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MODIFICATION OF CERES-WHEAT TO ACCEPT LEAF AREA INDEX AS AN INPUT VARIABLE

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Summary: CERES-Wheat is one in a family of crop simulation models used by the Decision Support System for Agrotechnology Transfer (DSSAT). Efforts have been devoted to integrating the DSSAT models with Geographic Information Systems (GIS) to account for spatial variation in soils and climate; however, validation and fine tuning of the models over large areas remain difficult and labor intensive tasks. The relationship between multispectral data and biophysical plant characteristics such as green leaf area index (LAI) has been demonstrated; therefore, multispectral images have the potential to enhance the spatial predictive capability of existing growth models. In order to take the first step in the process of linking remotely sensed data to existing growth models, CERES-Wheat was modified to accept observed LAI at defined times during the season. Related parameters in the model (green plant area, senescent plant area, and total leaf weight) were also adjusted as a function of LAI. The method was evaluated using three seasons of growth and meteorological data collected as part of the Free-Air CO_2 Enrichment (FACE) experiment conducted near Maricopa, Arizona. Initial results indicate that the proposed procedures are only effective when the growth stages of the model are properly predicted and leaf area index observations are available soon after the completion of leaf development. Future efforts will focus on an iterative approach to adjusting the model's parameters.

Keywords:
Wheat model, remote sensing, precision farming

Introduction

The development of crop models has been progressing since the 1970s (e.g., Stapleton, 1970; Young et al., 1979). Since that time various models have been integrated with decision support systems for farm management (Lemmon, 1986; Jones et al., 1987). Both the models and decision support systems were originally designed to simulate average field conditions; however, more recently tools have been developed to integrate growth models with geographic information systems (GIS) at either regional (Carbone et al., 1996; Papajorgi et al. 1994) or field scales (Paz et al., 1997). One limitation to simulating spatial variations in crop production is the large amount of input data necessary to accurately prediction conditions. Even when the input data is available, the model's predictions may be inaccurate due to improper cultivar parameters or the inability of the model to account for certain stress parameters such as insects or weeds (Kenig et al., 1993). The broad objective of this study is to determine how remotely sensed observations can be used to improve a growth model's ability to simulate actual field scale variability. Dependable methods to forecast of the impact of variability in the crop canopy during the early season on yield would provide a new tool for producers to make informed decisions in the application of precision farming practices. This paper is the first step in fulfilling that objective, by examining the level of improvement in a model's predictions when leaf area indices are forced to match observations.

Previous Applications of Remote Sensing and Growth Models

One of the strongest correlations between remotely sensed data and crop status is green leaf area index (LAI, the ratio of green leaf area per area of ground). Near-infrared light (~ 0.8 to 0.9 μm) is scattered by the leaf mesophyll, while red light (~ 0.68 μm) is strongly absorbed by chlorophyll (Wiegand et al., 1972). The changes in canopy reflectance spectra for different stages of canopy development are illustrated in figure 1 for a cotton crop. When compared to a bare soil, the growing canopy has a consistent increase in NIR reflectance and a corresponding decrease in red reflectance. These spectral responses are the basis for many vegetation indices that involve some mathematical relationship between red and NIR reflectances, such as the ratio vegetation index (RVI):

$$\mathrm{RVI} = \frac{\mathrm{NIR}}{\mathrm{Red}}, \tag{1}$$

or the normalized difference vegetation index (NDVI):

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}}, \tag{2}$$

where NIR and Red are the reflected radiance in the near-infrared and red part of the spectrum, respectively. For a more complete description of vegetation indices see Jackson and Huete (1991). Both of these indices have shown usefulness for monitoring the crop growth cycle (Gupta, 1993). Several studies have documented relationships between reflectance and leaf area

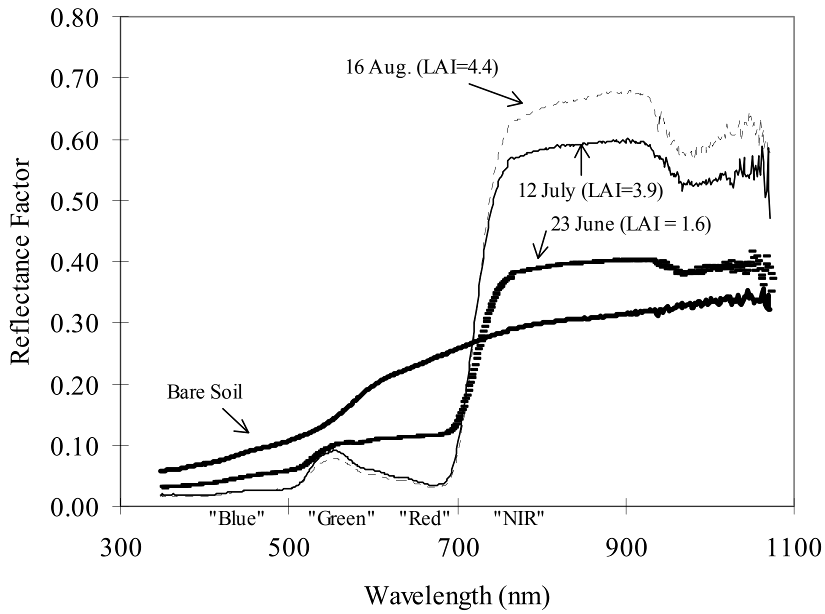


Figure 1: High-resolution reflectance spectra for both a bare soil and a cotton canopy on different dates. Measurements of green leaf area index (LAI) are shown for the dates the spectra were acquired.

index for various crops such as rice (Shibayama and Akiyama, 1989), wheat (Korobov and Railyan, 1993), sorghum (Wiegand and Richardson, 1984), and corn (Wiegand et al., 1990). It should be noted that the accuracy of LAI estimates from remotely sensed data is subject to illumination conditions, view angle and site specific conditions such as row spacing (Qi et al., 1995).

Wiegand et al. (1979) discuss the possibilities of using LAI as either an input or a calibration check for crop models. They found that remotely sensed estimates of LAI for wheat was sufficient to provide information on crop development and growing conditions. Lo Seen et al. (1995) discuss the possibilities of integrating vegetation indices with a grassland growth model. The growth model, combined with a canopy reflectance and atmospheric model, is used to simulate top of atmosphere reflectance values. These simulated values are then compared to satellite actual observations to track the performance of the model. Maas et al. (1992) and Moran et al. (1995) utilized remotely sensed estimates of LAI and evapotranspiration as inputs to a simple alfalfa growth model. The remotely sensed estimates were used to adjust the model's parameters throughout the season using an iterative process. They found the model performed best when remotely sensed observations were evenly distributed during the course of the growing season. While all of these studies were focused on regional estimates of crop production, similar applications should be possible to describe field scale variability in crop development.

Background on the CERES-Wheat Model

Several simulation models are available for wheat (e.g., Porter, 1984; Hammer et al., 1987). CERES-Wheat (Ritchie and Otter, 1985) was selected for use because it is a process oriented model capable of simulating different management practices, while maintaining reasonable input requirements that would not prevent its application by a farm manager. Additionally, the model has been integrated as part of the Decision Support System for Agrotechnology Transfer (DSSAT, Hoogenboom et al., 1994), providing several tools with which to manipulate the model's output for use in decision making. Routines are included in the DSSAT package to link the model with a GIS (Papajorgji et al., 1994). The model is capable of simulating plant response to environmental conditions, and soil-moisture and nitrogen availability. Only the details relevant to the modifications made to the model are presented in the following discussion. For additional information on the model see Ritchie and Otter (1985) and Ritchie (1991). Jones and Kiniry (1986) provide extensive documentation for the CERES-Maize model.

The model's prediction of crop phasic development is controlled primarily by a growing-degree day approach as described by Ritchie (1991). In general, when the accumulated growing-degree days exceed a given threshold, a new growth phase begins. The growth phases predicted by the model are included in Table 1, with a brief description of the threshold parameters.

Table 1: Growth or management phases defined in CERES-Wheat

Stage	Growth Phase or Management Event	Threshold Parameter
7	Fallow	--
8	Sowing to germination	Soil moisture [a]
9	Germination to emergence	Sowing depth [b]
1	Emergence to terminal spiklet initiation	PHINT [c]
2	Terminal spiklet to end of leaf growth	3*PHINT
3	End of leaf growth to end of preanthesis ear growth	2*PHINT
4	End of preanthesis ear growth to beginning of grain filling	200 ^{o}C-day
5	End of grain filling	P5 [d]
6	End of grain filling to harvest	--

[a] Germination (better defined as water imbibition) occurs in one day if there is sufficient soil moisture.
[b] Thermal time required for emergence is equal to 40 + 10.2 * (sowing depth in cm)
[c] PHINT is the interval of thermal time between leaf tip appearance (degree-days). The length of stage 1 is also modified for vernalization and photoperiod requirements.
[d] The threshold parameter for stage 5 is considered to be variety specific and can be modified by the user.

Notice that the threshold parameters for stages 1 to 3 are all a function of a single parameter, the interval of time between leaf tip appearance (PHINT). For stage 4, the model assumes a variety independent time period for stage 4 of 200 ^{o}C days. To allow the model to have the capability of simulating different wheat varieties, the model makes use of a cultivar file. It is in that file that PHINT and P5 are defined, as well as other parameters that relate to grain filling rate and stem size.

LAI is a relatively important prediction in the CERES model. It is used in the calculation of evapotranspiration rates and potential dry matter production. In the growth subroutine, the potential dry matter production (PCARB, g per plant) is calculated as a function of planting geometry and LAI by:

$$\mathrm{PCARB} = 1.48\,\frac{\mathrm{SRAD}}{\mathrm{PltPop}}(1-\exp(-\mathrm{Y1\,LAI})), \tag{3}$$

where,

$$\mathrm{Y1} = 1.5 - \frac{0.768}{(0.01\,\mathrm{RowSp})^2\,\mathrm{PltPop}}, \tag{4}$$

SRAD is solar radiation (MJ m^{-2} d^{-1}), PltPop is the number of plants per square meter, and RowSp is row spacing (m). Equation 3 assumes 50% of total solar radiation is photosynthetically active and there is a radiation use efficiency of 2.96 g MJ^{-1}. If there is either water or nitrogen stress predicted, the potential dry matter production is decrease in proportion to the level of stress. The partitioning of the total dry matter production in the plant to individual plant components (e.g., roots, stems, leaves, and grain) is primarily controlled by the predicted growth stage. In stage 1, leaf mass is assumed to accumulate as a function of thermal time and then the remaining dry mass is partitioned to the roots, with certain exceptions for water or nitrogen limited conditions. In stage 2, dry mass is first partitioned to the roots and stems and the remaining mass is used for leaf growth. The later stages of development, more priority is given to development of the grain in the distribution of dry matter. Further background on specific aspects of the model is discussed in the next section.

Materials and Methods

Model Modifications

The specific version of the model used in this study was Generic CERES 3.10, distributed with the DSSAT 3.1 software package (Tsuji et al., 1994). The term "Generic" is an indication that the model contains subroutines that allow it to simulate maize, wheat, barley, millet, sorghum, and pasture grass. The focus of this study is only on the wheat subroutines; however, the same principals should apply to the other crops considered by the model.

The first modification made to the model was the creation of the WOBSLAI subroutine shown in Appendix A. That subroutine is called at the end of the wheat growth subroutine only on days when there is a LAI observation. On a daily basis, CERES does not define green plant area, but instead predicts total plant leaf area (PLA, cm^2 per plant) and senescent plant leaf area (SENLA).

Green plant area is defined at the beginning of a growth stage as the difference between PLA and SENLA. The subroutine first reads a file containing the observed LAI, and if available, senescent leaf area index. Also included in the file are tolerance values for each measurement. In this study the tolerance values represent the standard error of the LAI observations; however, they could also represent a confidence interval about a regression line relating LAI to remotely sensed observations. The index values are first converted to measures of plant leaf area using the plant population defined in the model. Included in the subroutine are procedures for estimating senescent leaf area when these values are not provided; however, these procedures currently tend to provide inaccurate estimates of leaf weight and need further development. Therefore, the emphasis of this presentation is the case when the amount of senescent leaf area is known. SENLA may not be easily determined by remotely sensed data directly; however, it could be estimated as the difference between the maximum observed LAI and the observed LAI on a later date for time periods after the end of leaf expansion.

After converting the index values to plant leaf area, it is determined if the SENLA is within the specified tolerance value. If SENLA is within the tolerance value, no adjustments are made, otherwise the SENLA predicted by the model is set equal to the observed value. Having modified SENLA, the difference in predicted PLA and SENLA is compared to the observed green plant area. If the magnitude of this difference exceeds the tolerance value, PLA is set equal to the observed green plant area plus SENLA. In this case, the total leaf area of the plant has been modified, and therefore leaf weight (LFWT, g per plant) is adjusted by:

$$\mathrm{LFWT} = \mathrm{LFWT} + \frac{\mathrm{PLA} - \mathrm{PLAOLD}}{\mathrm{AWR}}, \tag{5}$$

where PLAOLD is the total plant leaf area before any adjustments were made (cm^2 per plant) and AWR is the area to weight ratio of a leaf ($cm^2\ g^{-1}$). After stage 1, CERES assumes a constant value of 115 $cm^2\ g^{-1}$ for AWR; however, for the wheat variety considered in this study, observations indicated a value of 200 $cm^2\ g^{-1}$ was more appropriate. Therefore, this value was used both in the WOBSLAI subroutine as well as in the main wheat growth subroutine of CERES. In stage 1, AWR is assumed to vary as a function of thermal time using the equation:

$$\mathrm{AWR} = 150 - 0.075\ \mathrm{TDU}, \tag{6}$$

where TDU is thermal development units (^{o}C-day), which is approximately equivalent to accumulated growing degree days; however, TDU has been modified to account for the effects of vernalization and photoperiod. In order to provide continuity between stages 1 and 2, the constant of 150 in equation 6 was replaced by the value 250. Treating AWR as a variety independent parameter does not appear to be appropriate, and consideration to adding this parameter to the user defined cultivar file would be appropriate for future versions of the model.

It was also determined that modifying LAI alone would not be sufficient if there were errors in the predicted growth stage of the crop. For example, if LAI observations indicate that leaf development is still occurring and the model predicts the crop has entered stage 3, the model will allow no further leaf development. While the LAI could be corrected for the day of observation, the model would still not predict any further leaf development. To allow some method to correct for such a case, a subroutine was created called CHKPHEN, as shown in Appendix B. The subroutine allows the user to define a specific date or ranges of dates in which a transition between growth stages must occur. The dates can be defined based on the user's knowledge of the current growth stage of the plant or some stages can be defined based on temporal trends in the RVI (to be discussed). The routine is called from CERES phenology subroutine, immediately before the point at which the model considers whether or not transition should occur to a new growth stage. While it may not be possible to define all of the growth stages based on remotely sensed data, the ability to control the end of stages 9, 1, 2, 3, 4 and 5 was added. In addition to accounting for calibration errors, the user control of the growth stages is also necessary for conditions of extended water or nitrogen stress, as the model will not account for increased development rates under these conditions.

When the CHKPHEN subroutine is called, the accumulated growing-degree days (SOMEDT) and the appropriate threshold parameter are passed to the routine. If based on the dates provided by the user, a change in growth stage should occur and SOMEDT has not exceed the threshold parameter, the threshold parameter is set equal to (SOMEDT - 1). Similarly, if SOMEDT has exceeded the threshold parameter and a change in growth stage should not occur, the threshold parameter is set to (SOMEDT+1). If there are no constraints on the growth period, or the simulation time period falls between a user specified range, no adjustments are made to the threshold parameter.

Evaluation Data Set

The modifications made to the model were evaluated using a wheat growth data set collected during the wheat Free Air Carbon Dioxide Enrichment (FACE) experiments conducted in Maricopa, Arizona. Kimball et al. (1995) and Pinter et al. (1996) provide details of the experimental procedures and setup. Three seasons of growth data are used in the evaluation. In each year a hard red spring semi-dwarf wheat (*Triticum aestivum* L. cv. Yecora Rojo) was planted at a 0.25 m row spacing. One treatment always corresponded to plots exposed to elevated CO_2 concentrations. Additional treatments included two irrigation levels in first two seasons and 2 nitrogen levels in the second season. The total treatment levels are shown in Table 2. While the CERES model does have the ability to simulate plant response to elevated CO_2 levels, the focus of this evaluation will only be on the irrigation and nitrogen treatments.

Destructive plant sampling from each of the treatments began each season soon after emergence and continued through crop maturity. Treatments were sampled by taking 3 plants per row for 2 rows in each repetition. Once harvested, fresh and dry weights were obtained and both green and brown leaf area indexes determined using a Li-Cor model 3100 area meter.

Table 2: Irrigation and nitrogen treatment totals for the evaluation data set.

Experiment	Treatment Wet	Dry
	Irrigation (mm)	
1992-93	919	592
1993-94	629	287
	High	Low
	Nitrogen (kg/ha)	
1995-96	350	70

Simulation Techniques

The first step in the simulation process was to determine the appropriate cultivar parameters to use to represent Yecora Rojo. As a starting point, six spring wheat cultivars included with the model were simulated for the wet irrigation treatments with the 1992-3 and 1993-4 data. Of the cultivars evaluated, the one providing the best overall simulation results (predicted leaf, stem, LAI and grain weights to observed data during the season) for the 1992-93 data set was selected. The parameters for this cultivar where then adjusted to provide a better predictions for the 1993-94 data set, as it was difficult to determine cultivar parameters that provided reasonable results in both years. Simulations were then conducted using both of these cultivar parameter sets for each year, both with and without adjustment of LAI values. In the case when LAI was adjusted, observations were available at a seven to ten day interval between emergence and maturity. The only limits placed on the growth stage were the transition from stage 2 to 3 and from 5 to 6, as these stages have potential to be determined from remotely sensed estimates (to be discussed). The stages were specified to occur within a 10 day time period, centered on the day they were observed. The range of 10 days was selected, as it represents what could be inferred from weekly satellite or aircraft observations. The primary goal of these simulations was to determine the effectiveness of the modifications in accounting for improper model calibration.

Additional simulations were conducted using only the Yecora Rojo cultivar parameters to determine the use of observed LAI to correct for inaccurate input data. In the first test, the leaf area index values corresponding to either the wet or high nitrogen treatments were used as an input the model when the dry or low nitrogen conditions were simulated. Similarly, the leaf area index values corresponding to either the dry or low nitrogen treatments were input to the model when the wet or high nitrogen conditions were simulated.

Remotely Sensed Data

Remotely sensed data was also collected during the FACE experiment using a hand-held Exotech radiometer. The data collection techniques used to process the radiometer data and convert it to units of reflectance (ratio of reflected radiance at the radiometer to incident radiation) is described by Pinter et al. (1994). Data collected for the wet treatments during the 1993-94 season are currently used to illustrate the relationship between near-infrared and red reflectance with LAI. Future work will be aimed at using LAI estimates derived from this data with the model.

During the 1995-96 experiment, Datron/Transco Inc. provided an image of the field in the blue, red, green and NIR portion of the spectrum using aircraft mounted digital cameras. The image spatial resolution was approximately 2 m and was acquired on March 31, 1995, approximately 10 days after maximum canopy cover had been reached. The data were used to generate a RVI map of the field. Additional, supervised classification of the image was used to group different areas of the field into LAI classes. The classification was done using a maximum likelihood classifier with Erdas Imagine 8.1 image processing software. The training data for the classification procedure was obtained by using measured LAI of the plots sampled near the time of the over flight. Yield predictions were made for the various LAI classes obtained in the images using the modified CERES model.

Results and Discussion

Remotely Sensed Estimates of LAI

Note, the primary objective in presenting the results in this section is to demonstrate the capabilities of multispectral techniques to quantify and map trends in LAI. Further work will be conducted to determine the significance of errors in the estimates to the application in growth models. Temporal trends in both LAI and RVI are shown in Figure 2. Note that without any calibration, the temporal trends of LAI and RVI are much the same. From the figure, it can be seen where remotely sensed data could be used to place limits on the occurrence of wheat growth stages. An upper limit on the time of emergence could be determined by noting the time period when the RVI values begin to consistently increase. The end of leaf development corresponds to the time when the RVI values reach a maximum. Maturity can also be determined by noting when the RVI values reach a minimum at the end of the season. There is some hysterisis in the relationship, as the RVI values are relatively higher for the same LAI values during crop development compared to the values once senescence has begun. The large drop in the RVI value near day 70 is due to cloud cover and wet soil conditions during the time of measurement. Using least squares linear regression for the data shown in figure 1 with RVI as the independent variable, the standard error of the regression relationship with LAI was 0.92, with a coefficient of determination (r^2) of 0.88. A regression relationship between LAI and RVI will typically hold between seasons if the same field, planting geometry and crop variety are maintained.

Both the RVI and LAI classification maps generated from the aircraft-based images taken during the 1995-96 experiment are shown in Figure 3. There is a great deal of similarity in the patterns of both maps, with the LAI map appearing coarser due to the limited number of classes used. The rings that appear in the images are due to the pipe for the air handling system around the treatment plots. The horizontal bands of consistently higher RVI levels splitting the rings correspond to the high nitrogen treatments applied during this experiment. As the different nitrogen treatments started at the beginning of the season, the wheat in the high nitrogen treatments had consistently higher LAI values by the time this image was taken. The areas between the rings that tend to have lower RVI values correspond to strips between the treatment areas that were planted at a wider row spacing and had a less dense network of drip tubing (1 m spacing versus a 0.5 m spacing in the treatment areas).

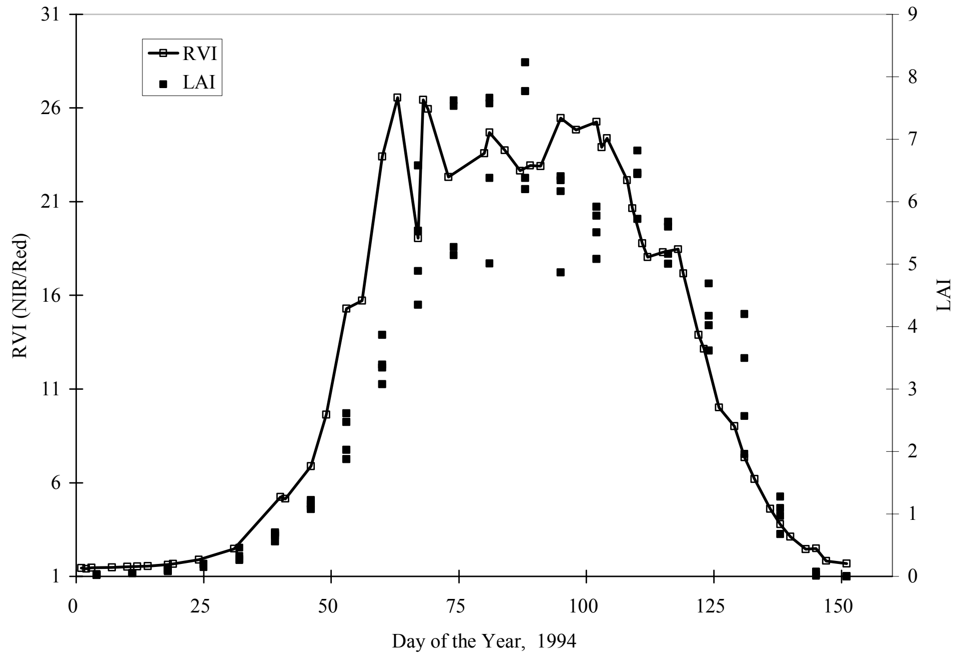
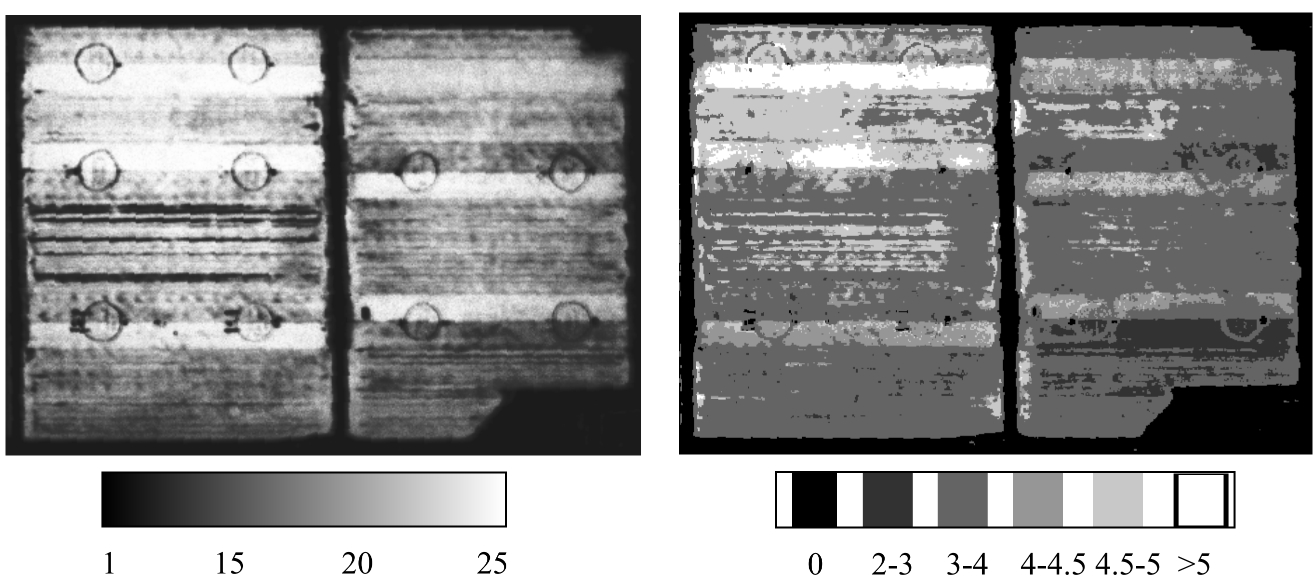


Figure 2: RVI and LAI versus time for the wet treatment of the 1993-94 growing season.



a)RVI Map

b) LAI classification map.

Figure 3: Maps derived from the March 31, 1996 image data (a) RVI and (b) LAI classification.

Simulation Results

The two cultivar parameter sets used in this evaluation are shown in Table 3. Also included in the table is a brief definition of the parameters. Note that the only two parameters that differ between the cultivar definitions are the sensitivity of the crop to photoperiod (P1D) and the leaf tip appearance rate (PHINT). A large value for PHINT was needed in order to slow down the predicted development of the crop in the early season. Part of the problem may be that the model is basing its growth stage on air temperature; however, in the arid climate of Arizona, the crop and soil can be several degrees cooler than the air. Further investigation is planned to determine if this is indeed the case.

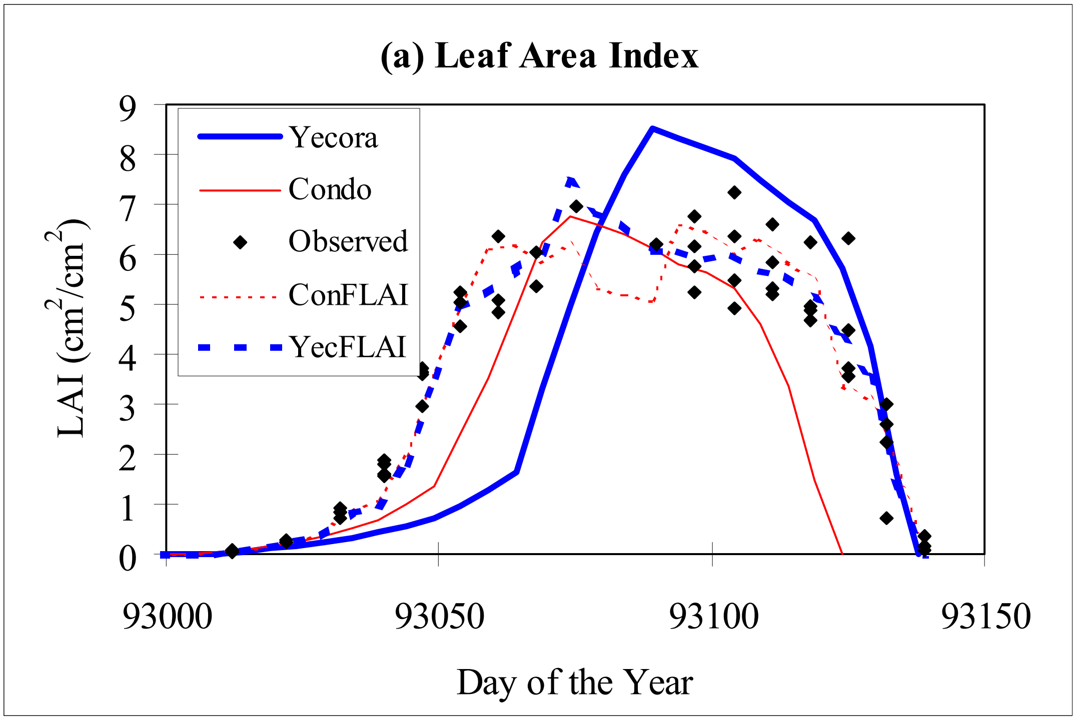
Table 3: Cultivar parameters used in this evaluation

		Cultivar	
ID	Description	Condo	Yecora
P1V	Sensitivity to vernalization	0.5	0.5
P1D	Sensitivity to photoperiod	1.5	2.0
P5	Relative grain filling duration	2.0	2.0
G1	Kernel number per unit weight of stem (g^{-1})	5.3	5.3
G2	Optimal kernel filling rate	1.9	1.9
G3	Nonstressed dry stem weight (g)	1.9	1.9
PHINT	Leaf tip appearance rate	95	120
AWR*	Leaf area to weight ratio	200	200

* AWR is typically not a user defined variable, but the model assumes a constant value of 115 in stage 2. In this study, the value was modified within the source code of the model.

Predicted and observed LAI and grain weights are shown for the wet treatments of the 1992-93 and 1993-94 experiments in Figures 4 and 5. Figure 6 provides the same data for the 1994-95 experiment for the high nitrogen treatment. Four different predictions are shown in each chart. Two sets of predictions correspond to simulations using the two sets of cultivar parameters included in Table 4, without modifying LAI predictions. The other predictions shown again correspond to the two different cultivar parameters; however, in this case the LAI predictions have been forced to match observations, and limits have been placed on the time periods in which growth stages 2 and 5 can end.

The predicted yield results indicate that often the LAI adjustments actually increased the error in predicted yield in some cases, particularly when the Condo parameters were used during the 1993-94 and 1995-96 growing seasons. In these cases adjustment to match the LAI observations resulted in an over prediction of final yield. Part of this over prediction is a result of the fact that in these simulations no limits were placed on the transition from stage 1 to 2. For the Condo parameters, stage 1 occurs earlier than with the Yecora parameters, which result in stem



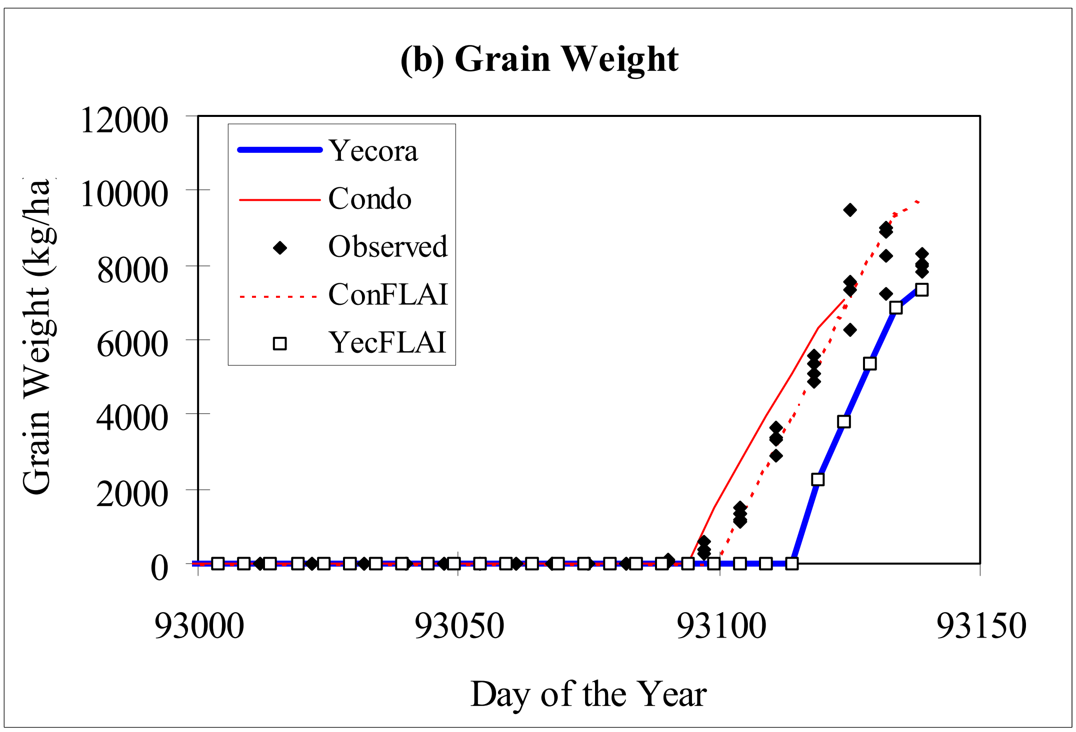


Figure 4: Observed and predicted leaf area index (a) and grain weight (b) for the 1992-93 experiment. In the legend captions, Yecora and Condo refer to predicted values using the Yecorra Rojo and Condo cultivar parameters. ConFLAI and YecFLAI are the predicted values for the same cultivar parmeters when the predicted LAI values are forced to match observations.

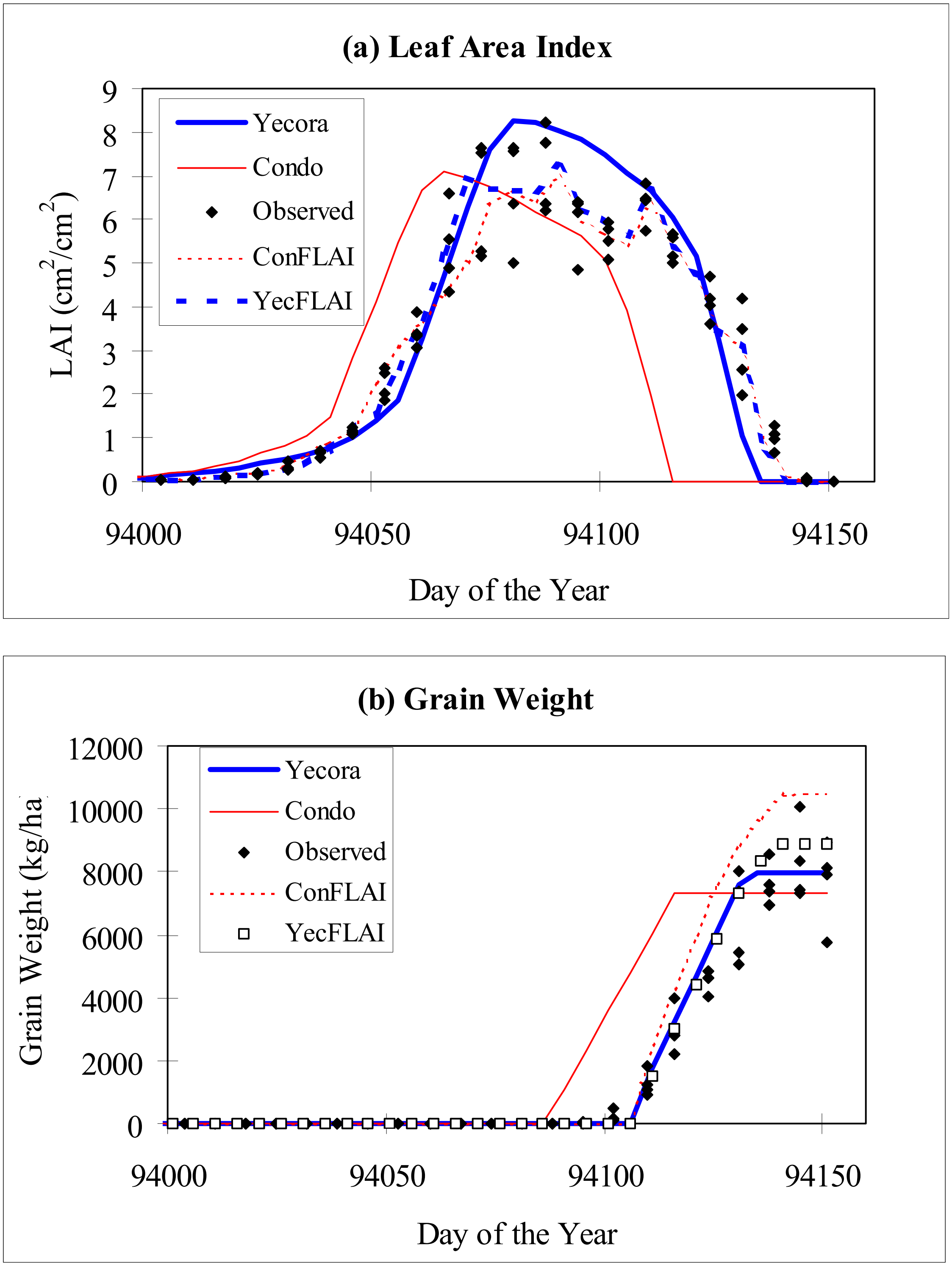


Figure 5: Observed and predicted leaf area index (a) and grain weight (b) for the 1993-94 experiment. The same legend captions are used as in Figure 4.

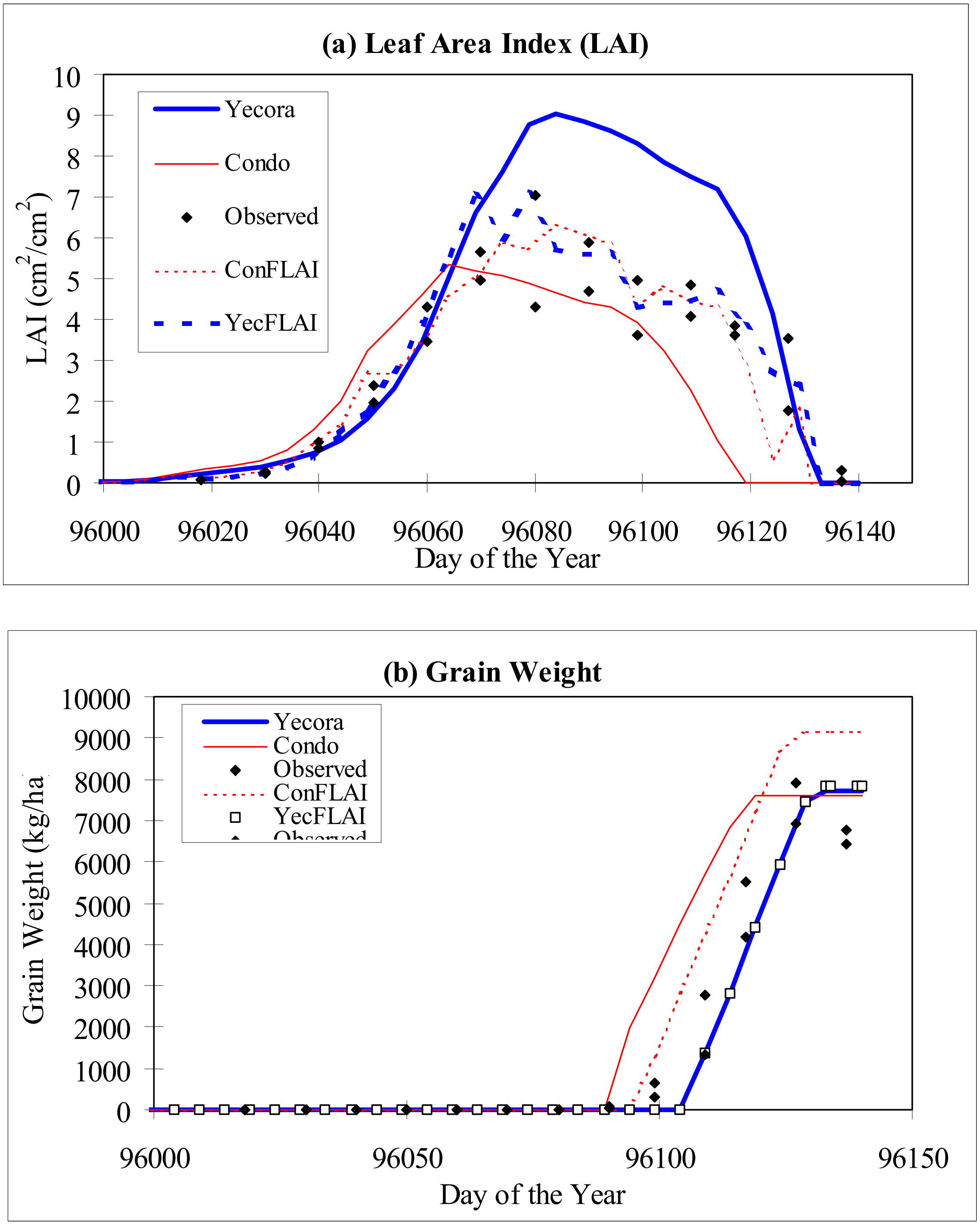


Figure 6: Observed and predicted leaf area index (a) and grain weight (b) for the 1995-96 experiment. The same legend captions are used as in Figure 4.

growth beginning earlier in the season. In the 1992-93 season, the Condo cultivar parameters resulted in a transition to stage 2 closer to the observed; however, in the other seasons, the same parameters predicted a much earlier transition to stage 2. The overall effect was to increase the predicted time in stage 2, resulting in an increase in stem mass, and ultimately an increase in predicted yield.

The timing of growth stages also limited the performance of the modifications during the 1992-93 growth season with the Yecora cultivar parameters. Because stages 1 and 3 were predicted later than their observed occurrences, the beginning of grain fill was improperly predicted. The adjustment of early season leaf area index for the Yecora parameters had no impact on the predicted yield when compared to the predicted yield without modification of LAI. In the other two experiments, modification of LAI when using the Yecora parameters also had a limited impact on yield. For the 1993-94 season, the predicted LAI of the model without adjustment was close to the observed for most of the season with the exception of the time just prior to maturity. At this point, the model over predicted the crop's senescence rate, and therefore the adjustment of LAI resulted in a slight increase in grain production at the end of the season. During the 1995-96 season, the unmodified model over predicted LAI during midseason, but provided accurate estimates at the beginning and end of the season. The modification of LAI during the midseason did not have a very significant impact on predicted yield (Figure 6b).

Correction of Input Errors

Table 4 shows the results of applying the observed leaf area index values as an attempt to correct for incorrect treatment information. For most of the treatments simulated, the use of the observed LAI with the model did not result in complete agreement between observed and simulated conditions; however, the use of the LAI observations did improve all except the high nitrogen treatment of 1995-96. In this case of ample nitrogen conditions, forcing a higher leaf mass increased nitrogen demand, and actually resulted in a lower yield than if the LAI values had not been increased. For all of the experiments, simulating optimal conditions and accounting for treatment differences resulted in greater improvement than simulating less than optimal conditions and then trying to correct with LAI.

The predicted and observed yields corresponding to the LAI ranges in Figure 3(b) are provided in Table 5. The use of one LAI observation and no adjustment to the growth stage did allow the model predict the range in observed yields to within 8%. However, the image was taken at an optimal time period, during the time of grain filling, when the model predictions of yield appears to be most sensitive to changes in LAI. Such predictions may useful as an alternative to yield mapping, but this does not provide the information needed earlier in the season when it is possible to change management practices.

Table 4: Application of the LAI modifications to correct input errors

Years	Treatment	Observed Yield (kg/ha)	%Diff Wrong Trt [a]	%Diff Cor LAI [b]	Percent Improvement
92-93	Wet	8369	-45	-34	11
	Dry	5955	23	-3	20
93-94	Wet	7436	-37	-23	14
	Dry	4744	87	37	50
95-96	High N	7400	13	17	**-4**
	Low N	5773	62	48	15

[a] Percent difference [100 (Predicted - Observed)/Observed] between observed and predicted yields when for example, dry conditions were simulated for the wet treatments.
[b] Wrong conditions still simulated; however, the correct LAI information was provided.

Table 5: Predicted and observed* wheat yields corresponding to the LAI classes of Figure 3(b).

LAI Class of Figure 3b.	Yield (kg/ha) Observed	Predicted	Percent Difference
> 5.0	8000	7454	6.8
4.5 to 5.0	7500	7417	1.1
4.0 to 4.5	7000	7366	5.2
3.0 to 4.0	6500	7008	7.8
2.0 to 3.0	5700	6045	6.0

[*] Observed is the approximate yield determined for the various treatments during the 1995-96 experiment and have been assigned to an LAI class based on the LAI of that treatment during the time the image was acquired.

Conclusions and Future Plans

Based on studies in the literature and the sample data provided, remotely sensed estimates of LAI are feasible, assuming there are some ground-based observations to develop empirical relationships. Additionally, temporal trends in RVI may be useful in identifying the time periods when key growth stages of wheat occur (emergence, end of leaf development and maturity). While there is a great deal of potential to integrate this information with growth models, the approach taken in this study still requires development. If the model's cultivar parameters do not provide correct predictions of the crops growth stage, knowledge of the occurrence of the three stages considered in this study (emergence, end of leaf growth, and maturity) are not sufficient to gain dependable predictions of final yield. When the growth stages are properly predicted, the data sets evaluated in this study indicate the model's prediction of final grain yield showed a greater sensitivity to changes in LAI during the end of the season, than during canopy development. There is evidence that when there is uncertainty in actual field conditions, the most accurate predictions can be obtained by simulating optimal conditions and then use the observed LAI to account for limiting conditions.

Future work will focus on the application of iterative techniques to adjust the model's predictions to match observed LAI. It is hoped that by using an iterative procedure to adjust key growth parameters, observations early in the season will have a greater impact on predicted yields. An iterative technique may also reduce the number of LAI observations needed to achieve accurate results in the model's predictions. One logical parameter to interpolate would be PHINT, as it is related to the leaf growth rate and also serves as a basis to determine the transition between three of growth stages considered by the model. Consideration will also be given to integrating remotely sensed estimates of evapotranspiration (ET) with the model. Through the combination of LAI and ET observations, it may be possible to determine if any departure in the model from observed conditions is related to its growth or soil parameters. Additional investigation will also be conducted to determine if the use of air temperature in driving the model's transition between growth stages is responsible for the different response in growth stage development seen for 1992-93 growing season. Results from the FACE experiment conducted during the 1996-97 growing season will also be added to the evaluation data set.

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Appendix A: WOBSLAI Subroutine

```
C=====================================================================
C  WOBSLAI, Subroutine (wobslai.for)
C
C  Options to adjust LAI for wheat based on observations.
C---------------------------------------------------------------------
C  Revision history
C
C  1. Written                                                  1-10-97
C---------------------------------------------------------------------
C  INPUT  : AWR, USENLA, PLTPOP, PLA, SENLA, LAI, LFWT, IOBLAI
C
C  LOCAL  : ADDPLA, OBGPLA, PLAOLD, LAITOL, SENTOL
C
C  OUTPUT : PLA, SENLA, LAI, LFWT
C---------------------------------------------------------------------
C  Called : WGROSUB
C
C  Calls  :
C---------------------------------------------------------------------
C                          DEFINITIONS
C
C  ADDPLA : Plant leaf area to be added as a result of the subroutine
C  AWR    : Area to weight ratio (square cm/g) *
C  IOBLAI : DOY for next LAI observation
C  IPLAOK : Switch used in tolerance checks
C  LAI    : Leaf area index
C  LAITOL : Leaf area index tolerance
C  LFWT   : Leaf weight
C  LFSKIP : Switch used in determining when to read the file
C  OBGPLA : Observed green plant area (square cm/plant)
C  OBLAI  : Observed green leaf area index
C  OBSEN  : Observed senescent LAI
C  PLA    : Total plant leaf area (square cm / plant)
C  PLAOLD : Plant leaf area before adjustments are made.
C  PLTPOP : Plant population *
C  SENLA  : Senescent leaf area
C  SENOLD : Senescent leaf area prior to modifications
C  SENTOL : Tolerance for senescent leaf area
C  USENLA : Unstressed senescent plant leaf area (square cm/plant)
C           Defined in wheat growth subroutine.
C
C  * = variables that are used in this subroutine, but are not
C     modified
C=====================================================================

      SUBROUTINE WOBSLAI (AWR, USENLA, PLTPOP, PLA, SENLA, LAI, LFWT,
     +                    IOBLAI)

      IMPLICIT NONE
      INTEGER   IOBLAI, IPLAOK, LAIDOY
      REAL      AWR, ADDPLA, LAI, LAITOL, LFWT,
     +          OBGPLA, OBLAI, OBSEN, PLA, PLAOLD, PLTPOP,
```

```
     +          SENLA, SENOLD, SENTOL, USENLA
C
      PLAOLD = PLA
      SENOLD = SENLA
C
C---------------------------------------------------------------------
C Begin adjustments if there is an observation for this day.
C---------------------------------------------------------------------
C
C Note, file unit 53 is opened in the main program.
C IOBLAI is initialized as the first DOY observations are in the
C file.
C
      READ(53, 253) LAIDOY, OBLAI, OBSEN, LAITOL, SENTOL, IOBLAI
C
C Convert observed LAI to green plant leaf area and tolerance.
C
      OBGPLA = OBLAI/(PLTPOP*0.0001)
      LAITOL = LAITOL/(PLTPOP*0.0001)
C
C See if the observed and predicted are within defined tolerance.
C
      IPLAOK = 1
      IF( ABS(OBGPLA - (PLA-SENLA)) .GT. LAITOL) IPLAOK = 0
C
C If there are observations of senescent LAI, then SENLA is
C adjusted if the predicted and observed exceed the tolerance
C value.  If the green plant area is also out of tolerance,
C adjust leaf weight as well.
C
      IF (OBSEN .GE. 0.0) THEN
         OBSEN = OBSEN/(PLTPOP*0.0001)
         SENTOL = SENTOL/(PLTPOP*0.0001)
C
C Adjust SENLA if it is out of tolerance.
C
         IF (ABS(OBSEN - SENLA) .GT. SENTOL) THEN
            SENLA = OBSEN
         ENDIF
C
C Also adjust PLA if it was or is now out of tolerance. Leaf
C weight is only adjusted if the total plant leaf area is changed.
C
         IF ( ABS(OBGPLA - (PLA - SENLA)) .GT. LAITOL) THEN
            PLA = OBGPLA + OBSEN
            LFWT = LFWT + (PLA - PLAOLD)/AWR
         ENDIF
         LAI = OBLAI
C
C Following lines are executed if there is not observations of
C SENLA available.
C
      ELSEIF (IPLAOK .EQ. 0) THEN  ! Observed SENLA not available
C
```

```fortran
C Begin adjustments if outside tolerance.
C
C Only leaf growth occurs in stages 1 and 2.  Therefore, it is
C most likely that any under prediction of plant leaf area is due
C to under prediction of growth.  Reset PLA to the observed green
C plant area plus unstressed senescent leaf area.
C
         IF (OBGPLA .GT. PLA) THEN
            PLA = OBGPLA + USENLA
            SENLA = USENLA
            LFWT = LFWT + (PLA - PLAOLD)/AWR
          ELSEIF ( OBGPLA .GT. (PLA - SENLA) ) THEN
C
C If the green leaf area is under predicted, then either SENLA is
C over predicted or PLA is under predicted or both.
C First see if there has been an increase in SENLA due to stress.
C If possible, make up the difference by only adjusting SENLA.
C
             ADDPLA = OBGPLA - (PLA - SENLA)
             IF( ADDPLA .LT. (SENLA - USENLA)) THEN
                SENLA = SENLA - ADDPLA
             ELSE
               PLA = OBGPLA + USENLA
               SENLA = USENLA
               LFWT = LFWT + (PLA - PLAOLD)/AWR
             ENDIF !ADDPLA
C
C Over prediction [i.e.,  OBGPLA < (PLA-SENLA) ]
C Assume that the SENLA has been under predicted.
C
         ELSE
           SENLA = PLA - OBGPLA
         ENDIF
C
C Update other related variables.
C

         LAI = OBLAI
      ENDIF ! PLA adjustment.
C
C     Report changes in output file - WLAI.OUT - opened in main
C
      WRITE(54, 254) LAIDOY, PLAOLD, PLA, SENOLD, SENLA, IPLAOK

      RETURN
C
C-----------------------------------------------------------------------
C     Format Strings
C----------------------------------------------------------------------
C Format for input of observed data
253   FORMAT(I5,1X,F6.3,1X,F6.3,1X,F6.3,1X,F6.3,1X,I5)
C Format for output file.
254   FORMAT('LAI: 'I5,1X,F7.1,1X,F7.1,1X,F7.1,1X,F7.1,1X,I3)
      END
```

Appendix B: CHKPHEN Subroutine

```
C=======================================================================
C  CHKPHEN, Subroutine
C
C  Checks phenology based on user supplied data
C-----------------------------------------------------------------------
C  Revision history
C
C  1. Written                                                  2-15-97
C-----------------------------------------------------------------------
C  INPUT  : PHLIMIT, SOMEDT, SOMEP, ISTAGE
C
C  LOCAL  : CHGSTG
C
C  OUTPUT : SOMEP
C-----------------------------------------------------------------------
C  Called : PHENOL
C
C  Calls  :
C-----------------------------------------------------------------------
C                          DEFINITIONS
C
C  PHLIMIT: Array containing day of year limits for growth stages
C           9 x 3, Each row is a stage with minimum and maximum or
C                  actual day of year at which stage changes. *
C  SOMEDT : Degree days or total thermal units *
C  ISTAGE : Crop stage *
C  SOMEP  : The threshold parameter which determines if a new stage should
C           begin
C  CHGSTG : Code to determine if user limits have been reached:
C            = -1, no data or OK to change, but not forced
C            =  0, the growth stage should not change
C            =  1, the growth stage must change
C  YRDOY  : Year and day of year (i.e., 96365)*
C  * = variables that are used in this subroutine, but are not
C      modified
C=======================================================================

      SUBROUTINE CHKPHEN (ISTAGE, YRDOY, PHLIMIT, SOMEDT, SOMEP)

      IMPLICIT NONE
      INTEGER   PHLIMIT(9,3), ISTAGE, YRDOY, CHGSTG
      REAL      SOMEDT, SOMEP
C
C See if the user has supplied a specific date on which this stage should
C be changed.
C
      CHGSTG = -1 !Initialize

      IF ( PHLIMIT(ISTAGE, 3) .NE. -999) THEN ! A
        IF ( PHLIMIT(ISTAGE, 3) .EQ. YRDOY ) THEN ! B
           CHGSTG = 1
        ELSE
           CHGSTG = 0
        ENDIF ! B
      ELSE ! See if a range is provided - A
        IF ( ( PHLIMIT(ISTAGE,1) .NE. -999 ) .AND. ( PHLIMIT(ISTAGE,2)
     +        .NE. -999) ) THEN ! C
C
C         Don't allow a change in growth stage if we have not reached
```

```
C          the minimum user specified limit.
C
           IF (YRDOY .LT. PHLIMIT(ISTAGE,1) )THEN ! d
             CHGSTG = 0
C          If passed the user specified limit, must change the stage
           ELSEIF (YRDOY .GT. PHLIMIT(ISTAGE,2) )THEN
             CHGSTG = 1
           END IF !D
         ENDIF !C
       ENDIF ! A
C
C If the model is not agreeing with the user specified conditions,
C adjust the growth parameter to gain the desired result
C
C     Model says change, but user says not to enter the next stage
      IF ( (CHGSTG .EQ. 0) .AND. (SOMEDT .GT. SOMEP) ) THEN !e
        IF(ISTAGE.NE.1) THEN
          SOMEP = SOMEDT + 1.0
        ELSE
          SOMEP = 95.0*SOMEDT/400.0 + 1.0
        ENDIF
C     Model says not time to change, but user says it is.
      ELSEIF ( (CHGSTG .EQ. 1) .AND. (SOMEDT .LT. SOMEP) ) THEN
        IF(ISTAGE.NE.1) THEN
          SOMEP = SOMEDT - 1.0
        ELSE
          SOMEP = 95.0*SOMEDT/400.0 - 1.0
        ENDIF

      ENDIF !e
C
C Give some output that will help determine appropriate parameters
C   Only output if a stage change is occurring.
C
      IF( (SOMEDT .GT. SOMEP) .AND. (ISTAGE .NE. 1) )THEN
        WRITE(54, 255)  YRDOY, ISTAGE, SOMEP, SOMEDT, CHGSTG
      ELSEIF ( (95.0*SOMEDT/400.0) .GT. SOMEP) THEN
        WRITE(54, 255)  YRDOY, ISTAGE, SOMEP, SOMEDT, CHGSTG
      ENDIF
C
      RETURN
C
C-----------------------------------------------------------------------
C     Format Strings
C-----------------------------------------------------------------------
C
C Format for output file.
255   FORMAT(I5,1X,I2,1X,F9.3,1X,F9.3,1X,I2)
C
      END
```