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Estimating Maize Grain Yield From Crop Biophysical Parameters Using Remote Sensing

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ESTIMATING MAIZE GRAIN YIELD FROM CROP BIOPHYSICAL PARAMETERS USING REMOTE SENSING

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The overall objective of this investigation was to develop a robust technique to predict maize (*Zea mays* L.) grain yield that could be applied at a regional level using remote sensing with or without a simple crop growth simulation model. This study evaluated capabilities and limitations of the Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Index 250-m and MODIS surface reflectance 500-m products to track and retrieve information over maize fields. Results demonstrated the feasibility of using MODIS data to estimate maize green leaf area index (LAI_g). Estimates of maize LAI_g obtained from Wide Dynamic Range Vegetation Index using data retrieved from MODIS 250-m products (e.g. MOD13Q1) can be incorporated in crop simulation models to improve LAI_g simulations by the Muchow-Sinclair-Bennet (MSB) model reducing the RMSE of LAI_g simulations for all years of study under irrigation. However, more accurate estimates of LAI_g did not necessarily imply better final yield (FY) predictions in the MSB maize model. The approach of incorporating better LAI_g estimates into crop simulation models may not offer a panacea for problem solving; this approach is limited in its ability to simulate other factors influencing crop yields. On the other hand, the approach of relating key crop biophysical parameters at the optimum stage with maize grain final yields is a robust technique to early FY estimation over large areas. Results suggest that estimates of LAI_g obtained during the mid-grain

filling period can used to detect variability of maize grain yield and this technique offers a rapid and accurate (RMSE < 900 kg ha^{-1}) method to detect FY at county level using MODIS 250-m products.

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INTRODUCTION

Accurate estimates of crop yield and production on regional and national scales are becoming increasingly important in developing countries and have sustained importance in developed countries. A challenging issue for the agricultural sector will be to supply food, fiber, and biofuel demands for a growing world population. The United States (U.S.) is the world leader in maize (*Zea mays* L.) biofuel production and the world's largest producer and exporter of maize (FAO, 2008; FAO, 2010; USDA, 2010). The U.S. produces about 40 percent of the total world production followed by China and Europe which produce about 19 and 12 percent, respectively (USDA, 2010). Estimates suggest that at least 107 million tons of maize could be used in the United States for production of biofuels in 2009/2010, representing an increase of 13 million tons compared to 2008/09 (FAO, 2010). Although less than 20 percent of the U.S. maize grain production is exported, world prices are largely established by the supply-and-demand relationship in the U.S. market.

More than 80 percent of the total U.S. maize production comes from the U.S. Corn Belt region so world maize trade and prices are affected by the production in this region. Iowa, Illinois, Nebraska, Minnesota, Indiana, and Ohio produce nearly 70 and 85 percent of total U.S. maize grain production and Corn Belt region production, respectively (Figure 1; USDA-NASS, 2009). The total U.S. maize grain production has increased around 87 percent in the last 30 years according to the U.S. Department of Agriculture (USDA) Census of 2007 (USDA-NASS, 2009). According to USDA long-term projections, the U.S. total maize production should be increased by 21 percent to supply the demand for 2019/20. Therefore, assessment of maize growing conditions and accurate maize yield predictions in the U.S. Corn Belt are important issues in food prices, food security and for other crucial decisions affecting agricultural policy and trade.

Yield forecasting around the world is done with crop simulation models, remote sensing, statistical techniques, scouting reports, and combinations of these methods. Scouting reports or sampling agricultural fields is a reliable way to estimate yield however this method is time-consuming, costly and does not allow yield estimates before harvest. In contrast, data obtained from remote sensing and crop simulation models allow government agencies, private industry, and researchers to estimate yield before harvest. Several studies have been conducted to predict crop yield at regional scales basically focusing on two approaches, remote sensing and a combination of remote sensing and crop simulation models.

The first approach used to predict yield at the regional level relates vegetation indices (VI) with crop final yield (FY). Previous studies focused their analyses on basically two techniques. The first technique relates VI with final yield at a specific growth stage (e.g. vegetative and reproductive stages) during the growing season (Shanahan et al., 2001; Lobell et al., 2002; Martin et al., 2007). The second technique relates FY with cumulative values of VI (e.g. Normalized Difference Vegetation Index, NDVI) obtained during the entire growing season or during a specific period during the growing season such as the vegetative or reproductive stages (Labus et al., 2002; Mkhabela et al., 2005; Wall et al., 2008). These techniques require an adequate time series of remotely acquired imagery and involve correlating historical pixel-level imagery values with historical regional values. For example, historical values of NDVI for a specific region are compared with current values of NDVI to detect NDVI anomalies or deviations from historical values and then the data are used to estimate yields (Kastens et al., 2005; Li et al, 2007).

The second approach used to predict yield at the regional level is the integration of remote sensing data with crop growth models. This approach suggests the modification of model state variables such green leaf area index (LAI_g) during the growing season with measurements obtained from remote sensing in order to correct simulated values of key crop biophysical parameters such as LAI_g (Bouman, 1995; Moulin et al., 1998). Because LAI_g constitutes a fundamental component of many crop simulation models, studies have proposed that more accurate estimates of LAI_g could improve model final yield (FY) predictions (Doraiswamy et al., 2005; Moriondo et al., 2007; Fang et al., 2008).

In spite of the fact that previous studies incorporating remote sensing data into crop models reported improvement in FY predictions; the successful application of this technique requires an understanding of limitations and potential capabilities of this approach. Most of the previous studies incorporating crop biophysical parameters such as LAI_g into crop simulation models have been conducted at regional scales. Reported regional yields were compared with model predictions with and without LAI_g incorporation in order to determine model FY prediction improvement. However, limitations and potential capabilities of the approach may not be detected at large scales and further assessment should be performed at field scales.

On the other hand, remote sensing may provide temporal information of crop biophysical parameters that could be related with crop FY without the use of crop growth models. One limitation linking information retrieve from remote sensing with agricultural crops is the lack of understanding of agricultural crop dynamics. For example, a better understanding of how maize yield is formed and which crop biophysical parameter(s) is most involved in determining yield should allow improved the accuracy of agricultural crop monitoring and enhance FY estimates. In addition, comparison of historical VI with the current season values should be analyzed in conjunction with knowledge of agricultural crop dynamics. Under the assumption that a crop biophysical parameter (e.g. LAI_g) is closely related with the VI during the growing season, the next step will be to determine how to analyze the information of VI retrieved from one year in light of previous or historical information. Due to agricultural crop dynamics, several questions require a better analysis including: What are the capabilities and limitations of the remote sensor in terms of spatial, spectral, and temporal resolution?, Does comparison of VI with information from previous years make sense?, How should valid comparisons be made in light of changes in management practice, such as hybrids and planting dates, soils, and environments?

This study is based on improving the incorporation of crop biophysical parameters retrieved from remote sensing into crop simulation models and the approach of relating VI with FY. The overall objective of this investigation was to develop a robust technique to predict maize grain yield that could be applied at a regional level using remote sensing with or without a simple crop growth simulation model. The effort included a literature review related to maize grain yields to gain understanding of the key processes of maize growth and development and limitations to FY. Three maize crop systems were evaluated under irrigated and rainfed conditions to identify the key crop biophysical parameters and the optimum development stage that can be related to maize grain yield. Final yields at the field level were estimated using two approaches. The first approach related the key crop biophysical parameters at the optimum development stage with maize grain yield using remote sensing data obtained from MODIS products. The second approach integrated LAI_g into the Muchow-Sinclair-Bennet (MSB) maize model (Muchow et al, 1990) over irrigated maize fields from 2006 to 2009. This model has been used by U.S. government agencies and researchers to estimate maize yield at regional scales because it requires a few input parameters and it is responsive to soil and climatic factors (Reynolds, 2001; Doraiswamy et al., 2005). In addition, improvements in FY predictions were reported with the incorporation of LAI_g during the growing season into the MSB maize model over regional scales (Doraiswamy et al., 2004; Doraiswamy et al., 2005). This study also evaluated capabilities and limitations of the Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Index (MOD13Q1) and MODIS surface reflectance (MOD09A1) products to track and retrieve information over a maize field based on a temporal resolution of 16 and 8 day composites and spatial resolution of 250 and 500 meters, respectively. Finally, the best approach (or the combination of them) was validated with reported maize yields from several counties in the states of Nebraska, Iowa, and Illinois for 2006 and 2007.

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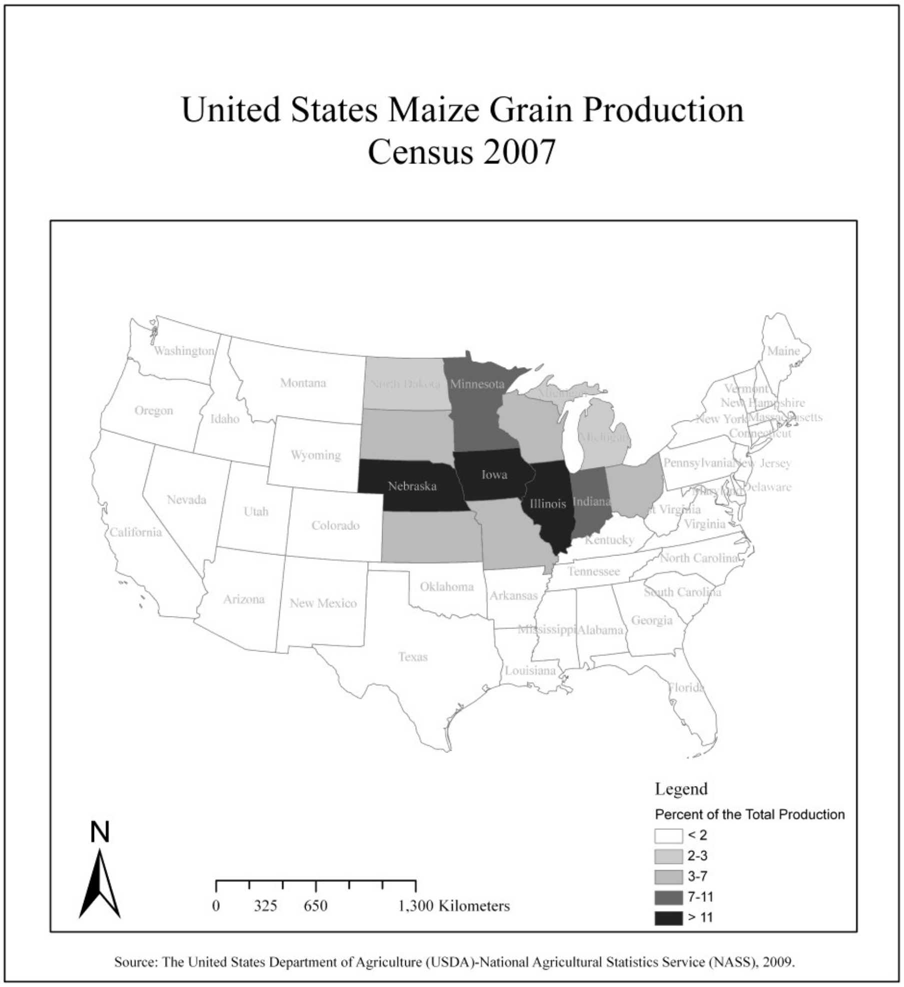

Figure 1. Maize grain production by state as a percent of the total United States production.

CHAPTER 1

AN EVALUATION OF MODIS 8 AND 16 DAY COMPOSITE PRODUCTS: IMPORTANCE OF DAY OF PIXEL COMPOSITE WHEN MONITORING AGRICULTURAL CROPS

ABSTRACT

The seasonal patterns of green leaf area index (LAI_g) can be used to relate crop condition, yield potential and to incorporate in crop simulation models in order to update simulated values of LAI_g. This study focused on examining the potential capabilities and limitations of satellite data retrieved from MODIS 8 and 16 day composite products to track and retrieve LAI_g data over maize (*Zea mays* L.) fields for crop simulation applications. Results clearly demonstrated the variability of pixel temporal resolution obtained from MODIS 8 and 16 day composite periods and the importance of day of pixel composite information from MODIS products for monitoring agricultural crops. Due to the maize LAI_g dynamics and changes in MODIS pixel temporal resolution, the inclusion of day of pixel composite has important implications to retrieve and monitor agricultural crop dynamics. The results of this study showed that MODIS 250-m resolution provide more accurate estimates of maize LAI_g during the entire growing season compared to MODIS 500-m resolution for crop simulation applications. Based on the nine years of data used in this study, maize LAI_g can be accurately estimated with root mean square error (RMSE) and coefficient of determination (R^2) of 0.60 m^2 m^{-2} and 0.90, respectively, using a WDRVI linear model for data retrieved from the 250-m resolution product (MOD13Q1). Results indicated that the optimum MODIS composite product to monitor agricultural crops should be MODIS Vegetation Index 8 day

composite 250-m instead of the product of MODIS Vegetation Index 16 day composite 250-m used by government agencies.

Key words: MODIS, temporal resolution, vegetation indices, maize, green leaf area index

INTRODUCTION

Remote sensing has been used to estimate crop biophysical parameters (CBP) such as green leaf area (LAI_g), canopy chlorophyll content, the fraction of the photosynthetically active radiation absorbed by the crop (fAPAR), biomass, vegetation cover and gross primary production using different vegetation indices (VI) (Hatfield et al., 2008). Most of the VI are combinations of reflectance in the visible or photosynthetically active radiation (400-700 nm), especially red reflectance (620-700 nm), and near infrared (NIR; 700-1300 nm) reflectance. For instance, the most used VI in agricultural applications is the Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974). One limitation to retrieving CBP such as LAI_g is the nonlinearity relationship of NDVI at medium to high densities of green biomass ($LAI_g > 2$ m^2 m^{-2}). However, NDVI sensitivity could be improved with the Wide Dynamic Range Vegetation Index (WDRVI) (Gitelson, 2004). On the other hand, new approaches have been proposed using regions of the light spectrum that do not show saturation to different concentrations of pigments and green biomass such as red-edge and green regions (Buschman and Nagel, 1993; Gitelson et al., 1996; Gitelson et al., 2003). However, the main limitations to use specific spectral bands are the availability of these bands in satellite sensors as well as the spatial and temporal resolution and cost of images from satellite sensors with specific bands.

Data obtained from satellite products without the appropriate temporal and spatial resolution and processing could affect accuracy of data interpretation. Limitations to monitoring vegetation and/or retrieving CBP related with the satellite sensors include temporal and spatial resolutions, low quality of the data due to appearance of clouds, low viewing angles, and poor geometry (Chen et al., 2002; Duchemin and Maisongrande, 2002; Chen et al., 2003). For instance, Chen et al. (2003) showed that seasonal profiles of NDVI were mainly influenced by cloud contamination and atmosphere composition. The previous authors demonstrated that NDVI profiles without cloud contamination improved the detection of maximum value of maize LAI_g reached around silking. In addition to atmospheric interference (e.g. clouds, haze, etc.), NDVI profiles also could be affected by contamination from surrounding areas due to spatial resolution. Studies have smoothed the data obtained from a VI such as NDVI over study areas to reduce effects of contaminated signals (Swets et al., 1999; Funk and Budde, 2009). An alternative to reduce or eliminate pixel contamination is the selection of finer spatial resolution. Data obtained from spatial resolution of 250-meter (m; about 6.25 ha) should allow the identification of pixels covered by specific crops compared with spatial resolution of 1 kilometer (km; about 25 ha). Finally, the ability of obtaining frequent data of agricultural crops such as CBP is limited by the satellite temporal resolution. The estimation of CBP and the detection of developmental stages of agricultural crops have a relevant importance for government agencies, private industry, and researchers.

Satellite data obtained from Moderate Resolution Imaging Spectroradiometer (MODIS) products offers the advantage to acquire high quality data at consistent, spatial and temporal resolution derived daily, every 8 or 16 days for monitoring vegetation (Huete et al., 1999; Huete et al., 2002; Didan and Huete, 2006). One advantage using MODIS 8 and 16 day composite is that these products contains the best possible observation obtained during the period composite based on several parameters such as low view angle, absence of clouds or clouds shadow and aerosols (Vermote and Kotchenova, 2008). MODIS 8 and 16 day composite period has been used in many agricultural applications; to develop land cover/land use (Lobell and Asner, 2004; Sedano et al, 2005; Lunneta et al., 2006;), monitor phenology (Zhang et al. 2003; Sakamoto et al., 2005; Wardlow et al., 2006), and estimate CBP (Zhu et al., 2005; Chen et al., 2006; Rochdi and Fernandes, 2010). MODIS products have been used to estimate LAI_g for crop modeling applications. For example, Fang et al. (2008) retrieved LAI_g from MODIS leaf area index 8 day composite at 1000m product to incorporate into a maize crop simulation model. Doraiswamy et al. (2004) used data retrieved from MODIS surface reflectance 8 day composite at 250m product to incorporate in a radiative transfer model to estimate LAI_g during the growing season and then incorporate into a maize crop simulation model. Chen et al. (2006) evaluated the potential use of data retrieved from MODIS VI 250, 500 and 1000m to track maize LAI_g and phenology for crop modeling applications. However, an evaluation of temporal resolution of MODIS 8 and 16 day composite to monitor and estimate CBP such as maize LAI_g has not been investigated to date.

Monitoring of maize LAI_g requires a good understanding of LAI_g changes according to the developmental stage or crop dynamics in order to evaluate potential capabilities and limitations of the satellite data retrieved from MODIS 8 and 16 day composite periods. A period of 8 and/or 16 days could represent significant changes in maize LAI_g especially during vegetative stages. Consequently, the information included in some MODIS products of day of pixel composite (DOYCMP) is fundamental information to accurately monitor and estimate maize LAI_g. This study evaluated data retrieved over maize fields from three MODIS products: MODIS Vegetation Index 16 day composite 250-m (MOD13Q1), MODIS surface reflectance 8 day composite 250-m (MOD09Q1), and MODIS surface reflectance 8 day composite 500-m (MOD09A1). The main objective of this study was to demonstrate the importance of the day of pixel composite information from MODIS products to monitor maize LAI_g. This study investigated whether the temporal resolution from 8 and 16 day composite periods differs from 8 and 16 days, respectively, and its implications to monitoring maize LAI_g.

MATERIALS AND METHODS

Field measurements

This research used field data from the Carbon Sequestration Project at the University of Nebraska-Lincoln in the Agricultural Research and Development Center located in Saunders County, Nebraska, USA. Field data was collected over three large study sites with different cropping systems. Site 1 (41˚ 09'54.2"N, 96˚ 28'35.9"W, 361m) was 48.7 ha planted in continuous maize from 2001 until 2009 and was irrigated. Site 2 (41˚ 09'53.5"N, 96˚ 28'12.3"W, 362m) was planted in maize-soybean rotation over an area of 52.4 ha under irrigation. Site 3 (41˚ 10'46.8"N, 96˚ 26'22.7"W, 362m) was 65.4 ha planted in maize-soybean rotation under rainfed conditions. The soils in the three sites are deep silty clay loams and consisting of four soil series: Yucan (fine-silty, mixed, superactive, mesic Mollic Hapludalfs), Tomek (fine, smectitic, mesic Pachic Argialbolls), Filbert (fine, smectitic, mesic Vertic Argialbolls), and Filmore (fine, smectitic, mesic Vertic Argialbolls). Nitrogen (N) was applied in one and three applications in rainfed (site 3) and irrigated sites (site 1 and 2), respectively, according to guidelines recommended in Shapiro et al. (2001). This study used nine years of data (2001-2009) from site 1 and five years of data (2001, 2003, 2005, 2007, and 2009) from sites 2 and 3. Within each site, six plot areas (20 m x 20 m) were established and called intensive management zones (IMZs) for detailed process-level studies (details in Verma et al., 2005). Destructive samples consisting of 5 or more continuous plants were collected from a one meter linear row sections in the six IMZ for each site at 10 to 14 day intervals until maturity. Field measurements of total and green leaf areas harvested per plant (m^2 $plant^{-1}$) were measured with an area meter (Model LI-3100, LI-COR, Inc., Lincoln, NE). The total and LAI_g were calculated using the plant population density (plants m^{-2}) by:

$$LAI_{total} = plant\_population * \frac{total\_leaf\_area}{plant} \qquad \text{eq. 1}$$

$$LAI_g = plant\_population * \frac{green\_leaf\_area}{plant} \qquad \text{eq. 2}$$

LAI_{total} and LAI_g were obtained by averaging all the six IMZ measurements at each site. MATLAB® was used to estimate the daily values of the LAI_{total} and LAI_g measurements using the cubic spline interpolation method.

Remote sensing data

A time series of MODIS Terra Vegetation Index 16-day composite 250-m (MOD13Q1), MODIS Surface Reflectance 8-day composite 250-m (MOD09Q1), and MODIS Surface Reflectance 8-day composite 500-m (MOD09A1) images were downloaded from National Aeronautic and Space Administration (NASA) Land Process

Distributed Active Archive Center (LPDAAC) (https://lpdaac.usgs.gov/lpdaac/get_data/data_pool) from April through October (of each growing season) for the study area (MODIS tile h10v04) from 2001 until 2009. All MODIS images were processed, reprojected, and converted to GeoTIFF format using the MODIS Reprojection Tool Version 4.0 (MRT) downloaded from LPAAC (https://lpdaac.usgs.gov/lpdaac/tools). MODIS images are labeled with the format "MOD13Q1.A2001129.h10v04.005.20070251153610.hdf" where MOD13Q1 is the product name, A2001129 year and day of year, h10v04 the tile, collection and 20070251153610 the processing date and time for this image. The day of year (DOY) for each MODIS image represents the first day of the period of 8 and 16 day composite. The period of 8 or 16 days is used to select the best observation based on several parameters such as low view angle, absence of clouds or cloud shadows, and aerosols (Vermote and Kotchenova, 2008). The day during the period composite where the best observation is observed is called the day of pixel composite (DOYCMP). The information of DOYCMP is included in MOD09A1 and MOD13Q1 products but it is not available in the MOD09Q1 product. MOD09A1 provides surface reflectance in 7 bands (Band 1=620-670nm; Band 2= 841-876nm; Band 3= 459-479nm; Band 4= 545-565nm; Band 5= 1230-1250nm; Band 6= 1628-1652nm; Band 7= 2105-2155nm) with resolution of 500-m. MOD09Q1 provides reflectance values for band 1 and 2. MOD13Q1 included data for NDVI and Enhanced Vegetation Index (EVI), surface reflectance from band 1, 2, 3, and 7 with a 250-m resolution. EVI was developed by the MODIS Land Discipline Group for use with MODIS data. This VI is a modified NDVI and has improved sensitivity to high biomass in comparison with NDVI (Huete et al., 2002).

Each study site was geolocated on each MOD13Q1 (Figure 1). Information retrieved of NDVI and EVI from each pixel over the study sites was used to choose pixel(s) close to the center to avoid pixel contamination using data from 2001 until 2004. These pixels were located close to the center of the maize field and did not require the application of smoothing techniques. The temporal behavior of NDVI for each pixel in the study sites was evaluated to select pixels for analysis in this study (Appendixes 1, 2, and 3). The selected pixels for analysis in this study were pixel id 9, 10, and 17 on site 1; 12, 13, 19, and 20 on site 2; and 31 and 35 on site 3 (Figure 1). Because the spatial resolution of MOD13Q1 and MOD09Q1 was similar (250-m), the locations of selected pixels from MOD13Q1 were also used to retrieve reflectance data from MOD09Q1 over the study sites. A similar technique was used to retrieve data from MOD09A1 (Figure 2). However the spatial resolution of 500-m did not allow the selection of a pixel without possible contamination (Appendix 4). The selected pixels were pixel id 2, 3, and 5 and 6 for site 1, 2, and 3, respectively (Figure 2). Surface reflectance from band 1 and 2 were extracted from MOD09Q1 and MOD09A1 products and then, NDVI and WDRVI were calculated for the selected pixels in each study site from 2001 until 2009. EVI was calculated using the blue and red band for MOD09A1 and MOD09Q1from 2001 to 2004 and from 2001 to 2009, respectively. The average of the DOYCMP, NDVI, and EVI data of the selected pixels was used for analysis in this study (2001-2009). Temporal behaviors of NDVI from each pixel over the study sites were visually evaluated to identify any differences in their behavior due to spatial resolution of 250 and 500-m. Because information of DOYCMP was not available in the MOD09Q1 product, the temporal resolution of MODIS composite was only evaluated for MOD09A1 and MOD13Q1.

Data of LAI_g under rainfed and irrigated conditions from 2001 until 2004 was used to calibrate a model for LAI_g estimation as a function of the selected VI using SigmaPlot®. Evaluated VI were NDVI, EVI and WDRVI (Table 1). The WDRVI was evaluated using two weighting coefficients. Gitelson (2004) showed that the weighting coefficient (α) increases correlations with vegetation fraction for wheat, maize and soybean canopies in the WDRVI. The weighting coefficient values proposed by Gitelson (2004) for maize were α=0.2 and 0.1. The model to estimate maize LAI_g for each VI was validated with independent field data from 2005 until 2009 under rainfed and irrigated conditions.

RESULTS AND DISCUSSION

Temporal Resolution

Figure 3 shows the progress of maize LAI_g as a function of DOY and the DOYCMP from MOD13Q1 and MOD09A1 represented by the vertical bars from 2001 until 2003 on site 1 of this study. Dashed lines represent the first day of the period composite which corresponds to MODIS day of year (e.g. MOD13Q1.A2001<u>145</u>) for 16 and 8 day period composites. The number of days between the vertical bars corresponds to MODIS temporal resolution for study site 1. Based on these results, the temporal resolution of MOD13Q1 and MOD09A1 changed between composite periods during the entire growing season. Observed temporal resolution of MOD09A1 and MOD13Q1 ranged from 1 to 14 days and from 2 to 28 days, respectively during the nine years of study. The temporal resolution of these two MODIS products was not equal to the period composite of 8 or 16 days as previous studies suggested (Chen et al., 2006; Wardlow et al., 2006; Wardlow 2007). In other words, MODIS 8 and 16 day composite do not provided data every 8 or 16 consecutive days. For example, the MOD13Q1 data retrieved on image DOY 209 and 225 were composed on day 223 and 225, respectively which represents two days apart between the images for site 1 in 2001 (Figure 3-a). A period of twenty five days apart occurred between the information retrieved on image DOY 161 and 177 because the DOYCMP was on 161 and 186, respectively in 2001 (Figure 3-a). The temporal resolution from 2 consecutive periods composite could reach 15 and 30 days if the DOYCMP is obtained during the first day of the composite and the following DOYCMP is obtained the last day of the period composite from MODIS 8 and 16 day, respectively. The cause of the variability of pixel temporal resolution of MODIS products is because each pixel contains the best possible observation during the length of the composite period (8 or 16 days). The procedure of pixel compositing has been well explained in MODIS references (Huete el al., 2002; Didan and Huete, 2006; Vermote and Kotchenova, 2008). In summary, the temporal resolution of MOD09A1 and MOD13Q1 products is determined by the DOYCMP between two consecutive composite periods and typically varies for each pixel in the image.

The DOYCMP for composite period of 8 or 16 days in the field could represent significant changes in maize LAI_g especially during vegetative stages. Maize LAI_g dynamics change according to the crop development stage. During vegetative stages, maize LAI_g change rapidly especially after V6 until V12 which daily values ($\frac{\partial LAI_g}{\partial DOY}$) ranged from 0.20 to 0.14 m^2 m^{-2} day^{-1} observed under irrigated (Figure 3) and rainfed conditions, respectively in the study sites. Figures 4-a and 5-a summarize the number of days from the first day of composite of MODIS 16 (MOD13Q1) and the 8 day composite (MOD09A1), respectively during nine growing seasons (2001 until 2009) at site 1. The results suggested that the DOYCMP could change from the first day of the composite period (DOY) without any predictable pattern. This finding invalidates assumptions of previous studies that used the first, last, and mean day of the period composite in agricultural applications; other studies do not mention if the information of DOYCMP was included in their analyses. Wardlow et al. (2006) and Chen et al. (2006) assumed that NDVI values obtained from MOD13Q1 were always obtained from the final day of the period composite for phenology applications in agricultural crops. The previous authors based their assumption on the algorithm used to generate MODIS NDVI composites. However, this assumption should be avoided for agricultural applications due to crop dynamics or changes according to the crop development stage.

The range of variability spanned from 0 to 7 and 0 to 15 days from the first day of MODIS 8 and 16 day composite period (DOY). However, an increase in the number of days from the DOY of MODIS composite period does not necessarily represent a larger change in maize LAI_g. For example, a difference of nine days from the DOY of MODIS composite period could represent changes in LAI_g of 3.0 m^2 m^{-2} during the vegetative stages while changes of LAI_g could be lower than 1.00 m^2 m^{-2} during reproductive stages (Figure 4-b). Similar results were observed for the eight day period composite where changes in maize LAI_g were larger during vegetative stages compare to reproductive stages. A difference of seven days from the DOY of MODIS composite period could represent changes in LAI_g greater than 2.0 m^2 m^{-2} during vegetative stages (Figure 5-b). These results highlight two important aspects that require consideration for application of MODIS composite products to agricultural crops such as maize: LAI_g changes according to the development stage and MODIS temporal resolution changes between composite periods. Therefore, analysis over agricultural crops using MODIS composite (8 or 16 days) should be done using information of DOYCMP.

Although the previous discussion might seem basic knowledge linking remote sensing information and agricultural crop biophysical measurements, a concern is raised because information of DOYCMP is included in some MODIS products (MOD09A1 and MOD13Q1 collection 5) while it is not readily available in other products such as MOD09Q1. MODIS VI 16 day composite has been used in many agricultural applications such as phenology detection; however, none of these studies mention the importance of a period of 16 days on agricultural crop dynamics especially during the vegetative stage. The temporal resolution of MODIS 16 day composite (MOD13Q1) could be a limitation to detect critical developmental stages of agricultural crops due to the period of time between observations that could reach 30 days as explained previously. MODIS 8 day composite period could reach a maximum of 15 days between observations that should provide an opportunity for better estimation of crop phenology measurements. On the other hand, a technique used to evaluate crop condition and yields compares NDVI values obtained during a current growing season with historical NDVI values for the same location or study site to detect anomalies or deviation from historical

NDVI values (Kastens et al., 2005; Li et al, 2007). Analysis comparing NDVI values obtained over a 16 day composite period during vegetative stages could cause confusion in data interpretation. For instance, NDVI values obtained from MODIS 16 day composite over site 1 on DOY 161 ranged from 0.31 to 0.85 during nine years in site 1. It is not difficult to hypothesize that any analysis without the inclusion of DOYCMP should cause erroneous data interpretation. Although this study does not pretend to analyze the techniques used to develop the MODIS NDVI time series use by the United State Department of Agriculture (USDA) Foreign Agriculture Service (FAS), a concern is raise because the product has been assembled using a 16 day compositing period. The results presented in this study clearly demonstrated the importance of DOYCMP on analysis over agricultural crops especially using MODIS 16 day composite period. Based on this study, it is suggested that a product of MODIS NDVI using an 8 day compositing period be assembled for agricultural applications instead of the product of NDVI 250-m 16 day composite used by government agencies.

Spatial Resolution

Figure 6 summarizes the temporal values of NDVI obtained from MOD09Q1, MOD13Q1 and MOD09A1 as a function of DOY for selected pixels from site 1 from 2001 until 2004. Based on these results, the temporal values of NDVI over maize changed with the spatial resolution of 250-m and 500-m. Lower values of NDVI were obtained from 500-m especially after NDVI reached a maximum value compared with values of NDVI obtained from 250-m . For example, NDVI values of 0.78 and 0.91 were obtained from 8 day composite period at 500 and 250m resolution, respectively on DOY

201 in 2001 (Figure 6-a). The irregular up and down behavior of the NDVI values was associated with the limitation of the 500-m resolution to locate pixels without information of surrounding areas or pixel contamination (Figure 2 and Appendix 4). In contrast, NDVI values obtained with MODIS 250-m resolution for 8 and 16 day composite period showed similar values during the growing season. Based on these results, data obtained from 500-m resolution should require a smoothing technique. In contrast, data obtained from MODIS 250-m resolution should not require a smoothing technique because this resolution allows the selection of pixels closer to the center of the field (pure maize pixels) or pixels without contamination.

Many studies have smoothed the data obtained from a VI such as NDVI over study areas to reduce effects of contaminated signals while maintaining seasonal characteristics of the original data set (Swets et al., 1999; Funk and Budde, 2009). Based on these results, the temporal behavior of NDVI-500m might be difficult to smooth out in order to obtain similar values of NDVI as retrieved from NDVI-250m over site 1 (Figures 6-a, b, and c). Adequate spatial resolution should provide more accurate crop information such as identification of critical stages and estimation of CBP. Kastens et al. (2005) indicated that identification of image masks or pixels covered by crops rather than using all pixels in a scene as a way to successfully model and predict crop yields using remote sensing. The results of this study suggested that MODIS 250-m resolution should provide more accurate estimation of LAI_g over maize as a result of less pixel contamination. These results contrast with results reported by Chen et al. (2006), who found no difference in NDVI and EVI values obtained from MODIS 250-m compared with MODIS 500-m resolution over maize fields. As will be discussed next, the previous author did not find differences on data obtained from the two resolutions probably because information of DOYCMP was not included in the analysis.

Table 2 summarizes the results obtained from the relationship between NDVI, EVI, WDRVI and maize LAI_g using the DOY and the DOYCMP from 2001 to 2004 under irrigated and rainfed conditions. The results demonstrated an improvement in LAI_g estimation with a reduction of the root mean square error (RMSE) and an increase of the coefficient of determination (R^2) when the information of DOYCMP was included in the analysis. The RMSE of the relationship of VI with LAI_g decreased more than two fold when DOYCMP data was incorporated using MODIS 16 day period composite. A lower improvement of the RMSE was obtained with the incorporation of data from DOYCMP using MODIS 8 day period composite 250 and 500-m. However, two main points should be discussed related with the improvement of the RMSE. First, as discussed previously, the temporal resolution between two consecutive periods of MODIS 8 and 16 day period composite could reach 15 and 30 days, respectively. Consequently, the impact of the incorporation of DOYCMP depends on the temporal resolution or period of time between observation and changes according to the crop development stage. Second, the impact of the incorporation of DOYCMP also depends on the spatial resolution. A possible explanation for the lower impact of incorporation of DOYCMP for MODIS 8 day composite period was due to pixel contamination at 500-m resolution that might not have allowed accurate estimates of maize LAI_g. The quantitative results confirmed the previous discussion about the importance of DOYCMP for retrieving maize LAI_g using 16 day composite. Results from this analysis clearly demonstrate the importance of using DOYCMP information to retrieve maize LAI_g. These results can be used to explain results presented in Chen et al. (2006) who reported that data obtained from MODIS 250-m did not provid more accurate information over maize fields compared with MODIS 500-m resolution. For example, results from this analysis showed similar RMSE and R^2 of maize LAI_g estimation without the incorporation of DOYCMP data using 250 and 500-m resolution. Subsequently, the data obtained from this analysis would not detect differences from data obtained from the two resolutions. The results presented here clearly shows, contrary to results presented by Chen et al (2006), that MODIS 250-m resolution could provide more accurate estimates over agricultural crops compared with MODIS 500-m resolution for crop modeling applications.

Estimation of maize green leaf area index (LAI_g)

Figures 7, 8 and 9 present the relationship between NDVI, EVI, $WDRVI_{\alpha=0.1}$ and $WDRVI_{\alpha=0.2}$ and maize LAI_g under rainfed and irrigated conditions from 2001 to 2004 obtained from MODIS 250-m 8 and 16 day composite period and MODIS 500-m 8 day composite, respectively. Results support the nonlinear relationship between NDVI and LAI_g found in previous studies (Maas, 1993; Myneni et al., 1997; Gitelson et al., 2003). NDVI remained nearly invariant changing from 0.84 to 0.86 while LAI_g changed from 4 to 6 $m^2\ m^{-2}$. The best fit for NDVI and maize LAI_g was obtained with exponential and logistic models for data retrieved from MODIS 250 and 500-m, respectively. In contrast, the relationship between EVI, WDRVI and LAI_g showed more linearity during the entire growing season using MODIS 250-m 8 and 16 day composite period. For instance, the relationship between EVI and maize LAI_g was quadratic for data retrieved from MODIS 250-m 8 and 16 day composite (Figures 7 and 8). $WDRVI_{\alpha=0.1}$ and $WDRVI_{\alpha=0.2}$ showed a linear relationship with maize LAI_g for data retrieved from the three MODIS products although $WDRVI_{\alpha=0.2}$ showed a quadratic relationship with maize LAI_g for data retrieved from MODIS 250-m 8 day composite. The sensitivity analysis performed on the previous discussed vegetation indices shows that NDVI exhibited high sensitivity at LAI_g values lower than 3.00 m^2 m^{-2} for data retrieved from MODIS 250 8 and 500-m 8 day composite (Figure 10). EVI and $WDRVI_{\alpha=0.2}$ showed comparable sensitivities to each other for data retrieved from MODIS 250-m 8 day composite while the sensitivity of $WDRVI_{\alpha=0.1}$ remained constant along the entire range of LAI_g for data retrieved from MODIS 250-m 8 day composite (Figure 10-a). Results suggested that $WDRVI_{\alpha=0.1}$ and $WDRVI_{\alpha=0.2}$ showed higher sensitivity for LAI_g for values higher that 3.0 m^2 m^{-2} while NDVI and EVI decreased their sensitivity at LAI_g values greater than 3.00 m^2 m^{-2} for data retrieved from MODIS 250-m 16 day composite during 2001to 2009 (Figure 11). These results clearly showed that the sensitivity of NDVI is the best index for detecting changes in maize LAI_g < 3.0 m^2 m^{-2} but should not be used to detect changes in maize LAI_g > 3.00 m^2 m^{-2}.

Table 3 summarizes the calibration for quadratic and linear models for EVI and WDRVI (α=0.1 and 0.2) for data obtained from MODIS 250-m 16 day composite and MODIS 500-m 8 day composite. A RMSE and R^2 of 0.49, 0.53 and 0.58 m^2 m^{-2} and 0.94, 0.93, and 0.92 were obtained for $WDRVI_{\alpha=0.2}$, $WDRVI_{\alpha=0.1}$ and EVI models, respectively under rainfed and irrigated conditions from 2001 to 2004 (n= 50) using data retrieved from MODIS 250-m 16 day composite period. Although the lowest RMSE and highest R^2 were obtained with the $WDRVI_{\alpha=0.1}$ linear model followed by the $WDRVI_{\alpha=0.2}$, the RMSE for the EVI quadratic model was quite similar compared to WDRVI models.

In other words, the models developed using WDRVI (α= 0.1 and α=0.2) linear and quadratic EVI model could be used to estimate maize LAI_g during the entire growing season. In contrast, the relationship between LAI_g and EVI and WDRVI (α= 0.1 and α=0.2) showed larger RMSE and lower R^2 for data obtained at 500-m resolution compared to results obtained from MODIS 250-m resolution (Table 3). These results were not surprising because temporal values of NDVI and EVI changed with spatial resolution due to pixel contamination as was discussed previously. Based on these results, more accurate estimates of maize LAI_g could be obtained from the MOD13Q1 product. The results obtained from WDRVI (α= 0.1 and α=0.2) and EVI models showed acceptable results compared with estimates of LAI_g reported by previous studies using MODIS products 250-m resolution. Doraiswamy et al. (2004) estimated maize LAI with a RMSE of 1.11 and 0.63 m^2 m^{-2} using MODIS 250-m and field canopy reflectance, respectively. They attributed the difference in RMSE between field and satellite estimation to potential error associated with MODIS atmospheric correction. On the other hand, Zhu et al. (2005) reported a linear agreement in grass LAI estimation using EVI and NDVI retrieved from MODIS 250-m (R^2=0.82 and 0.78, respectively). Neither of these previous studies explained if information on DOYCMP was included in their analyses.

Figure 12 summarizes the validation results of EVI and WDRVI (α= 0.1 and α=0.2) models for maize LAI_g estimates under rainfed and irrigated conditions from 2005 to 2009 (n=78) using MODIS VI 250-m 16 day composite period. The EVI quadratic, EVI, $WDRVI_{\alpha=0.1}$ and $WDRVI_{\alpha=0.2}$ linear model for maize LAI_g estimates showed a RMSE of 0.61, 0.57, and 0.58 m^2 m^{-2}, respectively and accounted for nearly 90 percent of maize LAI_g variation. In contrast, higher RMSE and lower R^2 were obtained for EVI and WDRVI (α= 0.1 and α=0.2) linear model for maize LAI_g estimates using data retrieved from 500-m resolution (MOD09A1) (Figure 13). The RMSE was 0.80, 0.87, and 0.83 m^2 m^{-2} for EVI, and $WDRVI_{\alpha=0.1}$ and $WDRVI_{\alpha=0.2}$ models over rainfed and irrigated conditions using data from MOD09A1. Validation results confirmed that more accurate estimates of maize LAI_g can be obtained using data obtained from the 250-m resolution (MOD13Q1) compared to the 500-m resolution MODIS product (MOD09A1). Based on these results, estimates of maize LAI_g might be monitored using 500-m resolution but with larger estimate errors of LAI_g. Incorporation of LAI_g retrieved from MODIS 500-m resolution into crop models should add additional source of error rather than reduce uncertainties of simulated LAI_g.

In summary, better calibration and validation results were obtained from data retrieved from the MODIS product with spatial resolution of 250-m (MOD13Q1) compared with 500-m resolution (MOD09A1). The limitation to retrieve a pixel from 500-m without contamination of surrounding areas increased the error on maize LAI_g estimates on the study sites. Results obtained during nine years of data showed that crop biophysical parameters such as maize LAI_g can be monitored during the entire growing season with the EVI quadratic and $WDRVI_{\alpha=0.2}$ and $WDRVI_{\alpha=0.1}$ linear models with data retrieved from MOD13Q1. MODIS products with 250-m should be used for agricultural applications such as estimates of LAI_g for crop modeling applications. More frequent LAI_g estimates can be obtained using MODIS 250-m 8 day period composite product (MOD09Q1); however, the information of the DOYCMP is needed for agricultural applications based in the results obtained in this study. Including DOYCMP in the

MOD09Q1 product would dramatically enhance its utility in many agricultural applications.

CONCLUSIONS

This study evaluated capabilities and limitations of three MODIS products (MOD13Q1, MOD09A1, and MOD09Q1) to track and estimate maize agronomic parameters such LAI_g during the growing season. Results clearly demonstrated the variability of pixel temporal resolution obtained from MODIS 8 and 16 day composite periods and the importance of day of pixel composite information from MODIS products for monitoring agricultural crops. Due to the maize LAI_g dynamics and changes in MODIS temporal resolution, the inclusion of DOYCMP has important implications to estimate and monitor agricultural crop dynamics. The results of this study showed that MODIS 250-m resolution provides more accurate estimates of maize LAI_g compared to MODIS 500-m resolution. Although results from this study suggested that MOD09Q1 product could be the better product to monitor agricultural crops due to spatial resolution and temporal resolution, this product does not include information of DOYCMP (collection 5) which should be essential for agricultural applications.

Results suggested that crop biophysical parameters such as LAI_g could be monitored during the entire growing season with data retrieved from MOD13Q1. Based on nine years of data used in this study, maize LAI_g can be accurately estimated using a EVI quadratic and $WDRVI_{\alpha=0.2}$ and $WDRVI_{\alpha=0.1}$ linear models for data retrieved from the

250-m resolution product (MOD13Q1). An important result of this study is the ability to estimate maize LAI_g without the use of radiative transfer models.

Based on this study, it is suggested that the assembly of a product of NDVI 250-m 8 day composite would be useful for agricultural applications instead of the product of NDVI 250-m 16 day composite used by government agencies. A MODIS product of NDVI 250-m 8 day composite should allow regional and national government agencies to improve the accuracy of agricultural crop monitoring or comparison of NDVI values with historical or previous year values.

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Table 1. Summary of selected vegetation indices.

Vegetation Index	Equation	Reference
Normalized Difference Vegetation Index (NDVI)	$\frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}}$	Rouse et al., 1974
Enhanced Vegetation Index (EVI)	$2.5\frac{\rho_{NIR} - \rho_{red}}{1 + \rho_{NIR} + 6\rho_{red-} - 7.5\rho_{blue}}$	Huete et al., 2002
Wide Dynamic Range Vegetation Index (WDRVI)	$\mathrm{WDRVI} = \frac{(\alpha + 1)\mathrm{NDVI} + (\alpha + 1)}{(\alpha - 1)\mathrm{NDVI} + (\alpha + 1)}$	Gitelson, 2004

ρ_{NIR}= near infrared reflectance; ρ_{red}= red reflectance; ρ_{blue}= blue reflectance; α=weighting coefficient.

Table 2. Impact of incorporation of day of year (DOY) and day of composite (DOYCMP) on estimated maize green leaf area index (LAI_g).

		MOD13Q1			MOD09A1			MOD09Q1		
		RMSE (m^2m^{-2})	CV (%)	R^2	RMSE (m^2m^{-2})	CV (%)	R^2	RMSE (m^2m^{-2})	CV (%)	R^2
NDVI	DOY	1.22	38	0.67	1.01	28	0.73	0.71	21	0.87
	DOYCMP	0.49	14	0.94	0.82	22	0.81	0.50	14	0.93
EVI	DOY	1.28	39	0.63	1.22	34	0.60	0.80	23	0.84
	DOYCMP	0.59	17	0.91	0.80	22	0.82	0.56	15	0.92
WDRVI	DOY	1.23	38	0.66	1.01	28	0.73	0.73	23	0.87
	DOYCMP	0.53	15	0.93	0.84	23	0.80	0.93	16	0.51

MOD13Q1=Moderate Resolution Imaging Spectroradiometer (MODIS) Terra Vegetation Index 16 day composite 250 meter resolution; MOD09A1= Moderate Resolution Imaging Spectroradiometer (MODIS) Terra Surface Reflectance 8 day composite 500 meter resolution; MOD09Q1 = Moderate Resolution Imaging Spectroradiometer (MODIS) Terra Surface Reflectance 8 day composite 250 meter resolution.

Table 3. Calibration equation for maize green leaf area (LAI_g) estimation using EVI, $WDRVI_{\alpha=01}$ and $WDRVI_{\alpha=0.2}$ from MODIS data.

Vegetation Index	Model equation	RMSE (m^2 m^{-2})	CV (%)	R^2
MOD13Q1				
EVI	$LAI_g = -1.22 + 5.63 * EVI + 4.19 * EVI^2$	0.58	0.16	0.92
WDRVI $_{\alpha=0.2}$	$LAI_g = 5.60 * WDRVI_{\alpha=0.2} + 2.24$	0.53	0.15	0.93
WDRVI $_{\alpha=0.1}$	$LAI_g = 3.94 * WDRVI_{\alpha=0.1} + 5.82$	0.49	0.14	0.94
MOD09A1				
EVI	$LAI_g = 11.25 * EVI - 2.47$	0.80	0.22	0.82
WDRVI $_{\alpha=0.2}$	$LAI_g = 5.80 * WDRVI_{\alpha=0.2} + 2.63$	0.84	0.23	0.84
WDRVI $_{\alpha=0.1}$	$LAI_g = 5.81 * WDRVI_{\alpha=0.1} + 4.46$	0.90	0.25	0.78

MOD13Q1=Moderate Resolution Imaging Spectroradiometer (MODIS) Terra Vegetation Index 16 day composite 250 meter resolution; MOD09A1= Moderate Resolution Imaging Spectroradiometer (MODIS) Terra Surface Reflectance 8 day composite 500 meter resolution.

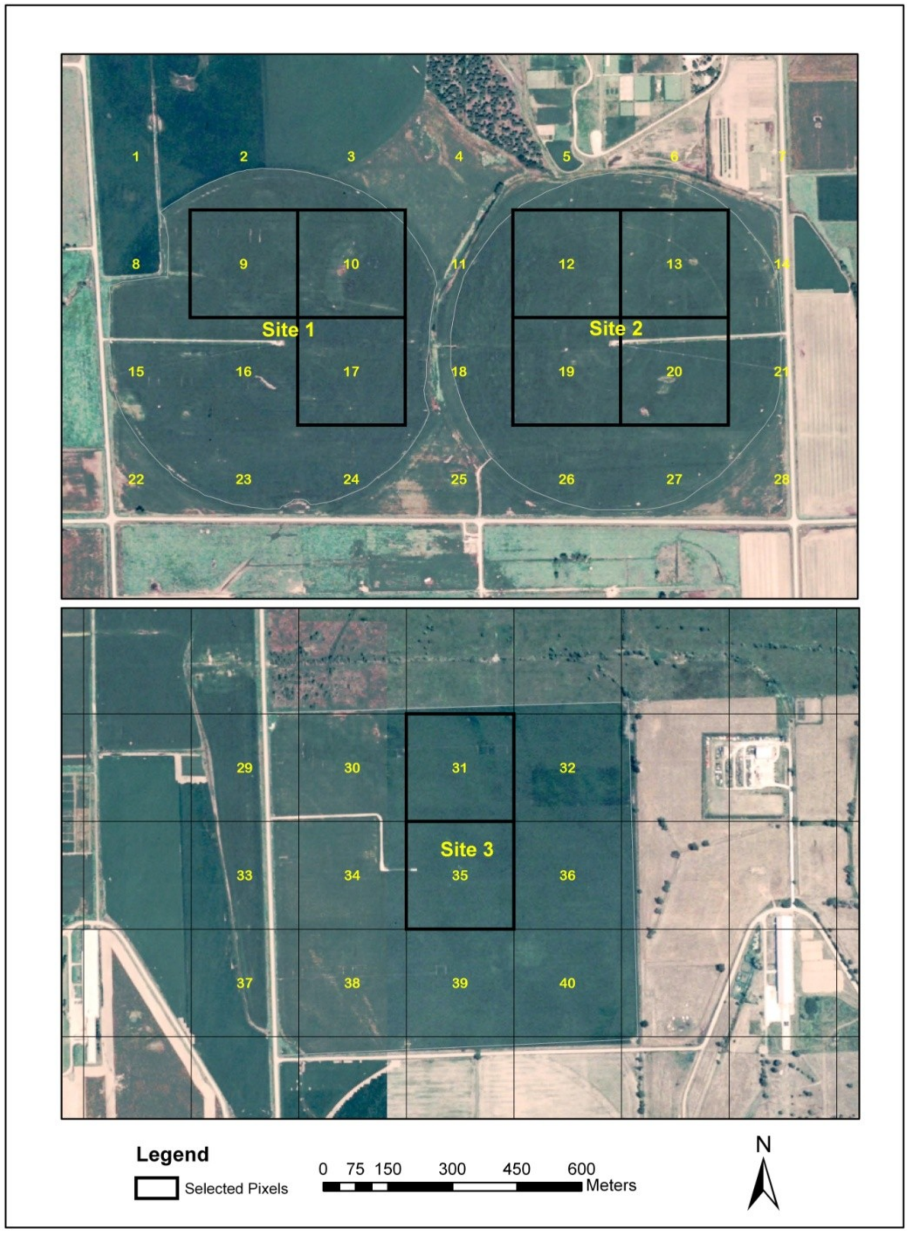


Figure 1. MODIS 250-m 16 day composite (MOD13Q1) pixel locations superimposed over study sites in Mead, Nebraska

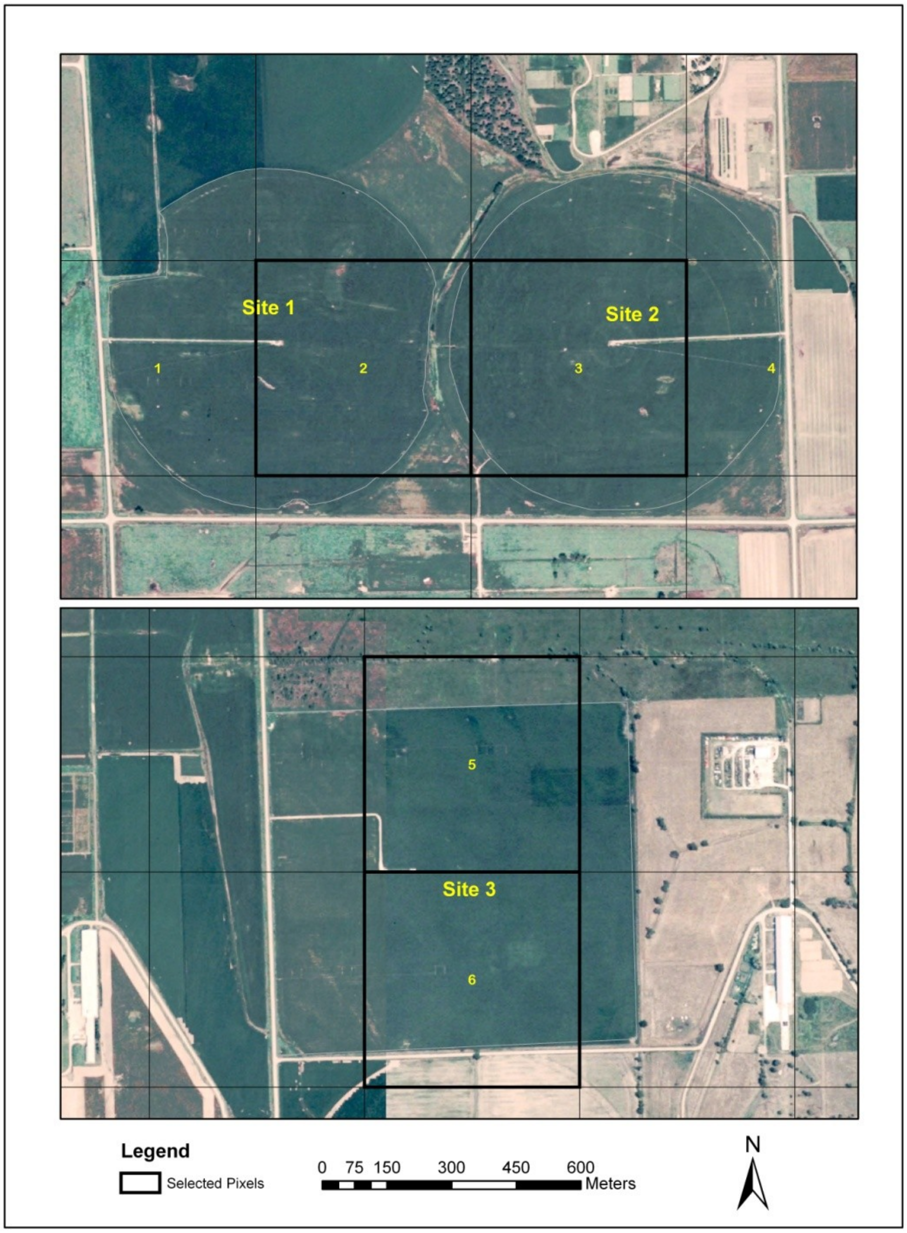


Figure 2. MODIS 500-m 8 day composite (MOD09A1) pixel locations superimposed over study sites in Mead, Nebraska.

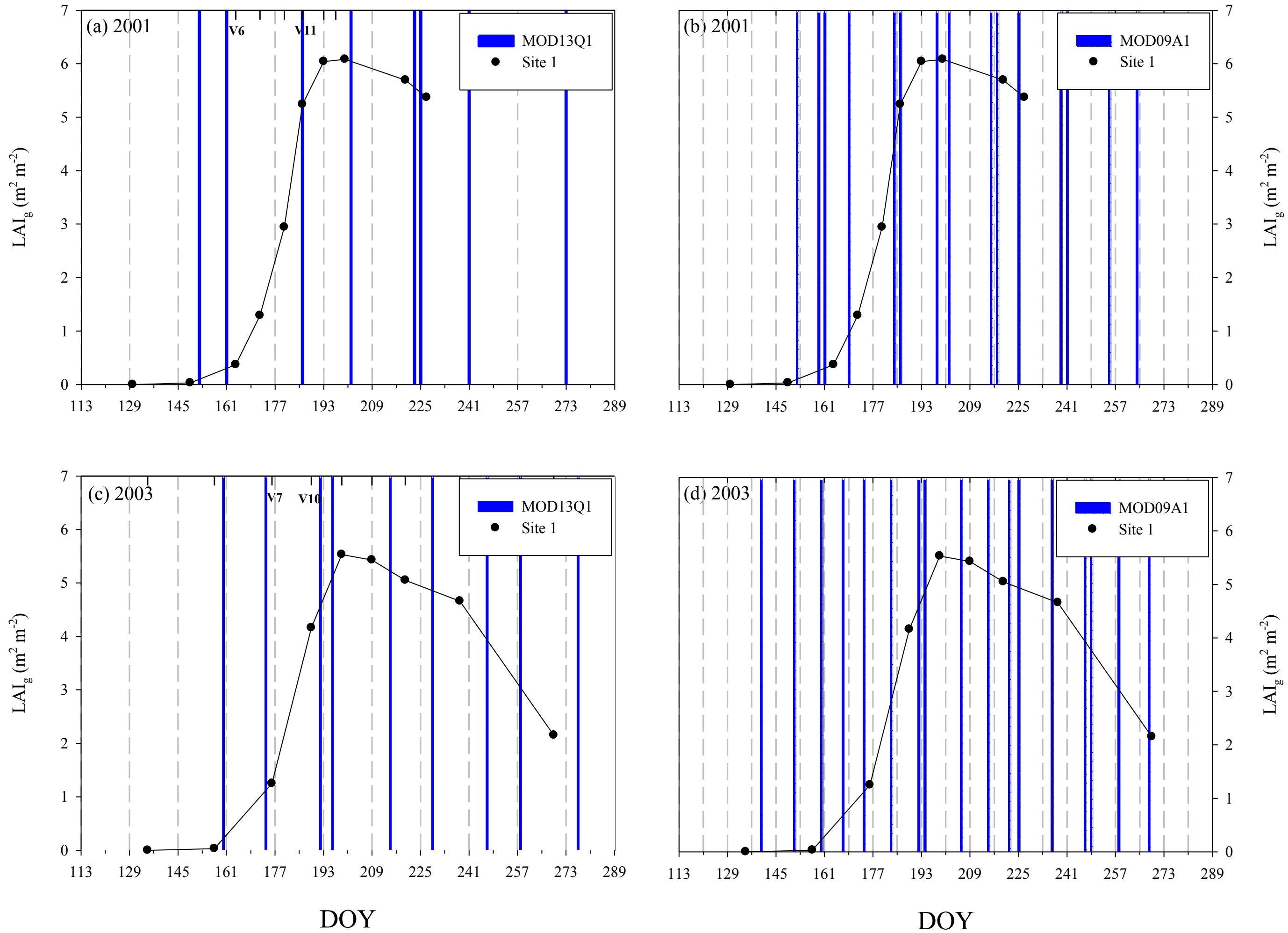


Figure 3. Progress of green leaf area index (LAI_g) as function of day of year (DOY) and day of pixel composite for MODIS Vegetation Index 250 meters 16 days composite (MOD13Q1) 2001 (a) and 2003 (c) and MODIS Reflectance 500 meters 8 days composite (MOD09A1) for 2001 (b) and 2003 (d). Dash lines correspond to MODIS first day of composite period.

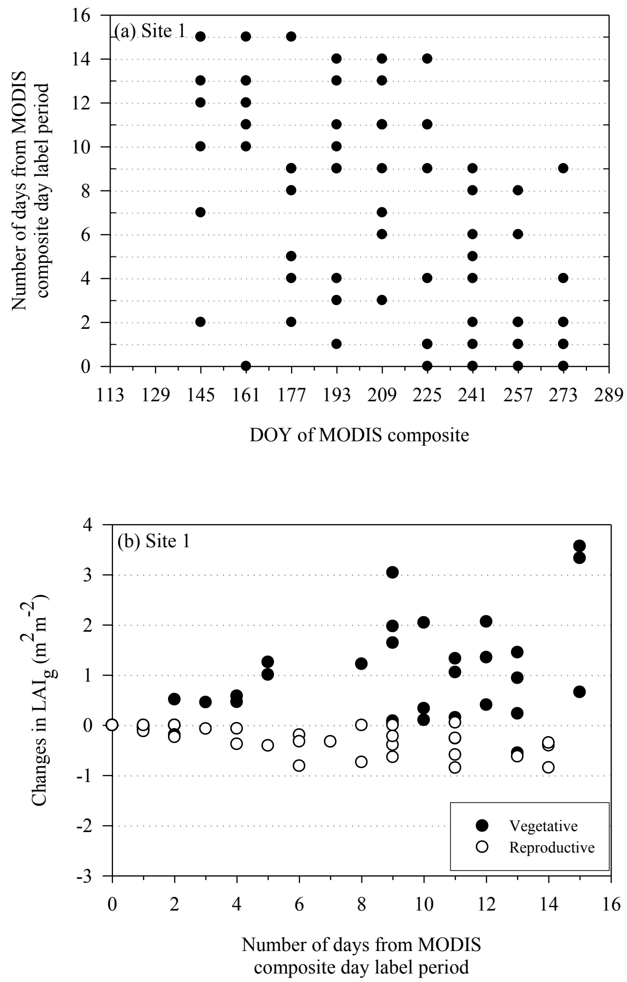


Figure 4. (a) Number of days from the first day of composite period as a function of day of year (DOY) of MODIS 16 day composite (MOD13Q1) and (b) Changes in LAI_g as a function of number of days from MODIS 16 day composite day obtained during nine growing season over site 1.

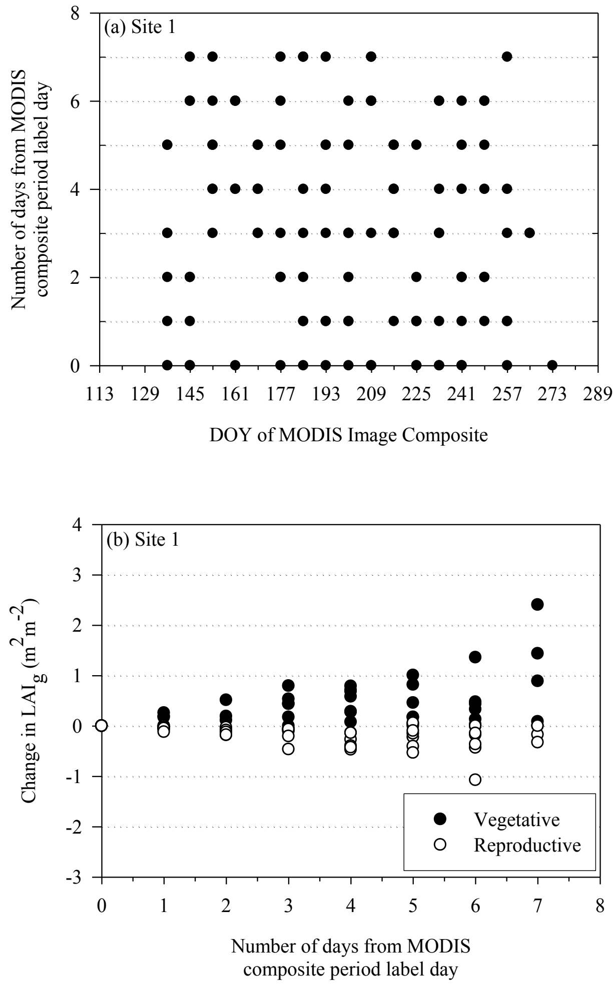


Figure 5. (a) Number of days from the first day of composite period as a function of day of year (DOY) of MODIS 8 day composite (MOD09A1) and (b) changes in LAI_g as a function of number of days from MODIS 8 day composite day obtained during nine growing season over site 1.

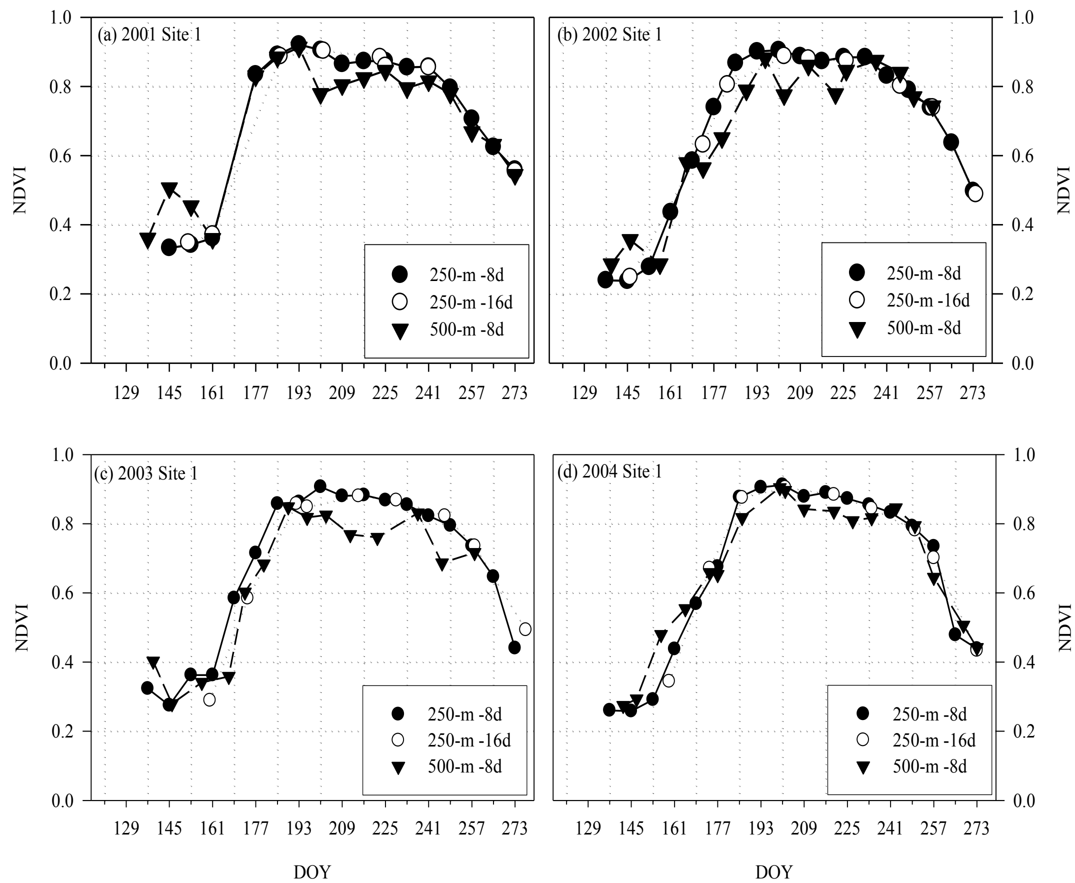


Figure 6. Temporal values of NDVI obtained from MODIS 250-m 8 day composite (MOD09Q1), MODIS 250- m 16 day composite (MOD13Q1), and MODIS 500- m 8 day composite (MOD09A1) as function of day of year (DOY) for the selected pixels over maize field at site 1.

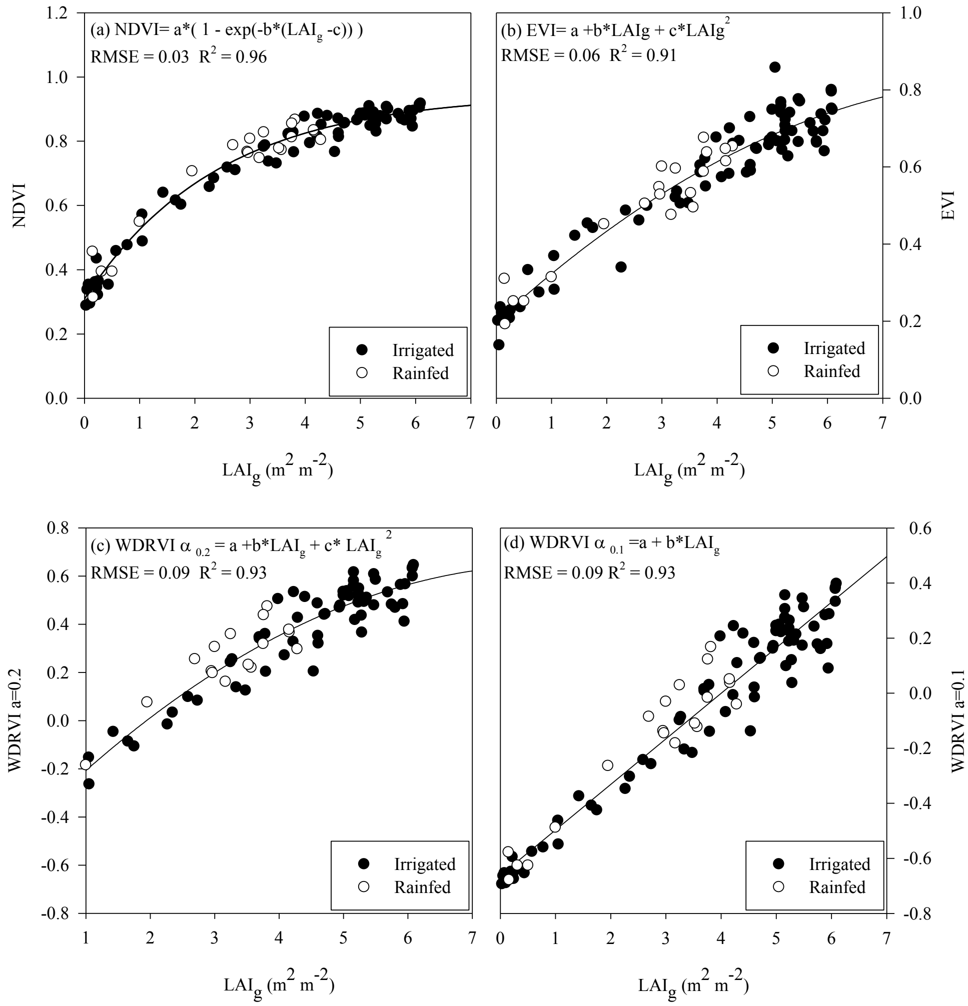


Figure 7. Relationships between the (a) Normalized Vegetation Index (NDVI), (b) Enhanced Vegetation Index (EVI), and Wide Dynamic Range Vegetation Index (WDRVI) with (c) α=0.2 and, (d) α=0.1 obtained from MODIS Surface Reflectance 250-m 8 day composite (MOD09Q1) as a function of green leaf area index (LAI_g).

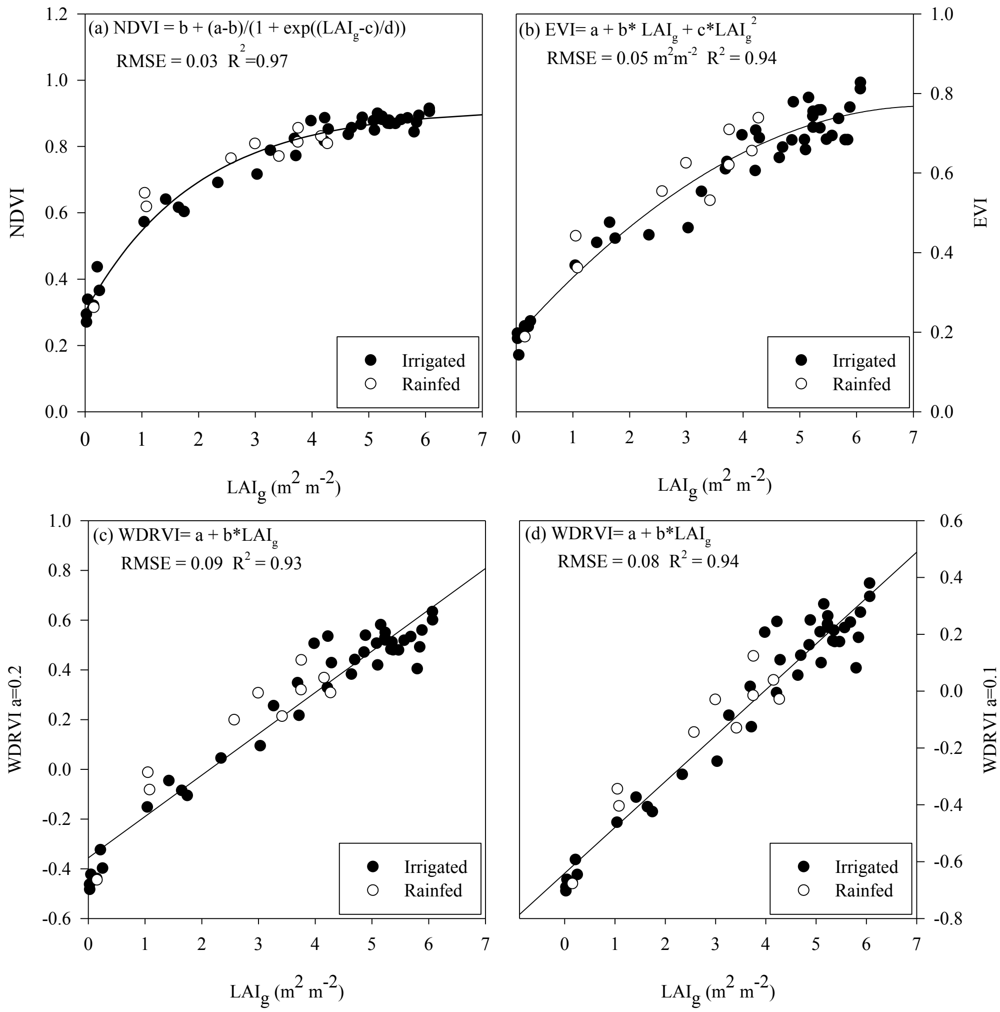


Figure 8. Relationships between the (a) Normalized Vegetation Index (NDVI), (b) Enhanced Vegetation Index (EVI), and Wide Dynamic Range Vegetation Index (WDRVI) with (c) α=0.2 and, (d) α=0.1 obtained from MODIS Vegetation Index 250-m 16 day composite (MOD13Q1) as a function of green leaf area index (LAI_g).

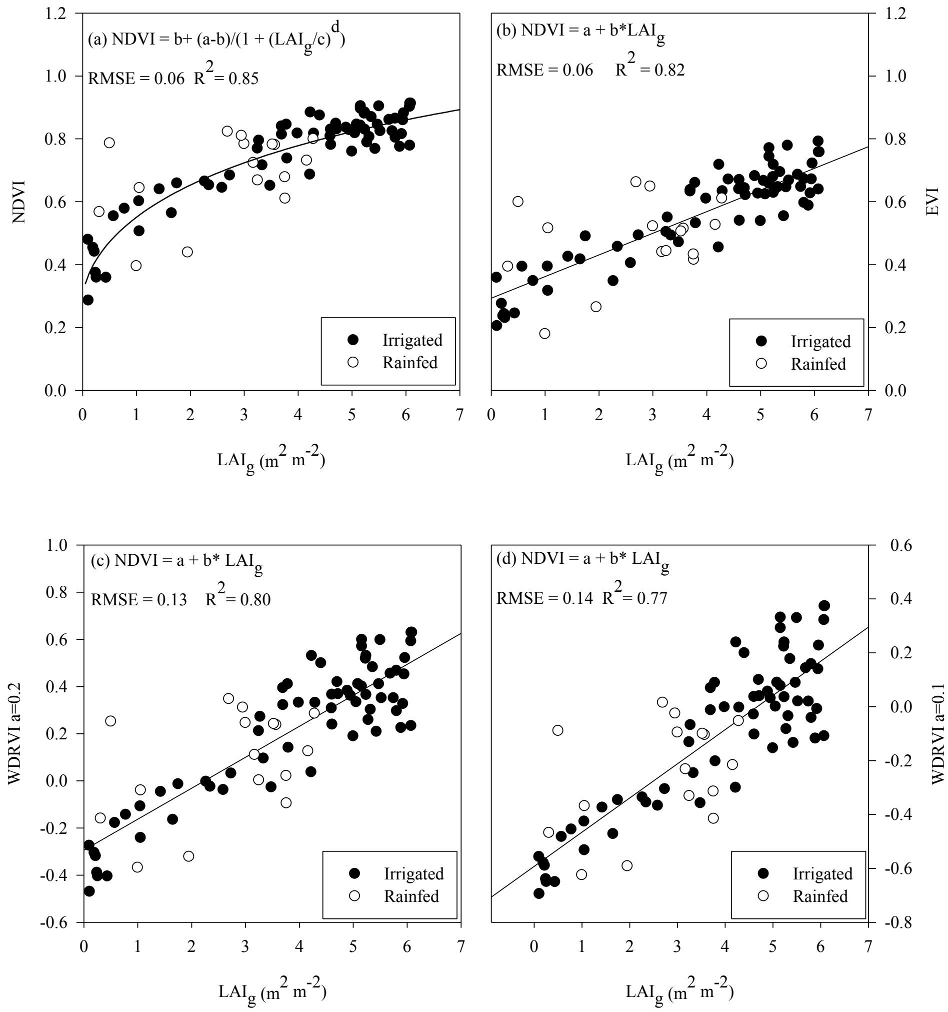


Figure 9. Relationships between the (a) Normalized Vegetation Index (NDVI), (b) Enhanced Vegetation Index (EVI), and Wide Dynamic Range Vegetation Index (WDRVI) with (c) α=0.2 and, (d) α=0.1 obtained from MODIS Surface Reflectance 500-m 8 day composite (MOD09A1) as a function of green leaf area index (LAI_g).

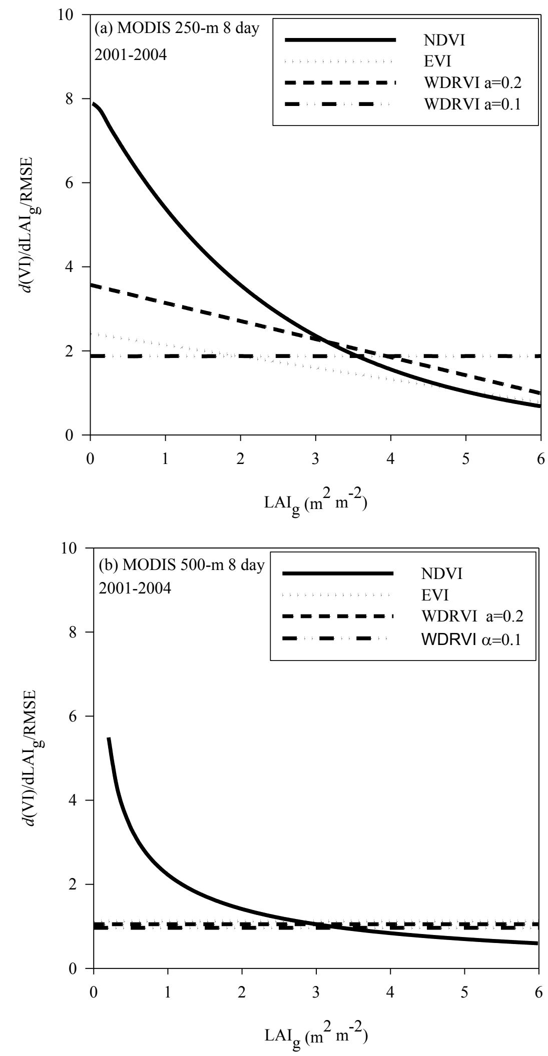


Figure 10. Sensitivity of NDVI, EVI, WDRVI with α= 0.1 and α= 0.2 to changes in maize green leaf area (LAI_g) irrigated and rainfed conditions obtained from MODIS (a) 250-m 8 day composite and (b) 500-m 8 day composite from 2001 to 2004. Sensitivity is defined as the ratio of the derivative of the best fit function to the RMSE.

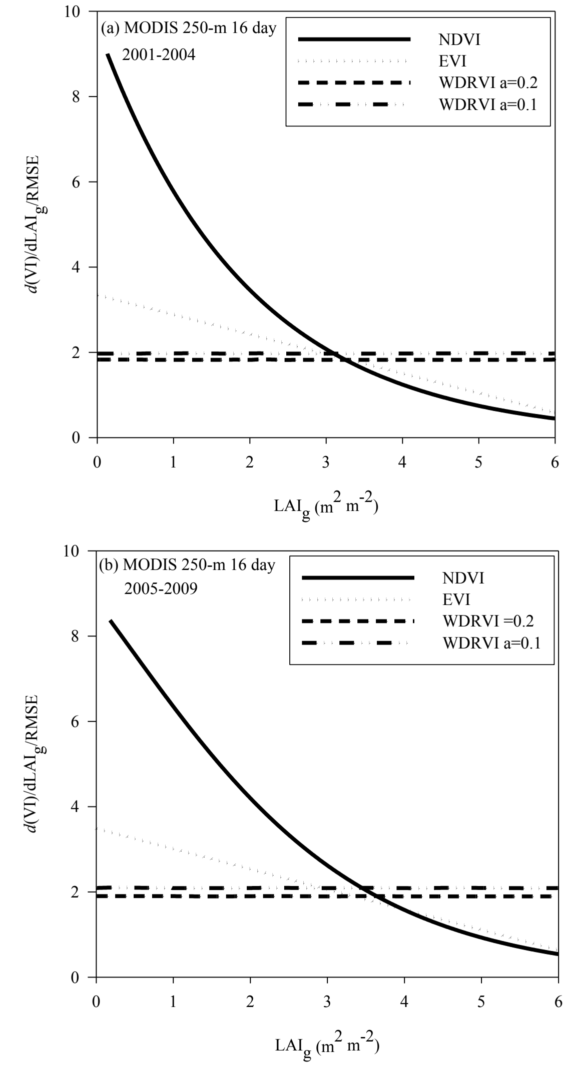


Figure 11 . Sensitivity of NDVI, EVI, WDRVI with α= 0.1 and α= 0.2 to changes in maize green leaf area (LAI_g) irrigated and rainfed conditions obtained from MODIS 250-m 16 day composite (a) from 2001 to 2004 and (b) from 2005 to 2009. Sensitivity is defined as the ratio of the derivative of the best fit function to the RMSE.

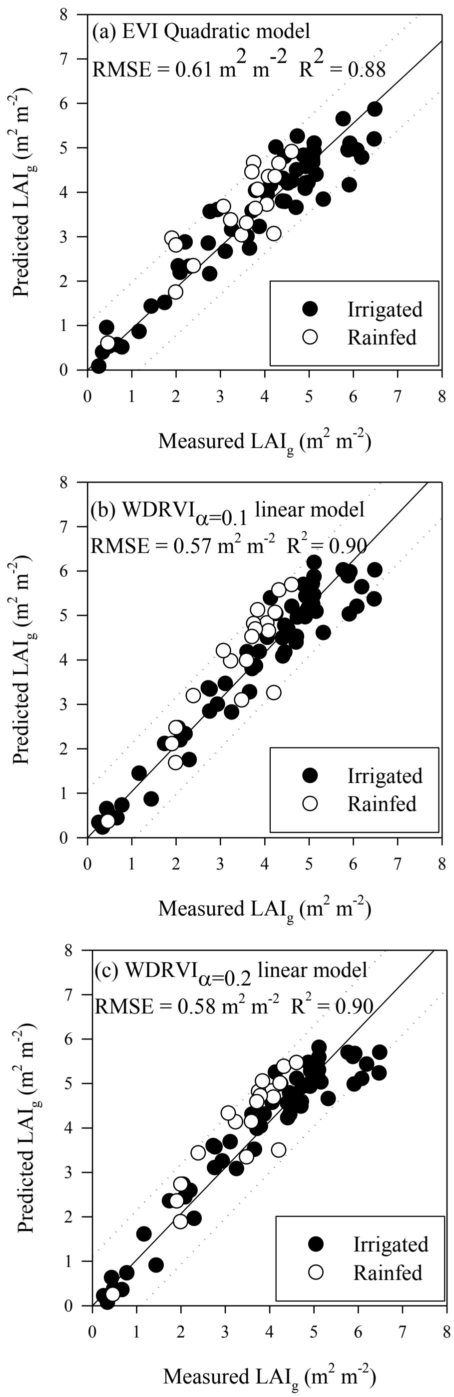


Figure 12. Validation of the (a) Enhanced Vegetation Index (EVI), and Wide Dynamic Range Vegetation Index (WDRVI) with (b) α=0.1 and (c) α=0.2 models for estimates of maize green leaf area index (LAI_g) under irrigated and rainfed conditions during 2005 until 2009 using MODIS Vegetation Index 250-m 16 day composite period (MOD13Q1).

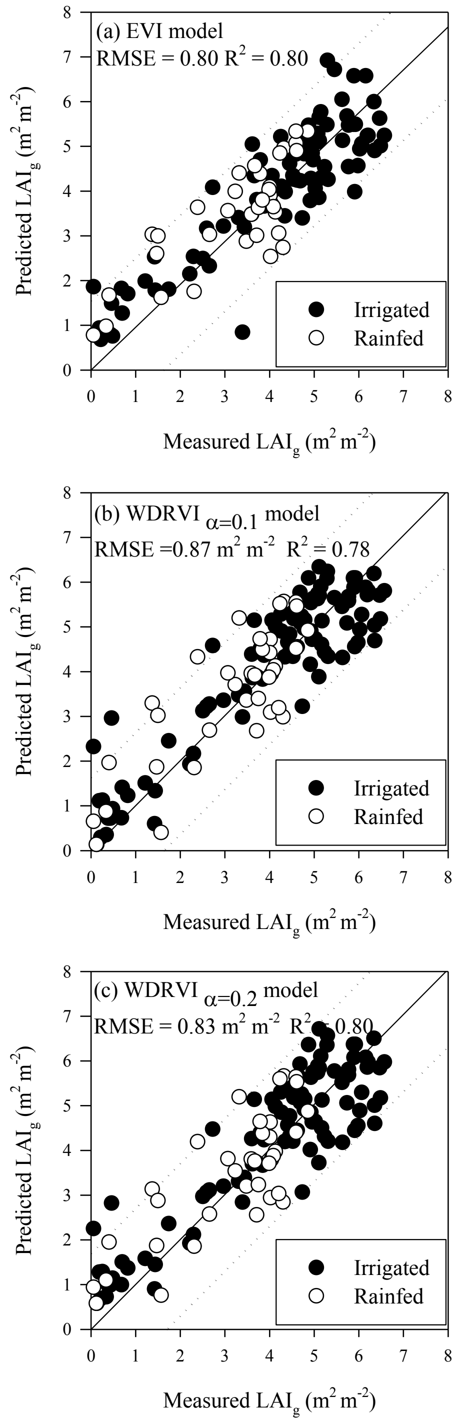
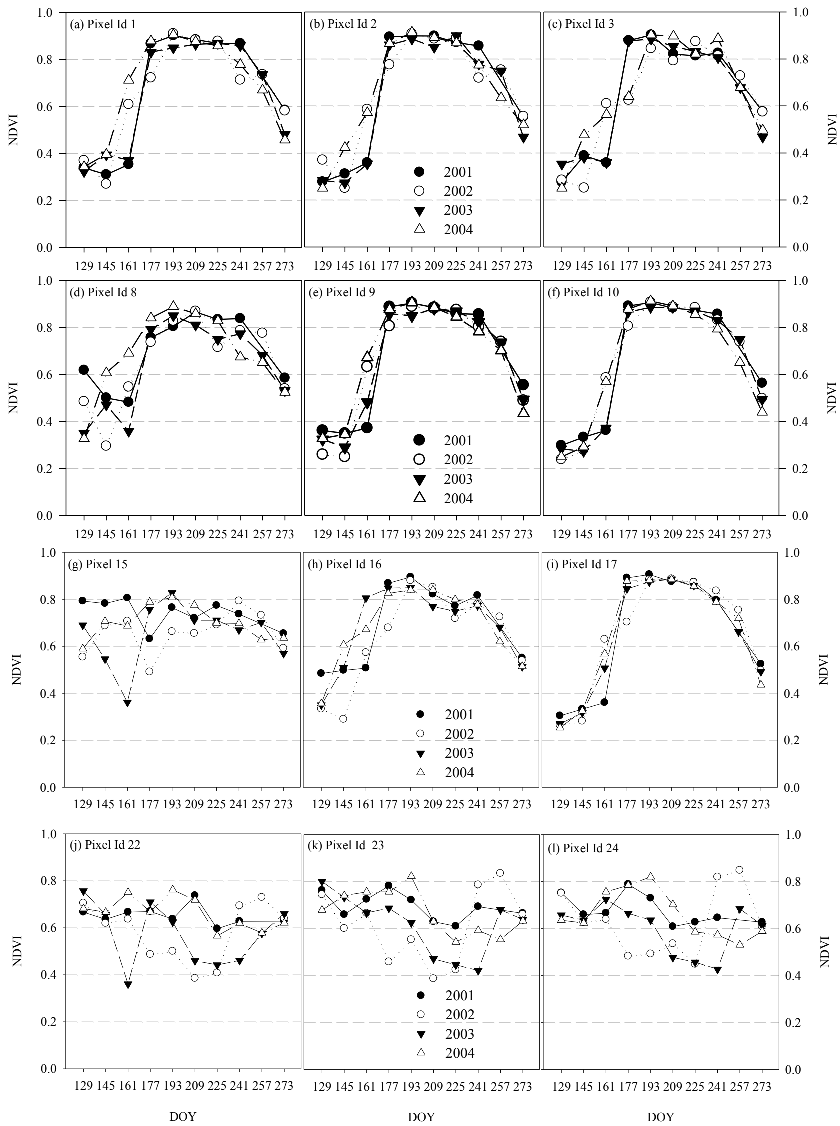
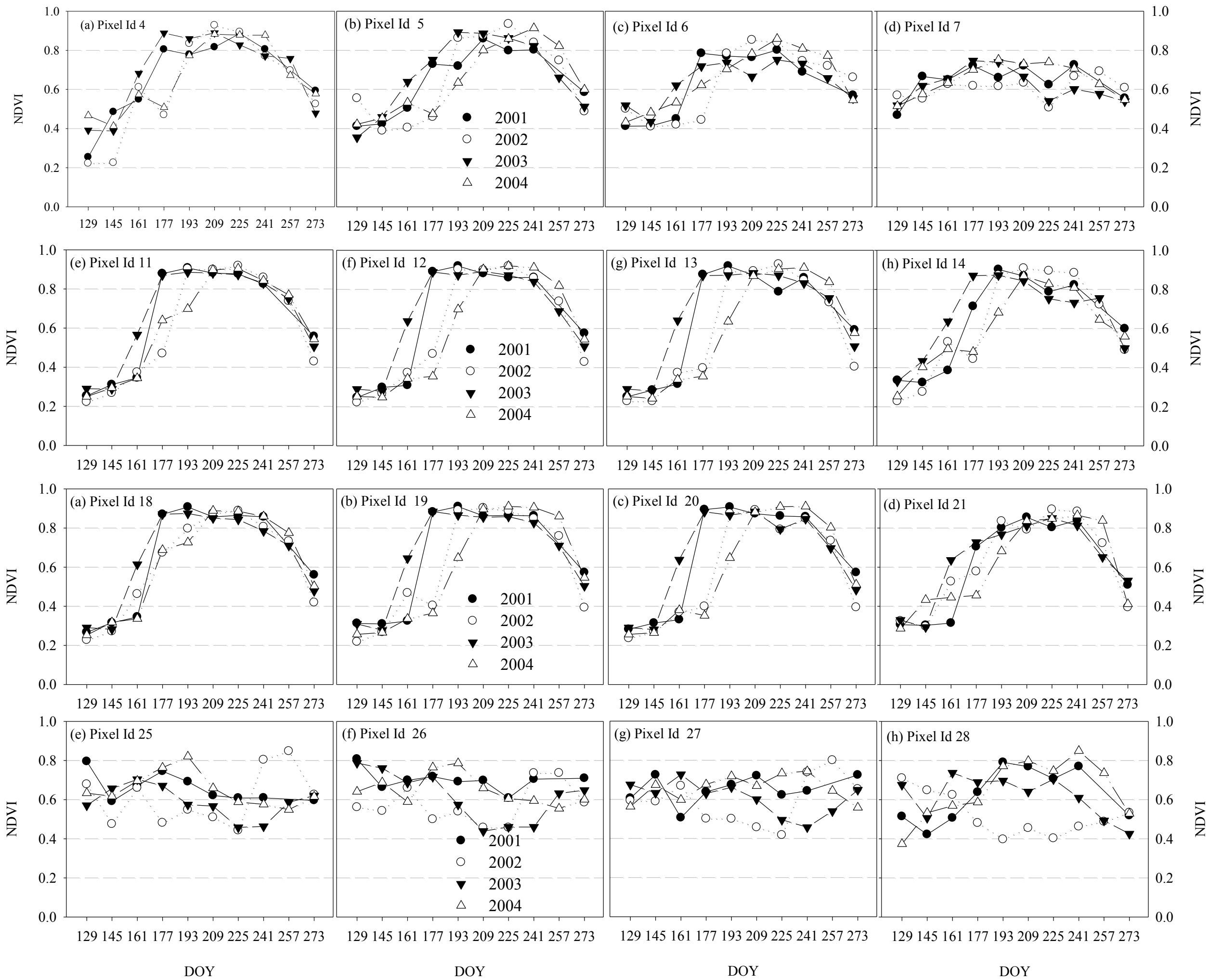


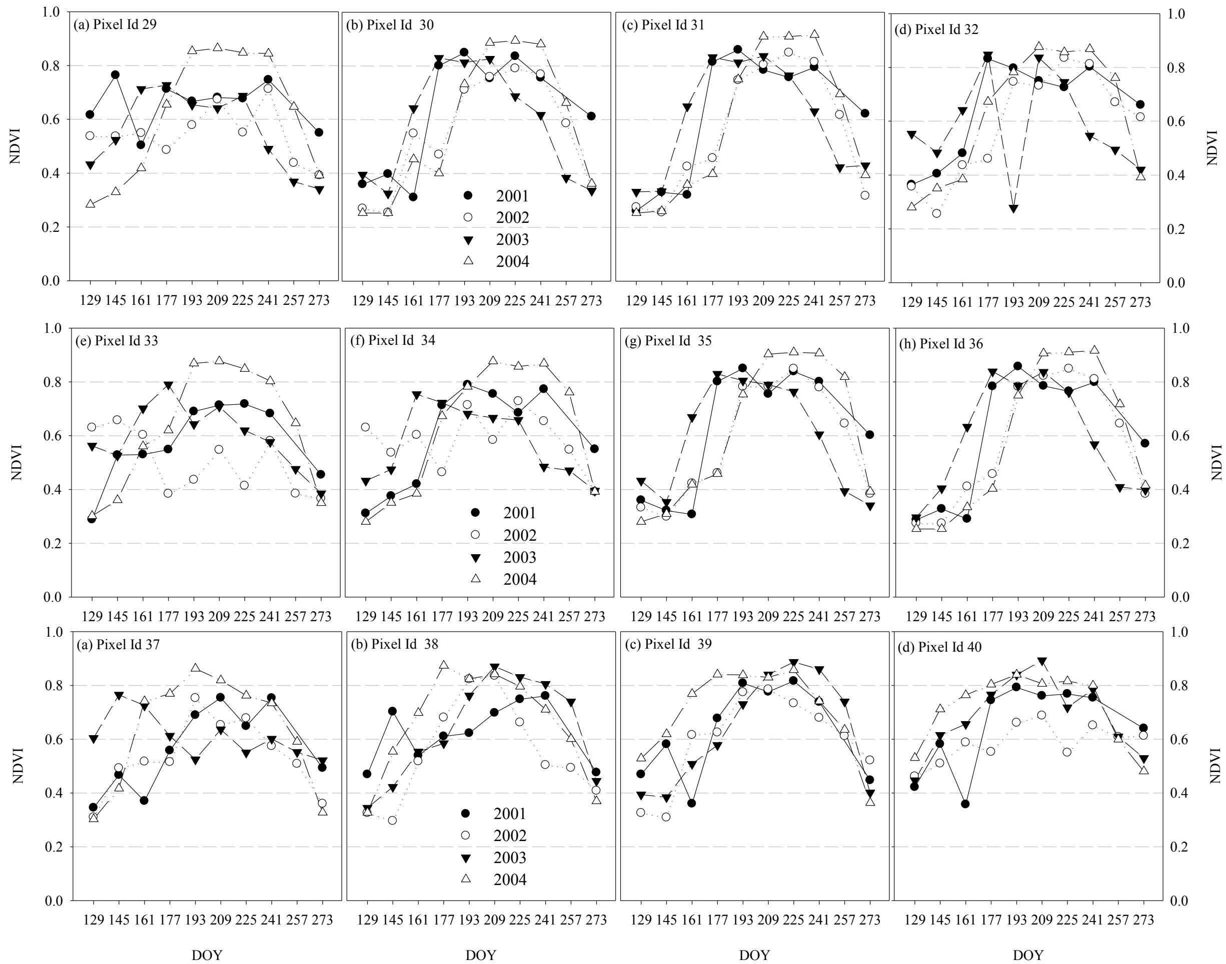
Figure 13 Validation of the (a) Enhanced Vegetation Index (EVI), and Wide Dynamic Range Vegetation Index (WDRVI) with (b) α=0.1 and (c) α=0.2 models for estimates of maize green leaf area index (LAI_g) under irrigated and rainfed conditions during 2005 until 2009 using MODIS Surface Reflectance 500-m 8 day composite (MOD009A1).



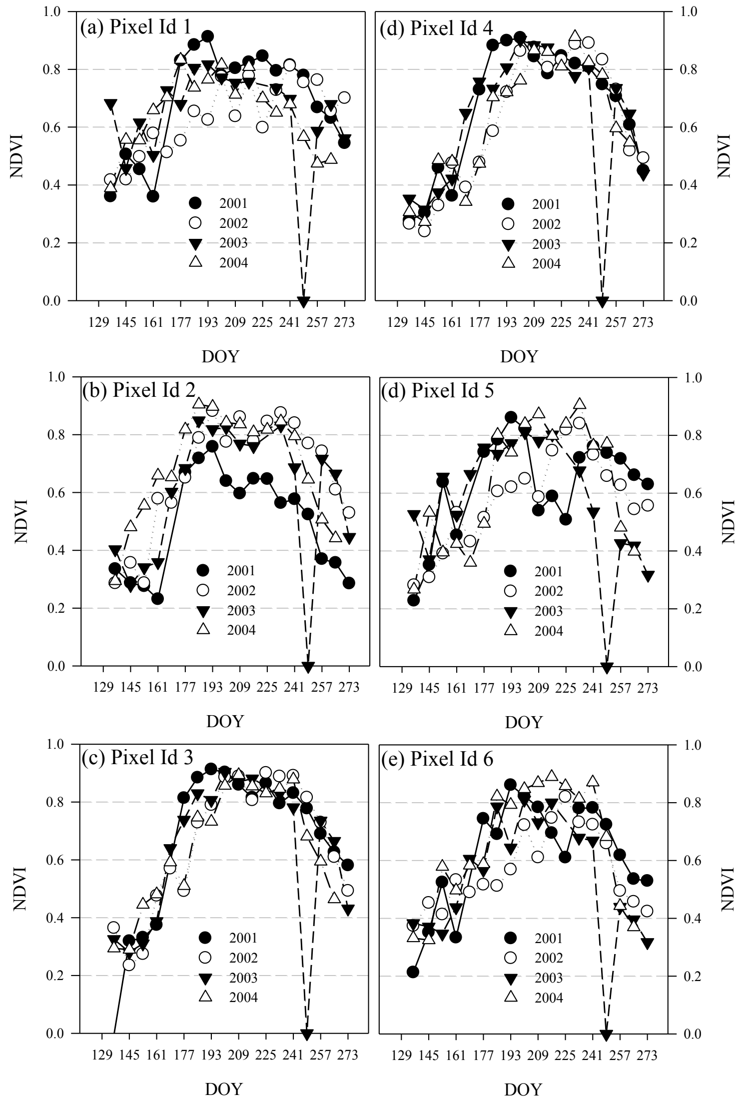
Appendix 1. Temporal profiles of NDVI for pixels retrieved from MODIS 250-m 16 day composite (MOD13Q1) over site 1.



Appendix 2. Temporal profiles of NDVI for pixels retrieved from MODIS 250-m 16 day composite (MOD13Q1) over site 2.



Appendix 3. Temporal profile of NDVI for pixels retrieved from MODIS 250-m 16 day composite period (MOD13Q1) over site 3.



Appendix 4. Temporal profiles of NDVI for pixels retrieved from MODIS 500-m 8 day composite (MOD09A1) over study sites.

CHAPTER 2

SIMULATING GREEN LEAF AREA INDEX AND FINAL YIELD IN MAIZE USING A CROP SIMULATION MODEL WITH MODIS INPUT DATA

ABSTRACT

Although crop simulation models are valuable tools to simulate optimal yields and yields under limiting conditions, studies have reported that inaccuracies in yield predictions were associated with uncertainties in input parameters relating to crop photosynthesis and leaf area index estimation. One approach to reduce uncertainties in simulated values from crop simulation models is the integration or incorporation of green leaf area index (LAI_g) obtained through remote sensing during the growing season. The overall objective of this study was to evaluate the potential use of MODIS Vegetation Index 250-m product to improve LAI_g simulations by the Muchow-Sinclair-Bennet maize model. Results from this study showed that estimates of LAI_g obtained from Wide Dynamic Range VI using MODIS 250-m products allowed the improvement of LAI_g simulations by the MSB model reducing the overall RMSE of LAI_g from 0.90 to 0.52 m^2 m^{-2} for all years of study under irrigated conditions. An important result is that WDRVI could allow the incorporation of accurate estimates of LAI_g from moderate to high values (LAI_g > 3.00 m^2 m^{-2}) into crop simulation models. The final yield predictions by the MSB model were improved by 23 and 26 percent with estimates of LAI_g obtained from MODIS 250-m 8 and 16 day composite under irrigated conditions, respectively.

Key words: crop simulation models, maize, green leaf area index, RUE

INTRODUCTION

Yield forecasting around the world is done with crop simulation models, remote sensing, statistical techniques, scouting reports, and combinations of these methods. Scouting reports or sampling of agricultural fields is a reliable way to estimate yield; however, the method is time-consuming and costly. In contrast, data obtained from remote sensing and crop simulation models allow government agencies, private sector parties, and researchers to estimate yield before harvest. Crop simulation models have been used to predict crop yields (Lal et al., 1993; Paz et al., 1998; Paz et al., 2001), impact of climate change (Tubiello et al, 1999; Tubiello et al., 2002; Weiss et al., 2003), and irrigation requirements (Hook, 1994; Guerra et al., 2004; Rinaldi et al., 2007) at different scales, from farm, to regional, to world levels. Although crop simulation models are valuable tools to simulate yields and yields under limiting factors, the amount of input data required and the spatial variation in model parameters can result in inaccurate predictions (Barnes et al., 1997; Batchelor et al, 2002).

Studies have reported that inaccuracies in yield predictions were associated with uncertainties in input parameters relating to crop photosynthesis and leaf area estimation in crop simulation models such as CERES-Maize (Carberry et al., 1989; Carberry, 1991; Lizaso and Ritchie, 1997; Lizaso, 2003), WTGROWS (Aggarwal, 1995) and SUCROS (Launay and Guerif, 2005). Because green leaf area (LAI_g) constitutes a fundamental component of many crop simulation models, a proposed approach to reduce uncertainties in crop simulation models is the integration or incorporation of crop parameters obtained through field observations or remote sensing during the growing season (Bouman, 1995;

Moulin et al., 1998; Leenhardt et al., 2006). This approach suggests that the modification of LAI_g during the growing season with measurements obtained from remote sensing, to correct simulated values of LAI_g, may improve future model predictions. Several studies have shown that the integration of LAI_g retrieved from remote sensing, into crop simulation models can improve final yield (FY) predictions of cotton (Maas 1988, 1993; Ko et al., 2006), wheat (Prevot et al., 2003; Moriondo et al., 2007; Duchemin et al., 2008), soybean (Seidl et al., 2004) and maize (Doraiswamy et al., 2004; Kiniry et al. 2004; Fang et al., 2008).

Several studies reported FY improvement with the incorporation of LAI_g retrieved from Moderate Resolution Imaging Spectroradiometer (MODIS) products. Fang et al. (2008) retrieved LAI_g from MODIS leaf area index 8 day composite at 1000m to incorporate into CERES-Maize. Doraiswamy et al. (2004) used data retrieved from MODIS surface reflectance 8 day composite at 250-m to incorporate in a radiative transfer model to estimate LAI_g during the growing season and then incorporate into a maize crop simulation model. However, the successful application of this technique requires an understanding of the limitations and capabilities of MODIS products and on how well the vegetation index (VI) accurately tracks and/or estimates LAI_g during the entire growing season. Data obtained from the MODIS Vegetation Index (VI) 250-m products provides an opportunity to acquire high quality data that can be used to estimate maize LAI_g and incorporated into crop simulation model to improve LAI_g simulations during the growing season. Results from Chapter 1 suggested that MODIS 250-meter (m) resolution products offer the opportunity to obtain more accurate estimates of maize LAI_g during the entire growing season compared to 500-m resolution without the use of radiative transfer models. The previous results (Chapter 1) demonstrated the importance of day of pixel composite (DOYCMP) included in some MODIS products for agricultural applications such as retrieving maize LAI_g. Maize LAI_g was accurately estimated (RMSE=0.60 m^2 m^{-2}) during the entire growing season using a Wide Dynamic Range Vegetation Index (WDRVI; Gitelson, 2004) linear model for data retrieved from MODIS 250-m resolution (MOD13Q1). Limitations have been reported incorporating accurate values of LAI_g into a crop simulation model due to limitations of the Normalized Difference Vegetation Index (NDVI) to accurately estimate LAI_g at high values of LAI_g (Hong et al., 2004; Rodriguez et al., 2004). One advantage of WDRVI is the capability to estimate LAI_g from moderate to high values of LAI_g (LAI_g > 3.0 m^2 m^{-2}) where other vegetation indices show limitations such as the NDVI. However, the performance of WDRVI for improving LAI_g simulation in crop simulation models has not been investigated to date.

The goal of this study was to evaluate the potential use of MODIS 250-m products to incorporate estimates of LAI_g into the maize model described by Muchow et al. (1990). This model (MSB) has been used by United States (U.S.) government agencies and U.S. government researchers to estimate maize yield at regional scales because it requires a minimum amount of input parameters and it is responsive to soil and climatic factors (Reynolds, 2001; Doraiswamy et al., 2005). The specific objectives of this study were (a) to evaluate the performance of WDRVI to improve LAI_g simulations by the MSB model using data from MODIS 250-m and (b) to determine the improvement in FY predictions by incorporating LAI_g into the MSB model.

MATERIALS AND METHODS

Field measurements

This research used field data from the Carbon Sequestration Project at the University of Nebraska-Lincoln collected at the Agricultural Research and Development Center located in Saunders County, Nebraska, USA. Field data were collected over two large study sites with different cropping systems. Site 1 (41˚ 09’54.2”N, 96˚ 28’35.9”W, 361m) was 48.7 ha and was planted in continuous maize from 2001 until 2009 and was irrigated. Site 3 was 65.4 ha planted in a maize-soybean rotation under rainfed conditions. The soils in the two sites are deep silty clay loams and consisting of four soil series: Yucan (fine-silty, mixed, superactive, mesic Mollic Hapludalfs), Tomek (fine, smectitic, mesic Pachic Argialbolls), Filbert (fine, smectitic, mesic Vertic Argialbolls), and Filmore (fine, smectitic, mesic Vertic Argialbolls). Irrigation schedules for site 1 were determined based on crop water budget maintaining 50 percent moisture content in the soil. This study used nine years of data (2001-2009) from site 1 and three years of data (2001, 2003, and 2005) from site 3. Site 1 represented maize grown under optimal water and nutrient conditions while optimal nutrient conditions under rainfed conditions was represented by site 3.

Within each site, six plot areas (20 m x 20 m) were established called intensive management zones (IMZs) for detailed process-level studies (details in Verma et al., 2005). Destructive samples consisting of 5 or more continuous plants were collected from one meter linear row sections in the six IMZ for each site. Field measurements of development stage, plant population density (POP), LAI_{total}, LAI_g, and total above-ground biomass (AGB) were taken at 10 to 14 day intervals until maturity for site 1

(2001-2009) and site 3 (2001, 2003, and 2005). The total and green leaf area were measured with an area meter (model LI-3100, LI-COR, Inc., Lincoln, NE) and converted to LAI_g using POP multiplied by the green leaf area per plant. All plant measurements were obtained by averaging all six IMZ measurements. Hand harvested yields were collected at each IMZ and averaged for each site-year. FY estimates were expressed on a grain dry matter basis per unit area in this study. MATLAB® was used to estimate the daily values of AGB and LAI_g using the cubic spline interpolation method.

Sensitivity analysis

A local sensitivity analysis was performed to determine the influence of variation in inputs parameters on yields predicted by the MSB model. Wallach (2006) defines a parameter as numerical value that is not calculated by the model and is not a measured or observed input variable. Examples of input parameters are radiation use efficiency (RUE) and the canopy extinction coefficient (k) for maize. Monod et al., 2006 recommended the identification of key input parameters to estimate before performing the sensitivity analysis to avoid impractical results due to complexity and the large number of parameters included in some crop models. The first step in this sensitivity analysis was to define the parameters and input variables and their nominal values and uncertainty ranges (Table 1). The range of uncertainty of RUE and the canopy extinction coefficient (k) was set according to minimum and maximum values of RUE reported for maize summarized by Sinclair and Muchow (1999) and Hay and Porter (2006), respectively. The uncertainty values for plant population density (POP) and planting date (DOP), and total number of leaves per plant (J) were set based on maximum and minimum values observed during the nine years of these experiments. The input parameter area of the largest leaf (AMAX) was varied in the range of ± 4 percent because AMAX was not measured in this study. A base output was set using the nominal values. For each combination of input parameters, a simulated maize yield output was obtained; all other parameters remained at their nominal values in a local sensitivity analysis. Monod et al. (2006) presents the basic approach to measure sensitivity from the relationship between a single input factor **Z** and a model output **Ŷ.** The goal was to identify which parameters had a small or large influence on the FY output. The Sensitivity index (SI) for the MSB model output (**Ŷ**) with respect to input variable (**Z**) was calculated as:

$$SI=\frac{\hat{Y}\,(Z)_{MAX}-\hat{Y}\,(Z)_{MIN}}{\hat{Y}(Z)_{MAX}} \qquad \text{eq. 2}$$

where $\hat{Y}_{MAX}$ and $\hat{Y}_{MIN}$ is the maximum and minimum of model yield output (**Ŷ**), respectively obtained for the evaluated input parameter (**Z**).

Model evaluation

The MSB model is a simple mechanistic crop simulation model that simulates the major effects of temperature and solar radiation on maize growth, development, and yield (Muchow et al., 1990). The total above-ground biomass accumulation (AGB) is estimated as the product of RUE and the daily incident solar radiation and k. The fraction of intercepted solar radiation (*f*ISR) is calculated from LAI_g. FY is estimated multiplying the AGB accumulation by the harvest index. The model has been tested across different environments under non-stressed conditions to show that maize yields are limited by temperature and solar radiation across the different environments (Muchow et al, 1990).

The MSB model was used to simulate maize yields from 2001 to 2009 and 2001, 2003, and 2005 under irrigated and rainfed conditions, respectively. Weather files (maximum and minimum air temperature, precipitation, and incoming solar radiation) for the MSB model were constructed using data collected by an automated weather station (maintained by the High Plains Regional Climate Center, http://www.hprcc.unl.edu) located at the Agricultural Research and Development Center (ARDC) in Mead, Nebraska. The input parameters such as POP and DOP were set according to field observation while J and AMAX were set at the default values (18 and 750 cm^2, respectively) during the experiment. The period from silking (R1) to physiological maturity (PM) was set to 1150˚Cd accumulated thermal time (ATT) in the MSB model as a default value; however, this ATT can vary between varieties. In this study, the MSB model was modified to simulate the duration of the period from silking (R1) to physiological maturity (PM) in agreement with field observations by increasing the ATT during grain filling periods.

A subroutine was modified to accept values of LAI_g from external sources (remote sensing or field measurements) and incorporate them into the MSB model. This subroutine reads a file containing observed LAI_g values, and if an observed value for this date was available, it replaced the simulated LAI_g values. The replaced value of LAI_g was used to predict the future evolution of LAI_g.

As will be discussed later, the input parameter with the largest influence in FY was RUE. Values of RUE were calculated as the slope of the relationship between the accumulated intercepted photosynthetically active radiation (IPAR; MJ m^{-2} d^{-1}) and AGB (g m^{-2}) from emergence to PM. RUE values based on IPAR were multiplied by 0.5 to covert to total solar radiation (SR) basis as explained in Sinclair and Muchow (1999).

Evaluation of model predictions with green leaf area index (LAI_g) modifications

The MSB model FY predictions were evaluated under two scenarios in order to determine if more accurate estimates of LAI_g during the growing season improved FY predictions over irrigated and rainfed conditions. Field data from 2001 to 2005 and 2001 and 2003 was used to evaluate the two scenarios under irrigated and rainfed conditions, respectively. Scenario 1 represented the model prediction without modifications (base scenario) under irrigated and rainfed conditions. Scenario 2 corresponded to the daily incorporation of LAI_g from one week after emergence until close to physiological maturity. Outputs from scenario 2 represent FY with no error in LAI_g model predictions.

Incorporation of green leaf area index (LAI_g) into the MSB using MODIS LAI_g estimates

The final part of this study was to evaluate the performance of WDRVI to improve LAI_g simulations by the MSB model with data obtained from MODIS 250-m over irrigated conditions from 2006 to 2009. A time series of MODIS Terra Vegetation Index 16-day composite 250-m (MOD13Q1) was downloaded from the National Aeronautic and Space Administration (NASA) Land Process Distributed Active Archive Center (LPDAAC) (https://lpdaac.usgs.gov/lpdaac/get_data/data_pool) from April through October (of each growing season) of the study area (MODIS tile h10v04). All MODIS images were processed, reprojected, and converted to GeoTIFF format using the MODIS Reprojection Tool Version 4.0 (MRT) downloaded from LPDAAC (https://lpdaac.usgs.gov/lpdaac/tools). Each study site was geolocated on each MODIS image. The NDVI and day of pixel composite (DOYCMP) data were retrieved from the center pixels over the study sites. NDVI values obtained from the 16 day composite were interpolated to estimate NDVI values from the 8 day composite 250-m product. NDVI values over the study site were used to calculate WDRVI. Estimates of LAI_g from 2006 to 2009 were obtained from results presented in Chapter 1. Appendix 1 summarizes the estimates of maize LAI_g obtained from WDRVI using MODIS data over site 1 from 2006 to 2009. These estimates of maize LAI_g were calculated using a linear model based on WDRVI calibrated using data from 2001 to 2004 under irrigated and rainfed conditions (details in Chapter 1). Estimates of LAI_g obtained from WDRVI were incorporated into the MSB model every 8 and 16 days from day of year (DOY) 161 until 241, respectively from 2006 to 2009. The period of time from DOY 161 to 241 covered the rapid development of LAI_g during vegetative stages until the late mid grain filling period during the years of study.

The MSB model LAI_g simulations with the incorporation of LAI_g using WDRVI estimates were compared with simulation of the original model to evaluate the performance of this VI. The root mean square error (RMSE) and relative RMSE (RRMSE) were used to determine the improvement of LAI_g simulation by the MSB model with the incorporation of LAI_g estimates obtained every 8 and 16 days using information of the day of pixel composite (DOYCMP) and the day of year (DOY) obtained from MODIS data.

RESULTS AND DISCUSSION

Sensitivity analysis

Figure 1 a-f shows the average maize yields predicted by changing one model parameter at a time while holding the other parameters at their nominal values. Sensitivity indices of 0.47, 0.25, 0.17, 0.07, and 0.02 were obtained for the input parameters of RUE, k, POP, J, and AMAX, respectively. Results obtained from this analysis suggest that uncertainties in AMAX, DOP, and J had low influence on FY predictions. In contrast, yield responses were more sensitive to POP, k, and RUE. These results can be explained with the model structure in which FY is calculated as a linear increased in harvest index (HI) so HI is closely related with AGB accumulation. FY was more sensitive to the main parameters that influence AGB accumulation in the maize model such as RUE, k, and POP. For example, AGB accumulation was calculated as the *f*ISR multiplied by RUE. Moreover, the *f*ISR depends on LAI_g and k; but LAI_g is also a function of POP. In other words, input parameters that affected AGB accumulation should also affect final yield in the maize model. These results clearly showed that the input parameter with the largest influence in FY prediction over the ranges tested was RUE.

The concept of RUE has been used in many crop simulation models because it simplifies the complex processes of photosynthesis and respiration. RUE also has been reported as the input parameter with the largest influence in FY predictions in the AUSIM-Maize model (Birch, 1996). Consequently, more accurate estimates of RUE may improve FY predictions by the MSB model under irrigated and rainfed conditions.

Evaluation of model predictions with green leaf area index (LAI_g) modifications using field measurements

Table 2 summarizes values of RUE measured during 2001 to 2005 and 2001, 2003, and 2005 under irrigated and rainfed conditions, respectively. Values of RUE measured over irrigated conditions from 2001 to 2005 varied between years which represented a variability of ± 8 percent from the default value of 1.6 g AGB MJ^{-1} used in the MSB model (Table 2). The average value of RUE was 1.6 g AGB MJ^{-1} under irrigated conditions; it was similar to the default value used by the MSB model. In contrast, lower values of RUE were measured under rainfed conditions that represented a reduction of 20, 26, and 7 percent in RUE values measured under irrigated conditions during 2001, 2003, and 2005, respectively (Table 2). Based on these results, the value of RUE was modified to the average value of 1.30 g AGB MJ^{-1} under rainfed conditions while remained as the default value of 1.6 g AGB MJ^{-1} used in the MSB model under irrigated conditions for this study. These measured values of RUE were similar values of RUE reported by Sinclair and Muchow (1999) for maize grown under irrigated (1.6 g AGB MJ^{-1}) and rainfed (1.2 g AGB MJ^{-1}) conditions.

The MSB model predictions of LAI_g and FY were compared with field measurements taken during the growing season over the study sites. Table 3 summarizes the $FY_{measured}$ and $FY_{predicted}$, RMSE and RMMSE obtained for overall FY and LAI_g predictions obtained during 2001 until 2005 under irrigated (S1) and rainfed (S3) conditions. Scenario 1 represents the model with the base scenario. The MSB model underpredicted FY by 1936 and 1640 kg ha^{-1} for 2001 and 2002, respectively, while overpredicted FY by 1187 kg ha^{-1} for 2004 under irrigated conditions. These differences represented an underprediction and overprediction of 16, 14 and 12 percent of FY for 2001, 2002 and 2004, respectively, the largest differences obtained over the five years analysis, under irrigated and rainfed conditions by scenario 1. In contrast, the MSB model underpredicted FY by 9 and 3 percent for 2003 and 2005, respectively, under irrigated conditions. The RMSE of the LAI_g simulations during the growing season ranged from a maximum and minimum of 1.13 to 0.38 m^2 m^{-2} obtained during 2001 and 2005, respectively under irrigation conditions (Table 3). Results from 2005 showed lower differences of FY prediction (299 kg ha^{-1}) and RMSE in LAI_g (0.38 m^2 m^{-2}) simulations during the entire growing season under irrigated conditions. In addition, larger FY prediction differences (1936 kg ha^{-1}) and LAI_g RMSE (1.13 m^2 m^{-2}) were obtained from 2001 results under irrigated conditions. These results suggested a possible association between FY predictions with the error in LAI_g simulations.

The differences between $FY_{measured}$ - $FY_{predicted}$ by the MSB model were less than 140 kg ha^{-1} under rainfed conditions. In contrast to the results obtained under irrigated conditions, differences in FY and RMSE of LAI_g simulations were not associated with inaccurate estimates of LAI_g (Table 3). For example, results showed a RMSE of 0.79, 1.40, and 0.89 m^2 m^{-2} while differences between $FY_{measured}$ - $FY_{predicted}$ were 18, 13, and 132 kg ha^{-1} for 2001, 2003, and 2005, respectively. The overall results showed a RMSE and RRMSE of 77 kg ha^{-1} under rainfed conditions. As explained in the previous section, the input parameter with the largest influence in FY prediction was RUE based on the local sensitivity analysis results. Consequently, accurate values of input parameters in the MSB mode can make significant improvements in FY predictions under rainfed conditions. For example, the MSB model overpredicted FY by 15, 45, and 13 percent for

2001, 2003, and 2005, respectively, with the default value of RUE used by the model of 1.6 g MJ^{-1}. Results suggested that the modification of input parameters with largest influence in the MSB model should improve FY predictions by the MSB model under rainfed conditions.

Scenario 2 represents the incorporation of daily values of LAI_g during the entire growing season with a RMSE of LAI_g simulation close to zero. Results suggested an overall improvement in FY predictions with a considerably reduction in RMSE from 1892 to 526 kg ha^{-1} and from 26 to 5 percent of the RMSE and RRMSE, respectively under irrigated conditions. The differences between $FY_{measured}$ - $FY_{predicted}$ were reduced to less than 10 percent during the five years of study by the MSB model under irrigated conditions with accurate estimation of LAI_g during the growing season. The differences between $FY_{measured}$ - $FY_{predicted}$ ranged from 969 and 43 kg ha^{-1} for 2001 and 2003, respectively. In contrast, the overall results showed an increase in the differences between $FY_{measured}$ - $FY_{predicted}$ by the MSB model under rainfed conditions. These results validate the previous discussion about the lack of association between RMSE of LAI_g and differences of FY predictions under rainfed conditions. Accurate estimates of LAI_g increased the FY predictions due to an increase in AGB accumulation under rainfed conditions. Although the overall results obtained from scenario 2 showed acceptable results with a RMSE of 803 kg ha^{-1} and a RRMSE of 11 percent under rainfed conditions, the approach of updating LAI_g simulation could worsen FY predictions in the MSB model. Based on these results, more accurate simulations of LAI_g by the MSB model could improve FY under irrigated conditions. These results were consistent with previous studies that associated inaccuracies in FY with inaccuracies in LAI_g predictions during the growing season (Aggarwal, 1995; Lizaso, 2003; Launay and Guerif, 2005).

Evaluation of model predictions with incorporation of LAI_g estimates obtained from WDRVI using MODIS 250-m data

Table 4 summarizes the RMSE and RRMSE for LAI_g predicted by the MSB model with and without the incorporation of LAI_g during the growing season from 2006 to 2009 under irrigated conditions. The base model represents the MSB model LAI_g simulations without LAI_g incorporation. MODIS DOYCMP and MODIS DOY summarizes the simulation results with the incorporation of LAI_g obtained from WDRVI using MODIS data with information of DOYCMP (MODIS DOYCMP) and DOY (MODIS DOY) every 8 and 16 day from day 161 to 241 during 2006 to 2009 under irrigated conditions. Results show that the incorporation of LAI_g every 8 days improved LAI_g predictions reducing the RMSE of LAI_g during all years of study compare to LAI_g prediction by the base model. For example, a maximum and minimum reduction of the RMSE from 0.95 to 0.32 and from 0.92 to 0.55 m^2 m^{-2} were obtained for 2007 and 2008, respectively, under irrigated conditions. The incorporation of LAI_g every 16 days also improved LAI_g predictions into the MSB model reducing RMSE to less than 0.60 m^2 m^{-2} for all years. Estimates of LAI_g obtained from WDRVI using data from MODIS 250-m every 8 and 16 days improved the model LAI_g predictions during all years of study compared to LAI_g prediction by the base model. The RMSE of LAI_g was reduced from 0.95 to 0.60 and from 0.92 to 0.68 m^2 m^{-2} a maximum and minimum obtained with the incorporation of estimates of LAI_g every 8 days on 2007 and 2008, respectively. The incorporation of LAI_g estimates every 16 days also reduced the RMSE for all years compared to LAI_g prediction by the base model. The lower reduction in the RMSE of LAI_g was obtained during 2008. The overall results obtained using WDRVI LAI_g estimates were closer to field measurements (Figure 2-a). This result indicates the robustness of the WDRVI, which accurately estimates maize LAI_g during the growing season. In contrast estimates of LAI_g obtained from MODIS without the incorporation of DOYCMP or using DOY (MODIS DOY) could increase the RMSE of LAI_g prediction (Figure 2-b). The RMSE of LAI_g using MODIS DOY increased compare to the RMSE of LAI_g using field measurements and MODIS DOYCMP (Table 4). The results were not surprising because information of DOYCMP has a relevant importance to the retrieval of LAI_g especially during vegetative stages (Chapter 1). Estimates of LAI_g obtained without information of DOYCMP are mostly overestimates during vegetative stages. For example, the estimate of LAI_g was 3.24 m^2 m^{-2} from information retrieved from MODIS DOY 161 in 2007; however, this estimate of LAI_g corresponds to DOY 171 based on information of DOYCMP (Appendix 1). In other words, an overestimation of approximately 2.00 m^2 m^{-2} was incorporated into the MSB model on DOY 161 when information of DOYCMP was not included (Figure 2-b). The simulations of LAI_g were worse for all years of study when inaccurate information of LAI_g was incorporated into the MSB model. The information of DOYCMP included in some MODIS products has important implications to the improvement of LAI_g simulation by the MSB model. Thus, the incorporation of estimates of LAI_g obtained from WDRVI into the MSB model should allow improvements of LAI_g simulations during the growing season if the information of DOYCMP is included. The next step that should be tested is whether or not more accurate simulation of LAI_g could improve FY predictions in the MSB model.

Table 5 summarizes the measured and predicted FY obtained from the MSB model by the base scenario and with the incorporation of estimates of LAI_g obtained from WDRVI using MODIS data from day 161 to 241 during 2006 to 2009 under irrigated conditions. The MSB model overpredicted FY by 758 kg ha^{-1} for 2006 while it underpredicted FY by 1981, 544, and 980 kg ha^{-1} for 2007, 2008 and 2009, respectively. The FY prediction for 2006 increased from 11123 to 11918 and 11752 kg ha^{-1} with the incorporation of LAI_g estimates obtained from MODIS 8 and 16 day composite, respectively. The result was not surprising because the MSB model overpredicted FY without modification (base scenario) for 2006. As previously explained, the MSB underestimated LAI_g during the growing season. Consequently, more accurate simulations of LAI_g should increased FY predictions due to an increase in AGB in the MBS model under irrigated conditions. On the other hand, the differences between $FY_{measured}$ - $FY_{predicted}$ decreased for 2007, 2008, and 2009, with the incorporation of estimates of LAI_g obtained from MODIS every 8 and 16 days. For example, differences between $FY_{measured}$ - $FY_{predicted}$ were reduced from 1981 to 766 and 669 kg ha^{-1} with the incorporation of LAI_g every 8 day obtained from field measurements and estimates from WDRVI, respectively, for 2007. The overall RMSE was reduced from 1200 to 919 and 878 kg ha^{-1} with the incorporation of estimates of LAI_g into the MSB obtained from MODIS DOYCMP model every 8 and 16 days, respectively. This is a moderate improvement of close to 25 percent with respect to the RMSE obtained by the base model. However, the overall results suggested that differences between $FY_{measured}$ - $FY_{predicted}$ can be reduced with the incorporation of LAI_g into the MSB model.

Results obtained in this study were in agreement with studies that suggest incorporation of LAI_g improved FY predictions in the MSB model (Doraiswamy et al., 2004; Doraiswamy et al., 2005) and other crop simulation models (Hong et al., 2004; Fang et al., 2008). However, some inconsistent results have also been reported. For example, Kiniry et al. (2004) reported improvement in maize yield prediction incorporating *f*APAR retrieved from remote sensing into ALMANAC model in three study sites; however the technique failed in one of the study sites.

CONCLUSIONS

This study presented an approach to incorporate LAI_g into a crop simulation model estimating maize LAI_g from MODIS data without the use of radiative transfer models. Results from this study showed that estimates of LAI_g obtained from WDRVI using MODIS 250-m products allowed the improvement of LAI_g simulations by the MSB model reducing the RMSE of LAI_g for all years of study under irrigated conditions. An important result is that WDRVI could allow the incorporation of accurate estimates of LAI_g from moderate to high values (LAI > 3.00 m^2 m^{-2}) into crop simulation models. Results presented in this study indicated that inaccurate estimates of LAI_g obtained from MODIS 8 and 16 day composite products without the incorporation of DOYCMP could affect the LAI_g simulations by the MSB model. The FY predictions by the MSB model can be improved with estimates of LAI_g obtained from MODIS 250-m 8 and 16 day composite under irrigated conditions.

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Table 1. List of input parameters, nominal values and ranges of uncertainty of the MSB model.

Parameter	Unit	Nominal value	Range of uncertainty		Variation step
Radiation Use Efficiency (RUE)	MJ m^{-2} day^{-1}	1.6	1.0	1.9	0.10
Area of the largest leaf (AMAX)	cm^2	750	720	780	2.0
Total number of leaves per plant(J)		18.3	16	21	0.3
Plant population density (POP)	Plants m^{-2}	8.1	5.0	8.2	0.10
Extinction coefficient (k)		0.4	0.3	0.7	0.10
Day of planting (DOP)		121	115	140	1

Table 2. Values of radiation use efficiency (RUE) of maize measured during the growing season over irrigated (S1) and rainfed (S3) conditions.

Year	Site	RUE entire growing season (g AGB MJ^{-1}ISR)
2001	S1	1.73
2002	S1	1.68
2003	S1	1.47
2004	S1	1.48
2005	S1	1.50
2001	S3	1.41
2003	S3	1.09
2005	S3	1.40

Table 3. Differences (Di) between observed (Yi) and predicted (Ŷ) final yields (FY) , root mean square error (RMSE) and relative RMSE (RRMSE) obtained for overall final yield (FY), and green leaf area (LAI_g) predictions obtained from the evaluated scenarios under irrigated (S1) and rainfed (S3) conditions.

Year	Measured FY	Scenario 1			Scenario 2		
		Predicted FY	LAI_g ($m^2 m^{-2}$)		Predicted FY	LAI_g ($m^2 m^{-2}$)	
	($kg\ ha^{-1}$)	($kg\ ha^{-1}$)	RMSE	RRME	($kg\ ha^{-1}$)	RMSE	RRME
2001 S1	12381	10445	1.13	0.31	11412	0	0
2002 S1	11615	9975	0.99	0.29	11073	0	0
2003 S1	11693	10667	0.99	0.28	11736	0	0
2004 S1	9986	11173	0.72	0.26	10260	0	0
2005 S1	10193	9894	0.38	0.12	10467	0	0
RMSE		1892			526		
RRMSE		0.26			0.05		
2001 S3	7250	7232	0.79	0.32	7844	0	0
2003 S3	6523	6536	1.40	0.51	6694	0	0
2005 S3	7690	7558	0.89	0.31	8936	0	0
RMSE		77			803		
RRMSE		0.01			0.11		

Scenario 1 = model prediction with the base scenario
Scenario 2 = model prediction with incorporation of green leaf area during the entire growing season

Table 4. Root mean square error (RMSE) and relative RMSE (RRMSE) for green leaf area index (LAI_g) predicted by the MSB model under irrigated conditions.

Year	LAI_g (m^2 m^{-2})											
	Base Model		Field Measurements				MODIS DOYCMP				MODIS DOY	
			8 day		16 day		8 day		16 day		8 day		16 day	
	RMSE	RRMSE	RMSE	RRMSE	RMSE	RRMSE	RMSE	RRMSE	RMSE	RRMSE	RMSE	RRMSE	RMSE	RRMSE
2006	0.76	0.24	0.38	0.12	0.42	0.13	0.46	0.14	0.55	0.17	0.70	0.22	0.77	0.24
2007	0.95	0.25	0.32	0.08	0.44	0.12	0.60	0.16	0.63	0.17	0.82	0.22	0.78	0.21
2008	0.92	0.26	0.55	0.16	0.59	0.17	0.68	0.19	0.72	0.21	0.98	0.28	0.91	0.26
2009	0.97	0.28	0.36	0.10	0.52	0.15	0.63	0.18	0.59	0.17	0.83	0.24	0.63	0.18

Table 5. Differences (Di) between observed (Yi) and predicted (Ŷ) final yields (FY), root mean square error (RMSE) and relative RMSR (RRMSE) obtained for overall final yield (FY), and green leaf area (LAI_g) predictions obtained from the maize model without modifications (base model) and the model with incorporation of LAI_g obtained from Moderate Resolution Imaging Spectroradiometer (MODIS) 250-m 8 and 16 day composite over irrigated conditions (S1).

Year	Measured FY	Predicted FY		
		Base scenario	MODIS 8 day	MODIS 16 day
	(kg ha^{-1})	(kg ha^{-1})	(kg ha^{-1})	(kg ha^{-1})
2006	10364	11123	11918	11752
2007	12915	10934	12246	11935
2008	12667	12124	13206	12980
2009	12430	11450	12905	12750
	RMSE	1200	919	878
	RRMSE	0.10	0.08	0.08

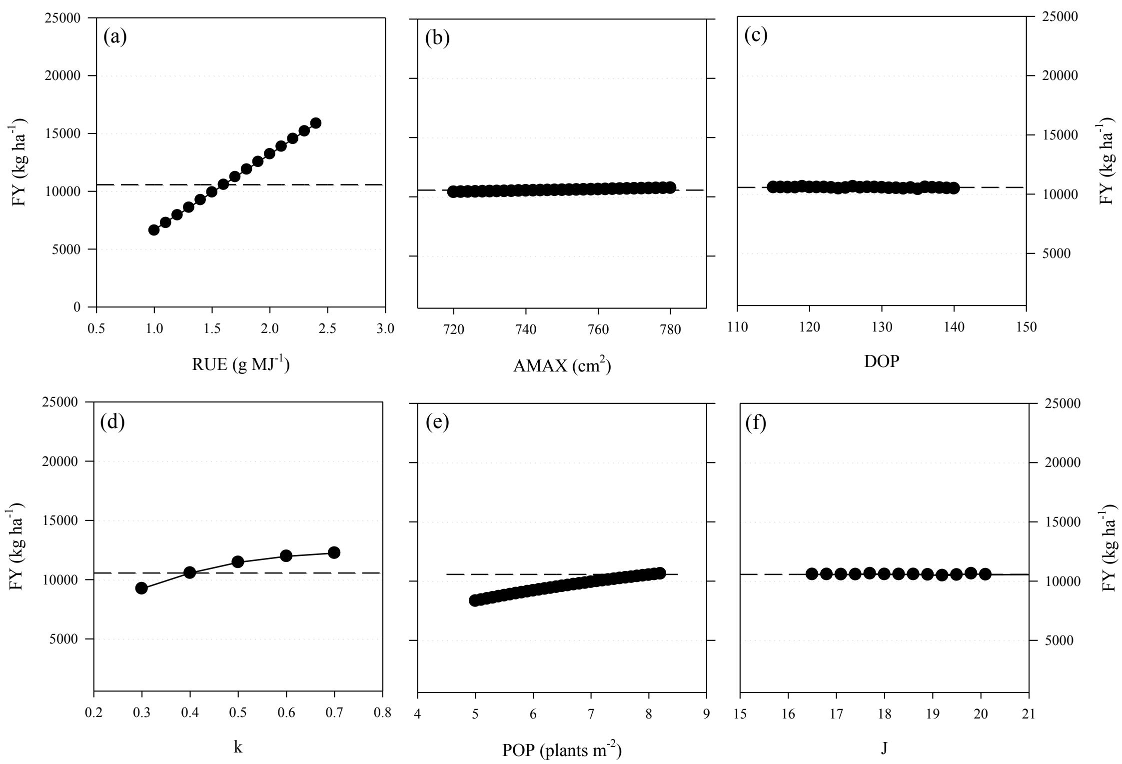

Figure 1. Maize final yield (FY) variations in response to changes in input parameters of (a) radiation use efficiency (RUE), (b) area of the largest leaf (AMAX), (c) day of planting (DOP), (d) extinction coefficient (k), (e) plant population (POP), and (f) total leaves per plant (J). Dash lines correspond to simulated maize FY at nominal scenario.

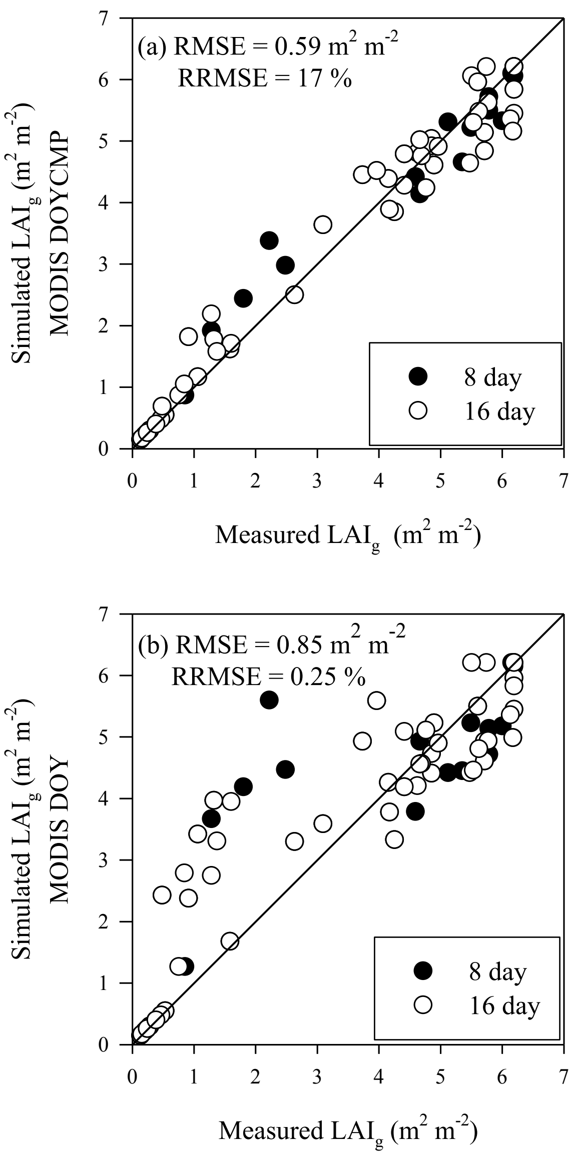

Figure 2. Green leaf area index (LAI$_g$) simulated by the MSB model with the incorporation of field measurements (FM) and estimates of LAI$_g$ obtained from WDRVI using information of (a) the day of pixel composite (DOYCMP) and (b) the day of year (DOY) from MODIS products.

Appendix 1. Estimates of green leaf area index (LAI_g) obtained from Moderate Resolution Imaging Spectroradiometer (MODIS) 250-m 16 day composite.

Year	DOY	DOYCMP	Estimates of LAI_g from MODIS LAI_g= 5.60*WDRVI + 2.24
2006 S1	145	157	0.37
	161	172	3.56
	177	182	4.92
	193	207	4.93
	209	216	4.72
	225	226	5.24
	241	241	3.59
2007 S1	145	160	0.73
	161	171	3.24
	177	185	5.10
	193	194	5.42
	209	223	5.02
	225	228	5.00
	241	242	4.30
2008 S1	145	158	0.21
	161	172	2.35
	177	183	4.55
	193	199	5.23
	209	220	4.98
	225	234	4.65
	241	244	4.29
2009 S1	145	160	0.24
	161	171	1.79
	177	185	5.01
	193	194	5.77
	209	224	5.67
	225	226	5.53
	241	242	4.91

CHAPTER 3

ESTIMATING MAIZE GRAIN YIELD FROM CROP BIOPHYSICAL PARAMETERS USING WDRVI AND MODIS DATA

ABSTRACT

Assessment of maize growing conditions and accurate maize yield predictions are important issues regarding food prices, food security and crucial decisions affecting agricultural policy and trade. Remote sensing has made important contributions to monitor crop and estimate final yield over regional levels. This study based its analysis on maize yield formation, a key crop biophysical parameter, and optimum developmental stages during the growing season that can be used to monitor and detect variability of maize grain FY. The main objective of this study was to detect variability of maize grain yield using estimates of green leaf area index obtained from the Wide Dynamic Range Vegetation Index using data retrieved from Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Index 250 meter 16 day composite (MOD13Q1) during the mid-grain filling period at county level. Estimates of green leaf area index obtained during the mid-grain filling period showed a strong correlation ($R^2 > 0.75$) with maize grain final yield reported by the United State Department of Agriculture (USDA) National Agricultural Statistic Service (NASS) over selected counties in Nebraska, Iowa, and Illinois. The approach presented in this study provides a robust technique to early FY estimation because it is based on a key crop biophysical parameter at the optimum development stage closely related with maize FY.

Key words: MODIS, green leaf area index, maize yield

INTRODUCTION

Accurate estimates of crop yield on regional and national scales are becoming increasingly important in developing countries and have sustained importance in developed countries. Although less than 20 percent of the United States (U.S.) maize production is exported, world prices are largely established by the supply-and-demand relationship in the U.S. market. More than 80 percent of the total U.S. maize production comes from the U.S. Corn Belt region. Iowa, Illinois, Nebraska, Minnesota, Indiana, and Ohio produce nearly 70 and 85 percent of total U.S. maize grain production and Corn Belt region production, respectively (Figure 1; USDA-NASS, 2009). Therefore, assessment of maize growing conditions and accurate maize yield predictions in the U.S. Corn Belt are important issues relating to food prices, food security and crucial decisions affecting agricultural policy and trade.

Previous remote sensing studies conducted to estimate final yield (FY) focused on basically three techniques. The first technique relates accumulated values of vegetation index (VI) obtained during the entire growing season or during a specific period during the growing season such as the vegetative or reproductive stages with FY. Tucker et al. (1980) first identified a relationship between wheat grain yields with accumulated values of the normalized difference vegetation index (NDVI) obtained around the time of maximum green leaf biomass. Rassmussen (1992) reported a relationship between accumulated NDVI and millet yield but only during reproductive stages. The authors attributed the lack of association between yield and accumulated NDVI to the quality of imagery used in the study. Mkhabela et al. (2005) related maize grain yield with cumulative average values of NDVI obtained over two months before harvest. The previous authors reported limitations of this technique for regions with high annual precipitation because values of NDVI remained high throughout the growing season. The second technique used to estimate FY related historical values of NDVI for a specific region with current values of NDVI to detect NDVI anomalies or deviations from historical values using multivariate regression and neural network techniques (Kastens et al., 2005; Li et al, 2007). This technique is also used to monitor crop conditions using NDVI obtained from MODIS 250 meters 16 day composite period by the U.S. Department of Agriculture (USDA; http://www.pecad.fas.usda.gov/glam.cfm). A limitation in this approach was related to the number of time series of satellite data required for a successful analysis. For example, Katens et al. (2005) suggested that eleven years of historical data were not enough to develop a robust linear model to estimate crop yields. Although many studies have been conducted to estimate FY using the two techniques discussed previously, the main limitation is that they have a strong empirical character. The third technique used related VI with FY at a specific development stage (e.g. vegetative and reproductive stages) during the growing season. For example, maize FY have been related with the (NDVI) and/or Green NDVI (GNDVI) between V8 to V12 development stages (Teal et al., 2006; Martin, et al., 2007; Solari et al., 2008) while other studies have reported close relationships between maize FY and NDVI and GNDVI during the reproductive stages (Shanahan et al., 2001; Elwadie et al., 2005). The main limitation of using this technique is the lack of clarity in relating crop biophysical parameters at the optimum developmental stage with FY. A better understanding of how maize is formed and which crop biophysical parameter(s) (CBP) is most involved in determining yield should improve the accuracy of agricultural crop monitoring and enhance FY estimates.

This study is based on information about maize yield formation, key CBP, and optimum developmental stages during the growing season that can be used to monitor and detect variability of maize grain FY. Information about maize crop growth and development grown under optimum conditions mostly depends on the amount of absorbed photosynthetically active radiation (APAR; MJ m^{-2}), the efficiency of conversion of APAR to dry matter or radiation use efficiency (RUE; g MJ^{-1}), and the partitioning of the dry matter to the grain. It is assumed that all the dry matter is allocated to the maize grain during reproductive stages (Below et al., 1981; Cliquet et al., 1990) so FY depends in part on the ability of the plant to allocate dry matter to the grain. Studies suggested that higher yields of maize hybrids planted in North America are closely related with the ability of the plant to increase the dry matter accumulation during the grain filling period. Lee and Tollenar (2007) attributed the increase in dry matter accumulation in new maize hybrids to the increase in light interception, the light utilization due to canopy architecture, the duration of green leaf area ("visual stay-green") and smaller decline in photosynthetic capacity ("functional stay-green") resulting in an increase of RUE. This attribute allows an increase of dry matter accumulation during the grain filling period increasing FY in the new hybrids (Tollenar and Aguilera, 1992; Rajcan and Tollenar, 1999a; Tollenar et al., 2004).

Conditions which adversely affect maize crop growth and development could result in a reduction of key crop biophysical parameters such as green leaf or photosynthetically active biomass. Consequently, key CBP at critical development stage can be used to relate with maize grain FY. The main objective of this study was to identify a key CBP that can be retrieved at an optimum development stage using Moderate Resolution Imaging Spectroradiometer (MODIS) data to estimate maize yields at regional levels.

MATERIAL AND METHODS

Relationship between maize grain final yield and crop biophysical parameters at field scale

This research used field data from the Carbon Sequestration Project at the University of Nebraska-Lincoln, Agricultural Research and Development Center located in Saunders County, Nebraska, USA. Field data were collected over three large study sites with different cropping systems. Site 1 (41˚ 09’54.2”N, 96˚ 28’35.9”W, 361m) was 48.7 ha planted in continuous maize from 2001 until 2008 and was irrigated. Site 2 (41˚ 09’53.5”N, 96˚ 28’12.3”W, 362m) was planted in maize-soybean rotation over an area of 52.4 ha under irrigation. Site 3 (41˚ 10’46.8”N, 96˚ 26’22.7”W, 362m) was 65.4 ha planted in maize-soybean rotation under rainfed conditions. The soils in the three sites are deep silty clay loams and consisting of four soil series: Yucan (fine-silty, mixed, superactive, mesic Mollic Hapludalfs), Tomek (fine, smectitic, mesic Pachic Argialbolls), Filbert (fine, smectitic, mesic Vertic Argialbolls), and Filmore (fine, smectitic, mesic Vertic Argialbolls). Nitrogen (N) was applied in one and three applications in rainfed (site 3) and irrigated sites (site 1 and 2), respectively, according to guidelines recommended in Shapiro et al. (2001). This study used eight years of data (2001-2008) from site 1 and four years of data (2001, 2003, 2005, and 2007) from sites 2 and 3. Within each site, six plot areas (20 m x 20 m) were established and called intensive management zones (IMZs) for detailed process-level studies (details in Verma et al., 2005). Destructive samples consisting of 5 or more continuous plants were collected from a one meter linear row sections in the six IMZ for each site at 10 to 14 day intervals until maturity. Field measurements of growth stage, plant population density (POP) and plant height were taken on 10 to 14 day intervals until maturity. Plants were dissected into green leaves, dead leaves, stems, and reproductive organs. The reproductive organs included the tassel, grain, cob, and husk. Field measurements of total and green leaf areas harvested per plant (m^2 $plant^{-1}$) were measured with an area meter (Model LI-3100, LI-COR, Inc., Lincoln, NE). The total and LAI_g were calculated using the plant population density (plants m^{-2}) by:

$$LAI_{total} = plant\_population * \frac{total\_leaf\_area}{plant} \qquad \text{eq. 1}$$

$$LAI_g = plant\_population * \frac{green\_leaf\_area}{plant} \qquad \text{eq. 2}$$

All plant parts were dried at 70˚C to constant weight and weighed to calculate the total above-ground biomass (AGB), green leaf biomass (LB_g), stem biomass (SB), and reproductive biomass (RB). Values of field plant measurements were obtained by averaging all six IMZ measurements for each site and each sampling date. MATLAB® was used to estimate the daily values of field measurements using the cubic spline interpolation method. Hand harvest yield were collected in each IMZ and averaged for each site-year. FY estimates were expressed on a grain dry matter basis per unit area in this study.

This study related CBP with maize grain FY during four periods during the growing season. The four periods were selected based on previous studies relating maize FY with VI using remote sensing and previous studies evaluating maize FY of new and old maize hybrids. Two periods selected during vegetative stages were V7 to V9 and V10 to V12. These two periods have been related with maize grain FY by previous studies using remote sensing (Teal et al., 2006; Martin et al., 2007; Solari et al., 2008). The third period was between tasseling and silking (VT- R1). Baez et al. (2005) related variability of maize grain FY with maximum values of LAI_g (LAI_{gmax}). Based on field measurements and observations obtained from this study, maize LAI_{gmax} were reached between tasseling and silking (VT- R1). The fourth period evaluated in this study was the period between R3 and R4 that represents the mid-grain filling period. This mid-grain filling period may be important because the duration of LAI_g during reproductive stages has been associated with cumulative photosynthesis, imbalance of supply and demand of dry matter (source: sink ratio), accumulation of dry matter, and RUE in maize (Tollenar and Aguilera, 1992; Rajcan and Tollenar, 1999b; Tollenar et al., 2004). In addition, Shanahan et al. (2001) reported high correlations between maize grain FY and VI during the mid-grain filling period. Linear correlation analysis was used to determine the relationship between LAI_g and maize grain FY for each period.

Relationship between maize grain final yield and green leaf area index at regional scale

The study area was selected based on the importance to the total U.S. maize grain production (Figure 1). The states of IA, IL, and NE produced about 48 and 58 percent of total U.S. maize grain production and the U.S. Corn Belt region production, respectively (USDA-NASS, 2009). Geospatial data from the states of NE, IA, and IL including county boundaries, average annual precipitation, and cropland layers developed by the United State Department of Agriculture (USDA) National Agricultural Statistic Service (NASS) were downloaded from http://datagateway.nrcs.usda.gov/. The USDA-NASS cropland data layer contains crop specific (e.g. corn, soybean, rice and cotton) digital data layers for some states including the states of NE, IA and IL. NE irrigated land coverage was acquired from the University of Nebraska-Lincoln (http://www.snr.unl.edu/data/geographygis/NebrGISwater.asp). County level yield estimates and crop progress and condition reported (CPCR) were downloaded from NASS for the years 2006 and 2007 for the states of IL, IA, and NE. The CPCR for IA and IL contained weekly information about maize progress by districts while NE reported the maize progress for the entire state. The selected counties for the states of NE, IA, and IL were summarized in Figures 2, 3, and 4, respectively. These counties were selected based on variability of yields reported by NASS during the years 2006 and 2007. Furthermore, the selected counties also varied in mean annual precipitation. Each selected county was associated with the district (IL and IA) or the state (NE) to retrieve information on the dates of silking, dough and dent stage. This information was used to estimate the mid-grain filling period over the selected counties in each state. The estimated the mid-grain filling period information was used to select satellite images covering this period of time over the selected counties.

MODIS VI 250-m 16-day composite (MOD13Q1) images were downloaded from the National Aeronautic and Space Administration (NASA) Land Process Distributed Active Archive Center (LPDAAC) (https://lpdaac.usgs.gov/lpdaac/get_data/data_pool corresponding to the period around mid-grain filling period for Nebraska (NE), Iowa (IA), and Illinois (IL) and during the entire growing season over selected counties in NE and IA during 2006 until 2007. The state of NE was covered by one tile (h10v04) while IL and IA were covered by two, (h10v05 and h11v04) and three (h10v05, h11v04, and h11v05) tiles, respectively. All MODIS images were processed, reprojected, and converted to GeoTIFF format using the MODIS Reprojection Tool Version 4.0 (MRT) downloaded from LPAAC (https://lpdaac.usgs.gov/lpdaac/tools).

MODIS images corresponding to parts of the states of IL and IA (tiles h10v05, h11v04, and h11v05 and tiles h10v04 and h11v04, respectively) were jointed using the mosaic tool available in ERDAS IMAGINE®. Areas planted in maize were retrieved from the USDA-NASS crop data layer for NE, IA, and IL during 2006 and 2007. Information of NDVI and the day of pixel composite (DOYCMP) data over areas planted in maize were obtained for each selected county using the mask tool that retrieved only the selected information. Estimates of LAI_g over areas planted in maize were obtained using the linear model calibrated and validated using field data from 2001 until 2005 and 2006 until 2009, respectively, under rainfed and irrigated conditions (Chapter 1).

$$LAI = 5.59 * WDRVI + 2.24 \qquad \text{eq. 3}$$

NDVI values over areas planted in maize for selected counties in the states of NE, IA, and IL were used to calculate the Wide Dynamic Range Vegetation Index (WDRVI: Gitelson, 2004) with the weighting coefficient $\alpha = 0.2$ using the equation presented by Viña and Gitelson (2005):

$$\mathrm{WDRVI} = \frac{(\alpha+1)\mathrm{NDVI}+(\alpha+1)}{(\alpha-1)\mathrm{NDVI}+(\alpha+1)} \qquad \text{eq. 4}$$

NASS FY over NE was broken down by irrigated and rainfed crops. The NE irrigated land coverage was used to locate pixels over rainfed and irrigated areas. The location of rainfed and irrigated maize fields was limited by the coverage of NE irrigated land that did not include all the counties and by the number of pixels over small rainfed areas. A time series of MODIS VI 250-m 16-day composite (from DOY 129 to 273) was used to estimate LAI_g profiles over NE calculated by eq. (3). LAI_g profiles as a function of DOY were estimated using the averages of LAI_g and DOYCMP from selected pixels over nine counties that were irrigated (Scotts Bluff, Banner, Kimball, Chase, Perkins, Hitchcock, Nuckolls, Kearney, and Phelps) and two counties that were rainfed (Furnas and Perkins) during the growing season of 2006. Estimates of maize LAI_g profiles were used to detect differences in LAI_g during reproductive stages and then, related with FY under irrigation and rainfed conditions reported by USDA-NASS for 2006. LAI_g estimates during the mid-grain filling period for counties in IA and IL included all pixels over maize planted areas.

RESULTS AND DISCUSSION

Relationship between maize grain final yield and crop biophysical parameters at field scale

Table 1 summarizes the relationship between CBP and maize grain FY yield under rainfed and irrigated conditions. The data included eight (2001-2008) and four (2001, 2003, 2005, and 2007) growing seasons under irrigated and rainfed conditions, respectively, and represented conditions of maize with no nitrogen limitations grown under irrigated and rainfed conditions in Mead, Nebraska. The results obtained from this analysis suggested that LAI_g and maize grain FY were correlated after VT but the stronger correlation was obtained during the mid grain filling period or R3- R4 under rainfed and irrigated conditions. Moreover, results also suggested that the correlation between LB_g, SB, RB, and AGB and maize grain FY increases with progress of development stages showing a correlation greater than 80 percent at R3-R4. Results suggested that the correlation between CBP and FY decreases after R4 although the correlation between AGB increases after R4. These results were not surprising because they were related with basic information of how maize FY formed. In maize all dry matter is allocated to grain during reproductive stages. Consequently, relationships between CBP and maize FY increase with progress of developmental stages reaching a maximum during reproductive stages. The high correlation between SB and LB_g and maize FY could be explained with their functions during reproductive stages. The stem and green leaves act as source components for grains during reproductive stages. Results suggested that measurements of LAI_g obtained during the mid grain filling period R3-R4 was the CBP closely related with maize FY. The next step should examine if differences between maize FY can be inferred from the patterns of LAI_g during reproductive stages.

Measured LAI_g profiles with time (DOY: day of year) from irrigated (S1and S2) and rainfed (S3) maize fields are summarized in Figure 5 for the 2001, 2003, 2005, and 2007 growing seasons at Mead, NE. Values of LAI_g were similar until DOY 187 despite different POP under irrigated and rainfed conditions. However, after DOY 190 differences in LAI_g were observed under both irrigated and rainfed conditions. The data shows the variability of LAI_g after it reached its maximum value or during the grain filling period. For example, values of LAI_g reached a maximum of 6.0 and 4.0 $m^2 m^{-2}$ under irrigated and rainfed conditions during 2001. A rapid decrease in LAI_g was observed during 2003 under rainfed conditions compared with LAI_g during 2001 and 2005. In fact, a 12 percent reduction in FY was observed for 2003 compared with FY in 2001 and 2005 under rainfed conditions. However, measured LAI_{gmax} values were close to 4.0 $m^2 m^{-2}$ during the four growing seasons under rainfed conditions. This suggests that the duration of LAI_g during reproductive stages should be closely related with variability of maize grain FY. On the other hand, LAI_g values were quite similar under irrigated conditions, although LAI_{gmax} varied between years. For example, values of LAI_{gmax} ranged 6.0 to 5.0 $m^2 m^{-2}$ a maximum and minimum value observed during 2001 and 2005 while FY varied from 12400 to 10200 kg ha^{-1}, respectively, under irrigated conditions. Based on field observations, variability of LAI_g under irrigated and rainfed conditions should be detected between LAI_{max} and/or during reproductive stages and not during vegetative stages. Moreover, differences of maize LAI_g lower than 0.2 $m^2 m^{-2}$ probably could be difficult to detect using remote sensing data due to the level of accuracy of the VI use to retrieve data from the satellite sensor. Measured maize grain FY was 15 and 12 percent higher in S2 compared to S1 during 2003 and 2005, respectively; however, differences in LAI_g profiles showed quite similar values in reproductive stages although the sites differed in the duration of LAI_g after DOY 255. The results obtained from this study validate the hypothesis of this study that proposed that variability of maize grain FY can be related with LAI_g measurements obtained during the grain filling period. The next step that should be to test whether or not estimates of LAI_g profiles obtained from MODIS VI 250-m (MOD13Q1) can be used to retrieve information about crop conditions and yield estimates at the county level.

Relationship between maize grain final yield and green leaf area index at regional scale

Figure 6 summarizes the average of LAI_g estimates as a function of day of year (DOY) over maize fields during 2006 in nine counties that were irrigated (Scotts Bluff, Banner, Kimball, Chase, Perkins, Hitchcock, Nuckolls, Kearney, and Phelps) and two counties that were rainfed (Furnas and Perkins) during the growing season of 2006. The data suggested that estimated values of LAI_g were quite similar during vegetative stages over study areas until they reached their maximum values around DOY 200. Differences of LAI_g were observed during the reproductive stages. For example, the value of LAI_{gmax} was 3.50 m^2 m^{-2} for Banner County while the estimate of LAI_g during the mid-grain filling period was 2.60 m^2 m^{-2} in 2006 (Figure 6-a). A lower reduction in LAI_g was observed for Scotts Bluff and Kimball counties. Estimates of LAI_{gmax} were 3.80 and 3.76 m^2 m^{-2} while estimates of LAI_g during the mid grain filling period were 3.30 m^2 m^{-2} for Scotts Bluff and Kimball counties in 2006 (Figure 6-a). Lower maize grain FY reported for Banner County was 10 percent lower compared with maize FY reported for Scotts Bluff and Kimball counties. A similar result was observed for Nuckolls County for which estimates of LAI_g suggested a rapid decrease or low duration of LAI_g after it reached a maximum value around DOY 180 and 200 (Figure 6-c). In fact, lower maize grain FY was reported for Nuckolls County compared with Phelps and Kearney counties in 2006. On the other hand, estimates of LAI_g showed low duration of LAI_g during the reproductive stages over rainfed conditions. The data shows more duration of LAI_g over Furnas rainfed maize fields compared with Perkins rainfed maize fields although similar values of LAI_{gmax} were observed for these locations. A 25 percent reduction in maize grain FY was reported in Perkins County compared to Furnas County in 2006 under rainfed conditions. In fact, CPCR reported precipitation below the normal for all districts and maize had reached the dent stage earlier than previous years. Low precipitation and soil moisture might explain the low duration of LAI_g over Perkins and Furnas rainfed maize fields.

These results were in agreement with field observations that suggested that LAI_g profiles during reproductive stages can be used to detect variability in maize grain FY. The results validated previous studies that suggested a close relationship between maize grain FY due to duration of green leaf area with the ability of the plant to increase the dry matter accumulation during the grain filling period at field level (Tollenar and Aguilera, 1992; Rajcan and Tollenar, 1999a; Tollenar et al., 2004). An important result is that estimates of LAI_g using WDRVI and MODIS data during the growing season can be used to obtain information of the crop condition. It is not difficult to relate the duration of LAI_g with more light absorption and increase in dry matter accumulation during reproductive stages. Therefore, estimates of LAI_g profiles during reproductive stages using remote sensing can be used to monitor and estimate potential maize grain FY over large regions.

Previous studies (Teal et al., 2006; Martin, et al., 2007; Solari et al., 2008) related maize FY with VI and/or LAI_g during vegetative stages (e.g. V10-V12); however, results obtained from this study did not show a strong relation with LAI_g during vegetative stages. Most of the previous studies that reported correlation between VI and/or LAI_g and FY during vegetative stages related chlorophyll meter readings with VI. The lack of association between VI and FY during reproductive stages was mainly due to limitations of the sensor used. In contrast, previous studies that reported association between VI and FY during reproductive stages have been done using satellite sensors and evaluating nearly the entire growing season (Shanahan et al., 2001; Mkhabela et al., 2005; Baez et al., 2005). The results obtained from this study could be used to explain results presented by Mkhabela et al (2005) and Shanahan et al. (2005). Although the previous authors related normalized vegetation index (NDVI) and green NDVI with maize grain FY under different nitrogen treatments, both VI have been related with LAI_g.

Figure 7 presents the relationship between average estimates of maize LAI_g during the mid-grain filling period and NASS maize grain FY reported for selected counties in Nebraska, Iowa, and Illinois during 2006 and 2007. These results showed linear relationships ($R^2 > 0.70$) between maize grain FY and average estimates of LAI_g. There was more variability in maize FY and LAI_g over NE compared with IA and IL. Lower maize yields were reported for Perkins, Hitchcock, and Webster Counties in 2006 under rainfed conditions. As discussed previously, below normal precipitation was reported in 2006 in most of NE districts for the period from April 1 until August 20 where ninety percent of maize had reached dough stage (R4).

On the other hand, estimates of LAI_g obtained during the mid-grain filling period showed a strong correlation (R^2=0.86) with maize grain FY reported by NASS over study sites in IA. Estimates of LAI_g were not related with reported NASS FY in 2006 and 2007 over Monona, Ida, and Des Moines counties in Iowa, respectively. Reported NASS FY was 6860 kg ha^{-1} while the estimate of LAI_g was 3.70 m^2 m^{-2} for Monona County in 2006. In contrast, the average estimate of LAI_g over Des Moines County was 4.22 m^2 m^{-2} while the reported NASS FY was 12459 kg ha^{-1} in 2007. Based on the results obtained from Figure 7, maize grain FY about 12000 and 7000 kg ha^{-1} should be associated with average estimates of LAI_g closed to 5.0 and 3.0 m^2 m^{-2}, respectively.

Results obtained over IL showed more scatter. The overall results between estimates of LAI_g during the mid-grain filling period and reported NASS FY showed a RMSE of 874 kg ha^{-1}(Figure 7-c). It was obvious that variability in maize FY did not depend only on the duration of LAI_g during the reproductive stages. Several factors should affect the partitioning of the dry matter to the grain such as environmental and management conditions. However, LAI_g plays an important role during the entire growing season and it has a significant importance during the grain filling period.

These results suggest that the development of a yield model based estimate of LAI_g during the mid-grain filling period needs to be calibrated for specific regions. Although this study did not compare differences in maize LAI_g profiles over NE, IA, and IL, differences in maize LAI_g profiles should be expected due to differences in POP, hybrids, management, and environmental conditions. Most of the maize planted in NE is grown under irrigated conditions compared to the rainfed environment for maize grown in IA and IL (USDA-NASS, 2009). Subsequently, the amount and distribution of the precipitation could cause that value of LAI_g during the mid grain filling period to change from region to region. The approach presented in this study should be enhanced with the development of critical values of LAI_g during the mid-grain filling period for specific regions.

The approach presented in this study has several limitations such as quality of the satellite image and crop layer, limitations of temporal and spatial resolution of the satellite image, and crop yield limitations that could not be detected by LAI_g. For example, this approach cannot account for other factors that could affect maize yield during the grain filling period such as diseases and extreme weather conditions. In addition, one limitation in retrieving accurate estimates of maize LAI_g depends on the ability of the VI to accurately track and/or estimate LAI during the entire growing season especially during the period mid-grain filling period where values of LAI_g could range from moderate to high ($LAI_g > 2$ m^2 m^{-2}). Finer spatial resolution would allow the selection of pixels nearly covered by crops to reduce pixel contamination to more accurately estimate CBP such as LAI_g. MODIS 250-m resolution can provide more accurate estimates of maize LAI_g during the entire growing season compared to MODIS 500-m resolution products (Chapter 1). The identification of maize mid-grain filling periods over areas could be another limitation. For example, this study estimated the mid-grain filling period using data available in the CPCP. However, the CPCP for Iowa and

Illinois included detailed information of the progress of maize by districts while the CPCP for Nebraska presented an estimate for the entire state. Despite these limitations, this approach should provide a robust technique for early estimation of maize grain FY because it is based on a LAI_g (a key CBP) at an optimum development stage closely related with maize FY. Maize yield estimates made during the mid grain filling period might allow state agencies to improve accuracy of regional yield estimates.

CONCLUSIONS

The approach presented in this study shows that maize grain FY can be closely related with the ability of the plant to maintain green leaf area during the grain filling period. Consequently, estimates of LAI_g obtained during the mid-grain filling period can be used to detect variability of maize grain FY at county levels. This approach should be a robust technique for early maize grain FY estimation because it is based on a key crop biophysical parameter at the optimum development stage closely related with maize FY. Maize yield estimates made during the mid-grain filling period should allow state agencies to improve accuracy of regional yield estimates. The technique of relating LAI_g with maize FY could be improved by developing critical values of LAI_g during the mid-grain filling period for specific regions that can be used to detect areas of potential high or low yields.

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Table 1. Relationships between crop biophysical parameters and maize grain final yield under irrigated and rainfed conditions.

Crop Biophysical Parameter	Correlation coefficient values (R)				
	Development stage				
	V7-V9	V10-V12	VT-R1	R3-R4	R5
LAI_g	0.27	0.61	0.84	0.94	0.61
LB_g	0.20	0.60	0.76	0.90	0.65
SB	0.12	0.39	0.83	0.86	0.75
TDM	0.17	0.49	0.82	0.92	0.95
RB	-	-	0.16	0.59	0.45

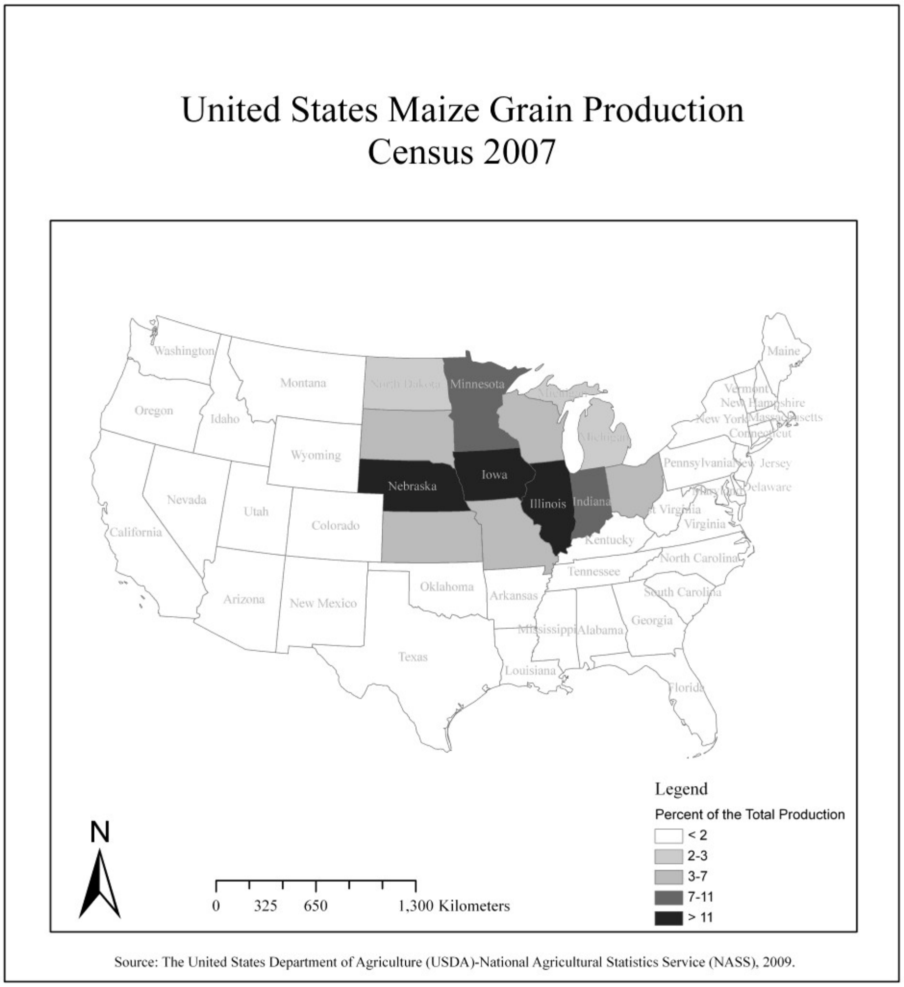

Figure 1. Maize grain production by state as a percent of the total United States production.

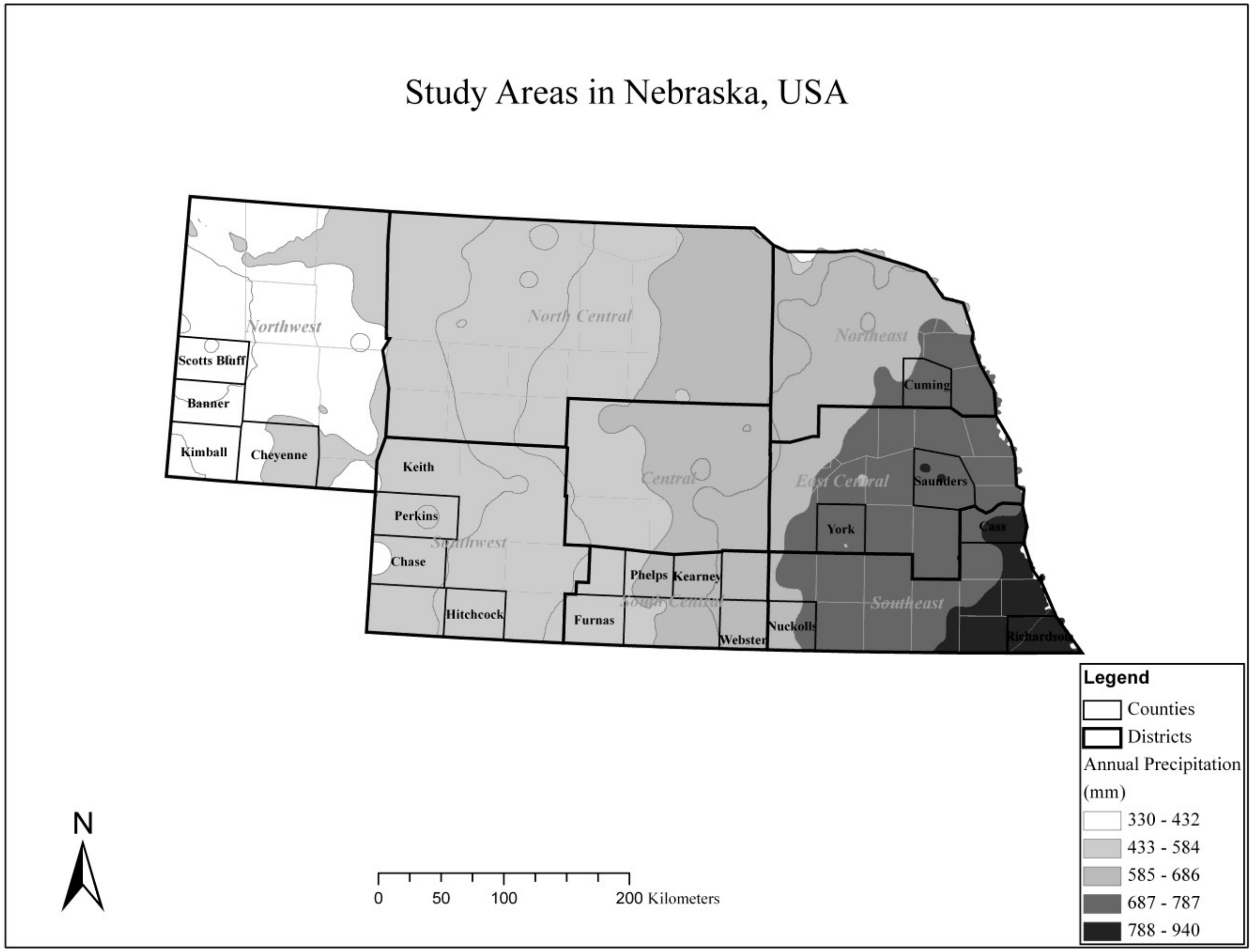

Figure 2. Location of the selected counties in Nebraska for maize final yield estimation.

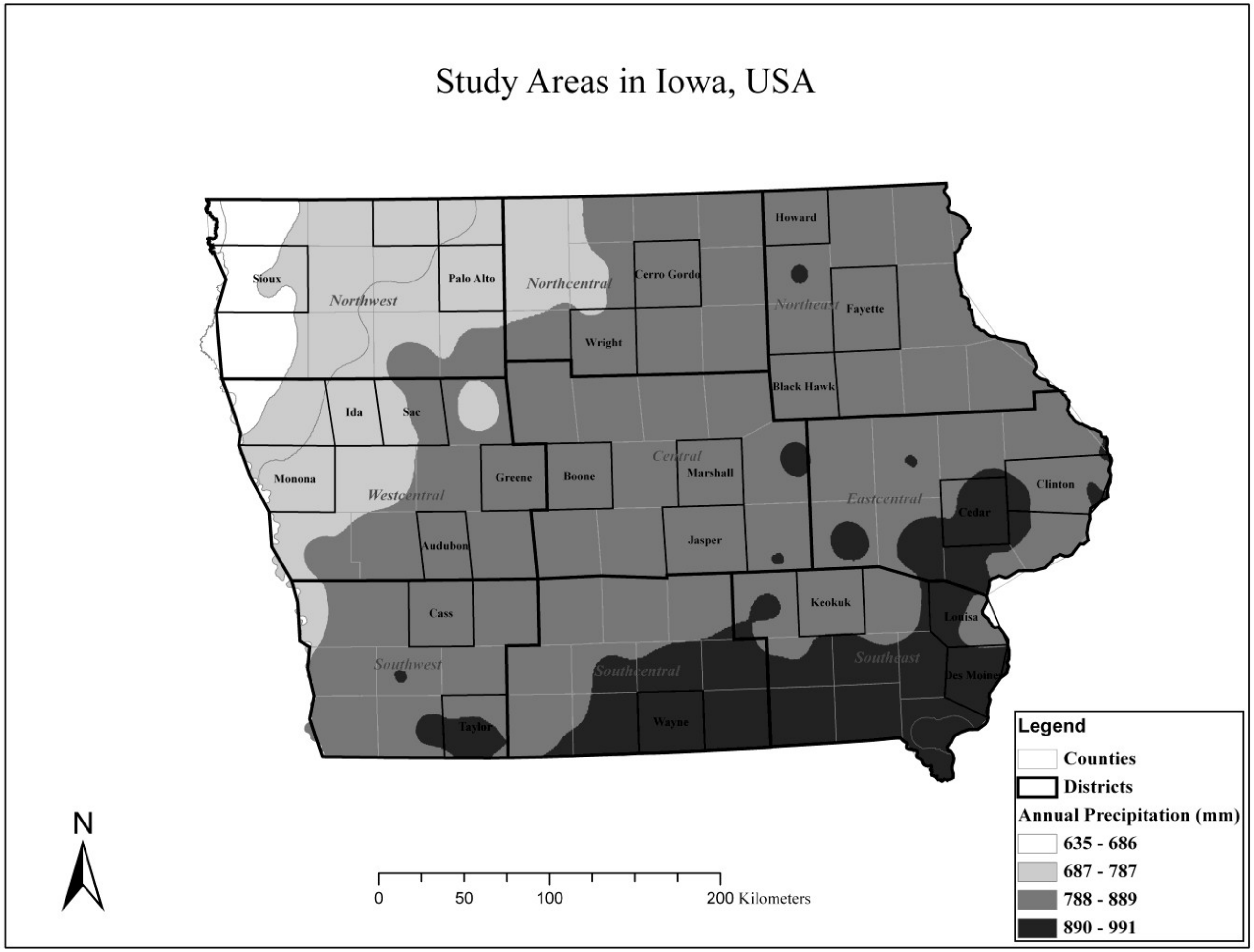

Figure 3. Location of the selected counties in Iowa for maize final yield estimation.

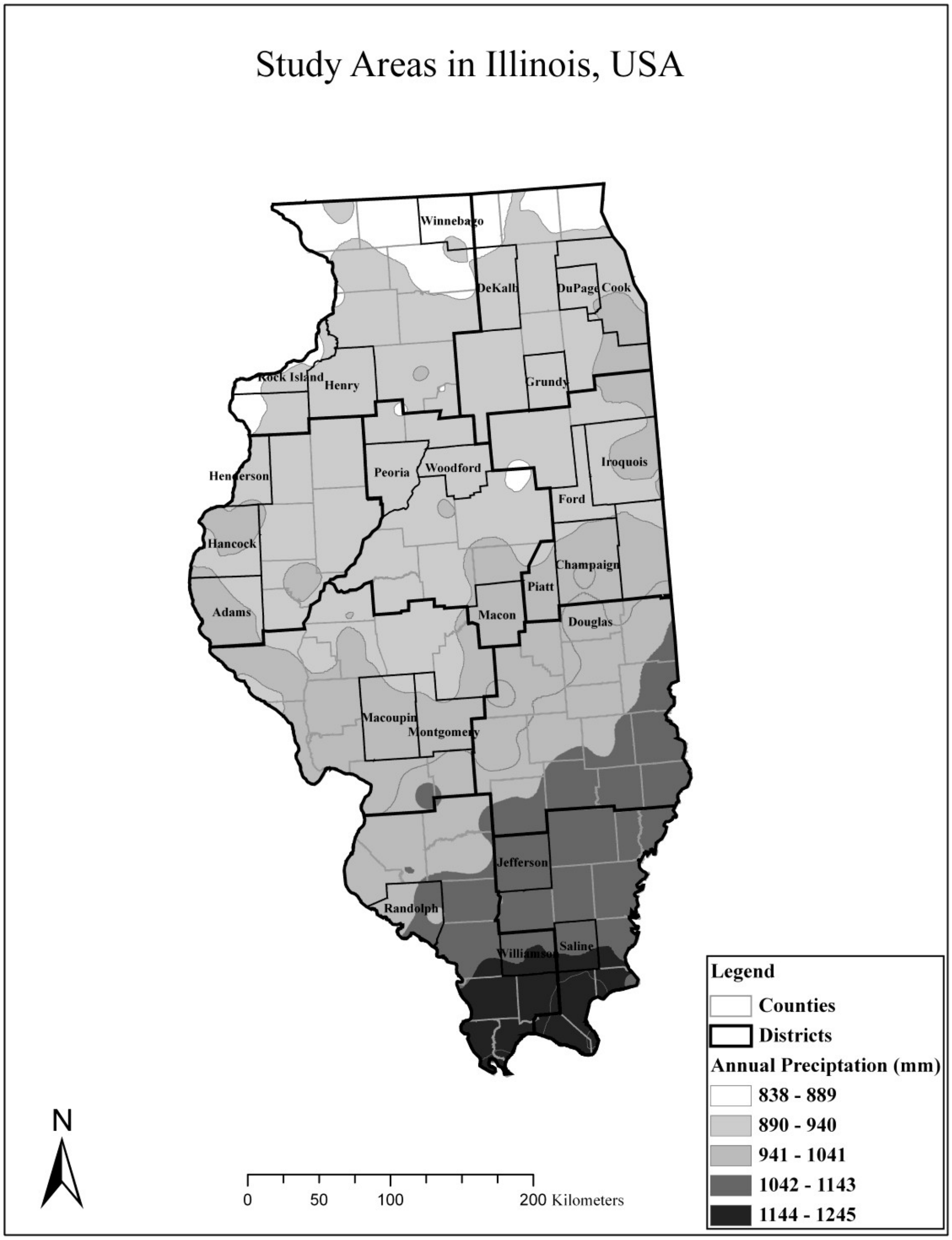

Figure 4. Location of the selected counties in Illinois for maize final yield estimation.

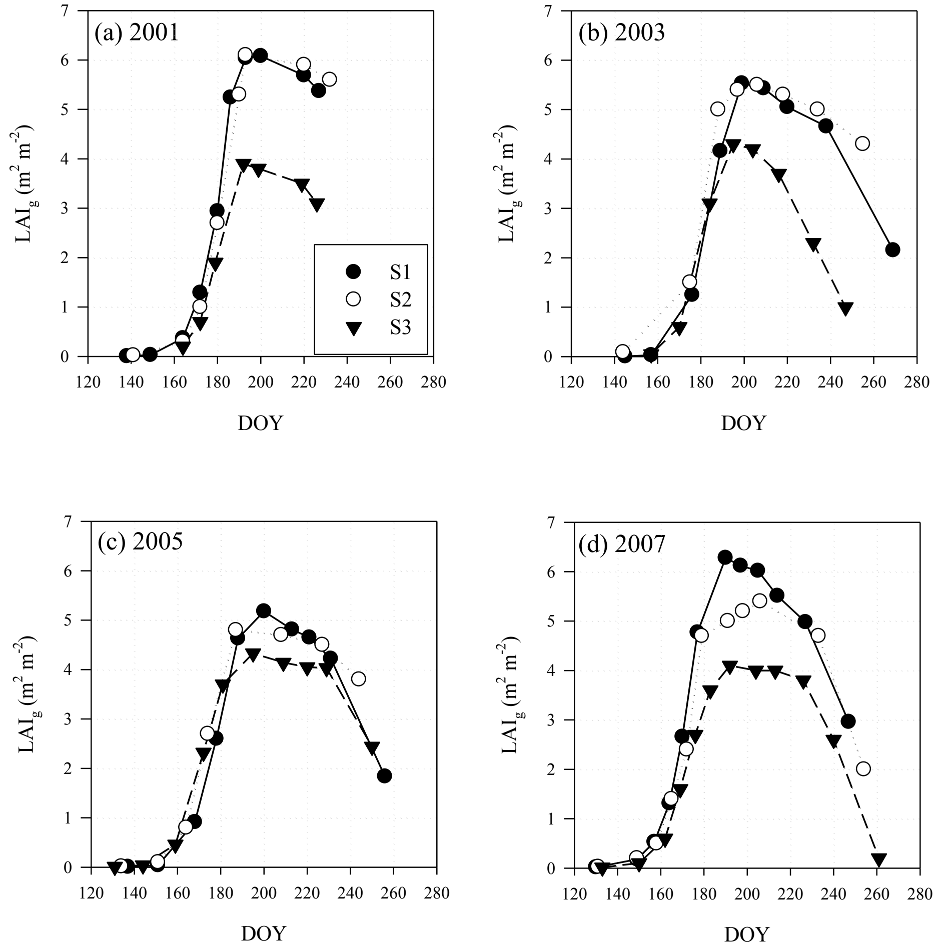

Figure 5. Measured green leaf area index (LAI_g) profiles as a function of day of year (DOY) under irrigated (S1 and S2) and rainfed (S3) conditions during (a) 2001, (b) 2003, (c) 2005, and (d) 2007.

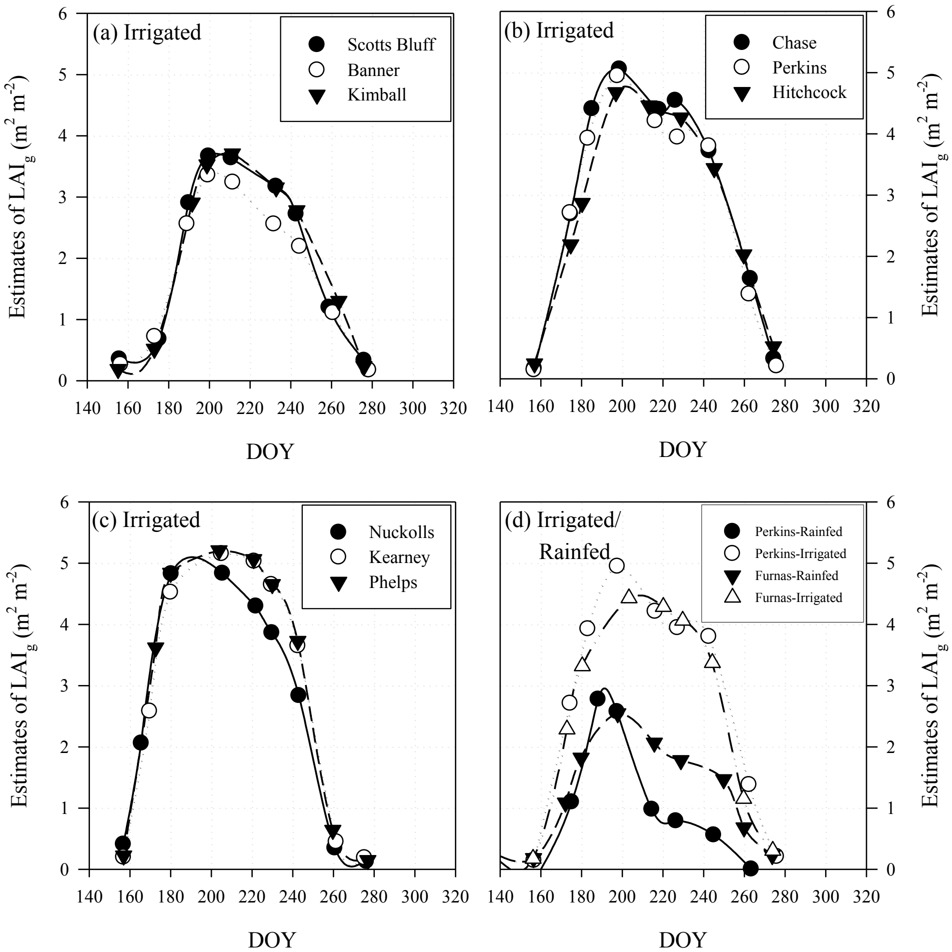

Figure 6. Estimates of average LAI$_g$ profiles over maize grown in Nebraska for (a) Scotts Bluff, Banner, and Kimball, (b) Chase, Perkins, and Hitchcock, (c) Nuckolls, Kearney, and Phelps counties under irrigated conditions and for (d) Perkins and Furnas counties under irrigated and rainfed conditions over during 2006.

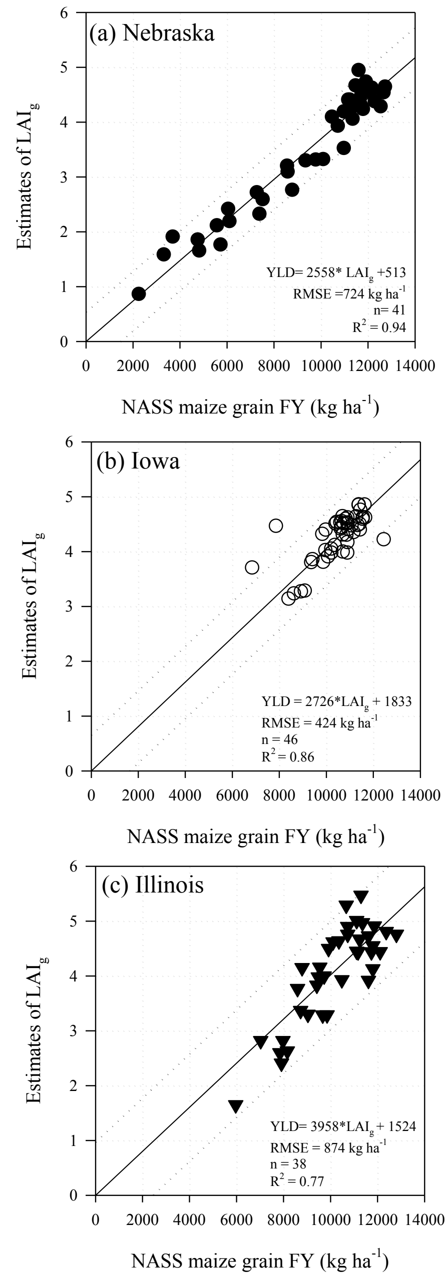

Figure 7. Relationships between green leaf area index and maize grain final yield (FY) reported by the National Agricultural Statistics Service (NASS) over study sites in (a) Nebraska, (b) Iowa, and (c) Illinois during 2006 and 2007.

SUMMARY

The main limitation to retrieving useful information regarding yield predictions for agricultural crops is the lack of understanding of how crops change according to developmental stage or crop dynamics in order to evaluate potential capabilities and limitations of satellite data. The feasibility of using remote sensing data from MODIS products to measure crop biophysical parameters such as maize LAI_g requires a good understanding of techniques used to assemble the satellite data in terms of temporal resolution. An important result from this study is the importance of day of pixel composite information from MODIS products for monitoring agricultural crops. Due to the maize LAI_g dynamics and changes in MODIS temporal resolution, the inclusion of DOYCMP has important implications for estimating and monitoring agricultural crop dynamics. The results of this study showed that MODIS 250-m resolution provides more accurate estimates of maize LAI_g compared to MODIS 500-m resolution. An important result of this study is demonstrating the ability to estimate maize LAI_g without the use of radiative transfer models.

Estimates of maize LAI_g obtained from Wide Dynamic Range Vegetation Index using data retrieved from MODIS VI 250-m 16 day composite (MOD13Q1) can be incorporated in crop simulation models to predict maize final yields over large regions such as a county. Results from this study showed that the incorporation of LAI_g obtained from MODIS products allowed the improvement of LAI_g simulations by the Muchow-Sinclair-Bennett maize model reducing the RMSE of LAI_g for all years of study under irrigated conditions. An important result is that WDRVI could allow the incorporation of accurate estimates of LAI_g from moderate to high values (LAI > 3.00 m^2 m^{-2}) into crop

simulation models. Results presented in this study suggested that inaccurate estimates of LAI_g obtained from MODIS 8 and 16 day composite products without the incorporation of DOYCMP could affect the LAI_g simulations by the MSB model. The overall FY predictions by the MSB model were improved by 23 and 26 percent with estimates of LAI_g obtained from MODIS 250-m 8 and 16 day composite under irrigated conditions, respectively. However, more accurate estimates of LAI_g did not necessarily imply better final yield (FY) predictions in the maize model for all years of study. The approach of incorporating LAI_g into crop simulation models may not offer a panacea for problem solving; this approach is limited in its ability to simulate other factors influencing crop yields.

The approach of relating a key crop biophysical parameter at the optimum stage with maize grain final yields is a robust technique for early estimation of maize grain FY over large areas such as a county. Results suggested that estimates of LAI_g obtained during the mid-grain filling period can used to detect variability of maize grain yield at county levels. Estimates of green leaf area index obtained during the mid-grain filling period showed a strong correlation ($R^2 > 0.75$ and RMSE < 900 kg ha^{-1}) with maize grain final yield reported by the United State Department of Agriculture (USDA) National Agricultural Statistic Service (NASS) over selected counties in Nebraska, Iowa, and Illinois. The approach presented in this study provides a robust technique to early FY estimation because it is based on a key crop biophysical parameter at the optimum development stage closely related with maize FY. This technique offers a rapid way to detect variability of FY at county level using MODIS 250-m products. The technique to relate LAI_g with maize FY could be improved by developing critical values of LAI_g

during the mid-grain filling period for specific regions that can be used to detect areas of potential high or low yields.