CAN ACTIVE SENSOR BASED NDVI CONSISTENTLY CLASSIFY WHEAT GENOTYPES?

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ABSTRACT

Precision agriculture utilizes advance technologies for improving crop production, enhance efficiency of farm inputs such as that of nitrogen (N) by quantifying and managing in-field variability and increase profit while reducing environmental impact. Remote sensing based indices such as Normalized Difference Vegetative Index (NDVI) can detect biomass and N variability in crop canopies. Active remote sensing tools such as Greenseeker® can measure NDVI using light reflected from crop canopies. The objective of this study was to determine if NDVI readings can consistently identify and classify multiple wheat genotypes into various classes. This study was conducted in north-eastern Colorado in 2009-2010. The NDVI readings were taken weekly on 24 winter wheat genotypes from March to end of June, 2010. The K-means clustering algorithm was used to classify NDVI and grain yield into three classes. Our results indicate more consistent association between grain yield and NDVI later in the season, after anthesis and during mid-grain filling stage. The results indicate that NDVI readings successfully classified multiple wheat genotypes across dryland and irrigated cropping systems. This study demonstrates the potential of using NDVI readings as a promising tool to differentiate and identifying superior wheat genotypes.

Keywords: Precision agriculture, active sensor, normalized difference vegetation index (NDVI), K-means clustering, wheat genotypes, dryland and irrigated.

INTRODUCTION

Precision agriculture (PA) utilizes advance technologies for improving crop production, enhance efficiency of farm inputs such as that of nitrogen (N) by quantifying and managing in-field variability and increase profit while reducing environmental impact. Remote sensing (RS) has become a key component of PA. It is used for monitoring crop development, and can provide nondestructive and rapid estimations of plant biomass, leaf area index (LAI), nitrogen (N) content, and grain yield (Aparicio et al., 2000; Babar et al., 2006). Active remote sensing tools such as Greenseeker® can measure vegetation indexes such as Normalized Difference Vegetative Index (NDVI) and simple ratio using light reflectance from crop canopies. The NDVI is determined by the amount of visible red light (R) and near-infrared light (NIR) that is reflected from the crop canopy. The NDVI value is calculated using the following equation and is referred to as Red NDVI:

$$NDVI= NIR - R / NIR + R, \qquad \text{Eq.1}$$

where R is the reflectance in the visible red light band (wavelengths 600 to 720 nm) from visible (VIS) light band (wavelengths 400 to 720 nm) and NIR is the reflectance in the near-infrared light band (wavelengths 720-1300 nm).

Aparicio et al. (2000) found that the correlation between NDVI and grain yield increased as growth stage progressed from booting to maturity, but it was significant only at the maturity stage (stage 11.4 of the Feekes scale; Large, 1954) for durum wheat under irrigated conditions. They also observed a positive correlation between NDVI and grain yield at all wheat stages under rainfed conditions. Moreover, Reynolds et al. (2001) showed that NDVI was correlated with yield and biomass at the grain filling stage (11.2 stage of the Feekes scale; Large 1954) for spring wheat under irrigated conditions, and suggested the use of NDVI as a fast screening tool for grain yield. Babar et al. (2006) observed red NDVI and other reflectance indices has the potential to differentiate among genotypes at heading to grain filling stages for grain yield under irrigated conditions. Ma et al. (2001) also reported that NDVI could differentiate between high from low grain yield among soybean genotypes. Therefore, they concluded that NDVI can be a reliable and fast index for screening soybean genotypes and estimating grain yield under irrigated conditions. However, review of the literature indicates no previous study was conducted on classification of winter wheat genotypes for grain yield based on the relationship between grain yield and NDVI readings

This study's hypothesis is that it is possible to use NDVI measured by active sensor as a tool to differentiate and classify multiple wheat genotypes. The objective of this study was to determine if NDVI readings can consistently identify and classify multiple wheat genotypes.

MATERIALS AND METHODS

Study sites

This study was conducted in Northeastern Colorado in 2009-2010 winter wheat growing season. The study was located at the USDA-ARS Limited Irrigation Research Farm, near Greeley, Colorado (40˚ 26′ 58.87″ N and -104˚ 38′22.56″ W). The study site was classified as Otera sandy loam (coarse –loamy, mixed superactive, calcareous, mesic Aridic Ustorthents) soil series with 0 to 3 percent slopes (Crabb et al. 1980).The experimental design was a split plot with three replications. Twenty four winter wheat genotypes were planted in experimental plots of 3.7 m x 1.4 m in size with 6 rows and a row spacing of 22.8 cm. Wheat was planted on October 11, 2009 at a rate of 197,600 seeds ha^{-1}. Based on soil analysis, nitrogen fertilizer was applied prior to planting at a rate of 84 kg N ha^{-1} as Urea (46-0-0) and phosphorous fertilizer was applied at a rate of 56 kg P_2O_5 ha^{-1} as Mono-Ammonium Phosphate (11-52-0).

Active remote sensing based NDVI measurements were acquired using Greenseeker® hand held optical sensor (NTech Industries Incorporation, Ukiah, California, USA). The sensor is designed to be held 81 cm to 122 cm above crop canopy (NTech Industries, Inc., 2005). The principles of operation of the Greenseeker® were illustrated in Inman et al. (2005). Measurements were taken holding Greenseeker® unit about 90 cm above the canopy and walking in the center of each wheat plot. Each plot was sensed for approximately two to five seconds, collecting 20 to 50 NDVI readings from each experimental plot. All reflectance measurements were acquired weekly between 10:00 am to 2:00 pm during cloud free days from early spring crop growth stage (March 29, 2010) (between 3 to 4 stages of the Feekes scale; Large 1954) to after mid grain filling wheat growth stage (June 21, 2010) (Fig.1). Statistical analysis (ANOVA) was

Figure 1.Collecting NDVI readings using Greenseeker® hand held optical sensor. Plot boundaries are highlighted with dashed lines.

performed in R statistical software (R Development Core Team., 2010) to determine differences among twenty four wheat genotypes based on grain yield and NDVI readings. The K-means clustering algorithm method was used to classify grain yield and NDVI into three classes (Low, Medium and High). The NDVI values were classified for three periods: early-season (stages 3-4 at Feekes scale), mid-season (stages 6-10.3 at Feekes scale), and late-season (stages 10.5-11.2 at Feekes scale; Large 1954). Grain yield classes were compared against NDVI classes to build contingency tables for each of these three periods. Kappa statistics were calculated for each contingency table to measure the agreement between grain yield and NDVI.

RESULTS AND DISCUSSION

NDVI Readings and Effects Growth Stages

Statistical analysis results from ANOVA showed significant differences among twenty four wheat genotypes ($p < 0.001$) based on NDVI readings. Differences were observed at 11 dates and at different growth stages from early spring, jointing, anthesis, and to mid grain filling under Irrigated and dryland conditions. As expected, the NDVI values were low at the early winter wheat crop growth stages (March 29th). The mean NDVI values were 0.21 and 0.20 under dryland and irrigated conditions (Fig. 1.2). The NDVI values gradually increased with crop growth stages and reached a plateau in midseason, between jointing to anthesis growth stages (between 6 to 10.5 stages of the Feekes scale; Large 1954). The mean NDVI values at mid-season were of 0.82 and 0.90 respectively for dryland and irrigated experiments. The NDVI values decreased at the end of the season (in June, at anthesis to mid grain filling crop stages) (between 10.5 to 11.2 stages of the Feekes scale; Large 1954). The mean NDVI values at late season were of 0.31 and 0.59 on respectively for dryland and irrigated experiments as illustrated in Fig.1.2.

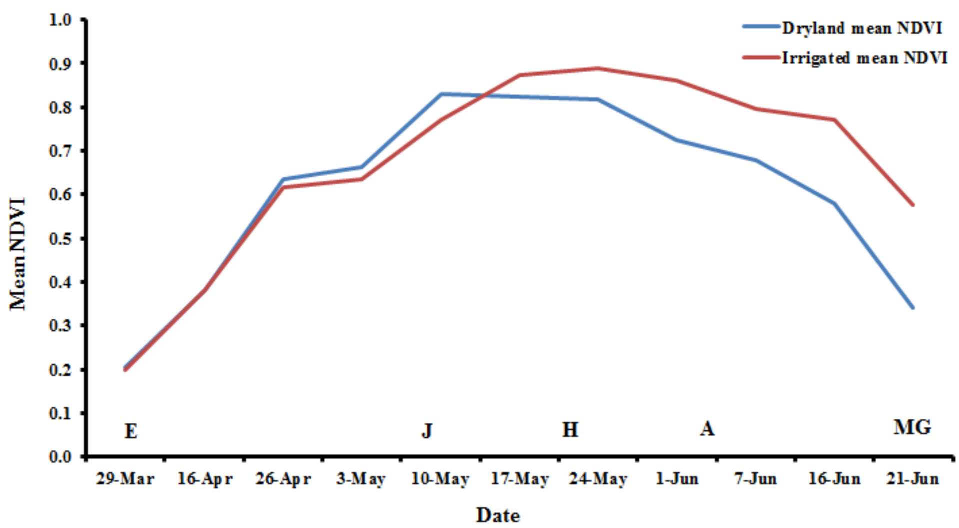

Figure1.2. Mean NDVI values for individual winter wheat genotype selected across the growing season under irrigated and dryland conditions for 11 dates for NDVI readings. Critical growth stages are indicated on the graph as E=early spring, J= jointing, H= heading, A= anthesis, and MG= mid grain filling.

The results indicate that the NDVI values consistently increased in early season with increasing crop growth stages. The NDVI values reached a plateau in midseason and decreased at the end of the crop growing season. The NDVI values decreased from anthesis to mid grain filling because reflectance from red band increased and reflectance from NIR band decreased. Low NDVI values could be attributed to crop vegetation under stress and reduction in the amount of green biomass with the progression of crop growth stages from anthesis to mid grain filling stage (Aparicio et al., 2000). Number of studies has reported similar findings with NDVI reflectance from wheat genotypes (Babar et al., 2006; Aparicio et al., 2000). The overall results indicate that active sensor based NDVI readings can differentiate among multiple wheat genotypes at many growth stages.

Comparison between NDVI and yield classification

Quantitative Approach

The quantitative clustering approach depend on K-means clustering algorithm to classify NDVI and grain yield data into three NDVI and yield classes (low, medium, and high) and it is described in details by Hartigan and Wong (1979). Table 1 presents an error matrix, also referred to as Contingency table that compares classifications among yield classes and NDVI classes for all wheat genotypes in this study. Kappa statistic was used in this study that measures the classification accuracy and assessment agreement between classifications. Kappa statistic gives precise measure of how well the classifications are compared to a chance agreement or random classification (Khosla et al., 2008). It ranges from 1 being perfect agreement to 0 being no agreement (Landis and Koch, 1977) as presented in Table 1.2.

Table. 1. Contingency table of the agreement between grain yield classes† and NDVI classes† for dryland.

	Early season			Mid-season			Late season		
	---NDVI class---								
Grain yield class	Low	Medium	High	Low	Medium	High	Low	Medium	High
	---Number of agreement---								
Low	4	2	0	3	3	0	4	1	1
Medium	5	5	0	1	7	2	2	7	1
High	2	3	3	0	3	5	0	1	7

†Grain yield classes and †NDVI classes were determined by used K-means clustering algorithm (k=3 clusters)

The guidelines to interpret Kappa Statistics are presented in Table 1.2, and the kappa statistic results for this study are presented in Table 1.3. The results from the quantitative clustering approach indicate that classification accuracy between NDVI and grain yield ranged from (0.25 to 0.61), which would indicate a fair to substantial agreement.

Table. 1.2. Guidelines to interpret kappa statistics according to (Landis and Koch, 1977).

Kappa statistic	Strength of agreement
< 0	poor
0-0.20	slight
0.21-0.40	fair
0.041-0.60	moderate
0.61-0.80	substantial
0.81-1.0	almost perfect

The classification accuracy at late season was the highest compared to that at mid-season and early season under dryland conditions. Whereas, Kappa statistic ranged from (0.10 to 0.21) under irrigated conditions indicated poor to fair agreement (data not shown). Similar results have been reported in (Inman et al., 2008) five out six sites had fair to substantial between NDVI and relative yield.

Table. 1.3. Results of kappa statistic for error matrix (contingency tables) of grain yield classes and NDVI classes under dryland conditions.

Grain yield class vs. NDVI class	Overall accuracy (%)	Kappa statistic	Strength of agreement
Early season	50	0.25	fair
Mid-season	63	0.40	fair
Late season	75	0.61	substantial

Overall, based on statistical K-means clustering approach the results show substantial agreement between NDVI and grain yield at late season, and only a slight to fair agreement at early season and at mid-season. The results from kappa statistic suggest that classification accuracy between NDVI and grain yield at late season was better than that at mid-season and early season. Our results agree with findings of (Babar et al., 2006) that spectral indices such as NDVI have potential to differentiate genotypes for their grain yield at late season under irrigated and rainfed conditions. In addition, these results are consistent with Ma et al., (2001). They observed that NDVI can differentiate between high and low grain yield among soybean genotypes and provide fast index for screening and ranking soybean genotypes under irrigated condition.

In this study overall classification accuracy percentage between grain yield and NDVI was better under dryland condition than under irrigated condition. The NDVI variability due to the different water status in two environments and the water is considred as a limiting factor for growth and grain yield wheat genotypes with uniform N rate and the same soil in Colorado. The study demonstrates the potential of using active sensor based on NDVI readings as a promising tool to classify and identifying superior wheat genotypes.

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