil line (Richardson and Wiegand, 1977). Vegetation has higher near-infrared and lower red reflectance than the underlying soil, so the vegetation spot will be on the top left corner of the scatterplot. As vegetation is increasing in density, the vegetation spot will be moving further towards the top left, away from the soil line. Soil-Adjusted Vegetation Index (SAVI) is a hybrid between NDVI and PVI. For the estimation of percentage ground cover (GC), Maas and Rajan (2008) explained the method using the raw DC values of the NIR and Red bands of a multispectral image. The pixels in these two bands are displayed in a 2-Dimensional scatter plot where the bare soil line and the point of 100% GC. Hence, the slope and intercept are calculated and put into the PVI formula.

Some other potentially useful indices include the Green-Red Vegetation Index (GRVI or Normalized Difference Green Index, NDGI) which is sensitive to seasonal differences in vegetation (Motohka et al., 2010; Nagai et al., 2012). The Generalized

Difference Vegetation Index (GDVI) according to Wu (2014) has the potential to characterize the plant canopy when the vegetation cover is low under dryland conditions. The EVI (enhanced vegetation index) was developed for satellites, but can be used with aerial and ground sensors. The EVI is more useful on NIR reflectance than on Red absorption, and therefore it does not get saturated as rapidly as NDVI in high vegetation (Huete et al., 2002; Jiang et al., 2008). The Enhanced Normalized Difference Vegetation Index (ENDVI) demonstrated the ability for detecting water stressed vegetation compared to NDVI (Zhang, 2014).

There are several approaches available for field phenotyping ranging from hand-held sensors, such as spectroradiometers (Ajayi et al., 2016; Gnyp et al., 2014), sensors mounted on in-field fixed or mobile platforms (Sui and Thomasson, 2006; Sui et al., 2012), to sensors on unmanned aerial vehicles (UAVs), and manned aircraft (Chapman et al., 2014; Shi et al., 2016).

Unfortunately, hand-held measurements are not very useful for the high throughput required for the effective phenotyping of large field trials with many replicates, as they tend to be excessively labor intensive and time consuming, so alternatives are of particular interest. The objective of this study is to evaluate the potential of the SVI as an indirect selection tool based on their correlated response for breeding purposes under rainfed and irrigated field conditions, using field data and sensor data from digital photography and aerial imagery at three growth stages at tillering, jointing and heading.

MATERIALS AND METHODS

Twenty wheat genotypes were considered for this study under rainfed and irrigated conditions at the Texas A&M AgriLife Research Experiment Station, Bushland, Texas (Lat. 35º11’N, Long. 102º06’W; elevation 1170m above the mean sea level) during the 2014-2016 growing seasons. The soil type was Pullman clay loam (fine, mixed, thermic Torrertic Paleustoll: USDA classification), the properties of which have been described by Unger and Pringle (1981). The experiment was a randomized complete block design with three replications. The seeding rate was 67 kg/ha, plot size was 1.52 m x 4.27 m (6.50 m^2) while the row spacing for all plots was 18 cm. The planting dates for rainfed field are 10/1/2014 and 10/13/2015. Irrigated field was planted on 10/20/2014 and 10/19/2015.

Weather data files (Table 18) were downloaded for the Bushland station for Year 1 and Year 2 from the United States Department of Agriculture, Agricultural Research Service website (https://www.ars.usda.gov). The climate was semi-arid with erratic precipitation and high evaporative demands. The long-term precipitation accumulated during the growing season was 287 mm, and the average maximum and minimum temperature during the growing season was 34.4 ºC and -6.7 ºC respectively.

Table 18 Mean Maximum (Max) and Minimum (Min) temperatures, and total monthly precipitation from October to June for the 2014-2015 (Year 1) and 2015-2016 (Year 2) winter wheat-growing season in Bushland, TX.

	Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	Apr.	May	June
Mean temperature (°C)									
Year 1									
Max	34.4	25.6	25.6	28.9	28.3	28.3	31.7	30.0	32.8
Min	4.4	-5.6	-3.9	-6.7	-5.6	-6.1	3.9	6.7	13.9
Year 2									
Max	21.8	15.6	11.5	10.1	15.1	19.4	21.1	24.1	32.2
Min	9.0	-0.2	-3.5	-4.9	-2.7	0.5	4.3	8.2	16.3
Total precipitation (mm)									
Year 1									
	58.2	56.6	14.2	61.5	16.51	46.2	66.3	280.7	111.3
Year 2									
	128.3	23.9	10.9	5.6	3.8	4.6	72.6	31.5	29.2

Acquisition of Aerial Imagery

Aerial images of the plots are being collected using a 12 band Multiple Camera Array (MCA) Tetracam system (Tetracam, Inc., Chatsworth, CA), from a manned aircraft (Figure 9). The camera unit in an MCA comprises a sensor, a camera/processor, a bandpass filter, and an objective lens. Each pixel in an image possesses an 8- or 10-bit depth. The altitude of the aircraft carrying the camera determines the ground resolution of the MCA, so images are taken 2950 – 5000 feet (899 – 1524 meters) above ground level.

Figure 10 showed the major steps taken for the aerial image analysis. The raw images for three growth stages were selected to include the rainfed field in one image and irrigated field in another image, so there was no need for mosaicking. The pre-processing of the images was done using the ENVI (ENvironment for Visualizing Images) 5.2.1 software version (Exelis Visual Information Solutions, Boulder, CO). Calibration panels with colors of white, black and gray were placed on the field to mark out the plots of interest. For radiometric correction, the reflectances of the calibration panels were recorded using a spectroradiometer. The purpose was to convert the digital count from the aerial images of the plots into reflectance values thereby correcting for atmospheric effects. It was achieved by using the regression equation ($Y = a + bx$; where Y is the reflectance, a; intercept, b; slope and x; digital count).

The images were geometrically corrected using an orthorectified image from TNRIS (Texas Natural Resources Information System). On the georeferenced image, region of interests (ROIs) were selected based on the plots of the twenty wheat genotypes under rainfed and irrigated fields (Figure 11). The image processing first involved the 12-bands in each image used in mathematical combinations for several vegetation indices (Table 19). After which the image is classified based on these indices and the statistics are exported for data analysis.

Figure 9 Pictures showing the manned aircraft and the multiple camera array Tetracam system.

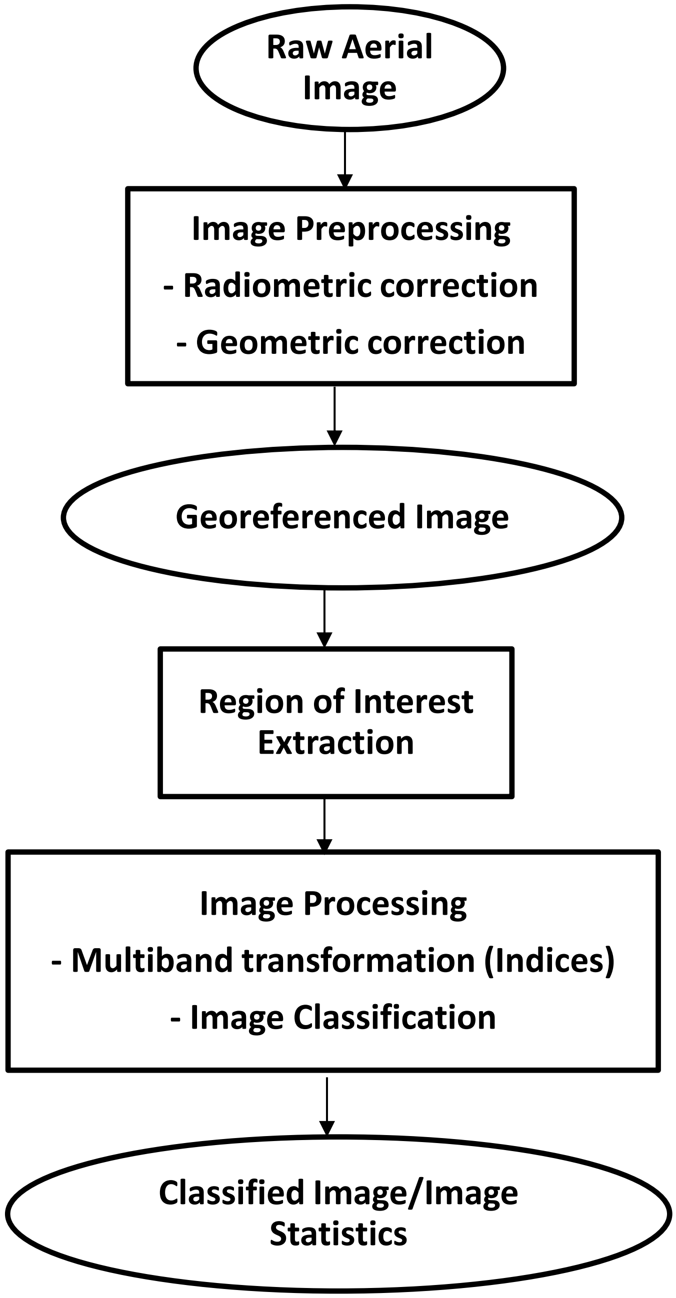

Figure 10 Flow chart of aerial image analysis.

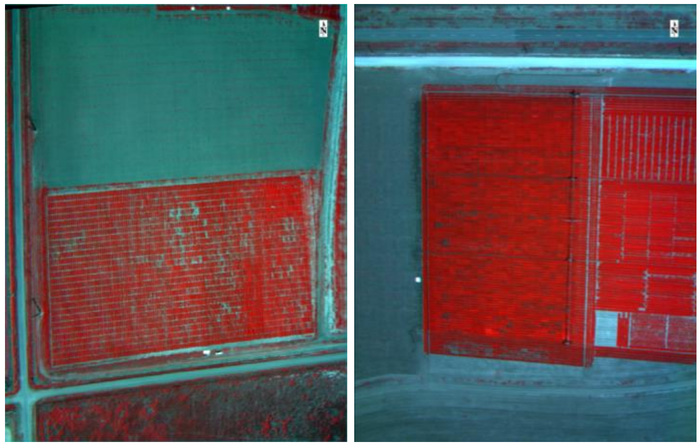

Figure 11 Aerial images of the rainfed (left) and irrigated (right) fields displayed in color infrared.

Table 19 Spectral vegetation index definition.

Name	Equation	Function
Normalized difference vegetation index (NDVI)	(NIR−VIS)/(NIR+VIS)	Estimation of canopy photosynthetic area
Red normalized difference vegetation index (RNDVI)	(NIR−Red)/(NIR+Red)	
Green normalized difference vegetation index (GNDVI)	(NIR−Green)/(NIR+Green)	
Ratio vegetation index (RVI)	(NIR/VIS)	
Generalized Difference vegetation index (GDVI)	$(NIR^n - Red^n)/(NIR^n + Red^n)$	
Difference vegetation index (DVI)	(NIR−VIS)	
Green leaf index (GLI)	(2*Green – Red – Blue)/(2 *Green + Red + Blue)	
Enhanced vegetation index (EVI)	$G*\{(NIR - Red)/[NIR + (C_1*Red) - (C_2*Blue) + L]\}$	
Green-Red Vegetation Index (GRVI)	(Green–Red)/(Green+Red)	
Perpendicular Vegetation Index (PVI)	$\{NIR - (Red * a_1) - a_0\}/\{\sqrt{1 + (-a_1)^2}\}$	
Water index (WI)	(R_{970}/R_{900})	Canopy water status
Normalized difference water index (NDWI)	(NIR – SWIR)/(NIR + SWIR)	
Simple ratio water index (SRWI)	(NIR/SWIR)	
Enhanced normalized difference vegetation index (ENDVI)	((NIR+Green)–(2*Blue)) / ((NIR+Green)+(2*Blue))	

† NIR: near-infrared; VIS: visible; n is power, an integer of the values of 1, 2, 3, 4… n; DC: digital count; a_0: intercept; a_1: slope; G = 2.5, C_1 = 6, C_2 = 7.5 and L = 1 are constants; R and the sub-index indicate the reflected light at that specific wavelength (in nm); SWIR: shortwave-infrared.

Ground truth data collection

Other field data collections to supplement as calibration of the remotely-sensed data include percent ground cover, aboveground biomass, and yield.

Digital photography for Ground Cover (GC) estimation

Digital photographs for GC estimation of the twenty genotypes was taken on during tillering stage for the two years. These photographs are compared to the aerial imagery data taken within 1-2 days of the photographs taken. Using a digital camera, photographs are taken at consistent height for accurately representative sections above each plot anytime of the day, when there is continuous cloud cover and minimal shadow. The digital photographs were opened in Adobe Photoshop CS6 (Adobe systems Inc., San Jose, CA) where the green leaf area pixels are selected and given a different color (i.e. red) contrast to the bare soil (Figure 12). After several processes, the ground cover is then quantified and expressed as percentage.

Figure 12 Screenshot showing the pre-processing of the digital photographs in Adobe Photoshop.

Aboveground biomass

Aboveground biomass is collected at anthesis; 1m of one row was cut at ground level from each plot. For each sample, the stems and heads were separated and counted. To determine the dry biomass, the stems and heads were dried at 60°C for 72 hours. The total weight in kilograms was expressed on per m^2 basis.

Yield

Yields of both dryland and irrigated plots will be obtained by machine-harvesting with a Wintersteiger plot combine. The yield is based on 10 % moisture content expressed on a kilogram per hectare basis.

Data Analysis

Statistical analysis carried out in this study was done using the SAS version 9.3 (Statistical Analysis System Institute, Cary, NC, USA) and XLSTAT developed by Addinsoft (2010) for Microsoft Excel. Analysis of variance (ANOVA) was performed using the General Linear Model to compare differences in each of the plant parameters for irrigated and rainfed conditions. Least significant difference (LSD) values at (5 % probability level) were used to compare means for each plant parameter and indices among the 20 wheat genotypes. For both irrigated and rainfed conditions, statistical associations (using Pearson correlation) were developed between the indices and field data - aboveground biomass and yield. The indices from the aerial imagery were evaluated for their relationship with the field data parameters collected. Using the level of significance (<5%), the coefficient of determination (R^2), adjusted R^2, root means square error (RMSE) and other information criteria, the best predictor was developed for each plant parameter. The indices that provided the best relationship with yield and other parameters were selected as explanatory variables for model development in multiple regression analysis, and validation processes for model performance with new dataset.

RESULTS

Genotypic variation, growth stage and water regime

Differences were observed for spectral behavior at different crop growth stages, namely tillering, jointing and heading under both field conditions; rainfed and irrigated (Table 20). Significant genotypic differences for NDVI was found only under irrigated field at tillering (0.27) and jointing (0.82) for year 1, at tillering (0.36) and heading (0.93) for year 2. At heading, NDVI values (0.93) were similar for both years but different range values. Under both field conditions, the genotypes showed more differences in the SVI mostly at tillering and jointing stages than at heading stage; such as DVI, RVI, GLI, EVI, GRVI and ENDVI. GDVI showed most variation among the genotypes at the squared exponential (GDVI^2) only under irrigated field at all stages in year 1, then at jointing and heading in year 2. The cubic GDVI (GDVI^3) was significant only in year one; at jointing under rainfed and at tillering under irrigated fields. Generally, most of the indices increased from tillering to heading except DVI under rainfed filed in year1, GRVI^3 (irrigated field year 1 and 2), GRVI^3 (irrigated field year 1), GLI (rainfed field year 1 and 2), GRVI (rainfed field year 1) and % GC from PVI (rainfed field year 1). The field data; % GC, aboveground biomass, and yield were mostly distinguished under irrigated condition than rainfed condition.

Table 20 Statistical summary of several spectral vegetation indices and field data at three growth stages, presented for two years under rainfed and irrigated conditions.

		2014-2015						2015-2016					
		Rainfed			Irrigated			Rainfed			Irrigated		
Indices	Stat	Tillering	Jointing	Heading	Tillering	Jointing	Heading	Tillering	Jointing	Heading	Tillering	Jointing	Heading
NDVI	Min	0.24	0.32	0.40	0.12	0.70	0.89	0.30	0.48	0.59	0.27	0.80	0.89
	Max	0.43	0.47	0.52	0.36	0.88	0.96	0.42	0.58	0.64	0.46	0.88	0.98
	Mean	0.34	0.40	0.45	0.27***	0.82**	0.93	0.36	0.54	0.61	0.36**	0.85	0.93*
	SE	0.06	0.04	0.04	0.07	0.04	0.02	0.03	0.02	0.02	0.05	0.02	0.02
DVI	Min	0.12	0.20	0.14	0.06	0.30	0.37	0.20	0.26	0.29	0.09	0.27	0.27
	Max	0.20	0.28	0.17	0.19	0.41	0.43	0.27	0.29	0.31	0.15	0.32	0.35
	Mean	0.15	0.24**	0.16	0.14***	0.35	0.39*	0.23	0.28	0.30	0.11***	0.30	0.31
	SE	0.02	0.02	0.01	0.04	0.03	0.02	0.02	0.01	0.01	0.02	0.01	0.02
RVI	Min	1.40	1.88	2.36	1.29	5.94	14.75	1.87	2.91	3.90	1.76	6.12	11.67
	Max	2.20	3.29	3.19	2.16	15.54	36.52	2.48	3.74	4.63	2.80	9.50	40.15
	Mean	1.81	2.40**	2.70	1.75***	11.12***	24.13	2.14	3.39	4.22	2.14**	7.54	16.91*
	SE	0.21	0.35	0.24	0.25	2.30	6.67	0.14	0.21	0.22	0.28	0.87	6.26
GDVI^2	Min	0.39	0.60	0.70	0.25	0.36	0.46	0.60	0.73	0.85	0.55	0.68	0.80
	Max	0.77	0.85	0.93	0.62	0.79	0.89	0.68	0.87	0.95	0.72	0.89	0.95
	Mean	0.58	0.74	0.83	0.49***	0.66***	0.77***	0.64	0.81	0.90	0.63	0.79**	0.89**
	SE	0.09	0.08	0.07	0.11	0.12	0.12	0.02	0.03	0.02	0.05	0.06	0.04
GDVI^3	Min	0.68	0.83	0.92	0.93	0.99	1.00	0.78	0.91	0.96	0.83	0.83	0.95
	Max	0.86	0.96	0.99	0.99	1.00	1.00	0.87	0.96	0.99	0.95	0.95	1.00
	Mean	0.77	0.90*	0.96	0.98**	1.00	1.00	0.83	0.95	0.98	0.91	0.91	0.99
	SE	0.06	0.04	0.02	0.02	0.00	0.00	0.02	0.01	0.01	0.03	0.03	0.01
GDVI^4	Min	0.60	0.75	0.85	0.94	0.98	0.99	0.72	0.87	0.95	0.86	0.95	0.98
	Max	0.78	0.91	0.97	0.99	1.00	1.00	0.84	0.95	0.99	0.96	0.99	1.00
	Mean	0.70	0.85	0.93	0.98	1.00	1.00	0.79	0.92	0.97	0.92	0.98	1.00
	SE	0.05	0.04	0.03	0.01	0.00	0.00	0.03	0.02	0.01	0.02	0.01	0.00
GLI	Min	0.16	0.10	0.17	-0.02	0.23	0.42	0.14	0.00	0.17	0.04	0.11	0.34
	Max	0.27	0.20	0.22	0.09	0.39	0.51	0.19	0.09	0.25	0.10	0.22	0.43
	Mean	0.21	0.15**	0.19	0.04**	0.31	0.46	0.16	0.05	0.20	0.07*	0.17	0.39
	SE	0.03	0.03	0.02	0.03	0.03	0.03	0.01	0.02	0.02	0.02	0.03	0.02
EVI	Min	0.19	0.22	0.28	0.08	0.50	0.72	0.29	0.37	0.52	0.18	0.50	0.72
	Max	0.37	0.42	0.37	0.27	0.74	0.81	0.40	0.45	0.59	0.33	0.66	0.87
	Mean	0.28	0.31**	0.32	0.19***	0.63*	0.76	0.34	0.42	0.55	0.24**	0.59	0.81
	SE	0.06	0.05	0.03	0.05	0.06	0.03	0.03	0.02	0.02	0.04	0.04	0.03
GRVI	Min	0.10	0.03	0.11	-0.20	0.37	0.50	0.04	0.07	0.11	-0.01	0.27	0.61
	Max	0.33	0.19	0.20	-0.06	0.58	0.73	0.11	0.15	0.20	0.09	0.50	0.88
	Mean	0.20	0.12*	0.15	-0.12**	0.48**	0.62	0.07*	0.12	0.16	0.03*	0.40	0.72**
	SE	0.06	0.04	0.03	0.03	0.05	0.07	0.02	0.02	0.02	0.03	0.06	0.07
ENDVI	Min	0.32	0.36	0.38	0.43	0.72	0.79	0.40	0.44	0.53	0.28	0.47	0.51
	Max	0.37	0.44	0.44	0.53	0.78	0.83	0.46	0.50	0.55	0.36	0.54	0.56
	Mean	0.34	0.40	0.41	0.49***	0.76*	0.81	0.43	0.47	0.54	0.32***	0.50	0.54

Table 20 Continued.

		2014-2015						2015-2016					
		Rainfed			Irrigated			Rainfed			Irrigated		
Indices	Stat	Tillering	Jointing	Heading	Tillering	Jointing	Heading	Tillering	Jointing	Heading	Tillering	Jointing	Heading
	SE	0.02	0.02	0.01	0.03	0.02	0.01	0.01	0.02	0.01	0.02	0.02	0.01
%GC_a	Min	46.17	46.39	47.61	12.73	50.84	66.84	68.53	69.70	84.86	34.29	58.55	70.59
	Max	61.74	63.60	57.51	38.41	66.92	81.67	84.27	79.77	91.93	64.69	72.82	95.35
	Mean	55.93	55.30**	52.42	27.1***	56.57*	72.23*	75.43	75.41	87.69	47.95***	65.31	80.98
	SE	4.36	4.75	3.24	7.10	4.33	3.41	4.38	2.80	1.97	9.02	4.06	5.69
%GC_p	Min		36.70			13.31		48.93			31.82		
	Max		72.13			40.56		55.99			46.26		
	Mean		59.05**			29.6**		51.39			38.06***		
	SE		10.66			6.80		1.84			4.26		
ABM	Min		255.38	556.39		110.16	748.71			528.20			951.46
	Max		453.51	1084.36		330.03	1543.46			928.23			1456.51
	Mean		334.03	736.21		204.8**	1165.5*			736.21			1177.08
	SE		51.42	131.82		52.87	193.13			115.92			147.23
Yield‡	Min							270.66		433.03			
	Max							379.22		548.53			
	Mean							317.93		506.75**			
	SE							31.94		33.04			

†ABM at JT and AN: aboveground biomass at jointing and anthesis; a: aerial image; p: digital photos; SE: standard error; ‡: yield at maturity; *, **, and *** significant at 0.05, 0.01, and <.0001, respectively

Interaction among genotypes, growth stages, years and water regime

The factorial analysis of variance is presented on Table 21. The four-way interaction was not significant for all the indices. Significant three-way interactions were recorded for year, water regime and growth stages for all the indices except GDVI^2, then genotype, year, and water regime for all the indices except RVI. All two-way interactions were significant except for genotype by growth stage which had only %GC from PVI significant. Year by water regime was significant for all the indices except GDVI^4 and EVI. The interaction for year by growth stage was not significant for GDVI^2 AND GDVI^4. Water regime by growth stage was significant for all indices except GDVI^2. The two-way interaction genotype by year showed no significance with RVI only. The ANOVA for the main effects genotype, growth stage, year and water regime was significant for all indices except year with GDVI^3. Replications were significant for DVI, GDVI^2, GDVI^3, EVI, ENDVI and %GC from PVI. The replication nested in year was significant for all indices except RVI and GDVI^2.

Table 21 Combined analysis of variance (ANOVA) mean sum of squares for several spectral vegetation indices across three growth stages, two years and under rainfed and irrigated conditions.

SOV	df	NDVI	RVI	DVI	GDVI^2	GDVI^3	GDVI^4	GLI	EVI	GRVI	ENDVI	GC
Rep	2	0.000	41.51	0.003**	0.03*	0.01**	0.000	0.003	0.03**	0.003	0.003**	0.08***
Rep(Y)	2	0.016**	37.80	0.003**	0.0007	0.05***	0.007*	0.02***	0.05***	0.03**	0.006***	0.05***
G	19	0.008**	33.84*	0.002***	0.05***	0.006***	0.004**	0.003**	0.01**	0.01***	0.002**	0.02***
Y	1	0.92***	286.53***	0.15***	1.69***	0.004	0.07***	0.90***	0.97***	0.18***	0.84***	6.41***
E	1	10.53***	11012.19***	0.52***	0.39***	0.78***	2.42***	1.69***	4.96***	11.99***	3.24***	1.36***
GS	2	10.88***	6094.38***	1.33***	4.30***	0.71***	1.03***	2.54***	7.50***	8.18***	2.17***	2.84***
G x Y	19	0.01***	19.22	0.002***	0.05***	0.005**	0.005**	0.003**	0.01***	0.01**	0.002***	0.02***
E x GS	2	3.53***	4467.12***	0.57***	0.003	0.27***	0.36***	2.30***	3.31***	8.72***	0.61***	1.89***
Y x E	1	0.24***	878.51***	1.27***	0.22***	0.44***	0.39***	0.02**	0.56***	1.43***	4.88***	0.67***
Y x GS	2	0.01*	153.64**	0.003**	0.001	0.01**	0.001	0.47***	0.18***	0.76***	0.04***	0.09***
G x E	19	0.005*	33.20*	0.002**	0.03***	0.003*	0.003	0.002*	0.006	0.01**	0.001**	0.008**
G x GS	38	0.003	24.41	0.0009	0.008	0.0005	0.0003	0.001	0.004	0.004	0.0005	0.007*
G x Y x E	19	0.006*	20.32	0.002**	0.03***	0.006***	0.006***	0.002	0.006*	0.009*	0.002**	0.007*
G x Y x GS	38	0.004	16.38	0.0006	0.006	0.0005	0.0002	0.001	0.003	0.004	0.0007	0.005
Y x E x GS	2	0.22***	289.99***	0.04***	0.003	0.04***	0.04***	0.12***	0.13***	0.14***	0.09***	0.29***
G x E x GS	38	0.002	23.08	0.0004	0.006	0.0003	0.0002	0.0011	0.001	0.005	0.0006	0.003
G x Y x E x GS	38	0.002	18.12	0.0006	0.008	0.0005	0.0004	0.0017	0.003	0.004	0.0006	0.005
Residual	476											
Total	719											

†SOV: source of variation; Rep: replication; G: genotypes; Y: year; E: water regime; GS: growth stages; df: degrees of freedom; *, **, and *** significant at 0.05, 0.01, and <.0001, respectively

Correlation between SVI and field data

The digital photo determined percent ground cover (% GC) for year 1 under rainfed condition showed positive association with the indices for most of the growth stages except NDVI at jointing, GDVI^2 at tillering, GDVI^4 at all stages, ENDVI at heading and %GC from PVI at heading (Table 22). Under irrigated condition for year 1, the %GC from the digital photos was correlated with all the indices except GDVI^3 and ENDVI both at heading. While for year 2, correlations were seen under rainfed condition between photo %GC and most of the indices at tillering stage only, except none significant for all the three GDVI. Irrigated condition for year 2 presented significant associations with NDVI at tillering, RVI at tillering and heading, DVI at tillering, GDVI^2 at all stages with negative association at tillering, GLI at tillering, EVI at tillering and heading, GRVI at tillering and jointing, ENDVI at tillering and heading, and %GC from PVI at tillering.

Aboveground biomass (ABM) at jointing stage under rainfed condition for year 1 was positively correlated with NDVI at tillering, DVI at tillering, GDVI^2 at jointing and heading, EVI at tillering, GRVI and %GC from PVI at both tillering. Irrigated condition for year 1showed significant correlation with all the indices except RVI at heading, GDVI^3, GDVI^4 and GRVI at heading. Year 2 had no ABM at jointing stage. Aboveground biomass at anthesis for year 1 under rainfed condition showed significant correlation with most indices except NDVI at jointing, RVI and DVI at heading, GDVI^2 at tillering, GLI and EVI at heading, ENDVI at tillering, %GC from PVI at heading, and photo %GC at tillering. ABM at anthesis under irrigated condition was positively associated with almost all indices and growth stages except GDVI^3 at heading and GLI at jointing. For year 2 under rainfed condition, ABM at anthesis correlated with DVI at heading, GLI at jointing and heading, and ENDVI at tillering. Under irrigated condition, correlation was recorded with DVI at heading also, GDVI^3, EVI at heading, ENDVI at tillering and heading, and %GC from photos at tillering.

Yield data was obtained for year 2 only. Under rainfed condition, yield positively associated with NDVI and RVI at heading, DVI at jointing and heading, GDVI^2 at tillering, GDVI^4 at all stages, EVI at heading, %GC from PVI at tillering, and heading, and %GC from digital photos at tillering. Irrigated condition were mostly correlated except with NDVI and RVI at jointing, GDVI^2 at tillering, GDVI^3 at tillering and jointing, GDVI^4 and GLI at all stages, GRVI at jointing, and ENDVI at jointing. The association among the SVI was also recorded (Table A3).

Table 22 Correlation coefficients between the spectral vegetation indices and field data.

		2014-2015						2015-2016					
		Rainfed			Irrigated			Rainfed			Irrigated		
Indices	Growth stages	%GC_p	ABM at AN	ABM at JT	%GC_p	ABM at AN	ABM at JT	%GC_p	ABM at AN	Yield	%GC_p	ABM at AN	Yield
NDVI	Tillering	**0.40**	**0.37**	**0.34**	**0.92**	**0.58**	**0.78**	**0.72**	-0.24	-0.24	**0.97**	0.22	**0.41**
	Jointing	0.12	0.05	-0.03	**0.74**	**0.45**	**0.64**	0.05	-0.01	0.13	0.29	0.06	0.05
	Heading	**0.44**	**0.32**	0.08	**0.38**	**0.47**	**0.35**	0.01	0.11	**0.39**	0.28	-0.16	**0.41**
RVI	Tillering	**0.43**	**0.35**	0.27	**0.91**	**0.60**	**0.79**	**0.76**	-0.25	-0.23	**0.96**	0.21	**0.39**
	Jointing	**0.45**	**0.64**	-0.06	**0.69**	**0.38**	**0.65**	0.03	-0.05	0.14	0.23	0.08	0.21
	Heading	**0.45**	0.27	0.03	**0.35**	**0.45**	0.29	0.01	0.13	**0.38**	**0.48**	-0.10	**0.31**
DVI	Tillering	**0.38**	**0.31**	**0.34**	**0.91**	**0.59**	**0.79**	**0.78**	-0.10	-0.18	**0.97**	0.27	**0.43**
	Jointing	**0.47**	**0.53**	0.14	**0.80**	**0.48**	**0.67**	-0.07	0.02	**0.36**	0.19	0.22	**0.35**
	Heading	**0.38**	0.20	0.06	**0.63**	**0.45**	**0.79**	0.18	**0.30**	**0.37**	0.21	**0.57**	**0.45**
GDVI^2	Tillering	0.22	0.01	-0.24	**0.92**	**0.56**	**0.77**	-0.13	-0.16	**-0.32**	**-0.41**	0.16	0.15
	Jointing	**0.51**	**0.42**	**0.39**	**0.92**	**0.54**	**0.75**	0.66	-0.23	-0.25	**0.96**	0.23	**0.44**
	Heading	**0.55**	**0.44**	**0.39**	**0.91**	**0.52**	**0.74**	0.61	-0.23	-0.25	**0.94**	0.24	**0.45**
GDVI^3	Tillering	**0.46**	**0.62**	0.09	**0.73**	**0.46**	**0.61**	0.07	0.02	0.13	0.11	**0.40**	0.29
	Jointing	**0.45**	**0.60**	0.10	**0.69**	**0.47**	**0.56**	0.09	0.05	0.13	0.11	**0.40**	0.29
	Heading	**0.43**	**0.57**	0.11	-0.12	-0.24	0.19	0.11	0.08	0.13	0.15	**0.42**	**0.31**
GDVI^4	Tillering	0.28	**0.38**	0.15	**0.55**	**0.55**	**0.39**	-0.05	0.04	**0.65**	0.19	-0.01	0.13
	Jointing	0.22	**0.38**	0.16	**0.47**	**0.51**	**0.30**	-0.06	0.02	**0.62**	0.22	-0.02	0.07
	Heading	0.15	**0.37**	0.16	**0.40**	**0.47**	0.23	-0.07	0.00	**0.59**	0.25	-0.04	0.00
GLI	Tillering	**0.38**	**0.34**	0.28	**0.90**	**0.60**	**0.83**	**0.72**	-0.18	-0.19	**0.90**	0.13	0.27
	Jointing	**0.56**	**0.46**	0.08	**0.55**	0.29	**0.47**	0.09	**0.36**	0.00	0.27	0.20	0.06
	Heading	**0.35**	0.26	0.08	**0.45**	**0.46**	**0.48**	-0.02	**0.31**	-0.12	0.18	-0.14	0.27
EVI	Tillering	**0.39**	**0.37**	**0.35**	**0.91**	**0.59**	**0.79**	**0.80**	-0.18	-0.23	**0.97**	0.24	**0.40**
	Jointing	**0.46**	**0.59**	-0.01	**0.87**	**0.53**	**0.71**	0.01	0.06	0.10	0.13	0.35	**0.32**
	Heading	**0.42**	0.29	0.02	**0.56**	**0.57**	**0.70**	0.00	0.11	**0.37**	**0.32**	**0.54**	**0.55**
GRVI	Tillering	**0.31**	**0.30**	**0.32**	**0.89**	**0.57**	**0.83**	**0.76**	-0.17	-0.22	**0.94**	0.15	**0.31**

Table 22 Continued.

		2014-2015						2015-2016					
		Rainfed			Irrigated			Rainfed			Irrigated		
Indices	Growth stages	%GC_p	ABM at AN	ABM at JT	%GC_p	ABM at AN	ABM at JT	%GC_p	ABM at AN	Yield	%GC_p	ABM at AN	Yield
	Jointing	**0.50**	**0.52**	0.14	**0.73**	**0.38**	**0.78**	0.23	0.26	-0.13	**0.36**	0.09	0.07
	Heading	**0.48**	**0.32**	0.05	**0.33**	**0.43**	0.29	-0.01	0.26	-0.02	0.26	-0.20	**0.32**
ENDVI	Tillering	**0.40**	0.27	0.11	**0.90**	**0.58**	**0.78**	**0.40**	**-0.35**	-0.09	**0.92**	**0.33**	**0.53**
	Jointing	**0.65**	**0.37**	-0.20	**0.60**	**0.39**	**0.59**	-0.06	-0.22	0.25	0.15	0.08	0.17
	Heading	0.25	**0.32**	0.26	0.27	**0.56**	**0.33**	0.03	0.18	0.27	**0.45**	**0.30**	**0.62**
%GC_a	Tillering	**0.48**	**0.43**	**0.44**	**0.91**	**0.58**	**0.79**	**0.42**	-0.28	**-0.30**	**0.96**	**0.32**	**0.50**
	Jointing	**0.52**	**0.38**	-0.04	**0.82**	**0.56**	**0.74**	-0.10	0.08	0.01	0.05	**0.30**	**0.39**
	Heading	0.14	-0.08	0.00	**0.59**	**0.34**	**0.76**	0.24	0.24	**0.46**	0.20	**0.56**	**0.39**
%GC_p	Jointing		0.29	-0.06		**0.57**	**0.77**		-0.05	**-0.31**		0.27	**0.40**
ABM	Anthesis			**0.39**			**0.44**			0.02			**0.47**

†ABM at JT and AN: aboveground biomass at jointing and anthesis; a: aerial image; p: digital photos.
Values in bold are different from 0 with a significance level alpha=0.05

Regression analysis

The 11 indices at three growth stages were run for the ABM at anthesis and jointing and yield for each water regime in a stepwise regression analysis. The regression statistics are presented in Tables 23, 24, 25 and 26. The number of predictor indices in the regression models ranged from 1 (Tables A4 and A5) to 11 selected. This was based on the high coefficient of determination (R^2) and adjusted R^2 values, while low values of AIC, BIC, MSE, RMSE, SBC, and SSE. These values were mostly significant at less than 5% probability level.

The functional relationship between the best single indices and field data is showed in figures 13 a-h. Under rainfed condition (figure 13 a-d), 19% of variation in ABM at jointing was explained by the variation in %GC from PVI (fig. 5a). ABM at anthesis had 41% variability explained by RVI at jointing. %GC from digital photos expressed 27% predictability with %GC from PVI, and 43% with ENDVI at jointing. Irrigated condition (figure 13e-h) had 61% variability in ABM at jointing explained by variability in NDVI at tillering. ABM at anthesis recorded 37% variability explained by RVI at tillering. %GC from digital photos expressed 83% predictability with %GC from PVI, and 84% with NDVI at tillering.

The performance of the model for %GC from PVI and NDVI from year 1 was validated using year 2 data to estimate the %GC from digital photo (figure 14). Based on the coefficient of determination (R^2 = 0.93/0.94), PVI and NDVI served as the best predictors of the %GC.

Table 23 Regression models and their statistics between ABM at anthesis and the spectral vegetation indices for year 1.

Rainfed									
No.	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE	Indices
1	0.41	0.38	187.73	183.73	10850.60	104.17	189.72	195310.89	RVI_2
2	0.48	0.41	187.32	181.32	10182.30	100.91	190.30	173099.02	RVI_2; $\%GC_1$
3	0.58	0.50	184.76	176.76	8615.84	92.82	188.75	137853.43	$NDVI_2$; RVI_2; $\%GC_1$
4	0.66	0.57	182.56	172.56	7446.17	86.29	187.53	111692.53	$NDVI_2$; RVI_2; $ENDVI_2$; $\%GC_1$
5	0.74	0.64	179.48	167.48	6188.86	78.67	185.45	86643.97	$GDVI_4$^2; GLI_2; GLI_3; $GRVI_2$; $\%GC_3$
6	0.86	0.79	169.41	155.41	3645.31	60.38	176.38	47389.09	$NDVI_1$; $NDVI_2$; RVI_2; RVI_3; EVI_3; $\%GC_2$
7	0.91	0.86	161.22	145.22	2372.51	48.71	169.18	28470.07	$NDVI_2$ DVI_3 $GDVI_2$^3 $GDVI_4$^4 GLI_3 EVI_3 $ENDVI_1$
8	0.96	0.93	148.32	130.32	1228.60	35.05	157.28	13514.59	$NDVI_1$ $NDVI_2$ RVI_2 RVI_3 GLI_2 EVI_3 $GRVI_2$; $\%GC_2$
9	0.98	0.97	133.71	113.71	589.09	24.27	143.67	5890.92	$NDVI_2$; DVI_3; RVI_3; $GDVI_2$^3; GLI_2; EVI_2; EVI_3; $GRVI_2$; $\%GC_2$
10	0.99	0.99	112.98	90.98	210.05	14.49	123.93	1890.45	$NDVI_2$; $NDVI_3$; $GDVI_2$^3; $GDVI_4$^3 GLI_2; EVI_2; EVI_3; $GRVI_2$ $\%GC_2$; $\%GC_3$

Irrigated									
No.	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE	Indices
1	0.37	0.33	204.40	200.40	24969.65	158.02	206.39	449453.75	RVI_1
2	0.48	0.42	202.41	196.41	21656.61	147.16	205.40	368162.39	GLI_1 $ENDVI_3$
3	0.53	0.45	202.27	194.27	20671.87	143.78	206.25	330749.91	RVI_1 $GDVI_1$^4 $GDVI_2$^3
4	0.63	0.53	199.47	189.47	17344.63	131.70	204.45	260169.38	$NDVI_1$ RVI_1 $GDVI_2$^3 $GRVI_2$
5	0.72	0.63	195.77	183.77	13980.35	118.24	201.75	195724.94	RVI_1 $GDVI_2$^2 EVI_1 EVI_3 $GRVI_2$
6	0.78	0.68	192.94	178.94	11822.03	108.73	199.91	153686.35	$NDVI_2$ RVI_1 GLI_3 EVI_1 EVI_3 $GRVI_2$
7	0.89	0.82	181.79	165.79	6638.03	81.47	189.76	79656.35	DVI_3 RVI_1 $GDVI_3$^4 EVI_3 $GRVI_2$ $GRVI_3$ $ENDVI_3$
8	0.92	0.86	176.58	158.58	5048.48	71.05	185.54	55533.24	DVI_3 RVI_1 RVI_3 $GDVI_3$^4 EVI_3 $GRVI_2$ $GRVI_3$ $ENDVI_3$
9	0.95	0.91	167.83	147.83	3243.59	56.95	177.78	32435.95	DVI_3 RVI_1 RVI_3 $GDVI_3$^4 GLI_3 EVI_3 $GRVI_2$ $GRVI_3$ $ENDVI_3$
10	0.97	0.94	159.48	137.48	2148.44	46.35	170.43	19335.92	DVI_1 RVI_1 RVI_2 RVI_3 $GDVI_3$^4 GLI_3 EVI_3 $GRVI_2$ $ENDVI_3$ $\%GC_3$
11	0.99	0.97	145.08	121.08	1064.40	32.63	157.03	8515.18	DVI_1 RVI_1 RVI_3 $GDVI_3$^3 $GDVI_3$^4 EVI_3 $GRVI_2$ $GRVI_3$ $ENDVI_3$ $\%GC_1$ $\%GC_3$

†Subscript imply growth stages 1, 2, 3 as tillering, jointing, and heading; R^2: r squared coefficient of determination; Adj R^2: adjusted r squared; AIC: Akaike information criterion; BIC: Sawa's Bayesian information criterion; RMSE: root mean square error; SBC: Schwarz criterion; SSE: sum of square error of prediction. All R^2 are significant at <0.01.

Table 24 Regression models and their statistics between ABM at jointing and the spectral vegetation indices for year 1.

Rainfed									
No.	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE	Indices
1	0.19	0.14	156.38	152.38	2262.43	47.56	158.37	40723.67	$\%GC_1$
2	0.35	0.28	153.86	147.86	1910.83	43.71	156.84	32484.15	$GDVI_1$^4 $ENDVI_2$
3	0.57	0.49	147.80	139.80	1357.31	36.84	151.79	21716.95	$GDVI_1$^4 $GRVI_2$ ENDVI2
4	0.66	0.57	144.83	134.83	1128.84	33.60	149.80	16932.66	$NDVI_2$ DVI_2 $GDVI_1$^4 $ENDVI_2$
5	0.80	0.73	136.21	124.21	711.31	26.67	142.18	9958.38	$NDVI_2$ DVI_1 DVI_3 $GDVI_2$^2 $ENDVI_2$
6	0.87	0.81	129.34	115.34	491.61	22.17	136.31	6390.98	$NDVI_2$ RVI_3 DVI_1 DVI_3 $GDVI_2$^2 $ENDVI_2$
7	0.90	0.84	127.23	111.23	433.63	20.82	135.19	5203.61	$NDVI_2$ DVI_1 DVI_2 $GDVI_1$^3 $GDVI_1$^4 $ENDVI_2$ $ENDVI_3$
8	0.96	0.93	110.56	92.56	186.03	13.64	119.52	2046.37	$NDVI_2$ $NDVI_3$ RVI_3 DVI_1 $GDVI_2$^2 $GDVI_3$^4 $ENDVI_2$ $\%GC_3$
9	0.98	0.96	100.83	80.83	113.82	10.67	110.79	1138.16	RVI_3 DVI_1 DVI_2 $GDVI_1$^2 $GDVI_3$^2 $GDVI_3$^4 EVI_2 $GRVI_2$ $ENDVI_1$
10	0.98	0.97	95.06	73.06	85.74	9.26	106.01	771.65	$NDVI_2$ $NDVI_3$ RVI_3 DVI_1 $GDVI_2$^2 $GDVI_3$^2 $GDVI_3$^3 $GDVI_3$^4 $ENDVI_2$ $\%GC_3$

Irrigated									
No.	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE	Indices
1	0.68	0.67	138.62	134.62	931.10	30.51	140.61	16759.83	$GRVI_1$
2	0.79	0.77	132.34	126.34	651.68	25.53	135.33	11078.55	$GDVI_2$^4 GLI_1
3	0.85	0.82	128.35	120.35	513.09	22.65	132.33	8209.40	DVI_3 $GDVI_2$^4 GLI_1
4	0.88	0.85	125.40	115.40	427.39	20.67	130.38	6410.86	$NDVI_3$ $GDVI_2$^4 GLI_1 EVI_3
5	0.91	0.87	122.01	110.01	349.79	18.70	127.99	4897.10	DVI_1 DVI_3 $GDVI_2$^4 $GRVI_1$ $\%GC_1$
6	0.93	0.90	118.09	104.09	280.17	16.74	125.06	3642.23	DVI_1 $GDVI_2$^4 EVI_1 $GRVI_1$ $\%GC_1$ $\%GC_3$
7	0.94	0.91	116.65	100.65	255.51	15.98	124.61	3066.10	$NDVI_1$ $NDVI_3$ DVI_1 $GDVI_2$^4 EVI_3 $GRVI_1$ $\%GC_1$
8	0.96	0.93	111.46	93.46	194.59	13.95	120.42	2140.52	$NDVI_1$ $NDVI_3$ RVI_2 DVI_1 $GDVI_2$^4 EVI_3 $GRVI_1$ $\%GC_1$
9	0.98	0.96	99.20	79.20	104.93	10.24	109.16	1049.27	$NDVI_1$ RVI_3 $GDVI_1$^2 $GDVI_1$^3 GLI_1 EVI_2 $GRVI_1$ $ENDVI_1$ $\%GC_3$

†Subscript imply growth stages 1, 2, 3 as tillering, jointing, and heading; R^2: r squared coefficient of determination; Adj R^2: adjusted r squared; AIC: Akaike information criterion; BIC: Sawa's Bayesian information criterion; RMSE: root mean square error; SBC: Schwarz criterion; SSE: sum of square error of prediction. All R^2 are significant at <0.05.

Table 25 Regression models and their statistics between ABM at anthesis and the spectral vegetation indices for year 2.

					Rainfed				
No.	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE	Indices
1	0.13	0.08	190.25	186.25	12303.60	110.92	192.24	221464.73	GLI_2
2	0.30	0.22	187.87	181.87	10466.78	102.31	190.86	177935.18	$GDVI_2$^4 $ENDVI_2$
3	0.56	0.47	180.80	172.80	7067.92	84.07	184.79	113086.64	$GDVI_2$^4 $ENDVI_2$ $\%GC_1$
4	0.75	0.69	171.05	161.05	4189.69	64.73	176.03	62845.28	DVI_1 $GDVI_2$^4 EVI_1 $ENDVI_2$
5	0.81	0.74	167.87	155.87	3463.49	58.85	173.84	48488.90	$NDVI_2$ RVI_2 $GDVI_2$^3 $GDVI_2$^4 $ENDVI_2$
6	0.99	0.99	86.75	72.75	58.44	7.64	93.72	759.76	$NDVI_2$ RVI_2 $GDVI_1$^3 $GDVI_2$^3 $GDVI_2$^4 $GRVI_1$

					Irrigated				
No.	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE	Indices
1	0.30	0.26	183.77	179.77	14366.28	119.86	185.66	244226.75	DVI_3
2	0.45	0.38	181.17	175.17	11981.77	109.46	184.00	191708.32	DVI_3 $GDVI_1$^2
3	0.53	0.43	180.42	172.42	11060.58	105.17	184.20	165908.66	DVI_1 DVI_3 $GDVI_1$^2
4	0.60	0.48	179.30	169.30	10055.72	100.28	184.02	140780.08	RVI_2 $GDVI_1$^2 EVI_1 EVI_2
5	0.70	0.59	175.52	163.52	7990.95	89.39	181.19	103882.34	$NDVI_3$ DVI_3 $GDVI_1$^2 $\%GC_1$ $\%GC_3$
6	0.80	0.70	170.08	156.08	5850.98	76.49	176.69	70211.80	RVI_2 $GDVI_1$^2 $GDVI_2$^2 EVI_2 $GRVI_1$ $GRVI_2$
7	0.88	0.81	161.72	145.72	3699.55	60.82	169.27	40695.07	RVI_2 DVI_2 $GDVI_1$^2 EVI_2 $GRVI_3$ $\%GC_1$ $\%GC_2$
8	0.93	0.88	153.80	135.80	2414.82	49.14	162.30	24148.18	$NDVI_3$ RVI_2 DVI_2 $GDVI_1$^2 GLI_1 EVI_2 $GRVI_2$ $ENDVI_2$
9	0.96	0.92	145.67	125.67	1573.72	39.67	155.11	14163.45	RVI_1 RVI_2 RVI_3 DVI_2 $GDVI_1$^2 $GDVI_2$^3 $GDVI_3$^4 GLI_3 $GRVI_1$
10	0.98	0.95	134.49	112.49	884.83	29.75	144.88	7078.62	$NDVI_2$ RVI_1 RVI_2 RVI_3 $GDVI_1$^2 $GDVI_3$^4 GLI_3 EVI_2 $GRVI_1$ $\%GC_2$

†Subscript imply growth stages 1, 2, 3 as tillering, jointing, and heading; R^2: r squared coefficient of determination; Adj R^2: adjusted r squared; AIC: Akaike information criterion; BIC: Sawa's Bayesian information criterion; RMSE: root mean square error; SBC: Schwarz criterion; SSE: sum of square error of prediction. All R^2 are significant at <0.05.

Table 26 Regression models and their statistics between Yield and the spectral vegetation indices for year 2.

Rainfed									
No.	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE	Indices
1	0.42	0.39	130.63	126.63	624.57	24.99	132.63	11242.17	$GDVI_3$^2
2	0.49	0.42	130.25	124.25	586.88	24.23	133.23	9976.97	$GDVI_1$^2 $GDVI_3$^2
3	0.55	0.47	129.44	121.44	541.92	23.28	133.42	8670.73	$GDVI_1$^2 $GDVI_3$^2 $GRVI_2$
4	0.65	0.56	126.50	116.50	451.59	21.25	131.48	6773.89	$GDVI_1$^2 $GDVI_3$^2 GLI_2 $GRVI_2$
5	0.76	0.67	121.27	109.27	337.05	18.36	127.25	4718.73	DVI_2 $GDVI_1$^2 GLI_2 EVI_1 $ENDVI_2$
6	0.81	0.73	117.92	103.92	277.76	16.67	124.89	3610.90	RVI_2 DVI_1 $GDVI_2$^4 EVI_1 $ENDVI_3$ %GC_2
7	0.92	0.88	102.42	86.42	125.46	11.20	110.39	1505.58	RVI_1 RVI_2 $GDVI_1$^3 $GDVI_2$^4 $GRVI_1$ $GRVI_2$ %GC_1
8	0.99	0.99	9.25	-8.75	1.17	1.08	18.21	12.91	RVI_1 DVI_3 $GDVI_1$^3 $GRVI_1$ $GRVI_2$ $GRVI_3$ $ENDVI_2$ %GC_1

Irrigated									
No.	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE	Indices
1	0.38	0.35	133.34	129.34	714.90	26.74	135.33	12868.22	$ENDVI_3$
2	0.50	0.44	131.01	125.01	609.73	24.69	134.00	10365.38	$GDVI_3$^4 $ENDVI_3$
3	0.61	0.53	128.19	120.19	509.08	22.56	132.17	8145.28	$NDVI_3$ $GDVI_3$^2 %GC_3
4	0.71	0.63	124.39	114.39	406.37	20.16	129.37	6095.51	DVI_2 $GDVI_1$^2 $ENDVI_1$ $ENDVI_2$
5	0.81	0.74	117.49	105.49	278.93	16.70	123.46	3905.04	$NDVI_3$ $GDVI_1$^4 $GDVI_3$^4 GLI_1 %GC_3
6	0.88	0.82	111.01	97.01	196.59	14.02	117.98	2555.69	$GDVI_1$^3 $GDVI_3$^2 GLI_1 EVI_1 $GRVI_3$ %GC_3
7	0.92	0.88	103.98	87.98	135.64	11.65	111.95	1627.69	$NDVI_2$ $NDVI_3$ DVI_2 $GDVI_1$^2 GLI_1 $GRVI_1$ $ENDVI_1$
8	0.97	0.95	85.91	67.91	54.24	7.36	94.87	596.66	$NDVI_2$ DVI_3 $GDVI_1$^2 GLI_1 $GRVI_1$ $ENDVI_1$ $ENDVI_2$ %GC_3
9	0.99	0.98	68.91	48.91	23.07	4.80	78.87	230.74	$NDVI_1$ RVI_1 DVI_2 $GDVI_1$^2 $GDVI_1$^3 $GDVI_1$^4 $GDVI_3$^2 GLI_1 $ENDVI_2$

†Subscript imply growth stages 1, 2, 3 as tillering, jointing, and heading; R^2: r squared coefficient of determination; Adj R^2: adjusted r squared; AIC: Akaike information criterion; BIC: Sawa's Bayesian information criterion; RMSE: root mean square error; SBC: Schwarz criterion; SSE: sum of square error of prediction. All R^2 are significant at <0.05.

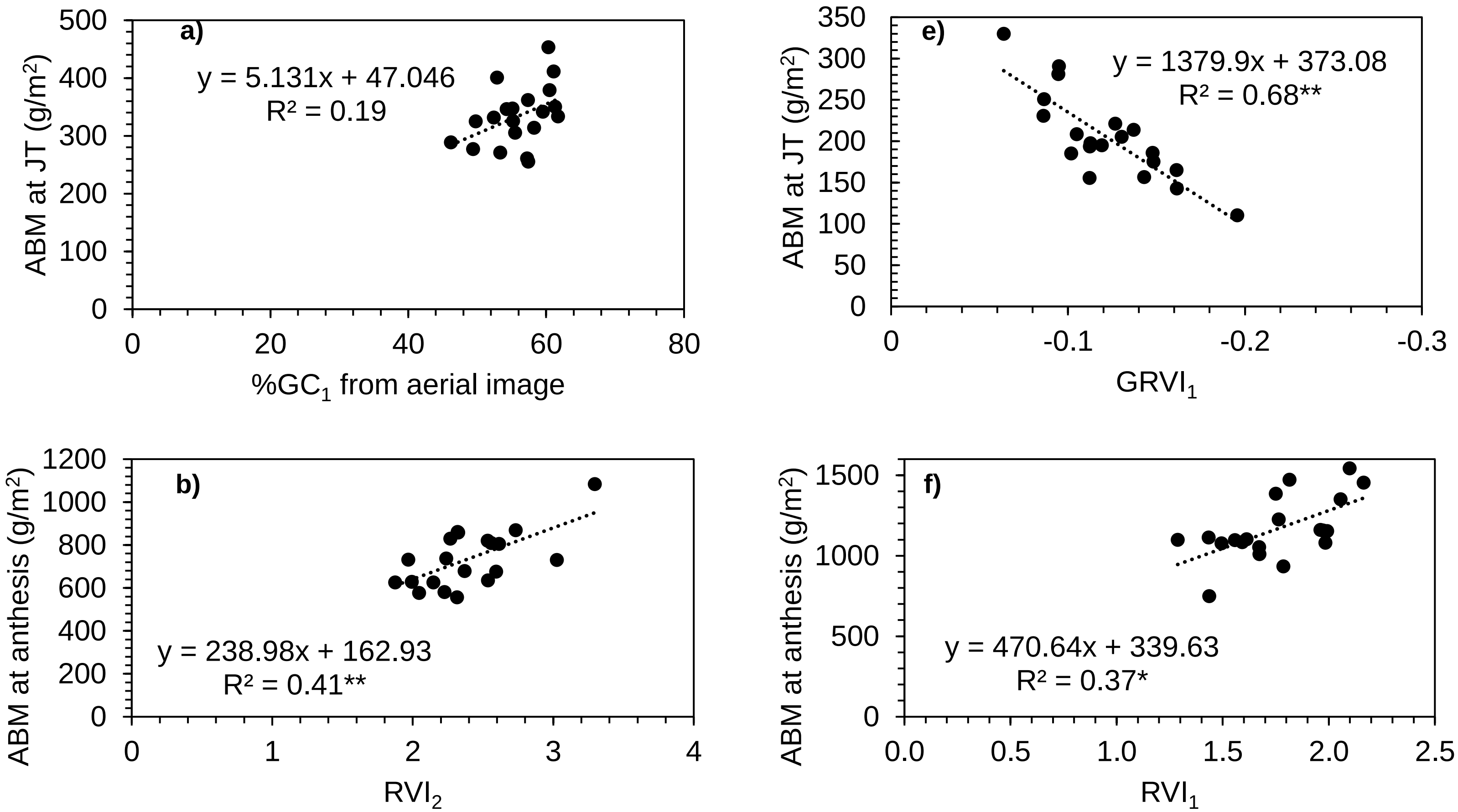

Figure 13 Best Functional Relationship between field parameters and SVI for year 1 under rainfed (a-d) and irrigated (e-h) fields. ABM at JT and AN: aboveground biomass at jointing and anthesis; Subscript imply growth stages 1, 2, and 3, as tillering, jointing, and heading. *, **, and *** significant at 0.05, 0.01, and <.0001, respectively.

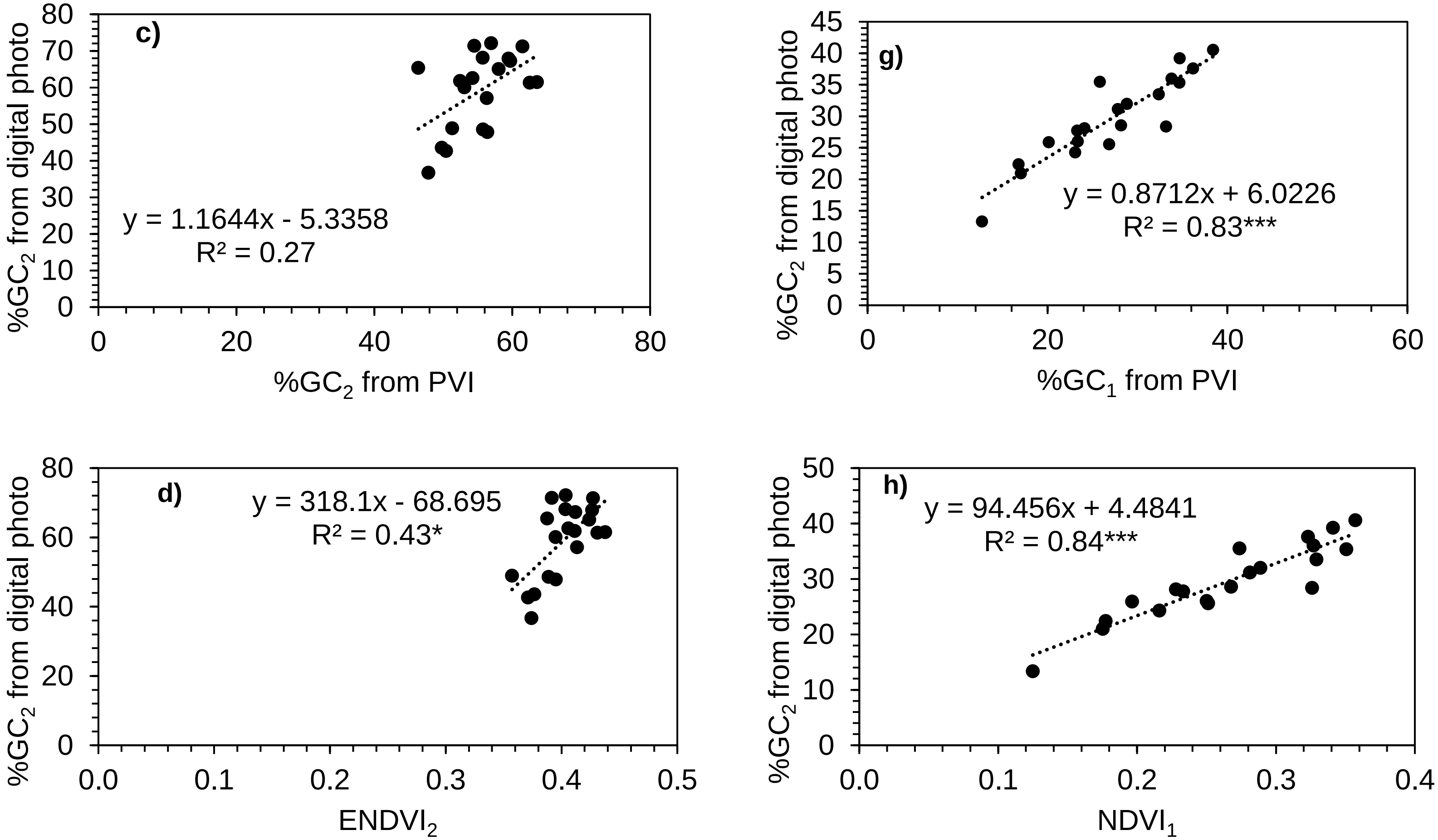

Figure 13 Continued

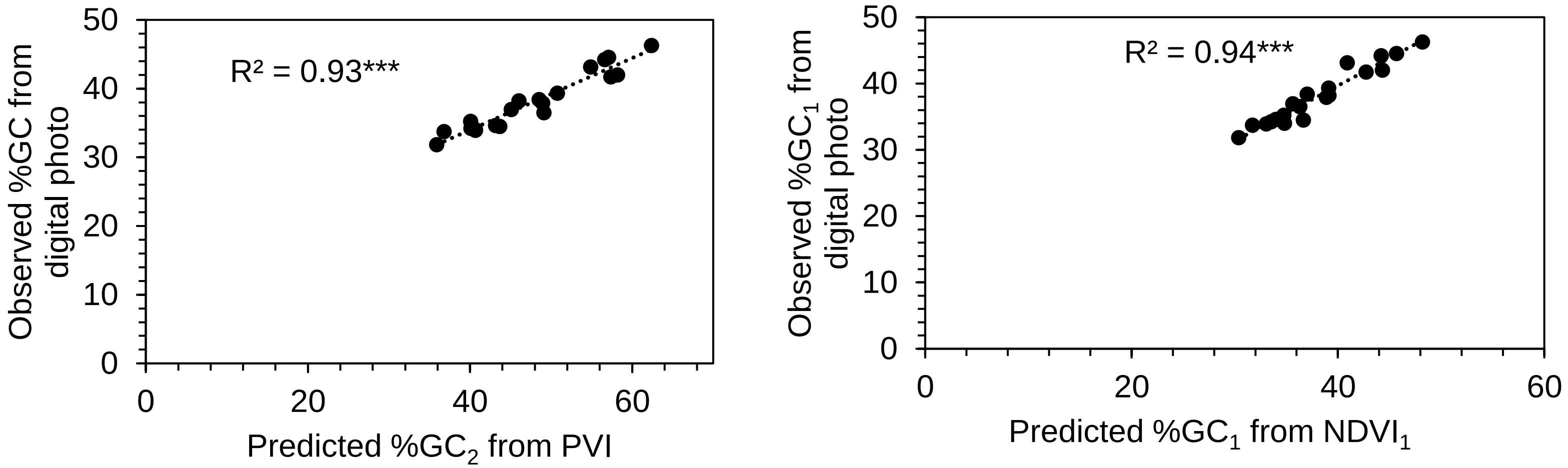

Figure 14 Model Performance with percent ground cover observed and predicted for year 2. Subscript imply growth stages 1, 2, and 3, as tillering, jointing, and heading. *** Significant at <.0001.

DISCUSSION

Genotypic variation and interaction between genotypes, growth stages, years and water regime

The genotypes used in this study have a wide genetic background which was confirmed by the significant genotypic variation in %GC, aboveground biomass, yield and the 11 indices at three growth stages under two water regimes. NDVI has been used to identify and interpret phenology which describe the events of the plant life cycle and how these are influenced by several vegetation characteristics. Thus, based on the well-watered condition, the genotypes showed discrimination in NDVI; their photosynthetic activity at the three growth stages. Most of the indices increased from tillering to heading except DVI, GRVI^3, GRVI^3, GLI, GRVI and % GC from PVI. The rate of change of these indices during the growing season may indicate the speed of increase or decrease of photosynthesis (Yengoh et al., 2014). Another may be due to their influence by several characteristics of the vegetation and the indices (Ross, 1981). Under rainfed condition in year 1, the water stress level at tillering was high until after heading based on the precipitation data. The field data; % GC, aboveground biomass, and yield were mostly distinguished under irrigated condition than rainfed condition, this may be because these genotypes are known to be drought tolerant however, under well-watered conditions they may perform variably depending on their ability to optimize the available resources.

Significant interaction was observed for year, water regime and growth stages (Table 21). This means that GDVI^2 did not perform the same for two years under the two water regimes and at the three growth stages. Only the RVI values was the same for all the twenty genotypes for both year and water regime. %GC from PVI was the only significant indices among others for genotype by growth stage interaction. This means the specific growth stages are a very important consideration when measuring the percent ground cover using the PVI. Aparicio et al. (2002a) made observation that when measuring spectral reflectance in rainfed durum wheat, the specific growth stages are very crucial.

Correlation and Regression analysis

The eleven published SVI used in this study generally showed positive correlations with %GC from digital photo, aboveground biomass and yield. Correlations in year 2 were poor compared to year 1 which had enough rainfall throughout the growing season. ABM at jointing did not provide better association with the indices compared to ABM at anthesis. The indices that showed weaker correlations may be linked to their sensitivity at particular growth stages with the plant parameter. According to Prasad et al. (2007), genotypes are easily differentiated at later vegetative and early productive phases. Yield correlated with NDVI, RVI, DVI, EVI, and %GC from PVI at heading under rainfed condition. This is similar under irrigated condition where all the indices correlated at heading except GDVI^4 and GLI. However, Royo et al. (2003) with wheat found SRI correlated better with yield at the reproductive growth stages than at early vegetative growth stages.

Different statistical models have been developed to determine the relationships between vegetation indices and plant biophysical/chemical data. Linear regression is commonly used to determine the basic relationships, while nonlinear models such as quadratic, power and exponential models are applied to further improve fitting. SVI provide a standardized approach to analysis; hence they have been advocated for spectral vegetation analysis. Although this argument has some appeal, its validity can be questioned when there is a need to estimate or predict plant parameters (as opposed to using indices for data visualization purposes). Regression analysis is mostly used if the study requires knowledge of a crop growth parameter of interest (e.g., leaf area index, biomass), to analyze the relationship between the spectral index used and the crop parameter variable (Lawrence and Ripple, 1998). However, the nature of the relationship varies with each study as in this present study also, so it is difficult to state that a certain NDVI generally equals a certain biomass, or a certain spectral model estimates one plant parameter or the other. This is supported by Chen and Cihlar (1996) that showed the regression formula can differ between seasons. Hence, the multiple regression approach that involves a wide range of different crop genotypes, and different water regimes has been carried out independently in this study (Tables 23-26), so as to allow clear and accurate estimations of crop growth parameters for plant breeding purposes and use by crop scientists. Besides, the reflectance at a particular wavelength or at a particular index that may be a good predictor model for a certain plant parameter under one condition may not be a good predictor in another condition. The models developed for year 1 were not able to predict for year 2 (result not presented here), except for %GC (figure 14). This is obvious in the single and multiple models developed for year 2 that different indices were selected for aboveground biomass at anthesis for each year.

Generally, results obtained were able to differentiate the genotypes and make estimation of their yield, aboveground biomass and %GC especially at jointing and heading stages (Tables 23-26). This supports studies that found the best growth stages to estimate plant parameters from spectral reflectance measurements were within jointing and heading stages (Ahlrichs and Bauer, 1983; Aparicio et al., 2000; Babar et al., 2006; Xavier et al., 2006). It was recommended by Prasad et al. (2007) that reflectance measurements at heading and at grain-filling be taken, and combine the information from the two readings. The combination of growth stages of SVI information was more predictive and had stronger relationship than individual growth stages, in agreement with Gutierrez et al. (2010). Babar et al. (2006); Prasad et al. (2007) noted that most associations were stronger at later growth stages than at early growth stages, this was similar with some of the indices in this study.

Compared to our previous work in chapter II, the indices (especially %GC from PVI and NDVI) that provided better estimation of aboveground biomass and yield can be applied to make estimation of the other studies under each field condition or water regime. That is, these can be done to provide the complete spectral information for each plot of the different studies on the aerial imagery for individual year. The prediction models in this chapter can be used as selection tools needed by breeders to screen large numbers of genotypes in a relatively short time before expensive yield trials are conducted.

CHAPTER V

SUMMARY AND CONCLUSION

This dissertation focused on the analysis of remote sensing systems to detect higher yielding and drought tolerant genotypes rapidly and efficiently among many early-generation lines and advanced wheat genotypes. This involved the evaluation of sensor output by the calculation of spectral vegetation indices and assessing their relationship to agronomic parameters such as ground cover, aboveground biomass, and yield.

In chapter II, the plant traits that contribute to yield were investigated under rainfed and irrigated conditions in the Southern Great Plains (SGP). Genetic variability was seen with biomass at maturity, harvest index, spikes/m^2, seeds/m^2, seeds/spike, yield, and TKW. Under water-stressed condition, yield correlated significantly with biomass at maturity, seeds per spike, harvest index, yield, seeds/m^2, and spikes/m^2. Wheat yield can be improved by selecting genotypes having higher performances for the above traits under water-stressed conditions.

In the third chapter, the handheld Greenseeker® and tractor-mounted sensor were evaluated for their ability to monitor the performance of wheat genotypes. NDVI (Normalized Difference Vegetation Index) was used to monitor the vegetation or vegetation health. The fourth chapter focused on the use of aerial imagery to assess the growth, performance, and yield of winter wheat under rainfed and irrigated conditions. The eleven spectral vegetation indices (SVI) at three growth stages that were used in this study mostly showed significant variation. SVI besides NDVI was used to monitor the wheat canopy, such as Enhanced Vegetation Index (EVI), Ratio Vegetation Index (RVI) and

Perpendicular Vegetation Index (PVI) that takes into account the soil background effects (one of the major limitations of NDVI).

NDVI at tillering ($R^2 = 0.84$, P<.0001) and percent ground cover (%GC) estimated from PVI ($R^2 = 0.83$, P<.0001) at tillering showed the best prediction for %GC from digital photo at jointing. The indices in early growth stages such as %GC from PVI and GRVI ($R^2 = 0.68$, P<0.01), both at tillering stages showed some association with aboveground biomass (ABM) at jointing compared to heading. RVI was presented as the single best indices that explained 37 – 41 % of the variability in ABM at anthesis in year 1 under both water regimes. GDVI^2 and ENDVI, both at heading showed the best estimation with yield as single indices under rainfed and irrigated conditions, respectively. The multiple regression models generally presented the combination of indices that can significantly explain the field data up to 99% variability.

However, the indices selected at different water regimes and year varied especially with the aboveground biomass at anthesis and %GC from digital photos. This may be attributed to the challenges encountered in this study, which affected the individual and combined relationship between the indices and field data. Some of the challenges encountered is the lack of calibration panels during the initial capture of images which made it difficult to recognize plots on the field. Another is the poor image resolution due to flight height being too high, hence the number of pixels per plot was small, so insufficient vegetation pixels were extracted for spectral data processing. This is because the number of the pixels available determine the ability to resolve spectral features and bands into their separate components (how fine the target plots on the field are, will determine how accurately defined they will be). Whereas on the field data the best representative section of each plot was selected. Also, the field data collected were not consistent with the aerial images with two days or more interval. Even for both years, the acquisition of aerial image was not consistent due to weather conditions. Yield data was available only in year 2 due to freeze and hail storm damage in year 1, which made it hard to verify yield estimation for an additional year with a new dataset.

Based on all the remote sensing techniques used in this study, the aerial imagery appears to be the best with the ability to capture an overview of the crop canopy of the wheat field, compared to the ground-based sensors. It has been easy to interpret visually with the whole field image and map. The manned aerial vehicle has some restrictions and challenges with flight height, as it cannot fly too low to the ground level. This has shown to affect the spectral data pre-processing and the analysis of the final data. Hence, future research would involve well-planned experiment to avoid the challenges. Generally, these challenges that lead to some errors may be due to sampling, environment or the remote sensing methods used. A clear understanding will assist in being able to extend the remote sensing tool beyond the studied environment for research to another environment within the same field of operations.

Most importantly the use of unmanned aerial vehicles (UAVs) with better spatial and spectral resolution should be employed, instead of a manned system which has the restriction of flight height. This will assist to broaden the understanding of spectral information to other wavelengths in the electromagnetic spectrum (such as the short-wave infrared, thermal infrared, and microwave regions). Instead of commonly having sensors with only the visible and near-infrared regions. This may create topics for new investigations and develop a complete knowledge of the potential of these less-often used wavelengths.

Overall, results from this study have provided models that can be used as an indirect selection tool for screening a large number of early-generation lines and advanced wheat genotypes. This has established the potential use of remote sensing techniques by breeders for high-throughput phenotyping of wheat genotypes to screen for drought-tolerant and high-yielding genotypes. Thus, this dissertation has provided crucial information for wheat breeding programs that can be used as a platform to improve selection in this important crop and applied to other crops as well.

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APPENDIX A

Table A1
Eigenvalues for principal component (PC) analysis for year 1 (a, b) and year 2 (c, d).

a) Rainfed	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	3.41	1.76	1.24	0.86	0.46	0.22	0.03	0.01
Variability (%)	42.63	21.98	15.50	10.80	5.81	2.78	0.39	0.11
Cumulative %	42.63	64.60	80.10	90.90	96.71	99.49	99.89	100.00

b) Irrigated	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	3.28	2.40	1.33	0.85	0.09	0.05	0.01	0.00
Variability (%)	40.97	30.02	16.57	10.58	1.19	0.57	0.07	0.03
Cumulative %	40.97	70.99	87.56	98.14	99.32	99.90	99.97	100.00

c) Rainfed	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	4.16	1.37	1.18	0.65	0.42	0.15	0.07	0.01
Variability (%)	51.99	17.09	14.69	8.13	5.27	1.85	0.81	0.17
Cumulative %	51.99	69.07	83.77	91.90	97.17	99.01	99.83	100.00

d) Irrigated	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	3.85	1.59	1.18	0.72	0.35	0.25	0.07	0.00
Variability (%)	48.07	19.82	14.76	8.94	4.41	3.12	0.83	0.05
Cumulative %	48.07	67.90	82.65	91.59	96.00	99.12	99.95	100.00

Table A2

Factor analysis for the variables based on the principal components (PCs) for year 1 (a, b) and year 2 (c, d).

a) Rainfed	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
BMS_MA	0.62	-0.36	0.43	-0.39	-0.38	-0.02	-0.06	-0.02
HI	0.59	0.74	0.01	0.03	0.19	-0.24	-0.08	-0.01
Spikes	0.62	-0.69	-0.02	-0.08	0.30	-0.18	0.07	-0.04
Seedspk	0.72	0.57	-0.24	0.14	-0.26	0.09	0.08	-0.04
Seeds	0.96	-0.07	-0.20	-0.02	-0.12	-0.10	0.04	0.07
BMS_AN	0.21	-0.21	0.55	0.78	-0.08	-0.03	-0.01	0.00
Yield	0.76	0.17	0.42	-0.13	0.33	0.30	0.00	0.01
TKW	-0.48	0.44	0.69	-0.26	-0.02	-0.15	0.09	0.01

b) Irrigated	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
BMS_MA	0.87	-0.22	0.21	0.37	-0.09	-0.08	-0.01	-0.03
HI	0.28	0.85	-0.36	-0.17	0.17	-0.03	-0.02	-0.02
Spikes	0.65	-0.71	-0.23	0.06	0.07	0.10	-0.04	0.01
Seedspk	0.29	0.87	0.31	-0.18	-0.16	0.07	-0.03	0.01
Seeds	0.98	0.04	0.08	-0.16	0.02	0.11	0.05	-0.01
BMS_AN	-0.17	0.07	0.96	0.15	0.15	0.02	-0.01	0.00
Yield	0.90	0.35	-0.04	0.22	0.04	-0.08	0.01	0.04
TKW	-0.38	0.48	-0.27	0.73	0.00	0.08	0.01	0.00

c) Rainfed	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
BMS_MA	0.71	-0.58	-0.14	0.32	-0.11	-0.17	0.07	-0.05
HI	0.78	0.05	0.57	-0.03	-0.19	0.05	-0.15	-0.04
Spikes	0.80	-0.05	-0.37	0.32	0.22	0.26	-0.02	-0.01
Seedspk	0.82	0.37	0.00	-0.34	-0.19	0.09	0.16	-0.02
Seeds	0.96	-0.17	0.05	0.04	-0.17	-0.04	-0.02	0.10
BMS_AN	-0.03	0.84	0.10	0.51	-0.10	-0.07	0.02	0.00
Yield	0.75	0.17	0.37	-0.10	0.50	-0.13	0.02	0.00
TKW	-0.50	-0.36	0.73	0.23	0.01	0.13	0.11	0.01

d) Irrigated	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
BMS_MA	0.85	0.22	-0.19	-0.34	-0.14	-0.26	0.05	-0.03
HI	0.42	0.22	0.86	0.02	-0.09	0.10	-0.10	-0.02
Spikes	0.81	-0.21	-0.28	-0.22	-0.19	0.37	0.03	0.00
Seedspk	0.79	-0.31	0.28	0.37	0.18	0.00	0.17	-0.01
Seeds	0.97	0.01	0.16	-0.07	-0.08	-0.15	-0.04	0.05
BMS_AN	0.20	0.71	-0.28	0.56	-0.24	0.02	0.00	0.00
Yield	0.58	0.65	-0.19	-0.11	0.44	0.09	-0.04	0.00
TKW	-0.60	0.64	0.32	-0.30	-0.07	0.06	0.15	0.02

Table A3
Correlations among all indices used in year 1 and year 2 under rainfed (a, b) and irrigated (c, d) conditions. Values in bold are different from 0 with a significance level alpha=0.05

a) Indices	$NDVI_1$	$NDVI_2$	$NDVI_3$	DVI_1	DVI_2	DVI_3	RVI_1	RVI_2	RVI_3	$GDVI_1$^2	$GDVI_1$^3	$GDVI_1$^4	$GDVI_2$^2	$GDVI_2$^3	$GDVI_2$^4
$NDVI_2$	**0.51**														
$NDVI_3$	**0.17**	**0.34**													
DVI_1	**0.97**	**0.44**	0.13												
DVI_2	**0.52**	**0.33**	**0.58**	**0.51**											
DVI_3	-0.04	**0.22**	**0.95**	-0.07	**0.46**										
RVI_1	**0.92**	**0.57**	**0.35**	**0.82**	**0.52**	**0.16**									
RVI_2	**0.44**	**0.31**	**0.54**	**0.45**	**0.81**	**0.41**	**0.38**								
RVI_3	**0.18**	**0.30**	**0.99**	**0.15**	**0.57**	**0.94**	**0.35**	**0.51**							
$GDVI_1$^2	**-0.44**	**-0.30**	**-0.27**	**-0.36**	**-0.16**	**-0.18**	**-0.60**	0.09	**-0.31**						
$GDVI_1$^3	**0.94**	**0.38**	0.07	**0.93**	**0.43**	-0.10	**0.82**	**0.46**	0.07	**-0.28**					
$GDVI_1$^4	**0.86**	**0.29**	0.02	**0.86**	**0.39**	-0.13	**0.73**	**0.45**	0.02	**-0.19**	**0.98**				
$GDVI_2$^2	**0.52**	**0.34**	**0.62**	**0.50**	**0.93**	**0.50**	**0.52**	**0.92**	**0.60**	**-0.17**	**0.49**	**0.48**			
$GDVI_2$^3	**0.52**	**0.34**	**0.62**	**0.50**	**0.91**	**0.51**	**0.53**	**0.91**	**0.60**	**-0.18**	**0.50**	**0.49**	**0.99**		
$GDVI_2$^4	**0.52**	**0.34**	**0.61**	**0.50**	**0.89**	**0.52**	**0.53**	**0.89**	**0.59**	**-0.18**	**0.50**	**0.49**	**0.98**	**0.99**	
$GDVI_3$^2	0.04	**0.35**	**0.89**	0.01	**0.40**	**0.87**	**0.19**	**0.53**	**0.84**	-0.07	-0.05	-0.09	**0.51**	**0.52**	**0.52**
$GDVI_3$^3	0.04	**0.39**	**0.84**	0.00	**0.37**	**0.82**	**0.18**	**0.51**	**0.78**	-0.06	-0.06	-0.11	**0.49**	**0.49**	**0.49**
$GDVI_3$^4	0.03	**0.42**	**0.78**	-0.01	**0.34**	**0.76**	**0.17**	**0.48**	**0.71**	-0.07	-0.08	-0.13	**0.46**	**0.46**	**0.46**
GLI_1	**0.94**	**0.35**	**0.21**	**0.96**	**0.55**	-0.01	**0.79**	**0.51**	**0.23**	**-0.35**	**0.86**	**0.78**	**0.55**	**0.55**	**0.54**
GLI_2	**0.54**	**0.37**	**0.59**	**0.55**	**0.92**	**0.46**	**0.48**	**0.84**	**0.58**	-0.11	**0.49**	**0.45**	**0.90**	**0.89**	**0.86**
GLI_3	**0.16**	**0.48**	**0.95**	0.11	**0.54**	**0.88**	**0.33**	**0.50**	**0.91**	**-0.24**	0.01	-0.07	**0.55**	**0.54**	**0.53**
EVI_1	**1.00**	**0.54**	**0.22**	**0.97**	**0.55**	0.01	**0.93**	**0.45**	**0.22**	**-0.46**	**0.92**	**0.83**	**0.55**	**0.55**	**0.55**
EVI_2	**0.44**	**0.32**	**0.64**	**0.45**	**0.84**	**0.54**	**0.40**	**0.98**	**0.63**	0.01	**0.42**	**0.41**	**0.94**	**0.94**	**0.93**
EVI_3	0.07	**0.33**	**0.98**	0.03	**0.57**	**0.97**	**0.26**	**0.51**	**0.97**	**-0.18**	-0.03	-0.07	**0.58**	**0.58**	**0.57**
$GRVI_1$	**0.95**	**0.41**	**0.20**	**0.97**	**0.57**	-0.02	**0.82**	**0.46**	**0.22**	**-0.44**	**0.84**	**0.76**	**0.55**	**0.55**	**0.54**
$GRVI_2$	**0.52**	**0.32**	**0.66**	**0.52**	**0.97**	**0.53**	**0.50**	**0.82**	**0.66**	**-0.21**	**0.44**	**0.40**	**0.93**	**0.91**	**0.88**
$GRVI_3$	**0.24**	**0.46**	**0.95**	**0.19**	**0.65**	**0.88**	**0.39**	**0.60**	**0.93**	**-0.20**	0.11	0.04	**0.65**	**0.65**	**0.63**
$ENDVI_1$	**0.85**	**0.39**	0.06	**0.88**	**0.37**	**-0.14**	**0.69**	**0.40**	0.08	**-0.21**	**0.79**	**0.72**	**0.36**	**0.33**	**0.30**
$ENDVI_2$	**0.53**	0.13	**0.48**	**0.57**	**0.81**	**0.39**	**0.49**	**0.78**	**0.50**	-0.11	**0.55**	**0.54**	**0.83**	**0.82**	**0.80**
$ENDVI_3$	0.13	**0.36**	**0.94**	0.11	**0.45**	**0.93**	**0.29**	**0.43**	**0.92**	**-0.31**	0.03	-0.02	**0.52**	**0.53**	**0.54**
$\%GC_1$	**0.71**	**0.55**	**0.40**	**0.64**	**0.45**	**0.30**	**0.80**	**0.45**	**0.35**	**-0.38**	**0.75**	**0.74**	**0.56**	**0.57**	**0.57**
$\%GC_2$	**0.41**	**0.26**	**0.68**	**0.44**	**0.88**	**0.62**	**0.38**	**0.82**	**0.69**	-0.04	**0.35**	**0.31**	**0.85**	**0.85**	**0.85**
$\%GC_3$	**-0.38**	-0.05	**0.65**	**-0.37**	0.05	**0.82**	**-0.20**	0.06	**0.68**	-0.03	**-0.40**	**-0.39**	0.09	0.11	0.13

Table A3 Continued

	GDVI$_3$^2	GDVI$_3$^3	GDVI3^4	GLI$_1$	GLI$_2$	GLI$_3$	EVI$_1$	EVI$_2$	EVI$_3$	GRVI$_1$	GRVI$_2$	GRVI$_3$	ENDVI$_1$	ENDVI$_2$	ENDVI$_3$	%GC$_1$	%GC$_2$
GDVI$_3$^3	**0.99**																
GDVI$_3$^4	**0.97**	**0.99**															
GLI$_1$	0.08	0.06	0.05														
GLI$_2$	**0.42**	**0.39**	**0.36**	**0.58**													
GLI$_3$	**0.92**	**0.89**	**0.86**	**0.16**	**0.53**												
EVI$_1$	0.09	0.08	0.08	**0.93**	**0.56**	**0.21**											
EVI$_2$	**0.61**	**0.59**	**0.55**	**0.50**	**0.86**	**0.60**	**0.46**										
EVI$_3$	**0.88**	**0.83**	**0.78**	0.09	**0.56**	**0.94**	0.12	**0.61**									
GRVI$_1$	0.05	0.04	0.03	**0.98**	**0.57**	**0.17**	**0.95**	**0.47**	0.08								
GRVI$_2$	**0.46**	**0.42**	**0.38**	**0.57**	**0.97**	**0.59**	**0.54**	**0.86**	**0.63**	**0.58**							
GRVI$_3$	**0.88**	**0.85**	**0.80**	**0.23**	**0.65**	**0.98**	**0.28**	**0.69**	**0.95**	**0.23**	**0.70**						
ENDVI$_1$	-0.01	0.00	0.00	**0.87**	**0.50**	0.07	**0.82**	**0.36**	-0.01	**0.83**	**0.42**	**0.16**					
ENDVI$_2$	**0.26**	**0.20**	**0.15**	**0.61**	**0.82**	**0.33**	**0.54**	**0.80**	**0.45**	**0.57**	**0.83**	**0.47**	**0.53**				
ENDVI$_3$	**0.90**	**0.87**	**0.82**	**0.18**	**0.45**	**0.89**	**0.18**	**0.56**	**0.92**	**0.18**	**0.53**	**0.85**	-0.02	**0.32**			
%GC$_1$	**0.37**	**0.38**	**0.38**	**0.54**	**0.47**	**0.38**	**0.73**	**0.45**	**0.34**	**0.56**	**0.45**	**0.45**	**0.47**	**0.39**	**0.37**		
%GC$_2$	**0.56**	**0.51**	**0.45**	**0.47**	**0.84**	**0.62**	**0.44**	**0.90**	**0.68**	**0.46**	**0.87**	**0.71**	**0.34**	**0.84**	**0.58**	**0.33**	
%GC$_3$	**0.69**	**0.65**	**0.61**	**-0.33**	0.05	**0.59**	**-0.34**	**0.20**	**0.70**	**-0.34**	0.11	**0.55**	**-0.37**	0.08	**0.68**	0.01	**0.32**

Values in bold are different from 0 with a significance level alpha=0.05

Table A3 Continued

b) Indices	$NDVI_1$	$NDVI_2$	$NDVI_3$	DVI_1	DVI_2	DVI_3	RVI_1	RVI_2	RVI_3	$GDVI_1$^2	$GDVI_1$^3	$GDVI_1$^4	$GDVI_2$^2	$GDVI_2$^3	$GDVI_2$^4
$NDVI_2$	0.09														
$NDVI_3$	0.09	**0.46**													
DVI_1	**1.00**	0.10	0.07												
DVI_2	0.07	**0.99**	**0.47**	0.09											
DVI_3	0.05	**0.44**	**0.99**	0.03	**0.45**										
RVI_1	**0.71**	**0.33**	0.09	**0.74**	**0.30**	0.08									
RVI_2	**0.22**	**0.62**	**0.53**	**0.22**	**0.62**	**0.50**	**0.39**								
RVI_3	**0.30**	**0.31**	**0.88**	**0.29**	**0.30**	**0.86**	**0.25**	**0.44**							
$GDVI_1$^2	**0.42**	**0.30**	0.08	**0.39**	**0.30**	0.04	0.13	**0.28**	**0.19**						
$GDVI_1$^3	**0.99**	0.05	0.11	**0.97**	0.04	0.07	**0.65**	**0.22**	**0.30**	**0.45**					
$GDVI_1$^4	**0.97**	0.03	0.12	**0.95**	0.03	0.09	**0.59**	**0.21**	**0.30**	**0.46**	**1.00**				
$GDVI_2$^2	0.10	**1.00**	**0.44**	0.12	**0.98**	**0.42**	**0.36**	**0.61**	**0.31**	**0.29**	0.06	0.04			
$GDVI_2$^3	0.11	**0.99**	**0.42**	0.13	**0.97**	**0.40**	**0.38**	**0.59**	**0.32**	**0.28**	0.07	0.04	**1.00**		
$GDVI_2$^4	0.12	**0.97**	**0.40**	0.14	**0.95**	**0.37**	**0.40**	**0.57**	**0.32**	**0.26**	0.07	0.04	**0.99**	**1.00**	
$GDVI_3$^2	**0.20**	**0.27**	**0.41**	**0.22**	**0.28**	**0.42**	**0.27**	**0.43**	**0.49**	-0.03	**0.15**	0.12	**0.26**	**0.25**	**0.24**
$GDVI_3$^3	**0.21**	**0.23**	**0.32**	**0.23**	**0.25**	**0.32**	**0.25**	**0.39**	**0.41**	0.01	**0.17**	**0.14**	**0.22**	**0.21**	**0.20**
$GDVI_3$^4	**0.22**	**0.18**	**0.21**	**0.24**	**0.20**	**0.21**	**0.24**	**0.34**	**0.32**	0.03	**0.18**	**0.15**	**0.17**	**0.16**	**0.15**
GLI_1	**0.66**	**0.35**	-0.11	**0.70**	**0.30**	-0.13	**0.82**	0.13	0.09	**0.16**	**0.57**	**0.51**	**0.38**	**0.41**	**0.44**
GLI_2	**-0.22**	**0.49**	**0.52**	**-0.24**	**0.51**	**0.55**	**-0.14**	**0.23**	**0.30**	**-0.22**	**-0.18**	**-0.15**	**0.48**	**0.47**	**0.46**
GLI_3	**-0.16**	**0.37**	**0.37**	**-0.15**	**0.38**	**0.38**	0.00	**0.54**	**0.26**	-0.09	**-0.17**	**-0.18**	**0.36**	**0.34**	**0.33**
EVI_1	**0.79**	**0.26**	0.05	**0.82**	**0.23**	0.04	**0.98**	**0.33**	**0.23**	**0.22**	**0.73**	**0.68**	**0.28**	**0.30**	**0.32**
EVI_2	0.11	**0.97**	**0.45**	0.12	**0.97**	**0.43**	**0.29**	**0.68**	**0.31**	**0.40**	0.10	0.09	**0.96**	**0.95**	**0.94**
EVI_3	0.09	**0.30**	**0.97**	0.07	**0.31**	**0.97**	-0.01	**0.41**	**0.88**	0.05	0.13	**0.15**	**0.28**	**0.26**	**0.24**
$GRVI_1$	**0.72**	**0.25**	-0.10	**0.75**	**0.19**	-0.12	**0.87**	0.08	**0.14**	**0.17**	**0.65**	**0.59**	**0.28**	**0.32**	**0.36**
$GRVI_2$	**-0.21**	**0.38**	**0.40**	**-0.21**	**0.38**	**0.44**	-0.07	0.06	**0.16**	**-0.34**	**-0.18**	**-0.16**	**0.37**	**0.37**	**0.36**
$GRVI_3$	-0.10	**0.44**	**0.59**	-0.10	**0.45**	**0.59**	-0.02	**0.56**	**0.44**	-0.04	-0.10	-0.09	**0.43**	**0.41**	**0.39**
$ENDVI_1$	**0.73**	0.06	**0.24**	**0.72**	0.07	**0.19**	**0.36**	**0.30**	**0.33**	**0.33**	**0.73**	**0.71**	0.06	0.06	0.06
$ENDVI_2$	-0.10	**0.90**	**0.28**	-0.07	**0.91**	**0.27**	**0.30**	**0.56**	0.07	0.07	**-0.15**	**-0.18**	**0.90**	**0.89**	**0.87**
$ENDVI_3$	**0.20**	**0.31**	**0.53**	**0.21**	**0.32**	**0.52**	**0.21**	**0.64**	**0.53**	**0.24**	**0.19**	**0.17**	**0.30**	**0.27**	**0.25**
$\%GC_1$	**0.77**	**-0.16**	-0.05	**0.73**	**-0.15**	-0.08	**0.27**	0.04	0.08	**0.45**	**0.82**	**0.84**	**-0.17**	**-0.18**	**-0.19**
$\%GC_2$	0.01	**0.87**	**0.25**	0.02	**0.86**	**0.22**	**0.24**	**0.74**	0.09	**0.37**	0.00	0.00	**0.86**	**0.86**	**0.84**
$\%GC_3$	**0.49**	0.11	**0.48**	**0.50**	0.08	**0.45**	**0.36**	**0.24**	**0.80**	**0.21**	**0.46**	**0.44**	**0.14**	**0.16**	**0.19**

Table A3 Continued

	$GDVI_3$^2	$GDVI_3$^3	$GDVI_3$^4	GLI_1	GLI_2	GLI_3	EVI_1	EVI_2	EVI_3	$GRVI_1$	$GRVI_2$	$GRVI_3$	$ENDVI_1$	$ENDVI_2$	$ENDVI_3$	$\%GC_1$	$\%GC_2$
$GDVI_3$^3	**0.99**																
$GDVI_3$^4	**0.96**	**0.99**															
GLI_1	0.12	0.10	0.10														
GLI_2	**0.14**	0.07	0.00	**-0.21**													
GLI_3	**0.21**	**0.14**	0.06	0.03	**0.38**												
EVI_1	**0.25**	**0.25**	**0.25**	**0.81**	**-0.24**	-0.11											
EVI_2	**0.18**	**0.14**	0.11	**0.30**	**0.47**	**0.39**	**0.22**										
EVI_3	**0.41**	**0.32**	**0.22**	**-0.19**	**0.50**	**0.32**	-0.02	**0.29**									
$GRVI_1$	0.09	0.08	0.07	**0.97**	**-0.27**	-0.07	**0.87**	**0.20**	**-0.16**								
$GRVI_2$	0.01	-0.06	-0.13	-0.11	**0.93**	**0.34**	**-0.17**	**0.32**	**0.39**	**-0.15**							
$GRVI_3$	**0.31**	**0.22**	0.13	0.01	**0.49**	**0.94**	-0.10	**0.46**	**0.55**	-0.09	**0.43**						
$ENDVI_1$	**0.38**	**0.39**	**0.39**	**0.22**	-0.10	-0.12	**0.46**	0.03	**0.26**	**0.27**	**-0.15**	-0.05					
$ENDVI_2$	**0.25**	**0.21**	**0.17**	**0.34**	**0.39**	**0.39**	**0.20**	**0.83**	0.11	**0.20**	**0.32**	**0.39**	-0.08				
$ENDVI_3$	**0.37**	**0.31**	**0.25**	0.13	0.11	**0.58**	**0.17**	**0.38**	**0.43**	0.05	0.00	**0.61**	0.11	**0.23**			
$\%GC_1$	**0.15**	**0.21**	**0.26**	**0.16**	**-0.21**	**-0.37**	**0.40**	-0.11	0.04	**0.26**	**-0.22**	**-0.29**	**0.65**	**-0.35**	-0.04		
$\%GC_2$	0.08	0.06	0.04	**0.19**	**0.42**	**0.40**	**0.16**	**0.92**	0.08	0.08	**0.27**	**0.40**	0.00	**0.82**	**0.35**	**-0.14**	
$\%GC_3$	**0.54**	**0.50**	**0.46**	**0.38**	-0.03	0.03	**0.37**	0.13	**0.52**	**0.43**	**-0.15**	**0.18**	**0.32**	-0.11	**0.34**	**0.25**	-0.08

Values in bold are different from 0 with a significance level alpha=0.05

Table A3 Continued

c) Indices	NDVI$_1$	NDVI$_2$	NDVI$_3$	DVI$_1$	DVI$_2$	DVI$_3$	RVI$_1$	RVI$_2$	RVI$_3$	GDVI$_1$^2	GDVI$_1$^3	GDVI$_1$^4	GDVI$_2$^2	GDVI$_2$^3	GDVI$_2$^4
NDVI$_2$	**0.80**														
NDVI$_3$	**0.45**	**0.43**													
DVI$_1$	**1.00**	**0.76**	**0.45**												
DVI$_2$	**0.79**	**0.95**	**0.48**	**0.76**											
DVI$_3$	**0.44**	**0.37**	**0.90**	**0.45**	**0.46**										
RVI$_1$	**1.00**	**0.79**	**0.44**	**0.99**	**0.77**	**0.43**									
RVI$_2$	**0.76**	**0.74**	**0.37**	**0.75**	**0.81**	**0.47**	**0.76**								
RVI$_3$	**0.59**	**0.49**	**0.38**	**0.60**	**0.50**	**0.39**	**0.61**	**0.54**							
GDVI$_1$^2	**1.00**	**0.82**	**0.44**	**0.99**	**0.80**	**0.43**	**1.00**	**0.75**	**0.59**						
GDVI$_1$^3	**0.99**	**0.84**	**0.43**	**0.98**	**0.81**	**0.41**	**0.99**	**0.75**	**0.59**	**0.990**					
GDVI$_1$^4	**0.98**	**0.86**	**0.42**	**0.96**	**0.82**	**0.39**	**0.98**	**0.74**	**0.58**	**0.99**	**0.99**				
GDVI$_2$^2	**0.75**	**0.98**	**0.40**	**0.71**	**0.88**	**0.31**	**0.74**	**0.65**	**0.46**	**0.77**	**0.80**	**0.83**			
GDVI$_2$^3	**0.70**	**0.94**	**0.39**	**0.65**	**0.81**	**0.27**	**0.68**	**0.57**	**0.43**	**0.72**	**0.75**	**0.78**	**0.99**		
GDVI$_2$^4	**-0.24**	**-0.20**	**-0.22**	**-0.23**	**-0.18**	**-0.26**	**-0.27**	**-0.28**	0.10	**-0.25**	**-0.25**	**-0.25**	**-0.20**	**-0.19**	
GDVI$_3$^2	**0.55**	**0.61**	**0.77**	**0.56**	**0.61**	**0.70**	**0.54**	**0.55**	**0.34**	**0.54**	**0.53**	**0.51**	**0.59**	**0.57**	**-0.27**
GDVI$_3$^3	**0.42**	**0.53**	**0.69**	**0.43**	**0.54**	**0.62**	**0.40**	**0.50**	**0.22**	**0.41**	**0.39**	**0.37**	**0.52**	**0.51**	**-0.24**
GDVI$_3$^4	**0.33**	**0.47**	**0.63**	**0.34**	**0.48**	**0.58**	**0.31**	**0.46**	0.13	**0.32**	**0.30**	**0.28**	**0.46**	**0.46**	**-0.21**
GLI$_1$	**0.98**	**0.82**	**0.48**	**0.98**	**0.81**	**0.45**	**0.98**	**0.75**	**0.64**	**0.98**	**0.97**	**0.96**	**0.77**	**0.72**	**-0.27**
GLI$_2$	**0.57**	**0.75**	**0.33**	**0.53**	**0.71**	**0.36**	**0.56**	**0.56**	**0.64**	**0.60**	**0.62**	**0.65**	**0.74**	**0.70**	-0.06
GLI$_3$	**0.40**	0.10	**0.70**	**0.45**	**0.19**	**0.63**	**0.42**	**0.35**	**0.39**	**0.38**	**0.34**	**0.30**	0.05	0.01	**-0.19**
EVI$_1$	**1.00**	**0.79**	**0.45**	**1.00**	**0.78**	**0.45**	**1.00**	**0.76**	**0.60**	**1.00**	**0.99**	**0.97**	**0.74**	**0.68**	**-0.24**
EVI$_2$	**0.80**	**0.85**	**0.37**	**0.79**	**0.87**	**0.43**	**0.80**	**0.97**	**0.53**	**0.81**	**0.81**	**0.81**	**0.78**	**0.71**	**-0.27**
EVI$_3$	**0.54**	**0.50**	**0.76**	**0.55**	**0.54**	**0.71**	**0.55**	**0.50**	**0.79**	**0.54**	**0.53**	**0.52**	**0.48**	**0.47**	-0.11
GRVI$_1$	**0.97**	**0.83**	**0.49**	**0.97**	**0.84**	**0.47**	**0.96**	**0.76**	**0.64**	**0.97**	**0.96**	**0.95**	**0.77**	**0.71**	**-0.20**
GRVI$_2$	**0.85**	**0.89**	**0.44**	**0.83**	**0.92**	**0.37**	**0.83**	**0.68**	**0.59**	**0.85**	**0.86**	**0.87**	**0.84**	**0.79**	-0.07
GRVI$_3$	**0.43**	**0.37**	**0.97**	**0.44**	**0.44**	**0.91**	**0.43**	**0.36**	**0.31**	**0.42**	**0.41**	**0.39**	**0.32**	**0.30**	**-0.29**
ENDVI$_1$	**0.97**	**0.75**	**0.37**	**0.97**	**0.72**	**0.36**	**0.98**	**0.74**	**0.59**	**0.97**	**0.96**	**0.95**	**0.71**	**0.66**	**-0.29**
ENDVI$_2$	**0.73**	**0.83**	**0.48**	**0.69**	**0.86**	**0.49**	**0.72**	**0.62**	**0.51**	**0.75**	**0.77**	**0.78**	**0.78**	**0.72**	**-0.23**
ENDVI$_3$	**0.40**	**0.40**	**0.75**	**0.42**	**0.48**	**0.76**	**0.40**	**0.42**	**0.60**	**0.39**	**0.38**	**0.36**	**0.34**	**0.31**	-0.09
%GC$_1$	**0.98**	**0.77**	**0.43**	**0.98**	**0.75**	**0.41**	**0.99**	**0.76**	**0.58**	**0.98**	**0.98**	**0.96**	**0.73**	**0.68**	**-0.33**
%GC$_2$	**0.78**	**0.67**	**0.42**	**0.78**	**0.69**	**0.51**	**0.78**	**0.89**	**0.76**	**0.77**	**0.76**	**0.74**	**0.62**	**0.57**	-0.12
%GC$_3$	**0.54**	**0.45**	**0.21**	**0.54**	**0.45**	**0.23**	**0.56**	**0.50**	**0.98**	**0.54**	**0.54**	**0.54**	**0.42**	**0.39**	**0.18**

Table A3 Continued

	GDVI$_3$^2	GDVI$_3$^3	GDVI$_3$^4	GLI$_1$	GLI$_2$	GLI$_3$	EVI$_1$	EVI$_2$	EVI$_3$	GRVI$_1$	GRVI$_2$	GRVI$_3$	ENDVI$_1$	ENDVI$_2$	ENDVI$_3$	%GC$_1$	%GC$_2$
GDVI$_3$^3	**0.98**																
GDVI$_3$^4	**0.94**	**0.99**															
GLI$_1$	**0.59**	**0.45**	**0.36**														
GLI$_2$	**0.38**	**0.29**	**0.23**	**0.58**													
GLI$_3$	**0.64**	**0.56**	**0.51**	**0.45**	-0.01												
EVI$_1$	**0.55**	**0.42**	**0.33**	**0.98**	**0.55**	**0.43**											
EVI$_2$	**0.61**	**0.55**	**0.50**	**0.81**	**0.65**	**0.30**	**0.80**										
EVI$_3$	**0.54**	**0.43**	**0.35**	**0.61**	**0.51**	**0.55**	**0.56**	**0.49**									
GRVI$_1$	**0.58**	**0.45**	**0.36**	**0.99**	**0.60**	**0.44**	**0.97**	**0.82**	**0.61**								
GRVI$_2$	**0.48**	**0.37**	**0.30**	**0.86**	**0.69**	**0.16**	**0.84**	**0.75**	**0.60**	**0.87**							
GRVI$_3$	**0.76**	**0.68**	**0.62**	**0.45**	**0.28**	**0.75**	**0.44**	**0.35**	**0.70**	**0.45**	**0.39**						
ENDVI$_1$	**0.49**	**0.37**	**0.28**	**0.94**	**0.52**	**0.37**	**0.97**	**0.77**	**0.51**	**0.91**	**0.81**	**0.37**					
ENDVI$_2$	**0.36**	**0.24**	**0.16**	**0.73**	**0.77**	0.04	**0.72**	**0.66**	**0.59**	**0.74**	**0.89**	**0.45**	**0.69**				
ENDVI$_3$	**0.68**	**0.61**	**0.56**	**0.44**	**0.48**	**0.58**	**0.41**	**0.40**	**0.67**	**0.45**	**0.43**	**0.74**	**0.36**	**0.48**			
%GC$_1$	**0.51**	**0.38**	**0.29**	**0.96**	**0.53**	**0.41**	**0.98**	**0.79**	**0.53**	**0.94**	**0.81**	**0.43**	**0.99**	**0.72**	**0.38**		
%GC$_2$	**0.59**	**0.52**	**0.47**	**0.77**	**0.64**	**0.44**	**0.78**	**0.88**	**0.66**	**0.76**	**0.66**	**0.40**	**0.78**	**0.54**	**0.52**	**0.77**	
%GC$_3$	**0.23**	0.10	0.03	**0.59**	**0.64**	**0.30**	**0.55**	**0.50**	**0.67**	**0.59**	**0.53**	**0.14**	**0.54**	**0.44**	**0.48**	**0.53**	**0.72**

Values in bold are different from 0 with a significance level alpha=0.05

Table A3 Continued

d) Indices	$NDVI_1$	$NDVI_2$	$NDVI_3$	DVI_1	DVI_2	DVI_3	RVI_1	RVI_2	RVI_3	$GDVI_1$^2	$GDVI_1$^3	$GDVI_1$^4	$GDVI_2$^2	$GDVI_2$^3	$GDVI_2$^4
$NDVI_2$															
$NDVI_3$	**0.55**														
DVI_1	0.10	**0.42**													
DVI_2	**1.00**	**0.53**	0.11												
DVI_3	**0.40**	**0.80**	**0.27**	**0.37**											
RVI_1	**0.31**	**0.37**	**0.85**	**0.34**	**0.20**										
RVI_2	**0.99**	**0.51**	0.05	**0.99**	**0.39**	**0.28**									
RVI_3	**0.35**	**0.65**	**0.18**	**0.31**	**0.82**	**0.19**	**0.34**								
$GDVI_1$^2	**0.15**	-0.03	**-0.28**	**0.15**	**0.15**	**-0.16**	**0.23**	**0.32**							
$GDVI_1$^3	**-0.57**	-0.13	**0.21**	**-0.57**	0.00	-0.05	**-0.59**	**-0.17**	**-0.27**						
$GDVI_1$^4	**0.99**	**0.56**	0.11	**0.98**	**0.44**	**0.29**	**0.98**	**0.40**	**0.14**	**-0.57**					
$GDVI_2$^2	**0.98**	**0.57**	0.12	**0.96**	**0.46**	**0.29**	**0.97**	**0.42**	0.13	**-0.55**	**1.00**				
$GDVI_2$^3	0.10	**0.46**	**0.19**	0.08	**0.70**	0.08	**0.14**	**0.49**	**0.39**	**0.23**	0.12	0.12			
$GDVI_2$^4	0.10	**0.46**	**0.19**	0.08	**0.70**	0.08	**0.14**	**0.49**	**0.39**	**0.23**	0.12	0.12	**1.00**		
$GDVI_3$^2	0.12	**0.43**	**0.30**	0.12	**0.56**	**0.15**	**0.16**	**0.36**	**0.45**	**0.23**	0.13	0.13	**0.94**	**0.94**	
$GDVI_3$^3	**0.23**	**0.51**	**0.54**	**0.21**	**0.53**	**0.58**	**0.20**	**0.50**	**0.26**	-0.03	**0.26**	**0.28**	**0.30**	**0.30**	**0.33**
$GDVI_3$^4	**0.29**	**0.54**	**0.46**	**0.27**	**0.52**	**0.52**	**0.26**	**0.50**	**0.24**	**-0.15**	**0.33**	**0.34**	**0.23**	**0.23**	**0.25**
GLI_1	**0.34**	**0.55**	**0.37**	**0.32**	**0.48**	**0.45**	**0.31**	**0.47**	**0.21**	**-0.25**	**0.37**	**0.39**	**0.14**	**0.14**	**0.16**
GLI_2	**0.93**	**0.49**	0.09	**0.92**	**0.43**	**0.31**	**0.92**	**0.37**	0.09	**-0.48**	**0.94**	**0.93**	**0.14**	**0.14**	**0.15**
GLI_3	**0.38**	**0.78**	0.12	**0.36**	**0.73**	0.09	**0.37**	**0.55**	0.11	-0.12	**0.40**	**0.41**	**0.59**	**0.59**	**0.54**
EVI_1	**0.28**	**0.67**	**0.69**	**0.28**	**0.54**	**0.57**	**0.23**	**0.34**	**-0.37**	**0.27**	**0.28**	**0.28**	**0.22**	**0.22**	**0.19**
EVI_2	**1.00**	**0.52**	0.09	**1.00**	**0.38**	**0.30**	**0.99**	**0.32**	**0.18**	**-0.58**	**0.98**	**0.97**	0.10	0.10	0.13
EVI_3	**0.20**	**0.55**	**0.16**	**0.17**	**0.87**	0.11	**0.23**	**0.79**	**0.42**	0.08	**0.23**	**0.24**	**0.90**	**0.90**	**0.77**
$GRVI_1$	**0.27**	**0.16**	0.05	**0.27**	**0.28**	0.11	**0.32**	**0.43**	**0.92**	**-0.23**	**0.26**	**0.24**	**0.50**	**0.50**	**0.60**
$GRVI_2$	**0.97**	**0.53**	0.10	**0.97**	**0.34**	**0.27**	**0.96**	**0.24**	0.08	**-0.50**	**0.96**	**0.95**	0.05	0.05	0.10
$GRVI_3$	**0.58**	**0.96**	**0.29**	**0.56**	**0.77**	**0.27**	**0.54**	**0.60**	-0.03	**-0.17**	**0.59**	**0.59**	**0.44**	**0.44**	**0.42**
$ENDVI_1$	**0.14**	**0.49**	**0.98**	**0.14**	**0.33**	**0.85**	0.08	**0.20**	**-0.35**	**0.25**	**0.14**	**0.15**	**0.18**	**0.18**	**0.27**
$ENDVI_2$	**0.89**	**0.55**	0.10	**0.88**	**0.52**	**0.32**	**0.92**	**0.49**	**0.34**	**-0.56**	**0.90**	**0.90**	**0.39**	**0.39**	**0.36**
$ENDVI_3$	**0.29**	**0.64**	**0.14**	**0.25**	**0.86**	**0.18**	**0.28**	**0.93**	**0.16**	-0.08	**0.34**	**0.36**	**0.56**	**0.56**	**0.39**
$\%GC_1$	**0.37**	**0.58**	**0.51**	**0.35**	**0.64**	**0.51**	**0.38**	**0.67**	**0.52**	**-0.17**	**0.40**	**0.40**	**0.53**	**0.53**	**0.54**
$\%GC_2$	**0.96**	**0.52**	0.06	**0.95**	**0.46**	**0.27**	**0.98**	**0.41**	**0.32**	**-0.60**	**0.96**	**0.95**	**0.26**	**0.26**	**0.25**
$\%GC_3$	0.10	**0.36**	0.06	0.07	**0.76**	0.05	0.13	**0.85**	**0.46**	0.03	**0.14**	**0.15**	**0.73**	**0.73**	**0.58**
$NDVI_2$	**0.15**	-0.08	**-0.41**	**0.15**	0.13	**-0.27**	**0.23**	**0.29**	**0.99**	**-0.29**	**0.14**	0.13	**0.36**	**0.36**	**0.39**

Table A3 Continued

	$GDVI_3$^2	$GDVI_3$^3	$GDVI_3$^4	GLI_1	GLI_2	GLI_3	EVI_1	EVI_2	EVI_3	$GRVI_1$	$GRVI_2$	$GRVI_3$	$ENDVI_1$	$ENDVI_2$	$ENDVI_3$	$\%GC_1$	$\%GC_2$
$GDVI_3$^3	**0.98**																
$GDVI_3$^4	**0.92**	**0.98**															
GLI_1	**0.23**	**0.27**	**0.29**														
GLI_2	**0.41**	**0.49**	**0.54**	**0.30**													
GLI_3	**0.34**	**0.27**	**0.20**	**0.27**	**0.21**												
EVI_1	**0.20**	**0.26**	**0.31**	**0.92**	**0.34**	**0.27**											
EVI_2	**0.44**	**0.38**	**0.31**	**0.24**	**0.63**	**0.29**	**0.18**										
EVI_3	**0.38**	**0.35**	**0.29**	**0.21**	**0.18**	-0.10	**0.29**	**0.52**									
$GRVI_1$	**0.19**	**0.25**	**0.30**	**0.95**	**0.32**	**0.30**	**0.97**	0.11	**0.19**								
$GRVI_2$	**0.41**	**0.48**	**0.52**	**0.51**	**0.87**	**0.54**	**0.55**	**0.53**	0.13	**0.54**							
$GRVI_3$	**0.55**	**0.47**	**0.39**	**0.14**	**0.17**	**0.78**	0.12	**0.18**	-0.03	**0.14**	**0.37**						
$ENDVI_1$	**0.35**	**0.40**	**0.42**	**0.84**	**0.54**	**0.15**	**0.88**	**0.47**	**0.43**	**0.82**	**0.57**	0.10					
$ENDVI_2$	**0.42**	**0.41**	**0.38**	**0.40**	**0.59**	**0.35**	**0.25**	**0.81**	**0.25**	**0.21**	**0.62**	**0.19**	**0.44**				
$ENDVI_3$	**0.73**	**0.68**	**0.60**	**0.34**	**0.36**	**0.43**	**0.38**	**0.66**	**0.71**	**0.30**	**0.45**	**0.48**	**0.53**	**0.54**			
$\%GC_1$	**0.27**	**0.33**	**0.36**	**0.89**	**0.43**	**0.21**	**0.96**	**0.35**	**0.40**	**0.91**	**0.55**	0.08	**0.96**	**0.34**	**0.48**		
$\%GC_2$	**0.36**	**0.30**	**0.22**	**0.18**	**0.43**	**0.14**	0.08	**0.92**	**0.52**	-0.02	**0.33**	0.05	**0.35**	**0.86**	**0.59**	**0.24**	
$\%GC_3$	**0.19**	**0.19**	**0.17**	0.10	0.12	**-0.45**	**0.18**	**0.39**	**0.86**	0.08	-0.06	**-0.47**	**0.34**	**0.15**	**0.43**	**0.32**	**0.44**

Values in bold are different from 0 with a significance level alpha=0.05

Table A4

Regression statistics for individual SVI and field data in year 1 under rainfed (a, b, c) and irrigated (d, e, f) conditions. Subscript imply growth stages 1, 2, 3 as tillering, jointing, and heading; R^2: r squared coefficient of determination; Adj R^2: adjusted r squared; AIC: Akaike information criterion; BIC: Sawa's Bayesian information criterion; RMSE: root mean square error; SBC: Schwarz criterion; SSE: sum of square error of prediction. All R^2 are significant at 0.05.

a) Aboveground biomass at jointing (Rainfed)								
Indices	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE
$\%GC_1$	0.19	0.14	156.38	152.38	2262	47.56	158.37	40724
$GDVI_1$^4	0.16	0.11	157.20	153.20	2357	48.55	159.19	42426
$GDVI_1$^3	0.15	0.11	157.27	153.27	2366	48.64	159.26	42581
EVI_1	0.12	0.07	157.97	153.97	2451	49.50	159.97	44111
$NDVI_1$	0.12	0.07	158.10	154.10	2467	49.66	160.10	44397
DVI_1	0.12	0.07	158.12	154.12	2469	49.69	160.12	44441
$GRVI_1$	0.10	0.05	158.45	154.45	2510	50.10	160.45	45181
GLI_1	0.08	0.03	158.98	154.98	2577	50.77	160.97	46390
RVI_1	0.07	0.02	159.11	155.11	2594	50.93	161.10	46695
$ENDVI_3$	0.07	0.02	159.16	155.16	2600	50.99	161.15	46795
$GDVI_1$^2	0.06	0.00	159.42	155.42	2634	51.33	161.41	47417
$ENDVI_2$	0.04	-0.01	159.77	155.77	2681	51.78	161.76	48261
$GDVI_3$^3	0.03	-0.03	160.05	156.05	2719	52.14	162.04	48941
$GDVI_3$^4	0.03	-0.03	160.06	156.06	2720	52.15	162.05	48955
$GDVI_3$^2	0.02	-0.03	160.12	156.12	2729	52.24	162.12	49115
$GRVI_2$	0.02	-0.03	160.16	156.16	2734	52.29	162.16	49216
DVI_2	0.02	-0.04	160.19	156.19	2738	52.32	162.18	49280
$ENDVI_1$	0.01	-0.04	160.32	156.32	2755	52.49	162.31	49591
$GDVI_2$^4	0.01	-0.04	160.35	156.35	2759	52.53	162.34	49669
$GDVI_2$^3	0.01	-0.05	160.38	156.38	2764	52.58	162.37	49755
$GDVI_2$^2	0.01	-0.05	160.42	156.42	2770	52.63	162.41	49851
$NDVI_3$	0.01	-0.05	160.43	156.43	2771	52.64	162.43	49885
GLI_3	0.01	-0.05	160.46	156.46	2774	52.67	162.45	49939
GLI_2	0.01	-0.05	160.46	156.46	2775	52.68	162.45	49947
DVI_3	0.00	-0.05	160.50	156.50	2780	52.73	162.49	50047
RVI_2	0.00	-0.05	160.51	156.51	2781	52.74	162.50	50067
$GRVI_3$	0.00	-0.05	160.53	156.53	2785	52.77	162.52	50130
$\%GC_2$	0.00	-0.05	160.54	156.54	2787	52.79	162.54	50158
RVI_3	0.00	-0.05	160.55	156.55	2788	52.80	162.54	50177
$NDVI_2$	0.00	-0.05	160.56	156.56	2789	52.81	162.55	50202
EVI_3	0.00	-0.05	160.56	156.56	2789	52.81	162.56	50209
EVI_2	0.00	-0.06	160.57	156.57	2790	52.82	162.56	50226
$\%GC_3$	0.00	-0.06	160.58	156.58	2791	52.83	162.57	50237

Table A4 Continued

b) Aboveground biomass at anthesis (Rainfed)								
Indices	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE
RVI_2	0.41	0.38	187.73	183.73	10851	104.17	189.72	195311
$GDVI_2$^2	0.38	0.35	188.67	184.67	11373	106.64	190.66	204711
$GDVI_2$^3	0.35	0.32	189.46	185.46	11832	108.78	191.46	212983
EVI_2	0.34	0.31	189.77	185.77	12015	109.61	191.76	216277
$GDVI_2$^4	0.32	0.29	190.41	186.41	12403	111.37	192.40	223247
DVI_2	0.28	0.24	191.73	187.73	13249	115.10	193.72	238476
$GRVI_2$	0.27	0.23	191.91	187.91	13368	115.62	193.90	240626
GLI_2	0.21	0.17	193.42	189.42	14422	120.09	195.41	259589
$GDVI_1$^4	0.19	0.15	194.01	190.01	14848	121.85	196.00	267262
%GC_1	0.19	0.14	194.05	190.05	14883	122.00	196.04	267901
$GDVI_1$^3	0.17	0.13	194.40	190.40	15144	123.06	196.39	272586
$GDVI_3$^3	0.14	0.10	195.10	191.10	15683	125.23	197.09	282296
$GDVI_3$^2	0.14	0.10	195.11	191.11	15692	125.27	197.10	282462
%GC_2	0.14	0.10	195.15	191.15	15719	125.37	197.14	282940
$ENDVI_2$	0.14	0.09	195.22	191.22	15781	125.62	197.22	284066
$NDVI_1$	0.14	0.09	195.26	191.26	15806	125.72	197.25	284515
EVI_1	0.14	0.09	195.27	191.27	15818	125.77	197.26	284717
$GDVI_3$^4	0.14	0.09	195.33	191.33	15865	125.96	197.32	285565
RVI_1	0.12	0.07	195.63	191.63	16103	126.90	197.62	289856
GLI_1	0.12	0.07	195.76	191.76	16213	127.33	197.76	291841
$ENDVI_3$	0.11	0.06	196.00	192.00	16409	128.10	198.00	295368
$GRVI_3$	0.10	0.06	196.02	192.02	16419	128.14	198.01	295544
$NDVI_3$	0.10	0.05	196.07	192.07	16464	128.31	198.06	296344
DVI_1	0.10	0.05	196.16	192.16	16536	128.59	198.15	297643
$GRVI_1$	0.09	0.04	196.29	192.29	16649	129.03	198.29	299683
EVI_3	0.08	0.03	196.46	192.46	16788	129.57	198.45	302191
RVI_3	0.07	0.02	196.69	192.69	16978	130.30	198.68	305599
$ENDVI_1$	0.07	0.02	196.77	192.77	17049	130.57	198.76	306891
GLI_3	0.07	0.02	196.83	192.83	17103	130.78	198.82	307852
DVI_3	0.04	-0.01	197.42	193.42	17616	132.73	199.42	317089
%GC_3	0.01	-0.05	198.10	194.10	18224	135.00	200.09	328034
$NDVI_2$	0.00	-0.05	198.17	194.17	18287	135.23	200.16	329169
$GDVI_1$^2	0.00	-0.06	198.23	194.23	18340	135.43	200.22	330119

Table A4 Continued

c) Percent ground cover at jointing (Rainfed)								
Indices	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE
$ENDVI_2$	0.43	0.40	86.47	82.47	68.64	8.29	88.46	1236
GLI_2	0.31	0.27	90.22	86.22	82.78	9.10	92.21	1490
$GDVI_1$^4	0.30	0.26	90.41	86.41	83.60	9.14	92.41	1505
$\%GC_2$	0.27	0.23	91.37	87.37	87.69	9.36	93.36	1578
$GDVI_1$^3	0.26	0.22	91.61	87.61	88.75	9.42	93.60	1598
$GRVI_2$	0.25	0.21	91.88	87.88	89.95	9.48	93.87	1619
$\%GC_1$	0.23	0.19	92.35	88.35	92.09	9.60	94.34	1658
$GRVI_3$	0.23	0.18	92.50	88.50	92.80	9.63	94.49	1670
DVI_2	0.22	0.17	92.75	88.75	93.96	9.69	94.74	1691
EVI_2	0.22	0.17	92.80	88.80	94.19	9.71	94.79	1695
$GDVI_2$^2	0.21	0.16	92.96	88.96	94.95	9.74	94.95	1709
RVI_2	0.20	0.16	93.07	89.07	95.47	9.77	95.06	1718
RVI_3	0.20	0.16	93.15	89.15	95.85	9.79	95.14	1725
$GDVI_2$^3	0.20	0.15	93.21	89.21	96.17	9.81	95.21	1731
$NDVI_3$	0.20	0.15	93.28	89.28	96.49	9.82	95.27	1737
RVI_1	0.19	0.14	93.47	89.47	97.42	9.87	95.46	1753
$GDVI_2$^4	0.18	0.14	93.65	89.65	98.27	9.91	95.64	1769
EVI_3	0.18	0.13	93.80	89.80	99.01	9.95	95.79	1782
$ENDVI_1$	0.16	0.12	94.07	90.07	100.36	10.02	96.06	1806
$NDVI_1$	0.16	0.11	94.15	90.15	100.79	10.04	96.14	1814
EVI_1	0.15	0.11	94.33	90.33	101.69	10.08	96.32	1830
GLI_1	0.15	0.10	94.44	90.44	102.27	10.11	96.44	1841
DVI_1	0.15	0.10	94.49	90.49	102.50	10.12	96.48	1845
DVI_3	0.14	0.10	94.57	90.57	102.89	10.14	96.56	1852
GLI_3	0.12	0.07	95.04	91.04	105.36	10.26	97.03	1897
$GRVI_1$	0.10	0.05	95.57	91.57	108.19	10.40	97.56	1947
$GDVI_3$^2	0.08	0.03	96.01	92.01	110.61	10.52	98.00	1991
$ENDVI_3$	0.06	0.01	96.40	92.40	112.75	10.62	98.39	2029
$GDVI_1$^2	0.05	0.00	96.64	92.64	114.13	10.68	98.63	2054
$GDVI_3$^3	0.05	-0.01	96.69	92.69	114.39	10.70	98.68	2059
$GDVI_3$^4	0.02	-0.03	97.21	93.21	117.45	10.84	99.20	2114
$\%GC_3$	0.02	-0.03	97.24	93.24	117.61	10.84	99.23	2117
$NDVI_2$	0.01	-0.04	97.36	93.36	118.29	10.88	99.35	2129

Table A4 Continued

d) Aboveground biomass at jointing (Irrigated)								
Indices	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE
$GRVI_1$	0.68	0.67	138.62	134.62	931	30.51	140.61	16760
GLI_1	0.68	0.66	138.74	134.74	937	30.60	140.73	16859
RVI_1	0.63	0.61	141.70	137.70	1086	32.96	143.69	19553
EVI_1	0.62	0.60	142.32	138.32	1120	33.47	144.31	20164
DVI_3	0.62	0.60	142.36	138.36	1123	33.51	144.35	20209
$\%GC_1$	0.62	0.60	142.42	138.42	1126	33.56	144.41	20269
DVI_1	0.62	0.60	142.45	138.45	1128	33.58	144.44	20296
$ENDVI_1$	0.61	0.59	142.61	138.61	1137	33.71	144.60	20461
$GRVI_2$	0.61	0.59	142.75	138.75	1145	33.84	144.75	20608
$NDVI_1$	0.61	0.58	143.09	139.09	1165	34.13	145.09	20962
$GDVI_1$^2	0.59	0.56	143.97	139.97	1217	34.88	145.96	21898
$\%GC_3$	0.57	0.55	144.73	140.73	1264	35.55	146.72	22745
$GDVI_1$^3	0.57	0.54	145.02	141.02	1282	35.81	147.01	23080
$\%GC_2$	0.55	0.53	145.55	141.55	1317	36.28	147.54	23698
$GDVI_1$^4	0.54	0.52	146.07	142.07	1351	36.76	148.06	24325
EVI_2	0.50	0.48	147.68	143.68	1465	38.27	149.67	26361
EVI_3	0.49	0.46	148.23	144.23	1506	38.81	150.23	27105
DVI_2	0.45	0.42	149.83	145.83	1631	40.38	151.82	29357
RVI_2	0.42	0.38	150.90	146.90	1720	41.48	152.89	30968
$NDVI_2$	0.41	0.38	151.10	147.10	1738	41.69	153.09	31281
$GDVI_2$^2	0.37	0.33	152.57	148.57	1870	43.25	154.56	33668
$ENDVI_2$	0.34	0.31	153.30	149.30	1939	44.04	155.29	34911
$GDVI_2$^3	0.32	0.28	154.07	150.07	2016	44.90	156.06	36289
GLI_3	0.23	0.18	156.56	152.56	2283	47.78	158.55	41095
GLI_2	0.22	0.18	156.67	152.67	2296	47.91	158.66	41320
$GDVI_3$^2	0.15	0.10	158.46	154.46	2511	50.11	160.45	45202
$NDVI_3$	0.12	0.07	159.18	155.18	2603	51.02	161.17	46851
$ENDVI_3$	0.10	0.06	159.47	155.47	2641	51.39	161.46	47539
$GDVI_3$^3	0.08	0.03	159.95	155.95	2705	52.01	161.94	48685
$GRVI_3$	0.08	0.03	159.97	155.97	2708	52.04	161.97	48749
RVI_3	0.08	0.03	160.00	156.00	2712	52.08	161.99	48820
$GDVI_3$^4	0.05	-0.01	160.74	156.74	2813	53.04	162.73	50643
$GDVI_2$^4	0.03	-0.03	161.10	157.10	2865	53.53	163.09	51579

Table A4 Continued

e) Aboveground biomass at anthesis (Irrigated)								
Indices	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE
RVI_1	0.37	0.33	204.40	200.40	24970	158.02	206.39	449454
GLI_1	0.36	0.33	204.52	200.52	25123	158.50	206.52	452219
EVI_1	0.35	0.31	204.97	200.97	25689	160.28	206.96	462401
DVI_1	0.35	0.31	205.01	201.01	25738	160.43	207.00	463289
$\%GC_2$	0.34	0.30	205.31	201.31	26129	161.64	207.30	470321
$ENDVI_1$	0.34	0.30	205.31	201.31	26132	161.65	207.30	470374
$NDVI_1$	0.34	0.30	205.33	201.33	26160	161.74	207.32	470880
$GRVI_1$	0.33	0.29	205.59	201.59	26495	162.77	207.58	476912
EVI_3	0.32	0.29	205.69	201.69	26629	163.18	207.68	479318
$GDVI_2$^2	0.32	0.28	205.87	201.87	26879	163.95	207.87	483813
$\%GC_3$	0.31	0.28	205.99	201.99	27038	164.43	207.98	486683
$ENDVI_3$	0.31	0.27	206.09	202.09	27172	164.84	208.08	489103
$GDVI_4$^2	0.30	0.27	206.26	202.26	27408	165.55	208.26	493338
$GDVI_2$^3	0.29	0.25	206.56	202.56	27818	166.79	208.55	500719
EVI_2	0.28	0.24	206.88	202.88	28265	168.12	208.87	508774
$GDVI_2$^4	0.27	0.23	207.26	203.26	28803	169.72	209.25	518463
$GDVI_4$^3	0.26	0.22	207.44	203.44	29067	170.49	209.43	523199
DVI_2	0.23	0.19	208.16	204.16	30131	173.58	210.15	542360
$NDVI_3$	0.22	0.18	208.45	204.45	30578	174.87	210.45	550412
$GDVI_3$^3	0.22	0.18	208.46	204.46	30582	174.88	210.45	550478
$GDVI_4$^4	0.22	0.18	208.47	204.47	30602	174.93	210.46	550828
$GDVI_3$^2	0.22	0.17	208.66	204.66	30902	175.79	210.66	556243
GLI_3	0.21	0.16	208.84	204.84	31171	176.55	210.83	561078
DVI_3	0.20	0.16	208.93	204.93	31322	176.98	210.93	563801
RVI_3	0.20	0.16	209.04	205.04	31482	177.43	211.03	566671
$NDVI_2$	0.20	0.15	209.10	205.10	31576	177.70	211.09	568370
$GRVI_3$	0.18	0.14	209.48	205.48	32189	179.41	211.47	579405
$ENDVI_2$	0.15	0.10	210.24	206.24	33443	182.88	212.24	601980
RVI_2	0.14	0.10	210.39	206.39	33694	183.56	212.39	606496
$GRVI_2$	0.14	0.10	210.41	206.41	33719	183.63	212.40	606951
$\%GC_4$	0.12	0.07	211.01	207.01	34749	186.41	213.00	625490
GLI_2	0.08	0.03	211.76	207.76	36084	189.96	213.76	649506
$GDVI_3$^4	0.06	0.00	212.36	208.36	37179	192.82	214.35	669224

Table A4 Continued

f) Percent ground cover at jointing (Irrigated)								
Indices	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE
$GDVI_1$^2	0.84	0.84	42.52	38.52	7.63	2.76	44.51	137.26
$GDVI_1$^3	0.84	0.83	42.84	38.84	7.75	2.78	44.83	139.43
$NDVI_1$	0.84	0.83	42.89	38.89	7.77	2.79	44.89	139.84
DVI_1	0.84	0.83	43.39	39.39	7.96	2.82	45.38	143.32
EVI_1	0.83	0.82	43.84	39.84	8.14	2.85	45.83	146.60
$GDVI_1$^4	0.83	0.82	44.15	40.15	8.27	2.88	46.14	148.91
$\%GC_1$	0.83	0.82	44.69	40.69	8.50	2.92	46.68	152.99
RVI_1	0.82	0.81	45.21	41.21	8.72	2.95	47.20	156.97
$ENDVI_1$	0.81	0.80	45.92	41.92	9.04	3.01	47.91	162.68
GLI_1	0.81	0.80	46.56	42.56	9.33	3.05	48.55	167.95
$GRVI_1$	0.79	0.78	48.30	44.30	10.18	3.19	50.29	183.24
EVI_2	0.75	0.74	51.79	47.79	12.12	3.48	53.78	218.15
$\%GC_2$	0.68	0.66	57.09	53.09	15.80	3.97	59.08	284.35
DVI_2	0.64	0.62	59.08	55.08	17.45	4.18	61.07	314.11
$NDVI_2$	0.55	0.53	63.47	59.47	21.73	4.66	65.46	391.20
$GDVI_2$^2	0.53	0.50	64.59	60.59	22.99	4.79	66.58	413.80
$GRVI_2$	0.53	0.50	64.65	60.65	23.06	4.80	66.64	415.01
RVI_2	0.48	0.45	66.75	62.75	25.61	5.06	68.75	461.04
$GDVI_2$^3	0.47	0.44	66.89	62.89	25.78	5.08	68.88	464.11
DVI_3	0.39	0.36	69.74	65.74	29.73	5.45	71.73	535.13
$ENDVI_2$	0.35	0.32	70.90	66.90	31.51	5.61	72.89	567.27
$\%GC_3$	0.34	0.31	71.23	67.23	32.04	5.66	73.22	576.68
EVI_3	0.32	0.28	71.99	67.99	33.28	5.77	73.98	599.08
GLI_2	0.31	0.27	72.33	68.33	33.85	5.82	74.32	609.33
$GDVI_3$^2	0.30	0.26	72.48	68.48	34.09	5.84	74.47	613.69
$GDVI_3$^3	0.22	0.17	74.79	70.79	38.27	6.19	76.78	688.90
GLI_3	0.21	0.16	75.05	71.05	38.79	6.23	77.05	698.14
$GDVI_3$^4	0.16	0.11	76.22	72.22	41.11	6.41	78.21	739.94
$NDVI_3$	0.15	0.10	76.49	72.49	41.68	6.46	78.48	750.16
RVI_3	0.12	0.08	77.01	73.01	42.78	6.54	79.00	769.97
$GRVI_3$	0.11	0.06	77.42	73.42	43.67	6.61	79.42	785.97
$ENDVI_3$	0.07	0.02	78.12	74.12	45.21	6.72	80.11	813.73
$GDVI_2$^4	0.01	-0.04	79.39	75.39	48.18	6.94	81.38	867.22

Table A5

Regression statistics for individual SVI and field data in year 2 under rainfed (a, b, c) and irrigated (d, e, f) conditions. Subscript imply growth stages 1, 2, 3 as tillering, jointing, and heading; R^2: r squared coefficient of determination; Adj R^2: adjusted r squared; AIC: Akaike information criterion; BIC: Sawa's Bayesian information criterion; RMSE: root mean square error; SBC: Schwarz criterion; SSE: sum of square error of prediction. All R^2 are significant at <0.01.

a) Aboveground biomass at anthesis (Rainfed)								
Indices	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE
GLI_2	0.13	0.08	190.25	186.25	12304	110.92	192.24	221465
$ENDVI_1$	0.12	0.08	190.43	186.43	12416	111.43	192.42	223492
GLI_3	0.09	0.04	191.11	187.11	12844	113.33	193.10	231188
DVI_3	0.09	0.04	191.27	187.27	12949	113.79	193.26	233076
$\%GC_1$	0.08	0.03	191.42	187.42	13049	114.23	193.41	234886
$GRVI_2$	0.07	0.02	191.65	187.65	13201	114.90	193.65	237618
$GRVI_3$	0.07	0.01	191.74	187.74	13257	115.14	193.73	238620
RVI_1	0.06	0.01	191.83	187.83	13318	115.40	193.82	239715
$\%GC_3$	0.06	0.01	191.87	187.87	13343	115.51	193.86	240171
$NDVI_1$	0.06	0.01	191.88	187.88	13349	115.54	193.87	240291
$GDVI_1$^3	0.05	0.00	191.98	187.98	13415	115.83	193.97	241479
$GDVI_1$^4	0.05	0.00	192.04	188.04	13460	116.02	194.03	242278
$ENDVI_2$	0.05	-0.01	192.12	188.12	13513	116.25	194.11	243242
$ENDVI_3$	0.03	-0.02	192.41	188.41	13708	117.08	194.40	246749
GLI_1	0.03	-0.02	192.41	188.41	13710	117.09	194.40	246772
EVI_1	0.03	-0.02	192.46	188.46	13745	117.24	194.45	247404
$GRVI_1$	0.03	-0.03	192.53	188.53	13789	117.43	194.52	248203
$GDVI_1$^2	0.03	-0.03	192.54	188.54	13800	117.47	194.53	248402
RVI_3	0.02	-0.04	192.77	188.77	13961	118.16	194.77	251302
$NDVI_3$	0.01	-0.04	192.84	188.84	14010	118.36	194.83	252173
EVI_3	0.01	-0.04	192.86	188.86	14022	118.41	194.85	252392
DVI_1	0.01	-0.05	192.90	188.90	14049	118.53	194.89	252873
$GDVI_2$^4	0.01	-0.05	192.95	188.95	14082	118.67	194.94	253468
$\%GC_2$	0.01	-0.05	192.95	188.95	14082	118.67	194.94	253479
EVI_2	0.00	-0.05	193.01	189.01	14127	118.86	195.00	254282
RVI_2	0.00	-0.05	193.04	189.04	14145	118.93	195.03	254611
$GDVI_2$^3	0.00	-0.05	193.04	189.04	14146	118.94	195.03	254623
$GDVI_3$^2	0.00	-0.05	193.06	189.06	14165	119.02	195.06	254973
DVI_2	0.00	-0.05	193.08	189.08	14176	119.06	195.07	255169
$GDVI_3$^3	0.00	-0.06	193.08	189.08	14179	119.07	195.07	255216
$GDVI_2$^2	0.00	-0.06	193.08	189.08	14179	119.08	195.08	255229
$NDVI_2$	0.00	-0.06	193.09	189.09	14182	119.09	195.08	255270
$GDVI_3$^4	0.00	-0.06	193.09	189.09	14184	119.10	195.08	255309

Table A5 Continued

b) Yield (Rainfed)								
Indices	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE
$GDVI_3$^2	0.42	0.39	130.63	126.63	625	24.99	132.63	11242
$GDVI_3$^3	0.39	0.35	131.72	127.72	659	25.68	133.71	11867
$GDVI_3$^4	0.35	0.31	133.05	129.05	705	26.55	135.04	12685
$\%GC_3$	0.21	0.17	136.73	132.73	847	29.11	138.72	15249
$NDVI_3$	0.15	0.11	138.19	134.19	911	30.18	140.18	16400
RVI_3	0.15	0.10	138.34	134.34	918	30.30	140.33	16527
DVI_3	0.14	0.09	138.59	134.59	930	30.49	140.58	16737
EVI_3	0.14	0.09	138.61	134.61	930	30.50	140.60	16749
DVI_2	0.13	0.08	138.81	134.81	940	30.66	140.81	16923
$GDVI_1$^2	0.10	0.05	139.40	135.40	968	31.11	141.39	17426
$\%GC_1$	0.09	0.04	139.58	135.58	977	31.26	141.57	17585
$ENDVI_3$	0.07	0.02	139.98	135.98	997	31.57	141.97	17941
$ENDVI_2$	0.06	0.01	140.21	136.21	1008	31.75	142.20	18145
$GDVI_1$^4	0.06	0.01	140.22	136.22	1008	31.76	142.21	18152
$GDVI_1$^3	0.06	0.01	140.25	136.25	1010	31.78	142.24	18184
$NDVI_1$	0.06	0.00	140.36	136.36	1016	31.87	142.35	18279
EVI_1	0.05	0.00	140.42	136.42	1019	31.92	142.41	18334
RVI_1	0.05	0.00	140.45	136.45	1020	31.95	142.45	18369
$GRVI_1$	0.05	-0.01	140.58	136.58	1027	32.04	142.57	18484
GLI_1	0.04	-0.02	140.77	136.77	1037	32.20	142.76	18665
DVI_1	0.03	-0.02	140.90	136.90	1043	32.30	142.89	18781
RVI_2	0.02	-0.03	141.13	137.13	1056	32.49	143.12	19001
$GRVI_2$	0.02	-0.04	141.18	137.18	1058	32.53	143.17	19046
$GDVI_2$^4	0.02	-0.04	141.18	137.18	1058	32.53	143.17	19049
$NDVI_2$	0.02	-0.04	141.19	137.19	1059	32.54	143.18	19059
$GDVI_2$^3	0.02	-0.04	141.20	137.20	1060	32.55	143.20	19071
$GDVI_2$^2	0.02	-0.04	141.21	137.21	1060	32.55	143.20	19077
GLI_3	0.01	-0.04	141.24	137.24	1061	32.58	143.23	19105
EVI_2	0.01	-0.04	141.33	137.33	1066	32.65	143.32	19187
$ENDVI_1$	0.01	-0.05	141.38	137.38	1069	32.69	143.37	19237
$GRVI_3$	0.00	-0.06	141.52	137.52	1076	32.81	143.51	19371
$\%GC_2$	0.00	-0.06	141.52	137.52	1077	32.81	143.52	19379
GLI_2	0.00	-0.06	141.53	137.53	1077	32.81	143.52	19381

Table A5 Continued

c) Percent ground cover at jointing (Rainfed)								
Indices	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE
EVI_1	0.64	0.62	7.12	3.12	1.30	1.14	9.11	23.38
DVI_1	0.61	0.59	8.54	4.54	1.39	1.18	10.54	25.10
$GRVI_1$	0.58	0.56	10.03	6.03	1.50	1.23	12.02	27.04
RVI_1	0.58	0.56	10.10	6.10	1.51	1.23	12.09	27.13
$NDVI_1$	0.53	0.50	12.51	8.51	1.70	1.30	14.50	30.60
GLI_1	0.51	0.49	12.96	8.96	1.74	1.32	14.95	31.30
$GDVI_1$^3	0.43	0.40	16.07	12.07	2.03	1.43	18.06	36.57
$GDVI_1$^4	0.38	0.34	17.97	13.97	2.23	1.49	19.96	40.22
%GC_1	0.18	0.14	23.40	19.40	2.93	1.71	25.40	52.77
$ENDVI_1$	0.16	0.11	23.88	19.88	3.00	1.73	25.87	54.04
%GC_3	0.07	0.02	25.99	21.99	3.34	1.83	27.98	60.05
$GRVI_2$	0.06	0.01	26.08	22.08	3.35	1.83	28.07	60.31
DVI_3	0.04	-0.01	26.56	22.56	3.43	1.85	28.55	61.80
$GDVI_1$^2	0.03	-0.03	26.87	22.87	3.49	1.87	28.86	62.76
$GDVI_2$^4	0.02	-0.03	26.96	22.96	3.50	1.87	28.95	63.04
%GC_2	0.02	-0.03	26.99	22.99	3.51	1.87	28.99	63.15
$GDVI_2$^3	0.02	-0.04	27.03	23.03	3.51	1.87	29.02	63.27
GLI_2	0.02	-0.04	27.04	23.04	3.52	1.88	29.04	63.30
DVI_2	0.02	-0.04	27.09	23.09	3.53	1.88	29.08	63.45
$GDVI_2$^2	0.01	-0.04	27.10	23.10	3.53	1.88	29.09	63.48
$GDVI_3$^4	0.01	-0.04	27.10	23.10	3.53	1.88	29.09	63.49
$GDVI_3$^3	0.01	-0.04	27.12	23.12	3.53	1.88	29.11	63.55
$ENDVI_2$	0.01	-0.04	27.13	23.13	3.53	1.88	29.12	63.58
$NDVI_2$	0.01	-0.04	27.15	23.15	3.53	1.88	29.14	63.63
$GDVI_3$^2	0.01	-0.04	27.16	23.16	3.54	1.88	29.15	63.67
$ENDVI_3$	0.01	-0.04	27.18	23.18	3.54	1.88	29.18	63.75
RVI_2	0.01	-0.04	27.19	23.19	3.54	1.88	29.18	63.75
GLI_3	0.01	-0.04	27.19	23.19	3.54	1.88	29.18	63.77
RVI_3	0.01	-0.04	27.20	23.20	3.54	1.88	29.19	63.78
$NDVI_3$	0.01	-0.04	27.20	23.20	3.54	1.88	29.19	63.79
$GRVI_3$	0.01	-0.04	27.20	23.20	3.54	1.88	29.19	63.79
EVI_2	0.01	-0.04	27.20	23.20	3.54	1.88	29.19	63.79
EVI_3	0.01	-0.04	27.20	23.20	3.54	1.88	29.19	63.80

Table A5 Continued

d) Aboveground biomass at anthesis (Irrigated)								
Indices	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE
DVI_3	0.30	0.26	183.77	179.77	14366	119.86	185.66	244227
$\%GC_3$	0.29	0.25	184.06	180.06	14592	120.80	185.95	248057
EVI_3	0.27	0.23	184.55	180.55	14970	122.35	186.44	254484
$GDVI_2$^4	0.17	0.12	187.15	183.15	17171	131.04	189.04	291901
$\%GC_2$	0.16	0.11	187.32	183.32	17317	131.59	189.20	294385
$GDVI_2$^2	0.15	0.10	187.49	183.49	17476	132.20	189.38	297098
$GDVI_2$^3	0.15	0.10	187.49	183.49	17476	132.20	189.38	297098
EVI_2	0.15	0.10	187.59	183.59	17569	132.55	189.48	298679
DVI_2	0.10	0.04	188.71	184.71	18634	136.51	190.60	316780
$GDVI_1$^2	0.08	0.03	189.00	185.00	18924	137.56	190.89	321708
$ENDVI_3$	0.08	0.03	189.03	185.03	18950	137.66	190.92	322153
$ENDVI_1$	0.07	0.02	189.22	185.22	19139	138.34	191.11	325367
$\%GC_1$	0.07	0.02	189.25	185.25	19168	138.45	191.13	325860
DVI_1	0.05	-0.01	189.67	185.67	19598	139.99	191.56	333168
$GDVI_1$^4	0.04	-0.02	189.88	185.88	19817	140.77	191.77	336884
EVI_1	0.04	-0.02	189.88	185.88	19820	140.78	191.77	336932
$GDVI_1$^3	0.04	-0.02	189.90	185.90	19844	140.87	191.79	337340
$NDVI_1$	0.04	-0.02	189.95	185.95	19889	141.03	191.84	338111
RVI_1	0.03	-0.02	189.99	185.99	19933	141.18	191.88	338859
$ENDVI_2$	0.03	-0.03	190.05	186.05	19998	141.42	191.94	339974
GLI_2	0.03	-0.03	190.10	186.10	20053	141.61	191.99	340901
$GRVI_3$	0.02	-0.04	190.24	186.24	20195	142.11	192.13	343323
$NDVI_3$	0.02	-0.04	190.32	186.32	20283	142.42	192.21	344808
RVI_2	0.01	-0.04	190.36	186.36	20327	142.57	192.25	345564
GLI_1	0.01	-0.04	190.37	186.37	20336	142.61	192.26	345716
$GRVI_1$	0.01	-0.05	190.40	186.40	20369	142.72	192.29	346266
GLI_3	0.01	-0.05	190.45	186.45	20425	142.92	192.34	347233
$GRVI_2$	0.01	-0.05	190.51	186.51	20482	143.12	192.39	348197
RVI_3	0.00	-0.06	190.57	186.57	20550	143.35	192.46	349358
$NDVI_2$	0.00	-0.06	190.58	186.58	20560	143.39	192.47	349514
$GDVI_3$^2	0.00	-0.06	190.58	186.58	20565	143.41	192.47	349609
$GDVI_3$^4	0.00	-0.06	190.62	186.62	20603	143.54	192.51	350244
$GDVI_3$^3	0.00	-0.06	190.62	186.62	20604	143.54	192.51	350270

Table A5 Continued

e) Yield (Irrigated)								
Indices	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE
$ENDVI_3$	0.38	0.35	133.34	129.34	715	26.74	135.33	12868
EVI_3	0.30	0.26	135.78	131.78	808	28.42	137.77	14538
$ENDVI_1$	0.28	0.24	136.28	132.28	828	28.78	138.27	14908
$\%GC_1$	0.25	0.21	137.14	133.14	865	29.41	139.14	15567
DVI_3	0.20	0.16	138.35	134.35	919	30.31	140.34	16536
$GDVI_1$^4	0.20	0.16	138.38	134.38	920	30.33	140.37	16560
$GDVI_1$^3	0.19	0.14	138.67	134.67	933	30.55	140.66	16803
DVI_1	0.18	0.14	138.85	134.85	942	30.69	140.84	16957
$NDVI_3$	0.17	0.12	139.21	135.21	959	30.97	141.21	17265
$NDVI_1$	0.17	0.12	139.22	135.22	959	30.97	141.21	17269
EVI_1	0.16	0.11	139.39	135.39	968	31.11	141.38	17419
$\%GC_2$	0.15	0.11	139.53	135.53	975	31.22	141.53	17543
$\%GC_3$	0.15	0.10	139.60	135.60	978	31.27	141.59	17601
RVI_1	0.15	0.10	139.61	135.61	978	31.28	141.60	17610
DVI_2	0.12	0.08	140.23	136.23	1009	31.76	142.22	18161
$GRVI_3$	0.11	0.06	140.63	136.63	1030	32.09	142.62	18532
EVI_2	0.11	0.06	140.65	136.65	1031	32.10	142.64	18553
$GRVI_1$	0.10	0.05	140.80	136.80	1039	32.23	142.79	18693
RVI_3	0.10	0.05	140.81	136.81	1039	32.23	142.80	18699
$GDVI_2$^4	0.10	0.05	140.81	136.81	1039	32.23	142.80	18700
$GDVI_2$^2	0.08	0.03	141.15	137.15	1057	32.51	143.14	19022
$GDVI_2$^3	0.08	0.03	141.15	137.15	1057	32.51	143.14	19022
GLI_3	0.08	0.02	141.32	137.32	1066	32.64	143.31	19181
GLI_1	0.07	0.02	141.38	137.38	1069	32.69	143.37	19239
RVI_2	0.04	-0.01	141.97	137.97	1101	33.18	143.97	19820
$ENDVI_2$	0.03	-0.02	142.25	138.25	1116	33.41	144.24	20092
$GDVI_1$^2	0.03	-0.03	142.36	138.36	1122	33.50	144.35	20204
$GDVI_3$^2	0.02	-0.04	142.52	138.52	1132	33.64	144.51	20370
$GRVI_2$	0.01	-0.05	142.76	138.76	1145	33.84	144.75	20612
$GDVI_3$^3	0.01	-0.05	142.76	138.76	1145	33.85	144.76	20619
GLI_2	0.00	-0.05	142.78	138.78	1146	33.86	144.77	20636
$NDVI_2$	0.00	-0.05	142.79	138.79	1147	33.87	144.78	20648
$GDVI_3$^4	0.00	-0.05	142.85	138.85	1150	33.92	144.84	20705

Table A5 Continued

f) Percent ground cover at jointing (Irrigated)								
Indices	R^2	Adj R^2	AIC	BIC	MSE	RMSE	SBC	SSE
DVI_1	0.95	0.94	2.00	-2.00	1.01	1.00	3.99	18.10
EVI_1	0.94	0.94	4.71	0.71	1.15	1.07	6.70	20.72
$NDVI_1$	0.94	0.93	6.25	2.25	1.24	1.12	8.24	22.38
$\%GC_1$	0.93	0.92	8.45	4.45	1.39	1.18	10.44	24.98
RVI_1	0.93	0.92	9.05	5.05	1.43	1.20	11.04	25.74
$GDVI^1$^3	0.91	0.91	12.12	8.12	1.67	1.29	14.11	30.02
$GDVI_1$^4	0.89	0.88	17.21	13.21	2.15	1.47	19.20	38.71
$GRVI_1$	0.88	0.87	18.43	14.43	2.29	1.51	20.42	41.16
$ENDVI_1$	0.85	0.84	22.65	18.65	2.82	1.68	24.64	50.83
GLI_1	0.80	0.79	28.36	24.36	3.76	1.94	30.35	67.59
RVI_3	0.23	0.19	55.80	51.80	14.81	3.85	57.79	266.58
$ENDVI_3$	0.20	0.15	56.55	52.55	15.37	3.92	58.54	276.72
$GDVI_1$^2	0.17	0.12	57.26	53.26	15.93	3.99	59.25	286.76
$GRVI_2$	0.13	0.08	58.19	54.19	16.69	4.09	60.19	300.50
EVI_3	0.10	0.05	58.85	54.85	17.25	4.15	60.85	310.58
$NDVI_2$	0.08	0.03	59.24	55.24	17.59	4.19	61.23	316.64
$NDVI_3$	0.08	0.03	59.35	55.35	17.69	4.21	61.34	318.34
GLI_2	0.07	0.02	59.52	55.52	17.84	4.22	61.51	321.09
$GRVI_3$	0.07	0.01	59.64	55.64	17.95	4.24	61.64	323.10
$GDVI_3$^4	0.06	0.01	59.73	55.73	18.03	4.25	61.73	324.56
RVI_2	0.05	0.00	59.91	55.91	18.19	4.27	61.91	327.48
$GDVI_3$^3	0.05	0.00	59.97	55.97	18.25	4.27	61.96	328.42
DVI_3	0.04	-0.01	60.09	56.09	18.36	4.28	62.08	330.42
$\%GC_3$	0.04	-0.01	60.20	56.20	18.45	4.30	62.19	332.15
DVI_2	0.04	-0.02	60.24	56.24	18.49	4.30	62.23	332.83
$GDVI_3$^2	0.04	-0.02	60.25	56.25	18.50	4.30	62.24	333.02
GLI_3	0.03	-0.02	60.32	56.32	18.56	4.31	62.31	334.15
$ENDVI_2$	0.02	-0.03	60.51	56.51	18.74	4.33	62.50	337.37
$GDVI_2$^4	0.02	-0.03	60.54	56.54	18.77	4.33	62.53	337.92
EVI_2	0.02	-0.04	60.67	56.67	18.89	4.35	62.66	340.07
$GDVI_2$^2	0.01	-0.04	60.76	56.76	18.98	4.36	62.75	341.57
$GDVI_2$^3	0.01	-0.04	60.76	56.76	18.98	4.36	62.75	341.57
$\%GC_2$	0.00	-0.05	60.94	56.94	19.15	4.38	62.93	344.68