ACTIVE REMOTE SENSING FOR IN-SEASON PRECISION N MANAGEMENT

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ABSTRACT

Uniform nitrogen (N) fertilizer applications across entire fields have been shown to be inefficient. Recent advances in agricultural technology have led to the development of active remote sensing equipment that can be used to detect crop biomass and potentially be used to improve N fertilizer application rates. The objective of this study was to evaluate the effectiveness of using a hand-held active remote sensing instrument to estimate yield potential in irrigated corn. This study was conducted over four site years on two irrigated corn fields in Eastern Colorado. At the eight-leaf crop growth stage, the GreenSeeker™ active remote sensing unit was used to measure red and near infrared reflectance of the crop canopy. The crop was hand-harvested at physiological maturity. Normalized difference vegetation index was calculated from the reflectance data and normalized by dividing by the number of days from planting to sensing. Regression analysis was used to model grain yield. Cross validation was used to validate regression models. Grain yields ranged from 5 to 24 Mg ha^{-1}. Coefficient of determination of the models for each site year ranged from 0.10 to 0.76. Exponential models were found to fit the individual site year data best. Site years I and III were modeled and cross validated using site years II and IV. The coefficient of determination of the best fit model for site years I and III was 0.54. An exponential model was determined to be the best model for predicting grain yield. Results of this study show that active remote sensing has potential to be used for accurately predicting grain yield in irrigated corn.

INTRODUCTION

Nitrogen use efficiency (NUE) in the United States is alarmingly low, especially in cereal crops, which have an estimated NUE of only 33% (Raun and Johnson, 1999). Low NUE in crops, if not improved, could have dramatic impact on food supplies and land-use worldwide (Frink et al., 1999). Scientists have realized the importance of improving crop NUE (Raun and Johnson, 1999), and hence have focused much research on this global problem.

Conventional corn (*Zea Mays L.*) crop fields in the United States and else-where are treated uniformly with regard to nitrogen (N) fertilizer application (i.e., the fields received one N application rate). Over the last ten years scientists have demonstrated, that uniform application of N fertilizer is not the most efficient practice (Mulla and Bhatti, 1997; Khosla and Alley 1999; Koch et al., 2004). Nitrogen fertilizer applications that take into account the variability of the crop's N needs could lead to increased NUE and thus more economically and environmentally sound farming practices (Mulla and Bhatti, 1997; Khosla and Alley, 1999). Scientists and engineers have investigated numerous techniques of characterizing the spatial variability of crop productivity potential and N status in order to facilitate variable rate application of N fertilizer, however there is yet to be a consensus on which method is best.

Studies have shown that remotely sensed imagery can provide more soil and crop information than conventional methods (Demattê et al., 2001) and is a rapid means to infer multiple crop parameters including: photosynthetic capacity, productivity, and potential yield (Peñuelas et al. 1994; Thenkabail et al. 2000; Ma et al. 2001; Raun et al. 2001; Báez-González et al. 2002). Although use of remote sensing imagery is promising, there are drawbacks including: cost, weather, timing, and remote sensing imagery often requires sophisticated computer programs and skilled labor to interpret and prepare the image for use. However, active remote sensing systems (i.e., a sensor that has its own source of light energy) that can be mounted on a fertilizer application boom and/or tractor is a very attractive alternative to the traditional soil and plant sampling methods as well as aerial/satellite-based remote sensing.

The objective of this study was to evaluate the effectiveness of using a hand-held active remote sensing instrument to estimate yield potential in irrigated corn.

MATERIALS AND METHODS

Study Sites

This study was conducted over four site years (two fields over two consecutive growing seasons). Sites were located in northeastern Colorado, USA under a continuous maize cropping system. Site years I and III were furrow irrigated, while site years II and IV were center-pivot sprinkler irrigated.

Site years I and III were on a field mapped as having Fort Collins Loam (fine-loamy, mixed, superactive, mesic Aridic Haplustalf). Site year III and IV was located on a field that was mapped as having Albinas loam (fine-loamy, mixed, superactive, mesic Pachic Argiustoll), Ascalon fine sandy loam (fine-loamy, mixed, superactive, mesic, Aridic Argiustoll), and Haxtun loamy sand (fine-loamy, mixed, superactive, mesic Pachic Argiustoll) soil series.

Maize was planted at 77,000 plants ha^{-1} for site years I and III and 84,000 plants ha^{-1} for site years II and IV. Row spacing was 76 cm for all site years. Site years I and II were planted with Garst hybrid 8802 and site year III and IV were planted with Pioneer hybrid 34K77.

Experimental Procedure

Experimental plots were randomly located within each field and replicated twelve times. Each experimental plot was 46.2 m^2 (15.2m by 3.02m) in size. Crop reflectance measurements were acquired at the eight-leaf crop growth stage using a GreenSeeker™[†] hand-held active remote sensing unit. The GreenSeeker™ hand held active remote sensing unit[†] (NTech Industries, Inc., Ukiah, CA, USA) measures the reflectance of a given crop over a 0.61 x 0.61-m area when the unit is positioned between 0.6 and 1.0 m above the target area. The sensor utilizes high intensity light emitting diodes (LED) to emit light in the red (650 ± 10 nm) and near infrared (770 ± 15 nm) bands. From these measurements, the normalized difference vegetation was calculated (NDVI) (Eq. 1). For each site year, NDVI data were normalized by dividing the NDVI by the number of day from planting to sensing. The normalized NDVI, or in-season estimated yield (INSEY) is essentially an estimate of accumulated biomass (Stone et al., 1996).

[†] Disclaimer: mention of trade name does not imply endorsement by either the authors or Colorado State University.

$$\text{NDVI} = (\text{near infrared} - \text{red})/(\text{near infrared} + \text{red}) \quad [1]$$

At the crop's physiological maturity (R6 crop growth stage) above-ground biomass samples were collected for grain yield analysis. One biomass samples was randomly located and collected from each experimental plot. Biomass samples consisted of two 1-m long sections of a corn row. Biomass samples were then analyzed for yield volume. Grain yield volume calculated as Mg ha^{-1} at 155g kg^{-1} moisture.

Data Analysis

Statistical analysis was performed using SPLUS 6.1 (Insightful corp., Troy NY, USA). Regression analysis was used to develop models relating INSEY to harvested grain yield for each site year. Data were then pooled by growing season. Data from the first growing season (site years I and III) were used for model building, while data from the second growing season (site years II and IV) were used for model validation. INSEY and grain yield data collected during the first growing season (site year I and III) were pooled and used to develop a model for estimating grain yield potential. Reflectance data collected during the second growing season (site year II and IV) was entered into the model to provide yield estimates. Yield estimates were then compared to observed yield. Mean squared error of prediction (MSPR) and model bias were calculated to assess the performance of the model. A two-sided t-test was used to test if the estimate bias was significant. Inman et al. (2005) provide a detailed discussion of the equations and procedures used to develop potential yield estimates.

RESULTS AND DISCUSSION

Grain yields were variable across sight years, ranging from 5 to 24 Mg ha^{-1}. Site years I and III were lower yielding than site years II and IV, likely because of the irrigation practices and lower planting density.

Scatter plots of INSEY versus observed and predicted grain yield for site year four is presented in Figure 1. Across all sites, the relationship between INSEY and grain yield was variable, with R^2 values ranging from 0.10 to 0.76. An exponential fit relating INSEY to yield has been proposed for both wheat and corn (NUE Web, 2005). In our regression analysis of the individual site years, we tested several different models (data not shown). However, the exponential fit was found to be the best fit-model in all four cases. Similar results were reported by Thenkabail et al (2000). In their study, it was reported that in most cases, non-linear exponential models were best for explaining variability between spectral vegetation indices and crop biophysical parameters across several agricultural crops (Thenkabail et al., 2000).

With the exception of site year III, regression models fit the data best at lower INSEY values. Variability in observed grain yield is greatest at high INSEY values. This observation could be because NDVI is less sensitive to changes in canopy closure, leaf area index, and other biophysical parameters at high NDVI values.

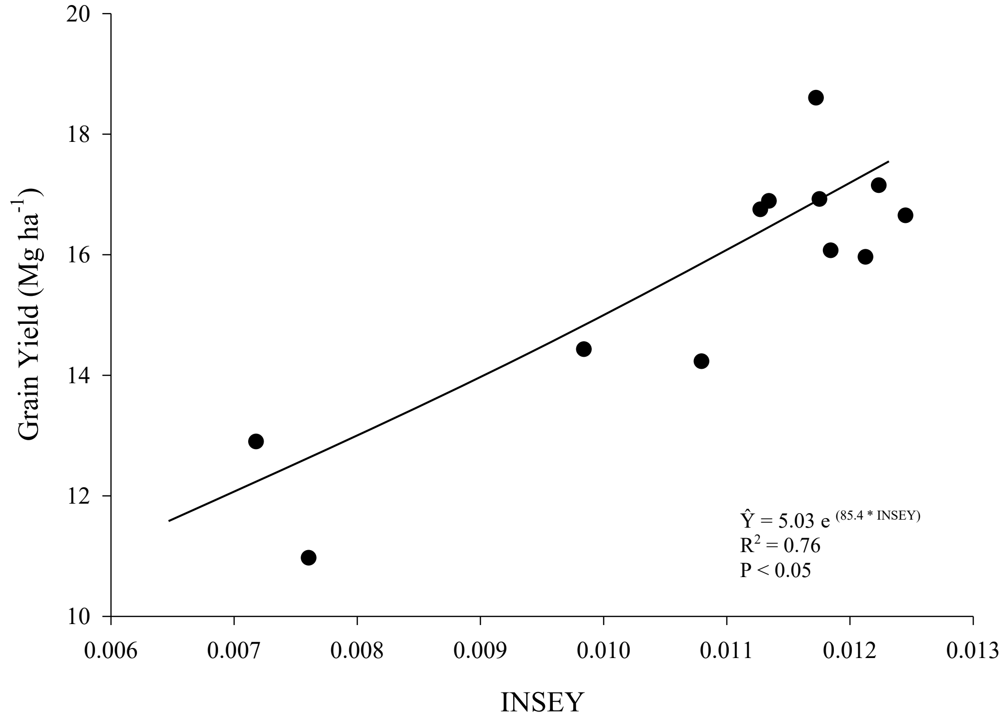

Figure 1. Scatter plot of INSEY versus observed yield (closed circles) and predicted yield (solid line) for site year IV. Regression model, coefficient of determination, and p-value are shown.

Regression analysis and cross-validation results are presented in Table 1 and Figure 2. Using site years I and III, regression analysis was used to investigate the different models. From the models tested, the linear and exponential models had lowest mean square error of prediction (MSPR), indicating that the model developed from site years I and III provided yield predictions that were close to the observed yield values for site years II and IV. The quadratic model had the lowest MSE, however the MSPR was high and the model bias was statistically significant. Overall, the exponential model was the best model tested for predicting grain yield. These results agree with (Thenkabail et al., 2000). To be sure, these results do not indicate that two site years of data are adequate for developing a yield prediction model using the GreenSeeker™ optical sensor. Our results do however, indicate that active remote sensors such as the GreenSeeker™ have potential to be used to develop models to effectively predict grain yield.

Table 1. Regression analysis and cross-validation results. The regression model, mean squared error (MSE) from the model building data set, coefficient of determination (R^2), mean squared error of prediction (MSPR), model bias, and the p-value of the bias are listed. All models listed were significant at $p < 0.05$.

Model	R^2	MSE	MSPR	Bias	Bias P
$\hat{Y}$ (Mg ha^{-1})= 2.92 $e^{(163.64\ (INSEY))}$	0.54	5.37	7.69	1.01	ns
$\hat{Y}$ (Mg ha^{-1}) = -0.27 + 1599.3 (INSEY)	0.21	4.94	4.54	1.38	ns
$\hat{Y}$ (Mg ha^{-1}) = 84.5 – 17250 (INSEY) + 1016987.9 INSEY^2	0.48	4.31	251.5	6.10	0.001

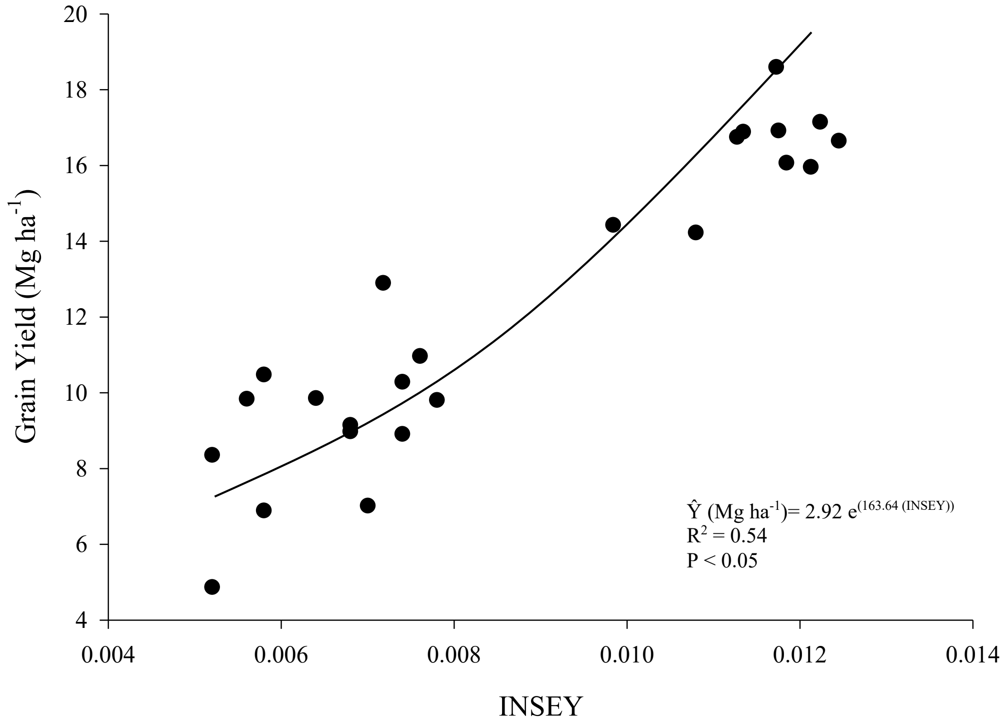

Figure 2. INSEY versus yield for site years II and IV. Graphs show observed yield (closed circles) and predicted yield (solid line). Data from site years I and III were used for model building; data from site years II and IV were used for model validation.

CONCLUSIONS

In this study, the ability of the GreenSeeker™ active remote sensing unit to predict grain yield in irrigated corn was evaluated. Results indicate that an exponential regression model is best for predicting yield using the GreenSeeker™. Similar findings have been reported in the literature (Thenkabail et al., 2000). Overall, our results are encouraging with regard to using the GreenSeeker™ to predict grain yield in irrigated corn. More research is needed, however to refine the yield models for irrigated corn.

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