한작지(Korean J. Crop Sci.), 52(4): 393~402(2007)

Use of Remotely-Sensed Data in Cotton Growth Model

Jonghan Ko*† and Stephan J. Maas**

*Texas A&M University Texas Agricultural Experiment Station, 1619 Garner Field Road, Uvalde, TX 78801-6205
**Texas Tech University Plant and Soil Sciences, Mailing address: USDA-ARS, 3810 4th Street, Lubbock, TX 79415, USA

ABSTRACT Remote sensing data can be integrated into crop models, making simulation improved. A crop model that uses remote sensing data was evaluated for its capability, which was performed through comparing three different methods of canopy measurement for cotton (*Gossypium hirsutum* L.). The measurement methods used were leaf area index (LAI), hand-held remotely sensed perpendicular vegetation index (PVI), and satellite remotely sensed PVI. Simulated values of cotton growth and lint yield showed reasonable agreement with the corresponding measurements when canopy measurements of LAI and hand-held remotely sensed PVI were used for model calibration. Meanwhile, simulated lint yields involving the satellite remotely sensed PVI were in rough agreement with the measured lint yields. We believe this matter could be improved by using remote sensing data obtained from finer resolution sensors. The model not only has simple input requirements but also is easy to use. It promises to expand its applicability to other regions for crop production, and to be applicable to regional crop growth monitoring and yield mapping projects.

Keywords : crop model, LAI, PVI, remote sensing, within-season calibration

Remote sensing and modeling are different techniques useful to evaluate crop growth and yield (Maas, 1992). Remotely sensed imagery can provide information for almost any spot on the surface of the earth but can provide information valid only at the time of image acquisition. Models can provide a continuous description of crop condition although they may not provide information as accurately as that provided by remote sensing. However, by combining the advantages of remote sensing and crop simulation modeling, the strengths of one technology may make up for weaknesses in the other (Maas, 1992).

There have been previous efforts to combine these different techniques. As one of the earliest attempts, Arkin *et al.* (1977) proposed the concept of a hybrid "spectral-physiological" model able to use Landsat data. This concept was described in the model SORGF (Maas and Arkin, 1978). Some of the efforts that followed were the models of SOYGRO (Wilkerson *et al.*, 1985) and SORKAM (Rosenthal *et al.*, 1989). Users of SOYGRO can adjust a parameter affecting photosynthesis rate to improve agreement between simulated and measured biomasses. In SORKAM, a parameter affecting leaf expansion rate can be adjusted to make agreement between simulated and measured leaf area index (LAI). More recently, Barns *et al.* (1997) modified CERES-Wheat (Ritchie and Otter, 1985) to allow the model to accept observed LAI and to adjust related parameters in the model as a function of LAI. While these procedures objectively calibrate model response to actual field conditions for each application of the model, they still require the acquisition of the same input requirements that CERES-Wheat requires. Recently, Baez-Gonzalez *et al.* (2002) reported a method using satellite and field data with crop growth modeling to monitor and estimate corn yield. They showed that a crop model integrated with satellite imagery and field data can be possibly used to monitor crop growth and to assess grain yield on a large scale.

Within-season calibration is one of the procedures used to improve the accuracy of model estimates using relatively simple input requirements (Maas, 1993b). GRAMI (Maas, 1992), a crop model that uses remote sensing data, includes a within-season calibration method allowing the model simulation to fit measured values using an iterative numerical procedure. Based on a comparison between measured and simulated values, model parameters and initial conditions that affect crop growth can be changed. The

†Corresponding author: (Phone) +1-830-278-9151
(E-mail) jko@tamu.edu (jonghanko2001@yahoo.com)
<Received May 5, 2007>

model is then re-executed to produce a new set of simulated values that minimizes the error between simulated leaf area and values of leaf area obtained from remote sensing. An advantage of this procedure is that it can use infrequent observations to calibrate the model. These observations can be obtained through non-destructive techniques such as remote sensing (Maas, 1992). Remote sensing, either from ground-based spectroradiometers, airborne sensors, or satellites can efficiently acquire data on crop canopy growth for numerous fields within an agricultural region. In some situations, the use of remotely sensed crop canopy data to calibrate a model can produce simulations of crop growth that are more accurate than those obtained using ground-based observations (Maas, 1993c).

Recently, Ko *et al.* (2005 and 2006) showed that the within-season calibration method could be extended to simulate the growth and lint yield of cotton by incorporating factors to calculate the appearance and growth of bolls. The procedure was demonstrated using cotton data from irrigated fields in the Texas High Plains. The objective of this study was to evaluate simulation performance of the previously developed cotton crop model that uses remote sensing data. The model was simulated using cotton data sets with three different methods of canopy measurement. The model verification was presented using field data from irrigated commercial cotton fields in the Texas High Plains, USA. The model was validated using field measured and remotely sensed data from independent sites in this region and its applicability will be discussed.

MATERIALS AND METHODS

Model Formulation

Crop Simulation

A cotton crop model that uses remote sensing data (Ko *et al.*, 2005) was used in this study. The four processes (Fig. 1) were involved in simulating daily cotton crop growth: (1) calculation of growing degree days (GDD); (2) absorption of incident radiation energy by leaves; (3) production of new dry mass by the leaf canopy and determination of boll production; and (4) determination of LAI partitioning of new dry mass. The mathematical equations to estimate these processes are described.

The accumulation of GDD is calculated as follows:

$$\Delta G = Max[T - T_b, 0] \qquad [1]$$

where ΔG is the daily change of GDD, T is the average daily air temperature (℃) and T_b is a base temperature specific to a crop species. The value of T_b is 15.6℃ (Wanjura and Supak, 1985).

The daily increase in above-ground dry mass (AGDM) is calculated as:

$$\Delta M = \varepsilon \cdot Q \qquad [2]$$

where ΔM is the daily increase in AGDM, ε is the radiation use efficiency (RUE) value specific for a given crop, and Q is the daily total photosynthetically active radiation (PAR, MJ m^{-2}) absorbed by the crop canopy (Rosenthal *et al.*, 1989; Jones and Kiniry, 1986; Charles-Edwards *et al.*, 1986). The value of ε is 2.3 g MJ^{-1} (Ko *et al.*, 2005). Absorption of PAR is calculated as:

$$Q = \beta \cdot R \cdot (1 - e^{-k \cdot LAI}) \qquad [3]$$

where R is the incident daily total solar irradiance (MJ m^{-2}), β the fraction of total solar irradiance that is PAR, and k a light extinction coefficient specific for a given crop (Charles-Edwards *et al.*, 1986). The value for β is 0.45 (Monteith and Unsworth, 1990). The value of k is 0.9 (Ko *et al.*, 2005).

The daily LAI increase (ΔL) with new leaf growth is calculated as follows:

$$\Delta L = \Delta M \cdot P_l \cdot S \qquad [4]$$

where ΔM is the daily increase in AGDM from Equation 2, P_l is the fraction of ΔM partitioned to new leaves and S is the specific leaf area (SLA) of the leaf tissues (Maas, 1993a). SLA was determined from the relations between leaf dry weight and LAI (Reddy *et al.*, 1989; Rhoads and Bloodworth, 1964). The value of SLA is 0.01 m^2 g^{-1} (Ko *et al.*, 2005). The dimensionless leaf-partitioning fraction (P_l) is calculated using the equation:

$$P_1 = Max[1 - a \cdot e^{b \cdot D}, 0] \quad [5]$$

where a and b are parameters that control the magnitude and shape of the function, and D is the cumulative GDD (Maas, 1993a). This function reduces the partitioning of new dry mass to leaves as the plant approaches the reproductive phase.

The leaf senescence used in the model was formulated to describe the loss of leaf area based on environmental conditions. Leaf senescence (L_s, m^2 m^{-2}) in the model is determined using the equation:

$$L_s = c \cdot (\Delta M_R - \Delta M) \quad [6]$$

where c is the parameter that controls LAI curve after maximum LAI, ΔM_R is daily maintenance respiration requirement converted to biomass, calculated using the equation:

$$\Delta M_R = 0.03 \cdot M \quad [7]$$

where M is total AGDM. In the model, an amount of LAI equal to L_s is deducted from the simulated canopy whenever the maintenance respiration exceeds the resources required for growth of existing tissues.

The daily increase in boll number (ΔB) used in this version of the model depends upon accumulated GDD and LAI and is calculated with the following equation:

$$\Delta B = \gamma \cdot D \cdot \Delta f \quad [8]$$

where γ is a fraction of boll production, D is accumulated GDD and Δf is daily boll production efficiency affected by LAI. The value of γ is 0.57 GDD^{-1} m^{-2} (Ko *et al.*, 2005). Δf is calculated by the equation:

$$\Delta f = \frac{\Delta L / \Delta G}{\lambda} \quad [9]$$

where λ is a parameter that affects daily boll production, and ΔL / ΔG is the rate of LAI increase per accumulated GDD. The value of λ is 0.0058 GDD^{-1} (Ko *et al.*, 2005).

A harvest index (HI) approach was used to estimate lint yield from the simulated boll numbers in the model. The HI was approximated from average boll numbers and lint yields found in the research fields (Ko *et al.*, 2005). The fraction of harvestable bolls was estimated as 0.67, and the amount of lint per boll was estimated as 1.84 g $boll^{-1}$. This result generally corresponds to the study by Jackson *et al.* (1988, 1990) and Howell *et al.* (1984). In this study, a value of 3.5 g $boll^{-1}$ was estimated as an expected boll size (seed-cotton) for the COTTAM model.

Within-season Calibration

The cotton model has within-season calibration procedures that result in a minimal error between simulation and measurements within the growing season. The within-season calibration procedures recalibrate the initial values of LAI and the parameters a, b, and c, referring to measured LAI or remotely sensed vegetation index (VI) within growing season. Since LAI or VI may be used as model input, the relations between LAI and VI were investigated and functions to convert one value to the other were included so that both LAI and VI could be used as model input (Ko *et al.*, 2005 and 2006).

The proposed cotton model uses the same within-season calibration procedures (Fig. 1) used in GRAMI, in which the simulated crop growth is compared to measured values. If the simulated values do not agree with the measured ones, an iterative numerical process is used to manipulate parameter values to improve agreement between the simula-

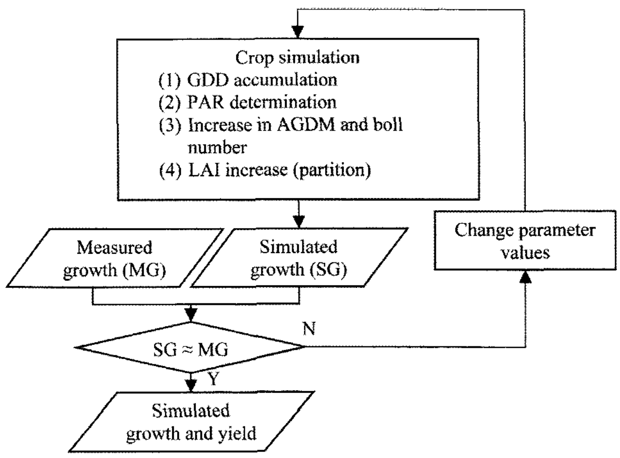

Fig. 1. Diagrammatic representation of the model that shows daily cotton growth processes and the within-season calibration. Measured and simulated growths refer to measured and simulated LAI or VI. GDD, growing degree days; PAR, photosynthetically active radiation; AGDM, above ground dry mass; LAI, leaf area index.

tion and the measurements. Determining the initial value of LAI at crop emergence is the first step in model calibration aimed at achieving a fit of simulated to measured LAI. As it is shown using an example of how the initial value of LAI at crop emergence affects simulation results (Fig. 2), all other parameter values were held constant during this initial calibration. Two statistics (E^+ and E^-) were used to describe the difference between the simulation and the measured LAI values. The E^+ represents the sum of the positive errors between simulated and measured LAI, for example, the sum of E1 and E3 (Fig. 2). Likewise, E^- represents the absolute value of the sum of the negative errors, for example, the sum of E2 and E4 (Fig. 2). A third statistic is the total error $E = E^+ + E^-$. In this model, a fit of the simulation to the measured LAI values is achieved when the computed values of E^+ and E^- are equal.

The secant method (Conte and De Boor, 1965, p. 32) was used in an iterative manner to determine the initial value of LAI (L0) that results in a best fit:

$$(L_0)_{j+1} = (L_0)_j + (E_f)_j \left[\frac{(L_0)_j - (L_0)_{j-1}}{(E_f)_j - (E_f)_{j-1}}\right] \qquad [10]$$

where $(L_0)_{j+1}$ is the value to be used in the next iteration, $(L_0)_j$ is the value used in the current iteration, $(L_0)_{j-1}$ is the value used in the iteration just prior to the current one, and $(E_f)_j$ and $(E_f)_{j-1}$ are the values of E from iterative simulations using $(L_0)_j$ and $(L_0)_{j-1}$. The numerical procedure for L_0 continues until the total error falls below a preset convergence criterion.

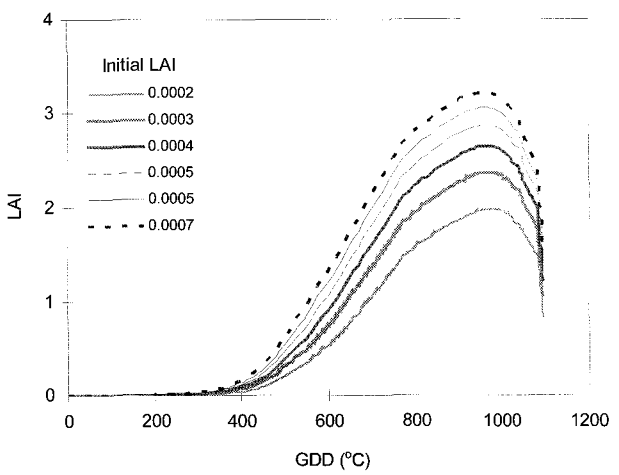

Fig. 2. Simulated LAI's calculated by the proposed cotton model using six different values for the initial LAI at emergence.

Though the previous procedure results in a best fit of the measurement, it is not necessarily the minimal error fit. Therefore, following the fit involving L_0, the value of the parameters a, b, and c are manipulated using iterative numerical procedures to achieve a minimization of E (Press *et al.*, 1986, p. 283). The parabolic interpolation is used to determine the value of the parameter at the minimum of the parabola (P):

$$P = P_{k-1} + \frac{1}{2}\,\frac{X - (P_{k-1} - P_k)^2[E_{k-1} - E_{k-2}]}{Y - (P_{k-1} - P_k)[E_{k-1} - E_{k-2}]} \qquad [11]$$

where, $X = (P_{k-1} - P_{k-2})^2[E_{k-1} - E_k], Y = (P_{k-1} - P_{k-2})[E_{k-1} - E_k]$ and P_k, P_{k-1}, and P_{k-2} are the parameters associated with the three-step simulations. E_k, E_{k-1}, and E_{k-2} are the corresponding total errors values resulting from these simulations. Before this parabolic interpolation, the combination of bracketing search is used in the model to establish the search direction based on values of the given parameter that increased or decreased from a starting value by a specific step size. Once the bracketing search reaches the minimal error, parabolic interpolation is used such that the values of the parameters are changed to reduce the value of E to less than an acceptable value in the iterative procedure.

The LAI initialization using the secant method, and parameterization using the parabolic interpolation procedure achieve a one-dimensional minimization of E because these procedures only change in one parameter at a time. Therefore, a multidimensional minimization of E involving L_0, a, b, c is employed such that convergence of the numerical procedures is first achieved for L_0 alone; then for the combination of L_0 and c; then L_0, c, and b; and then for L_0, c, b, and a.

Field Data

Verification

Cotton field data to develop and verify the model were collected from farmers' fields in the Texas High Plains during the summer of 2002. Three cotton fields were selected for this study. These were circular with about 45 ha for each, and the latitude and longitude of each field were: N34. 04459 and W102.03838; N34.06828 and W102.18609; and N34.19188 and W102.02124. The soils were Brownfield fine sands for the two fields and a Pullman clay loam, 0 to 1 percent slopes for the other (Soil survey for Lamb County, TX, issued in 1962, and Hale County, TX, issued in 1974, USDA Soil Conservation Service). Plant growth and development data, including plant height, leaf area index (LAI), and above ground dry mass (AGDM), were measured every 2 wk at four different locations in each field. The cotton variety Paymaster 2326 BG/RR (Delta and Pine Land Co., Scott, MS) was planted on 16 May at 1.0 m row spacing in all locations. During the cotton growing season (13 May-20 October), average photosynthetically active radiation (PAR) was 9.83 MJ m^{-2} d^{-1}, and rainfall was 107.2 mm. Irrigation was applied using Low Energy Precision Application (LEPA).

In each plot, ten representative plants were selected, cut and transported to the laboratory to measure several plant growth parameters, including leaf area, number of main stem nodes, squares, and bolls, and leaf, stem, square, and boll dry mass. Leaf area was measured using a LI-3100 area meter (LI-COR Inc., Lincoln, NE). LAI was calculated as leaf area per plant divided by ground area per plant. Plant samples were separated into leaves, stems, squares, and bolls and dried at 70℃ for 72-168 h depending on sample sizes to obtain dry mass.

Validation

The model was validated using the data sets collected with three different methods of plant canopy measurement at different sites, respectively. The measurement methods were LAI using destructive sampling, perpendicular vegetation index (PVI) (Richardson and Weigand, 1997) with a hand-held multispectral radiometer (CROPSCAN Inc., Rochester, MN), and PVI from Landsat satellite imageries.

The data sets of LAI measurement were collected in 1999 and 2001 from a 45 ha field at the Texas A&M University Agricultural Research farm (32°16'N, 101°56'W) near Lamesa, TX (Li *et al.*, 2001; Bronson *et al.*, 2003). The soil was an Amarillo sandy loam. Cotton variety Paymaster 2326 RR was planted on 10 May in 1999 and 28 May in 2001. Rainfall from May to mid-September was 130 mm in 1999 and 128 mm in 2001. Irrigation was applied using a LEPA irrigation system.

The hand-held remote sensing data sets were collected from 2002 to 2004 at the field of the USDA-ARS Plant Stress and Water Conservation Laboratory (N33°35'38", W101°54'04", altitude: 990 m) in Lubbock, TX (Wanjura *et al.*, 2004). The hand-held multispectral radiometer used to measure reflectance of plant canopies accommodates up to 16 bands to measure incident as well as reflected radiations. The center wavebands (CWB) and bandwidths (BW) for 2 filters used in this study were CWB 660 nm with BW 10.0 nm and CWB 800 nm with BW 65.0 nm. The soil was an Amarillo sandy loam. Cotton variety Paymaster 2326 BG/RR was planted on 13 May in 2002 and 2004. Rainfall from May to mid-September was 186 mm in 2002 and 218 mm in 2004. Irrigation was applied using a subsurface drip irrigation system.

The satellite remotely sensed data sets were collected in 2000 and 2002 from eight commercially managed fields near Olton, Lamb County, TX (Guo, 2005). Landsat-5 TM and Landsat-7 TM images were obtained and georeferenced to UTM World Geodetic Survey 1984 (WGS84) Zone 14. These images were radiometrically normalized so that reference in different bands on different dates was consistent (Rajapakse, 2005). For each image, an area of interest containing all the eight fields was obtained using the Environment for Visualizing Images (ENVI) software package (Version 4.0, Research Systems Inc., Boulder, CO). The areas of the fields planted to cotton were about 50 ha for the six circles and 25 ha for the others. Cotton variety Paymaster 2326 BG/RR was planted in these fields for the two years. Planting and harvest dates varied, but were typically in the middle of May and late October, respectively. Rainfall from May to mid-September was 124 mm in 2000 and 88 mm in 2002. Cotton was deficit-irrigated using center pivot LEPA irrigation systems.

From each remote sensing data set, the PVI values were calculated using the equation:

$$(R_{800} - a \cdot R_{660} - b)/\sqrt{1+a^2} \qquad [12]$$

where R_{800} and R_{660} represent the reflectance values of each waveband of 800 and 660. The values of a and b are the slope and intercept from the linear equation of the bare soil line (Richardson and Weigand, 1997). The values of a and b for the hand-held multispectral radiometer data were 1.24 and 0.02, while those for the satellite remote sensing data were 0.53 and 0.04. The model design includes provisions for including measured VI or LAI values as input for within-season calibration. To accomplish this, conversion functions (Table 1) were incorporated in the model.

RESULTS AND DISCUSSION

Verification

The crop model was used to simulate cotton growth and yield for the field data set used in model development. This was done to verify the performance of the model for the development data set. Field measurements of leaf area index (LAI) were used to calibrate the model rather than measurements of remote sensing. LAI or canopy ground cover of cotton can be estimated from remotely sensed scene reflectance obtained from a hand-held remote sensor (Maas, 1998) and from satellite data (Maas, 2000) using a linear mixture modeling approach. However, LAI estimation from plant sampling represents crop growths of experimental plots better than that from remotely sensed scene reflectance. LAI data from plant sampling rather than remote sensing one was used in the model.

The results demonstrated that the model was able to reproduce the field observations of LAI, AGDM, and lint yield with reasonable accuracy (Fig. 3). While there were some inaccuracies in AGDM, we believe that those are within acceptable ranges of measurement errors. Development of the model used in this study assumes that environmental and genetic factors affecting crop growth are expressed in the growth of the crop canopy. The GRAMI model (Maas, 1992 and 1993a and b) demonstrated that the assumption was generally appropriate. For crops with indeterminate growth habits, this expression may be less precise. However, in general there were significant relationships between simulated and measured values for the three fields. These results indicated that the model appeared capable of reproducing irrigated cotton growth and yield over the growing season.

Table 1. Relationships between the perpendicular vegetation index (PVI) and leaf area index (LAI).

Relation between PVI and LAI	r^2
H-PVI = 0.10 $LAI^{0.79}$ (n = 41)	0.83 ($P < 0.0001$)
S-PVI = 0.20 $LAI^{0.37}$ (n = 24)	0.55 ($P < 0.0001$)

H-PVI and S-PVI stand for hand-held and satellite remotely sensed PVI respectively.

Validation

Simulation performance of the model was demonstrated using data sets obtained with three difference methods of canopy measurement, which were LAI using destructive sampling, perpendicular vegetation index (PVI) with hand-held remote sensing, and PVI from Landsat satellite imageries. Simulated LAI values agreed with the measured LAI values with an r^2 value of 0.92 and a root mean squared error (RMSE) of 0.21 while simulated lint yields agreed with the measured lint yields with an r^2 value of 0.75 and a RMSE

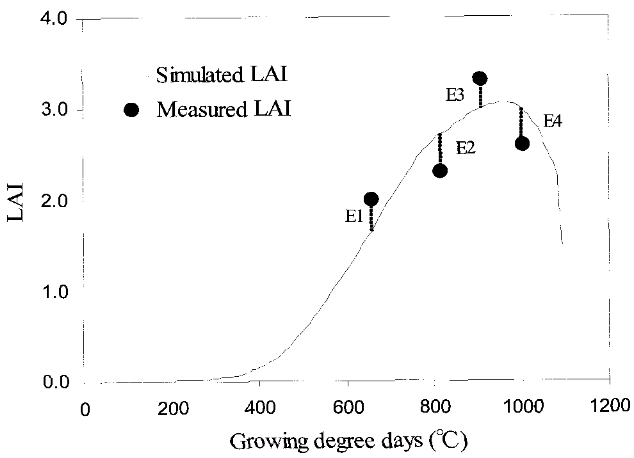

Fig. 3. An example of simulated LAI passing through measured LAI values. The dotted lines (E1 to E4) represent the errors between simulated and measured values of LAI.

of 89.36 kg ha^{-1} (Fig. 4). We evaluated the performance of the model iterative procedure using remote sensing data by comparing simulated PVI and lint yield with measured values (Fig. 5 and 6). For model simulation using hand-held remote sensing data, simulated PVI values were in agreement with the measured PVI values with an r^2 of 0.91 and a RMSE of 0.03. Simulated lint yields determined using the hand-held remotely sensed PVI showed general agreement with the measured lint yields, with an r^2 of 0.53 and a RMSE of 123.13 kg ha^{-1}. For model simulation using satellite remote sensing, simulated PVI values were in agreement with the measured PVI values with an r^2 of 0.88 and a RMSE of 0.03. However, simulated lint yields roughly agreed with the measured lint yields with an r^2 of 0.07 and a RMSE of 168.17 kg ha^{-1}.

The results show that simulated lint yields involving the hand-held remotely sensed PVI were somewhat underestimated in comparison with the measured lint yields until

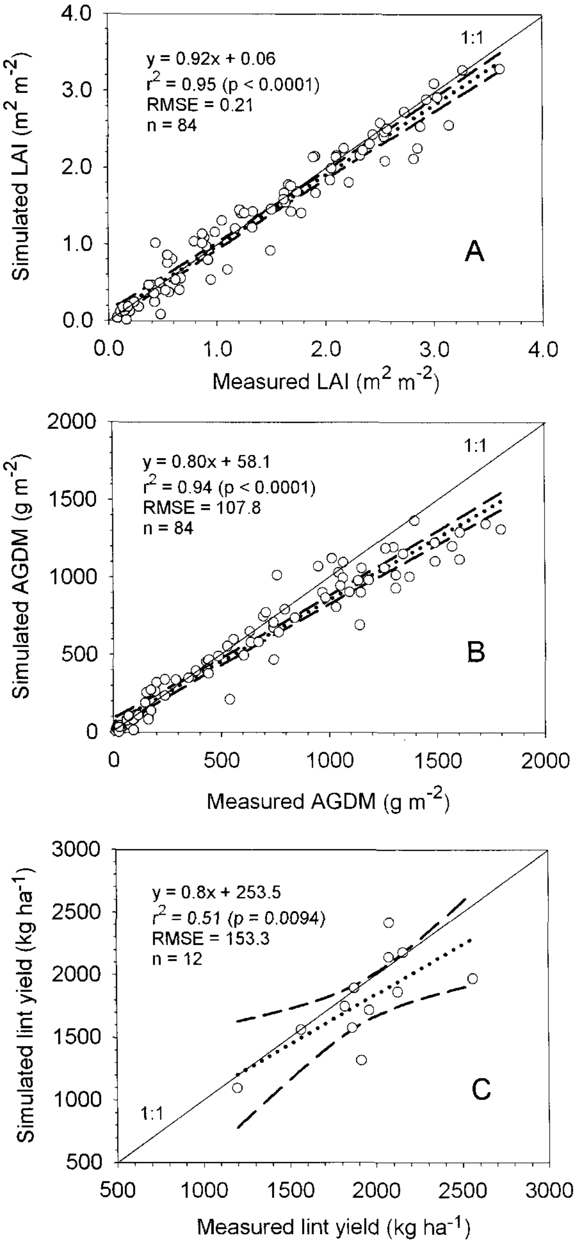

Fig. 4. Simulation vs. measurement of LAI (A), AGDM (B), and lint yield (C) using data obtained at three commercially managed fields near Olton, Lamb County, TX in 2002. Dotted and dashed lines represent linear regressions and 95% confidence intervals of the means. LAI, leaf area index and AGDM, above ground dry mass.

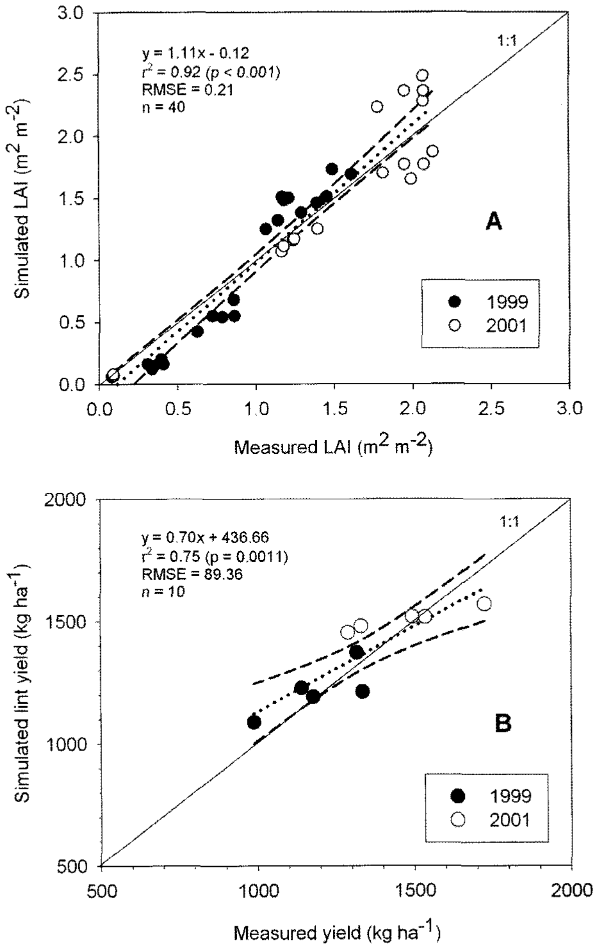

Fig. 5. Simulation vs. measurement of LAI (A) and lint yield (B) using data obtained at the Texas A&M University Agricultural Research farm near Lamesa, TX in 1999 and 2001. Dotted and dashed lines represent linear regressions and 95% confidence intervals of the means. LAI stands for leaf area index.

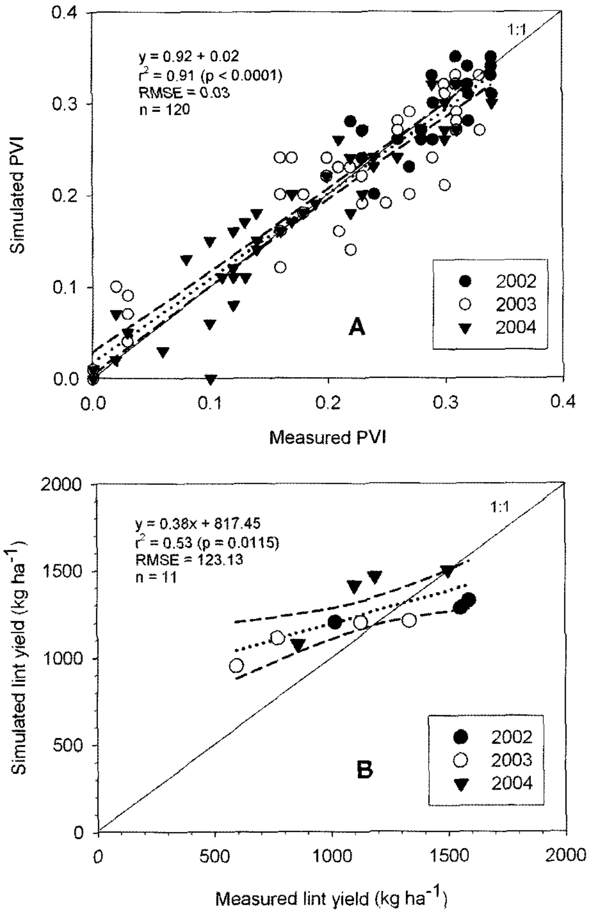

Fig. 6. Simulation vs. measurement of hand-held remotely sensed PVI (A) and lint yield (B) using data obtained at the field of the USDA-ARS Plant Stress and Water Conservation Laboratory in Lubbock, TX in 2002, 2003, and 2004. Dotted and dashed lines represent linear regressions and 95% confidence intervals of the means. PVI stands for perpendicular vegetation index.

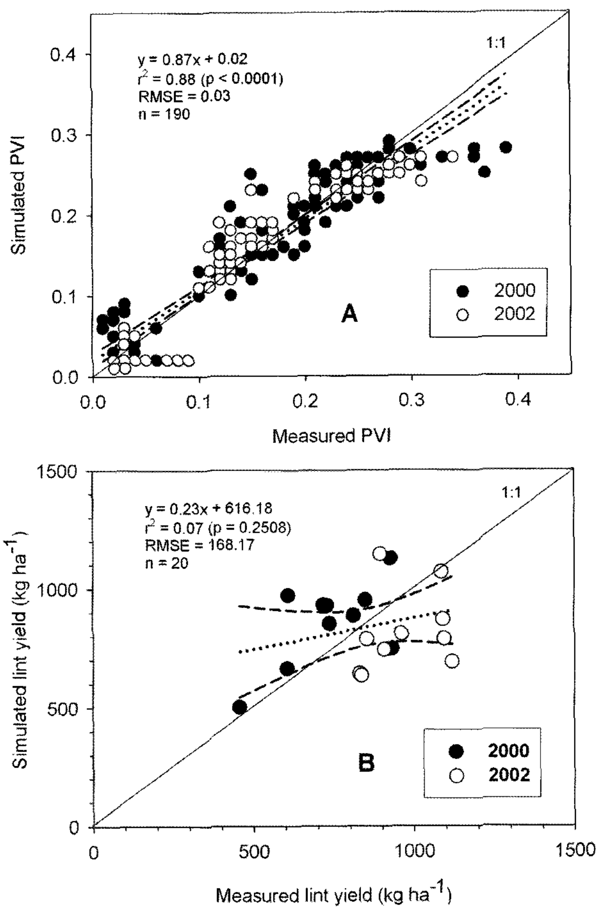

Fig. 7. Simulation vs. measurement of satellite remotely sensed PVI (A) and lint yield (B) using data obtained at eight commercially managed fields near Olton, Lamb County, TX in 2000 and 2002. Dotted and dashed lines represent linear regressions and 95% confidence intervals of the means. PVI stands for perpendicular vegetation index.

1,000 kg ha^{-1} and after 1,500 kg ha^{-1}. Polycarpic perennials generally reduce their partitioning to sexual reproduction under low availability of resources such as water stress (Chiarello and Gulmon, 1991). Our model was designed to reduce reproductive organs of cotton under soil moisture deficit condition. However, the model was not very sensitive to the different irrigation treatments at the lower and higher lint yields. It is assumed that canopy development was not different enough among the lower and higher irrigation treatments to represent yield differences while the model is sensitive to canopy development in estimating lint yield. Sandras *et al.* (1997), by contrast, reported that reproductive allocation of cotton was relatively stable in response to environmental factors. Other studies with cotton demonstrated that there is reasonably stable relationship between final harvest index and environmental factors including water availability (Constable and Hearn, 1981; Orgaz *et al.*, 1992; Kimball and Mauney, 1993). We believe that validation with more data sets is needed to deal with this matter. In addition, the previous studies (Ko, 2005 and 2006; Maas and Doraiswamy, 1995; Moran *et al.*, 1996) showed that simulation could agree more closely with measurement if data for within-season calibration occurs at times critical to plant growth and development.

Simulated lint yields involving the satellite remotely sensed PVI were in rough agreement with the measured lint yields. It is assumed that this is because the satellite image resolution (30 m × 30 m per pixel) is too coarse to deal with crop growth and yield seasonally and spatially at field level. We believe this matter could be improved by using remote sensing data obtained from finer resolution sensors such as data from airborne or higher resolution satellites. Maas (1993c) described that, in some situations, the use of remotely sensed crop canopy data to calibrate a model can produce simulations of crop growth that are more accurate than those obtained using ground-based observations. Use of the within-season calibration procedure allows the factors influencing crop growth to be incorporated into the simulation. These factors can be genetic and environmental, and examples of them include plant population, fertilization, and water stress. These are not only difficult to adequately incorporate into crop models but also increase the input requirements of them. Maas (1993a and 1993b) described that a crop model capable of within-season calibration can adequately simulate crop growth and yield under various conditions.

CONCLUSIONS

Simulated values of crop growth obtained with the new model showed reasonable agreement with the corresponding measurements when canopy measurements of LAI and hand-held remote sensing were used for model calibration. The proposed model has relatively simple environmental input requirements compared to other process-oriented cotton models. Since estimates of crop canopy growth used in calibrating the model can be obtained through remote sensing observations, it is applicable for regional cotton growth monitoring and yield mapping efforts.

ACKNOWLEGEMENT

The authors would like to express our appreciation to the following persons who made this research possible. We thank Drs Guo and Rajapakse for their works to process the satellite remote sensing data set. We also thank Dr. Wanjura for providing us the hand-held remote sensing data set and Dr. Lascano and Mr. Brightbill for allowing us to use their field data.

REFERENCES

Arkin, G. F., C. L. Wiegand, and H. Huddleston. 1977. The future role of a crop model in large area yield estimation. In Proceedings of the Crop Modeling Workshop, PP. 87-116. USDA-NOAA-EDIS-CEAS, Columbia, MO.

Baez-Gonzalez, A. D., P. Chen, M. Tiscareno-Lopez, and R. Srinivasan. 2002. Using satellite and field data with crop growth modeling to monitor and estimate corn yield in Mexico. Crop Sci. 42 : 1943-1949.

Barns, M. B. P. J. Pinter Jr., B. A. Kimball, G. W. Wall, R. L. LaMorte, D. J. Husaker, F. Adamsen, S. Leavitt, T. Thompson, and J. Mathius. 1997. Modification of CERES-Wheat to accept leaf area index as an input variable. The 1997 ASAE Annual International Meeting Sponsored by ASAE, Minneapolis, Minnesota, August 10-14. ASABE, St. Joseph, MI.

Bronson, K. F., J. W. Keeling, J. D. Booker, T. T. Chua, T. A. Wheeler, R. K. Boman, and R. J. Lascano. 2003. Influence of landscape position, soil series, and phosphorus fertilizer on cotton lint yield. Agron. J. 95 : 947-957.

Charles-Edwards, D. A., D. Doley, and G. M. Rimmington. 1986. Modeling plant and development. Academic Press, Orlando, FL.

Chiarello, N. R. and S. L. Gulmon. 1991. Stress effects on plant reproduction. In: Mooney H. A., Winner W. E., Pell E. J., Chu E, Eds. Response of plants to multiple stresses. New York: Academic Press, 161-168.

Constable, G. C. and A. B. Hearn. 1981. Irrigation of crops in a subhumid environment. VI. Effect of irrigation and nitrogen fertilizer on growth, yield, and quality of cotton. Irrigation Science 3 : 17-28.

Conte, S. D. and D. de Boor. 1965. Elementary numerical analysis: An algorithmic approach. McGraw-Hill, New York.

Guo, W. 2005. Spatial and temporal variability in cotton yield in relation to soil apparent electrical conductivity, topography, and remote sensing imagery. Ph. D. diss. Texas Tech Univ., Lubbock.

Howell, T. A., K. R. Davis, R. L. McCormick, H. Yamada, V. T. Walhood, and D. W. Meek. 1984. Water use efficiency in narrow row cotton. Irr. Sci. 5 : 195-214.

Jackson, B. S., G. F. Arkin, and A. B. Hearn. 1988. The cotton simulation model "COTTAM": fruiting model calibration and testing. Trans. of the ASAE. 31(3) : 846-854.

Jackson, B. S., G. F. Arkin, and A. B. Hearn. 1990. COTTAM: a cotton plant simulation model for an IBM PC microcomputer. College Station, Texas, The Texas Agricultural Experiment Station, The Texas A&M University System: 241p.

Jones, C. A. and J. R. Kiniry. 1986. CERES-MAIZE: A simulation model of maize growth and development. Texas A&M University Press. College Station, TX.

Kimball, B. A. and J. R. Mauney. 1993. Response of cotton to varying CO_2, irrigation, and nitrogen: yield and growth. Agron. J. 85 : 700-706.

Ko, J., S. J. Maas, R. J. Lascano, and D. Wanjura. 2005. Modification of the GRAMI model for cotton. Agron. J. 97: 1374-1379.

Ko, J., S. J. Maas, S. Mauget, G. Piccinni, and D. Wanjura. 2006. Modeling water-stressed cotton growth using within-season remote sensing data. Agron. J. 98 : 1600-1609.

Li, H., R. J. Lascano, E. M. Barnes, J. Booker, L. T. Wilson, K. F. Bronson, and E. Segarra. 2001. Multispectral reflectance of cotton related to plant growth, soil water and texture, and site elevation. Agron. J. 93 : 1327-1337.

Maas, S. J. 1998. Estimating cotton ground cover from remotely sensed scene reflectance. Agron. J. 90 : 384-388.

Maas, S. J. 1992. GRAMI: a crop growth model that can use remotely sensed information. USDA, ARS-91, 77p.

Maas, S. J. 1993a. Parameterized model of gramineous crop growth: I. Leaf area and dry mass simulation. Agron. J. 85 : 348-353.

Maas, S. J. 1993b. Parameterized model of gramineous crop growth: II. Within-season simulation calibration. Agron. J. 85 : 354-358.

Maas, S. J. 1993c. Within-season calibration of modeled wheat growth using remote sensing and field sampling. Agron. J. 85 : 669-672.

Maas, S. J. 2000. Linear mixture modeling approach for estimating cotton canopy ground cover using satellite multispectral imagery. Remote sensing. Environ. 73 : 304-308.

Maas, S. J. and P. C. Doraiswamy. 1996. Integration of satellite data and model simulation in a GIS for monitoring regional evaporation and biomass production. Proceedings of 3rd International Conference on Integrating GIS and Environmental Modeling, Santa Fe, NM, Jan. 21-26, 2006, CD-ROM. The National Center for Geographic Information and Analysis, Santa Barbara, CA.

Maas, S. J. and G. F. Arkin. 1978. User's guide to SORGF: A dynamic grain sorghum growth model with feedback capacity. Research Center Program and Model Documentation No. 78-1, Texas Agricultural Experiment Station. College Station, TX.

Monteith, J. L. and M. H. Unsworth. 1990. Principles of environmental physics, second edition. Edward Arnold. New York. 291p.

Moran, M. S, S. J. Maas, and P. J. Pinter, Jr. 1995. Combining remote sensing and modeling for estimating surface evaporation and biomass production. Remote Sensing Reviews 12 : 335-353.

Orgaz, F., L. Mateos, and E. Fereres. 1992. Season length and cultivar determine the optimum evapotranspiration deficit in cotton. Agron. J. 84 : 700-706.

Press, W. H., B. P. Flannery, S. A. Teukolsky, and W. T. Vetterling. 1992. Numerical recipes in Fortran: The art of scientific computing, second edition. Cambridge Univ. Press, New York.

Rajapakse, S. S. 2005. Automated radiometric normalization techniques for multi-temporal Landsat-TM and ETM+ imagery. Dissertation, Texas Tech University.

Reddy, V. R., B. Acock, D. N. Baker, and M. Acock. 1989. Seasonal leaf area - leaf weight relationships in the cotton canopy. Agron. J. 81 : 1-4.

Rhoads, F. M. and M. E. Bloodworth. 1964. Area measurement of cotton leaves by dry-weight method. Agon. J. 56 : 520-522.

Richardson, A. J. and C. L. Wiegand. 1977. Distinguishing vegetation from soil background information. Photogrammetric Engineering and Remote Sensing 43 : 1541-1552.

Ritchie, J. T. and S. Otter. 1985. Description and performance of CERES-Wheat: A User-oriented wheat yield model. P. 159-175. In ARS Wheat Yield Project. ARS-38. National Technology Information Service, Springfield, VA.

Rosenthal, W. D., R. L. Vanderlip, B. S. Jackson, and G. F. Arkin. 1989. SORKAM: A grain sorghum crop model. Texas Agric. Exp. Stn. Miscellaneous Publication MP-1669.

Sanders, V. O., M. P. Bange, and S. P. Milroy. 1997. Reproductive allocation of cotton in response to plant environmental factors. Annuals of Botany. 80 : 75-81.

Wanjura, D. F. and J. R. Supak. 1985. Temperature methods for monitoring cotton development. Beltwide Cotton Conferences. pp. 369-372.

Wanjura, D. F., D. R. Upchurch, and S. J. Maas. 2004. Spectral reflectance estimates of cotton biomass and yield. Beltwide Cotton Conference. pp. 838-851.

Wilkerson, G. G., J. W. Jones, K. J. Boot, and J. W. Mishoe. 1985. SOYGRO V5.0: Soybean crop growth and yield model. Technical Documentation, Univ. Florida, Gainesville, FL.