USING REMOTE SENSING AND MODELING TO MEASURE CROP BIOPHYSICAL VARIABILITY

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ABSTRACT

This study integrates field collection, crop modeling, and remote sensing to assess spatial variability in biophysical properties of a soybean crop. These tools are used to describe and predict leaf area index (LAI), intercepted photosynthetically active radiation (PAR), biomass, and yield for the 1998 growing season at the USDA-ARS Coastal Plains Soil, Water, and Plant Research Center. LAI and yield data collected in the field are compared with LAI, PAR, biomass, and yield modeled with CROPGRO-Soybean. Field and modeled data are then compared to six dates of SPOT 4 satellite imagery and associated vegetation indices (NDVI, SR, SAVI, and TSAVI). When averaged over the growing season, vegetation indices captured the spatial variability of observed LAI and simulated LAI, PAR, and biomass. Vegetation indices from individual dates were less successful, possibly due to the coarse spatial resolution of the SPOT imagery, or due to shortcomings in the index calculations. SPOT imagery did not capture the spatial variability of observed yield.

Keywords: **Crop modeling, Spatial variability, Remote sensing**

INTRODUCTION

Applications in precision agriculture require data on a spatial scale that allows for intra-field comparison of crop response to varying properties such as soil type or management practice. Advances such as satellite positioning

(GPS) and combine-mounted yield monitors allow for the collection of data requisite for precision agriculture, but the collection of field data may not always be feasible for spatially dense sampling or throughout a growing season. Remote sensing and crop modeling represent alternative methods for obtaining spatial and temporal crop data that overcome some field data collection problems.

In this paper, we examine intra-field variability in soybean biophysical properties such as yield, LAI, and PAR using satellite remote sensing, physiological crop modeling, and traditional field measurement. LAI, the percent of intercepted PAR (%PAR), biomass, and yield for the 1998 growing season of a soybean [*Glycine max*. (L.) *Merr*.] field in South Carolina were analyzed using field data, the CROPGRO-Soybean physiological crop model (Hoogenboom et al., 1992), and six SPOT satellite images. Yield, LAI, %PAR, biomass, leaf dry weight, seed number, and grain dry weight were simulated by the crop model. The remotely sensed imagery and computed vegetation indices were statistically analyzed to determine their relationship to *in-situ* LAI, yield and other biophysical variables. We seek to learn: a) the degree of spatial variability in observed biophysical variables, b) how well CROPGRO-Soybean captures such variability, and c) whether vegetation indices derived from remotely sensed imagery can characterize observed intra-field variability.

The CROPGRO-Soybean model is one of a group of models supported by the International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT). The models have successfully predicted crop biophysical parameters for soybean, grain, peanut, bean, and potato (Egli and Bruening, 1992; Hoogenboom et al., 1992; Moen et al., 1994) and have successfully estimated the agricultural impacts of climate variability and change (Mearns et al., 1992; Papajorgi et al., 1994; Curry et al., 1995; Carbone, 1995). Remote sensing has been tied to crop models by providing inputs (Mass, 1988; Carbone et al., 1996), and, inversely, LAI from crop models have been used for investigating crop spectral reflectance (Moulin et al., 1995).

The spatial aspects of modeling yield have been explored in several papers. Ritchie et al. (1990) identified soil and weather model inputs as the primary factors for defining spatial and temporal variability in crop models; other related factors include management practices such as irrigation or fertilizer application. Carbone et al. (1996) used varied weather and soil inputs to describe the spatial variability of soybean yield at the county level. Similar studies at the field level would require soil inputs at a scale larger than that generally produced in soil maps (Sadler and Russell, 1997) or measurements of intra-field weather variations. In an intra-field variability study, Sadler et al. (1995) found that simulated corn yield for soil units did not correlate well to observed yield, and suggested improvements in root and water balance algorithms. In a similar study of potatoes, Han et al. (1995) modeled yield on varied soil and irrigation units, but was unable to compare these data to observed yield. These studies suggest that current model treatments of spatially variable parameters might not be adequate for predicting within-field variability of crop biophysical properties.

Remote sensing (RS) has proven to be a valuable tool in field-level agricultural studies for yield estimation (Maas, 1988; Rudorf and Batista, 1991), soil mapping (Barnes et al., 1996; Schepers et al., 1996), and stress mapping (Blackmore and White, 1996). While some researchers have done biophysical monitoring using 20x20 meter SPOT data, 30x30 meter Landsat TM data, or aircraft-based systems, remote sensing for field-level studies have often been limited by low spatial resolution and high data costs (Sadler et al., 1998).

Remotely sensed imagery can also be an effective tool for estimating vegetative characteristics of crops (Moran et al., 1997). Vegetation indices use knowledge of plant physiology to maximize the information extractable from the imagery. Vegetation indices establish a ratio of red reflectance to near-infrared reflectance, based on the physical properties of vegetative leaf structure which absorbs red wavelengths for photosynthetic activity and reflects infrared wavelengths (Jensen, 1996). The use of multiple images through a growing season, combined with computed vegetation indices allows for the investigation of temporal and spatial patterns of crop properties (Qi et al., 1993).

Previous work suggests that vegetation indices do relate to the biophysical processes of soybeans. Thenkabail et al. (1994) used two dates of Landsat TM imagery for multiple fields in Ohio to develop linear and polynomial regression models to correlate *in situ* measurements of soybean and corn LAI, yield, biomass, and plant height to selected vegetation indices. For LAI, the highest R^2 was 0.63 using a linear model and SVI (simple ratio, referred to as SR in this paper). An R^2 of 0.62 was determined using a polynomial model and NDVI. In general, higher R^2 values were determined for vegetation index correlation to biomass and plant height. Yield had a low correlation attributed to the image dates occurring early in the growing season. Daughtry et al. (1992) measured LAI, phytomass, and PAR in soybeans and corn at Purdue University. An R^2 of 0.96 was determined in a linear model correlating NDVI to the fraction of absorbed photosynthetically active radiation (FPAR). Further relationships were determined to relate FPAR to LAI, PAR, and phytomass. Choudhury (1987) looked at SR and NDVI relationships for several crops. In soybeans, the relationship between daily mean PAR absorption was found to be curvilinearly related to the vegetation indices. These studies support both linear and curvilinear relationships of vegetation indices to LAI and PAR.

METHODS

The study area is a soybean field in Florence, South Carolina, maintained by the USDA Coastal Plains Soil, Water, and Plant Research Center. The field measures about 280 by 280 meters. Researchers at the Center measured LAI and plant height during the 1998 soybean growing season at 18 field locations with a plant canopy analyzer (LI-COR LAI-2000). LAI stations were chosen to capture 15 different soil mapping series (Sadler et al., 1995) and fall within irrigated and non-irrigated sections of the field (Figure 1). Destructive samplings of all 18 sites were performed on August 14, 1998. LAI measurements were taken weekly and fall within a few days before or after the imagery was acquired. Height measurements were acquired through September 4. Yield data was gathered at harvest with an AgLeader yield monitor and global positioning system attached to

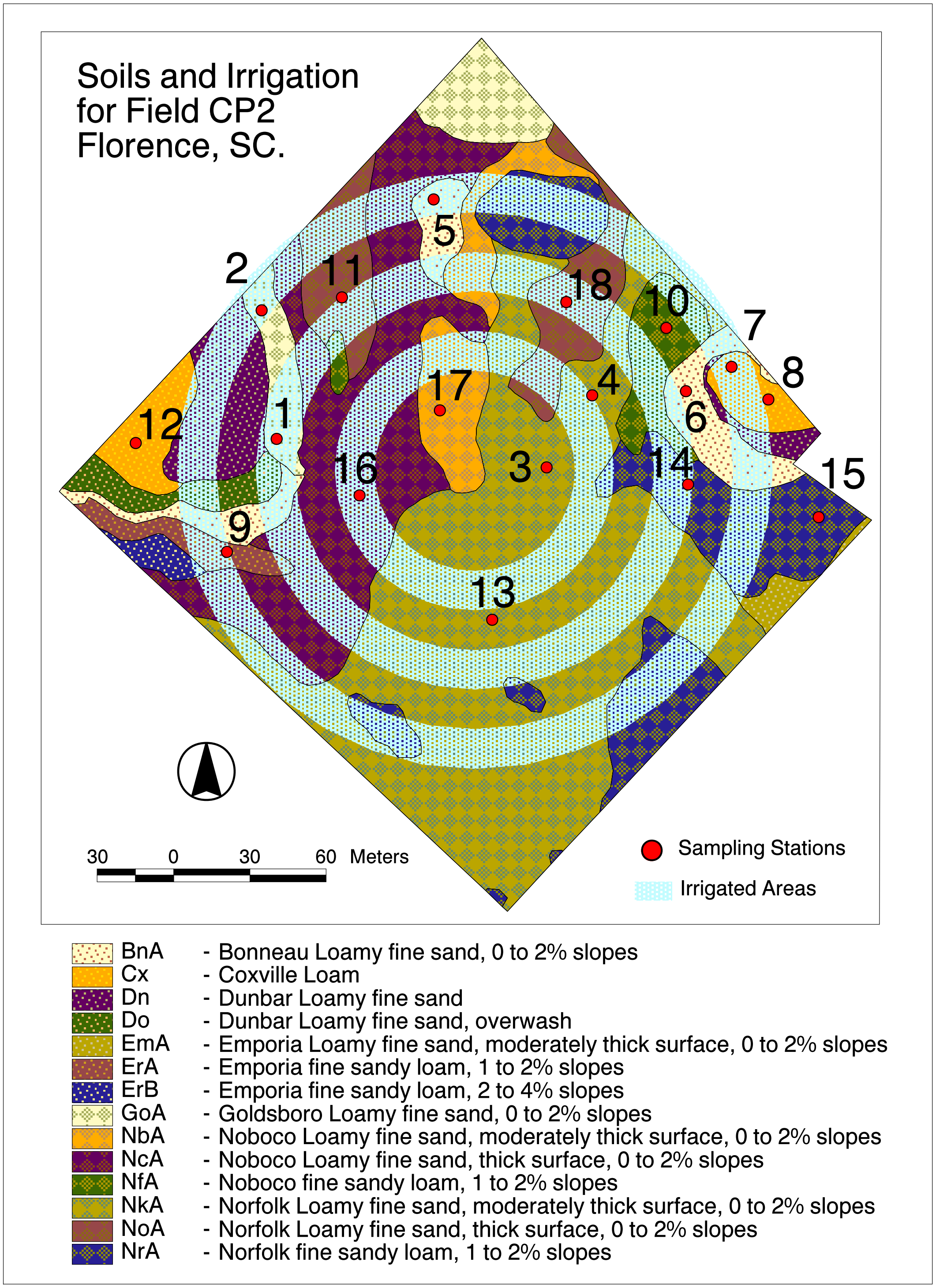

Figure 1. Soil map and classifications, sampling stations, and irrigated areas for the study site.

the combine. Instantaneous yields were gathered as point data and recorded in bushels per acre.

The Center researchers provided CROPGRO-Soybean inputs including: cultivar, meteorological and soil variables, irrigation, and other management information. Crop parameters for generic Maturity Group 7 were used in all simulations. Irrigated and non-irrigated soil types were chosen as the unit of simulation for the field. All other input variables were held constant. This choice of inputs resulted in 30 separate model runs, which output yield, LAI, %PAR, biomass, grain weight, leaf weight, and seed number. ASCII output files from CROPGRO-Soybean were then imported into a geographic information system (GIS) and matched to georeferenced irrigated and non-irrigated soil units. Within the GIS, modeled yield values were interpolated to 20x20 meter grids using block inverse distance weighting (IDW) to match the spatial resolution of SPOT satellite imagery. The 18 sampling station points were overlaid with the soil units and to extract values of simulated biophysical variables. Simulated LAI and yield were regressed against field LAI and yield to measure model precision. Simulated LAI, yield, %PAR, height, and biomass were regressed against vegetation indices computed for each SPOT overpass date.

Six multispectral SPOT 4 satellite images were acquired between the mid-vegetative stage and maturity to capture green up through senescence (Figure 2). Sensor calibration, atmospheric, and geometric corrections were made to minimize errors associated with atmospheric and sun angle differences between the different acquisition dates as well as for sensor gains and biases (Sellers et al., 1994; Jensen, 1996; and Goetz, 1997).

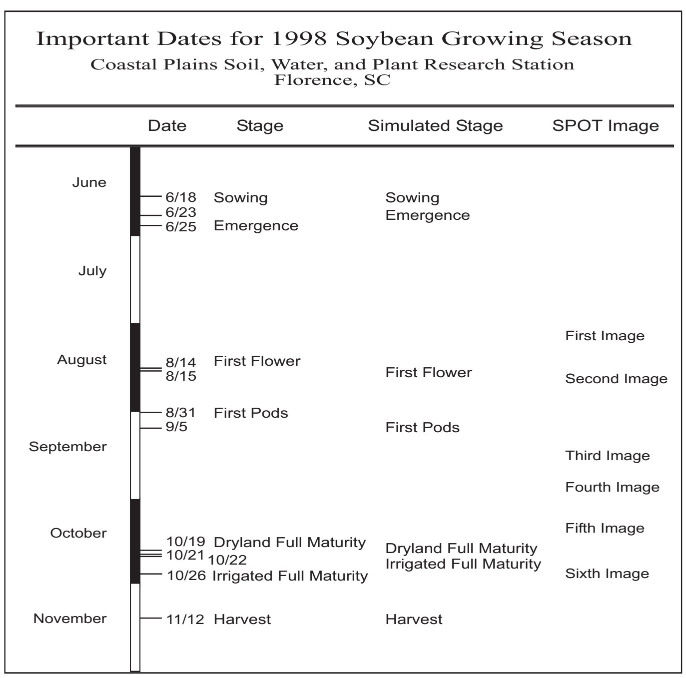

Figure 2. Soybean development stage, soybean stage as simulated by the crop model, and image acquisition dates.

The corrected images were used to compute four vegetation indices and were compared: the normalized difference vegetation index (NDVI), the simple ratio (SR) index (both non-adjusted indices), the soil adjusted vegetation index (SAVI), and the transformed soil adjusted vegetation index (TSAVI):

$$NDVI = \frac{NIR - \mathrm{Red}}{NIR + \mathrm{Red}} \qquad SAVI = \frac{NIR - \mathrm{Red}}{NIR + \mathrm{Red} + L} * (1 + L)$$

$$SR = \frac{NIR}{\mathrm{Red}} \qquad TSAVI = \frac{a * (NIR - a * \mathrm{Red} - b)}{a * NIR + \mathrm{Red} - (a * b) + X(1 + a * a)}$$

Following Huete (1988), the *L* coefficient for the SAVI equation was set at 0.5. An average soil line equation was also used for the TSAVI calculations as given in Baret and Guyot (1991). The *a* coefficient is the slope of the soil line and was set to 1.20. The *b* coefficient is the intercept of the soil line and was set to 0.04. The *X* coefficient is an adjustment factor and was set to 0.08.

The observed LAI and yield, and simulated LAI, %PAR, biomass, and yield were then regressed against each calculated vegetation index. Linear and curvilinear regressions were performed for each date of imagery and each vegetation index for pre- and post- LAI maximum.

ANALYSIS AND RESULTS

Analysis of soybean LAI, height, and yield as measured in the field is presented in this section. LAI varied spatially through the growing season, but all stations followed the same general pattern: LAI increased to around August 20, decreased for a 10-day period, increased through the pod filling stage reaching a maximum around September 18 – 24, and decreased thereafter (Figure 3).

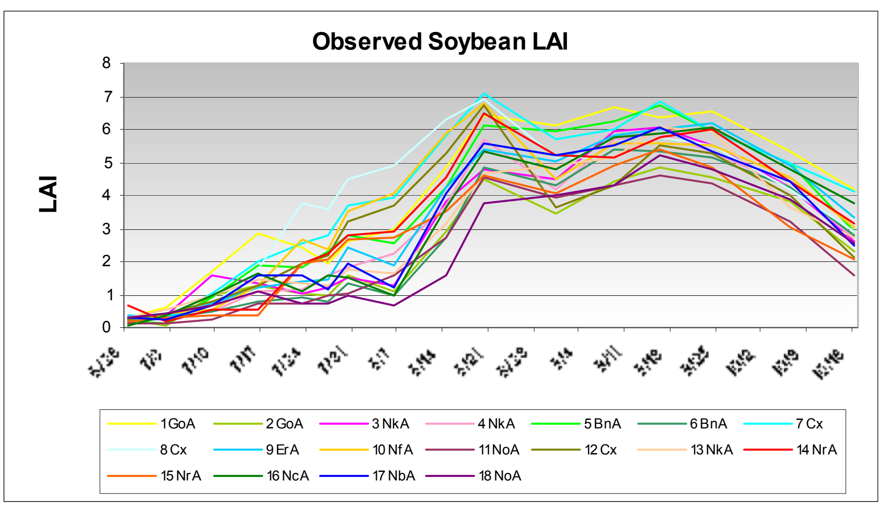

Figure 3. Observed soybean LAI for the 1998 growing season.

Table 1. Observed irrigated and non-irrigated yield, averaged to soil series.

Soil	Yield	
	Non-irrigated	Irrigated
	kg ha^{-1}	
BnA	1438.2	1972.1
Cx	1929.9	2036.5
Dn	1203.2	2451.2
Do	1297.1	2669.8
EmA	2292.3	4278.0
ErA	1613.5	1955.3
ErB	748.9	2260.8
GoA	1775.0	1590.6
NbA	2236.1	3095.6
NcA	2122.3	2492.3
NfA	2457.6	2058.1
NkA	1518.9	2168.5
NoA	1514.6	1937.9
NrA	1769.9	2697.1
Average	1708.39	2404.56

The spatial pattern of soybean yield was similar to those seen in other years (Sadler et al., 1995). Average irrigated and non-irrigated yield over all soil types was 2056 kg/ha; the standard deviation was 668 kg/ha (Table 1). The relationship between observed yield and LAI was weak, suggesting that the remotely sensed data, primarily displaying a leaf reflectance signal, might not be useful for predicting intra-field yield. This question will be explored further in the remote sensing analysis section. It should be noted however, that the methodology used for determining point yield at each sample site may not successfully address errors associated with combine-mounted yield monitors such as sensor yield lag or variable grain flow rates (Birrell et al., 1996; Missotten et al., 1996). The observed point yield included many zero values followed by large (6,000 to 7,000 kg/ha) yield values, perhaps indicating a variable flow rate through the yield sensor. The large range of yield for each sample station (127 to 4414 kg/ha) might indicate that a simple point IDW interpolation did not overcome the yield sensor limitations. Further research should address this issue.

The model simulated phenology very accurately; all simulated soybean development stages fell within a few days of those observed (Figure 2). The model accurately simulated the seasonal *pattern* of LAI, but simulated LAI values were generally lower and less variable than those observed (Figure 4). The model helps to explain why observed LAI decreases prior to the end of the reproductive stage. Figure 5 shows a period of high water stress around August 20, to which simulated and observed LAI responded. It is only after this period of stress that simulated LAI begins to differ among soil units, reflecting the models sensitivity to differences in soil water storage capacity.

The relationship between simulated and observed yield in the 20m grids was weak. Simulated yield for each soil type is comparable to observed yield that

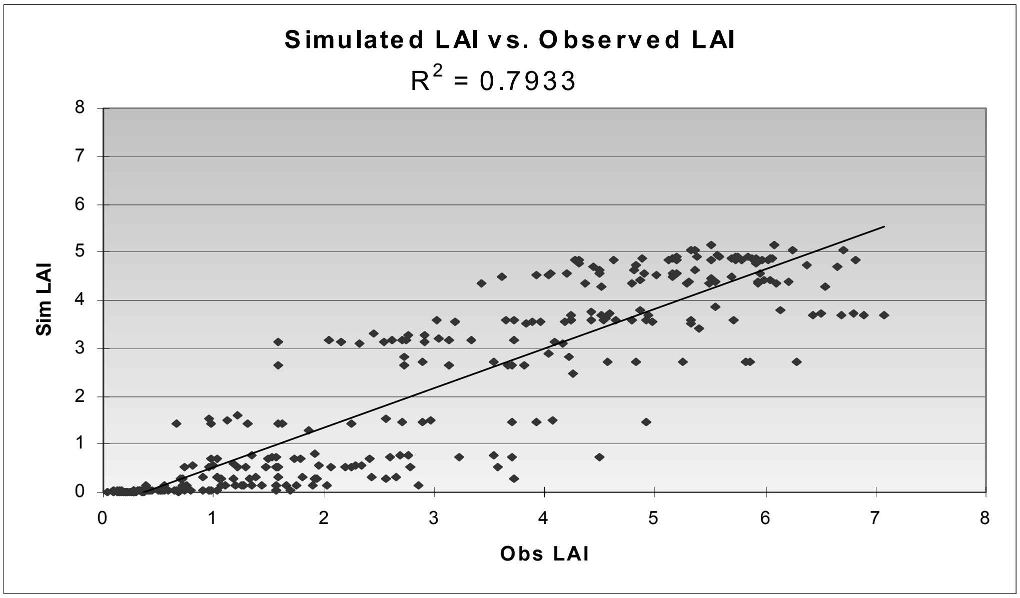

Figure 4. Simulated LAI regressed against observed LAI.

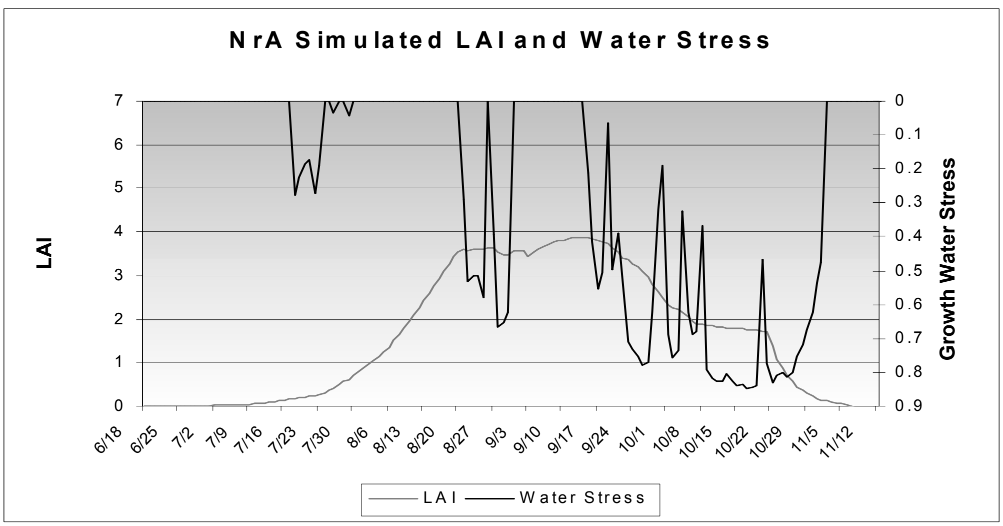

Figure 5. Simulated LAI and growth water stress for NrA soil units.

has been averaged for each soil type, although the simulated yields are lower for both irrigated and non-irrigated soils. These results suggest that the model predicts average field yield reasonably well, but does not capture spatial variability in yield. This inability to capture intra-field variability could be related to the choice of soil type as the model simulation unit. Such a strategy does not account for spatial variability within a soil that could be caused by environmental factors such as soil nitrogen levels, microclimate, or nonuniform topography. Another possible explanation is that soil type is a suitable unit for model simulation but that the model algorithms do not handle soil water interactions correctly. In either case,

Table 2. R-squared values for regressions of vegetation indices against observed LAI on individual dates.

	Vegetation Indices							
Date	SR	NDVI	SAVI	TSAVI	Green	Red	NIR	SWIR
8/4	0.628	0.570	0.593	0.585	0.299	0.520	0.537	0.276
8/19	0.124	0.101	0.140	0.130	0.135	0.075	0.140	0.033
9/14	0.132	0.063	0.226	0.151	0.041	0.031	0.435	1.87E-05
9/25	0.160	0.155	0.115	0.125	0.092	0.002	0.092	0.011
10/10	0.332	0.448	0.452	0.456	0.373	0.417	0.418	0.171
10/26	0.097	0.156	0.078	0.099	0.310	0.259	0.060	0.424

further research needs to be conducted for the use of the CROPGRO-Soybean model for intra-field yield studies.

The correlations between vegetation indices and observed LAI values were very low on four of the six individual image dates (Table 2). The first (August 4) and fifth (October 10) dates showed the highest correlation. Not coincidently, spatial variability in both LAI and the vegetation indices is highest on these dates. LAI values vary spatially in the first two images (August 4 and 19) and last two images (October 10 and October 25). The vegetation indices have highest spatial variability on August 4 and October 10. The green-up and senescence of the soybeans can thus be traced through the LAI/vegetation index feature space. This suggests that if limited dates of imagery are available they should be acquired before an LAI of around 3 to 5.

The vegetation indices and SPOT bands show a strong relationship with observed LAI when data are split in pre- and post-maximum LAI periods (Table 3). NDVI shows the strongest to observed LAI. Simulated LAI was also compared to vegetation indices for the six dates of imagery (Table 3). Similar slopes for the regression suggest that for season comparisons the simulated LAI mimics the observed LAIs relationship to the vegetation indices. These findings indicate that modeled data could be useful for establishing seasonal vegetation index relationships to LAI if observed LAI is not available.

The *in situ* yield data for the field represents a larger and denser data set for analyzing the remotely sensed imagery. The relationship between grid cell yield

Table 3. R-squared values for regressions of average seasonal vegetation indices against observed LAI.

	Observed LAI		Simulated LAI	
Index	Pre-LAI Max	Post-LAI Max	Pre-LAI Max	Post-LAI Max
NDVI	0.779	0.746	0.750	0.785
SR	0.482	0.685	0.718	0.726
SAVI	0.753	0.742	0.713	0.872
TSAVI	0.772	0.743	0.730	0.843
Green	0.638	0.712	0.801	0.381
Red	0.769	0.764	0.764	0.730
NIR	0.610	0.686	0.572	0.885
SWIR	0.481	0.745	0.754	0.915

Table 4. R-squared values for regressions of observed and simulated yield against seasonally averaged vegetation indices.

Index	Yield	
	Observed	Simulated
	kg ha^{-1}	
NDVI	0.416	0.030
SR	0.401	0.020
SAVI	0.415	0.022
TSAVI	0.424	0.025
Green	0.276	0.024
Red	0.322	0.028
NIR	0.365	0.014
SWIR	0.029	0.008

and vegetation indices on individual imagery dates is weak. However, when vegetation indices were averaged for each grid cell for all six dates, over 40% of the variance in yield

can be explained by the four vegetation indices (Table 4). These results suggest that vegetation indices could be used for intra-field yield mapping. Higher correlations of vegetation indices to observed yield might be found using imagery with a higher spatial resolution.

CONCLUSIONS

Several conclusions can be drawn about the performance of the crop model for estimating soybean biophysical properties. First, the crop model captures the temporal increase and decrease of LAI, and the LAI response to stresses during the growing season. The model did not capture the spatial variability of LAI, %PAR, or biomass. The model captured average field yield, but not the spatial variability of yield within the field. This indicates that the crop model does not currently provide data at a scale useful for variability studies in precision agriculture, but can be useful for examining general field biophysical responses. Modeled data could be improved by a better understanding of the factors causing spatial variability across a field, increased spatial resolution of input data, using improved model algorithms, or innovations such as the use of fuzzy logic allowing for uncertainty in intra-field soil type classifications (Ambuel et al., 1994). The ability of the model to simulate observed patterns of data suggests that such improvements should allow a crop model to be used successfully for studying variability in precision agriculture.

The remotely sensed imagery was linearly correlated to observed LAI for individual dates when LAI was below 3 to 5. With higher LAI, a seasonal series of images was able to construct a linear correlation to LAI. When looking at the seasonal imagery it was important to recognize the biphasic nature of the data. Simulated LAI, %PAR, and biomass showed similar linear correlations to the imagery and the biphasic relationship. Biomass was less correlated than the other properties. The relationship between yield and vegetation indices on individual dates was weak but stronger when vegetation indices were averaged for the season, suggesting imagery could possible be used for yield mapping. This conclusion indicates that techniques are available to extract biophysical information from remotely sensed imagery, and that this information is at a scale useful for intra-field variability studies in precision agriculture. However, the imagery must be collected at certain stages of crop development or for multiple dates through the growing season. Finally, the soil-adjusted indices did not show consistently lower error for low canopy situations than the non-adjusted indices.

Remotely sensed data show promise for yield and biophysical parameter mapping, and for creating temporal series of LAI and biomass from multiple dates of imagery. This information could then be used for evaluating field management practices, identifying stressed or low-yield field areas, and providing field-level inputs for crop models. Increased availability of higher spatial resolution imagery will allow for more detailed intra-field studies that should be more comparable to field sampling techniques. Crop modeling and remote sensing combined with field data collection can successfully be used for some applications in soybean biophysical property extraction. Physiological crop models will continue to grow in complexity and accuracy for modeling plant processes, and future research should lead to a better understanding of the simulation units appropriate for capturing intra-field variability.

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