Summary of the Presentation

ADVANCES IN ESTIMATING CROP YIELD THROUGH COMBINED REMOTE SENSING AND GROWTH MODELING

Stephan J. Maas

Plant Physiologist
USDA-ARS Subtropical Agricultural Research Lab
Weslaco, Texas

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This presentation describes the advances made over the past two years in a crop yield estimation technique that combines aspects of satellite remote sensing and crop simulation modeling. The technique responds to the challenge to meet the goal established at the ARS Remote Sensing Workshop (20-22 October 1987, Beltsville, MD) of developing hybrid remote sensing/agroclimatic models that can estimate foreign yields more accurately and domestic yields more economically than by current operational methods. From the start of the project, attention was paid to developing a technique that would require a minimum of input data, and the input data would be of a type routinely available in an operational program. It was also considered beneficial to develop a single technique that could be applied to both foreign and domestic yield estimation.

A number of yield estimation techniques have been proposed that make use of either remote sensing or growth modeling. These techniques rely on the inherent strengths of these technologies (Fig. 1). However, the inherent weaknesses of each technology have hindered the acceptance of these techniques in operational yield estimation programs. The technique described in this presentation combines aspects of remote sensing and growth modeling such that the strengths of one technology make up for the weaknesses of the other.

The Objective Yield Survey employed by the National Agricultural Statistics Service (NASS) was used as the starting point for developing the technique, since it sets the standard for yield estimation accuracy. It also demonstrates that observed data and models can be combined in an operational program. In the Objective Yield Survey, observed data are obtained by ground-level field sampling. These data drive the empirical regression models used to determine crop yield. NASS has investigated the use of growth simulation models driven by weather data, but typically these models were not consistently accurate or required weather or field data that were difficult to acquire operationally. Much of the detail in crop growth models is needed to accurately simulate the development of the leaf canopy, since leaf growth is highly sensitive to genetic influences, environmental conditions (temperature, water stress), fertilization and plant population density. If the leaf canopy development of a crop planting is known, modeling the biomass production and yield of the field is relatively uncomplicated. While leaf canopy development might be impractical to routinely measure by ground-based sampling for the large number of fields in an operational yield estimation program, it could effectively be estimated for many fields in a region from satellite (like Landsat or SPOT) observations. With the availability of remotely-sensed values of canopy development, a much simpler growth simulation model (requiring much simpler weather inputs) can be used. Like the empirical regression models currently in use by NASS, the estimates produced by this model will be brought into agreement with what is really happening in the fields through in-season observations.

Experience has shown that the main problem in using satellite estimates of canopy development in growth models is the infrequency of observations resulting from the normal overpass cycle of the satellite and the occurrence of clouds. Thus, a technique had to be found to incorporate infrequent satellite observations into the model simulation. A number of techniques were evaluated (Maas, 1988, Ecological Modelling 41:247-268), and one called re-parameterization was determined to satisfy this requirement. The manner in which it operates is shown in Fig. 2. The model contains relatively simple relationships that produce a leaf canopy growth curve with a shape that resembles what is typically observed in the field. Because the relationships are simple, however, the magnitude of this growth curve as determined from weather data alone might not match what actually occurs in the field. By comparing the simulated growth curve to infrequent observations of leaf canopy development, parameters in the relationships can be manipulated until the magnitude of the simulated canopy growth curve matches the observations. In practice, this is accomplished by an iterative numerical solution that produces a "best fit" of the simulation to the observations. This technique works with observations obtained at any time in the growing season, and works with as few as one observation.

A prototype operational model called GRAMI has been developed to test the accuracy of yield estimates to be expected from this technique. The model currently can simulate the growth of a number of grain and cereal crops. There is indication that it can also be adapted to simulate the growth of other crops, such as soybean, cotton and sunflower. To simulate growth, GRAMI requires observations of average daily air temperature, daily total solar irradiance, and an estimate of the planting date of the field. Rainfall, evapotranspiration or soil moisture data are not required, since the effects of water stress are assumed to be present in the observations of leaf canopy development and thus are implicitly incorporated into the simulation through the re-parameterization process. In an operational program, adequate values of average temperature could be interpolated to the field locations from existing weather stations, or inferred from weather satellite atmospheric soundings. Daily solar irradiance, which used to be difficult to acquire over large areas, can now be operationally estimated from satellite observations.

Examples of GRAMI simulations for four crops are presented in Figs. 3-6. Frequent ground-based observations of GLAI (a measure of leaf canopy development) were used to re-parameterize the model to determine how well GRAMI could simulate the details of crop growth over the growing season. In the case of winter wheat (Fig. 6), the simulation was started at mid-winter to estimate the spring growth of the crop. The simulations of GLAI in Figs. 3-6 represent the best fits of modeled to observed data obtained through the re-parameterization process. The simulations of biomass (AGDM) are not fits to the observed data. Rather, they were computed in the model based on temperature and the absorption of solar irradiance by the simulated leaf canopy. The fact that the biomass simulations reasonably match their respective observations emphasizes the earlier assertion that modeling crop biomass is relatively easy once the leaf canopy development has been adequately described. Simulated and observed values of yield displayed in Figs. 3-6 are also not markedly dissimilar.

An initial validation of GRAMI was performed to investigate the accuracy of model estimates based on infrequent satellite observations of crop canopy development. The yields of 37 grain sorghum fields grown during the period 1973-77 in Hidalgo County, Texas, were modeled using daily temperature and irradiance data measured at one location in the county. Of the 37 fields, 24 were under dryland cultivation and the remainder were irrigated. Values of GLAI used to re-parameterize the model were determined from digitized Landsat MSS images using established conversion procedures. No information from the study other than planting dates, the weather data, and remotely-sensed GLAI was used in simulating the growth and yield of the 37 fields. Results of the study are presented in Fig. 7, which shows that simulated versus observed yield values generally cluster along the 1:1 line. Statistical analysis of the results using SAS indicated that the sets of simulated and observed yields exhibited equal variances ($F'=1.65$ with 36 and 36 df, $P>F'=0.1377$). The means of the simulated and observed yields were not significantly different ($t=0.0832$ with 72 df, $P>t=0.9339$), while the mean difference between simulated and observed yield on an individual field basis was not significantly different from zero ($t=-0.1556$ with 36 df, $P>t=0.8772$). These results are encouraging, since only one Landsat MSS observation was available for 25 of the 37 fields in the study. The yield estimates involving only one Landsat observation are indicated in Fig. 8. It is apparent that the yield estimates exhibiting the greatest errors were determined using only one satellite observation.

More extensive data sets are in preparation for validating GRAMI. The 1983 Upper Midwest Study contains yield and Landsat MSS data for approximately 150 fields each of spring wheat, corn and soybean, and approximately 50 fields each of winter wheat, grain sorghum and sunflower. The 1985-86 North American Great Plains Study contains yield and ground-based remote sensing observations for approximately 250 small plots of winter wheat.

Preliminary results from these validation efforts should be available within a year.

In addition to estimating yields based on observed data, the modeling technique employed by GRAMI must be capable of providing in-season predictions of yield before harvest. A relatively simple means of predicting yields within the growing season would involve running the model up to the current day using observed weather data and available satellite obsrvations. The simulated values of biomass on the current day could then be used in an empirical regression model to predict yield at harvest. This procedure would be similar to that used operationally by NASS. A more sophisticated technique would involve running the model up to the current day using observed weather and satellite data, and completing the model simulations using "future" weather data. This future weather data could come from climatological records, long-range weather predictions, or computerized weather-synthesizing programs. Since future weather conditions are uncertain, the simulations could be completed using a number of individual sets of future daily weather, and the resulting distribution of yield values used to estimate the probabilities of yields occurring within certain ranges.

The current version of GRAMI assumes that the effects of water stress on crop growth are implicitly contained in the remotely-sensed observations of leaf canopy development. Thus, the current version of the model does not need to consider rainfall, evapotranspiration, or soil moisture. There is some evidence from physiological studies that water stress may produce an effect on leaf photosynthetic rate in addition to its effect on leaf canopy development. This additional effect is related to stress-induced closing of leaf stomata. The reduction in photosynthetic rate has been shown to be directly related to the value of the Idso-Jackson Crop Water Stress Index (CWSI). This index can be evaluated from remote sensing measurements of leaf canopy temperature. A model called HYDRO has been developed that can use remotely-sensed observations of canopy development and temperature to quantify these separate stress effects on the growth and yield of a crop. HYDRO consists of two submodels-- a crop growth submodel and a soil moisture balance submodel. The crop growth submodel is GRAMI modified to include the relationship that reduces photosynthetic production as a function of CWSI. The soil moisture balance submodel simulates CWSI over the growing season as a function of weather data, crop canopy development, and soil moisture-related parameters. Like GRAMI, the soil moisture submodel uses an iterative numerical solution to estimate the parameter values that result in a "best fit" of simulated to observed CWSI. This simulation is achieved without the input of rainfall, evapotranspiration, or soil moisture data.

HYDRO was tested using spring wheat irrigation treatment plot data from Phoenix, AZ (Maas *et al.*, 1989, Proc. 19th Conf. Agric. Forest Meteorol., AMS, pp. 228-231). The fit of the simulated to observed CWSI for six wheat varieties is shown in Fig. 9, while the fit of the simulated to observed leaf canopy cover (GLAI) is shown in Fig. 10. Also shown in Fig. 10 are biomass (AGDM) simulations made with and without the stress-related effects on photosynthesis. It appears that the biomass simulations that incorporate the stress-related effect match the observed biomass values more closely than the simulations that do not incorporate the effect. This would indicate that, when significant water stress conditions occur, models that do not explicitly contain this photosynthesis-related stress effect (including the current version of GRAMI) might tend to overestimate crop growth and yield. The results of this study are not conclusive. In the Phoenix experiments, water stress was imposed on the crop abruptly after a period of irrigated growth. Under natural conditions, water stress develops more gradually, with an opportunity for the crop plants to acclimate to the changing conditions. This may explain why some studies (Gibson and Schertz, 1977, Crop Sci. *17*:387-391) indicate that only the effect of water stress on leaf canopy development (and not photosynthesis) is evident under natural field conditions. This would indicate that the current formulation of GRAMI may be adequate for application to natural conditions. This will be known with more certainty upon completion of the current GRAMI validation efforts and continued experimentation with HYDRO.

In conclusion, a yield estimation technique has been developed that combines remote sensing and growth modeling in such a way that the strengths of one technology make up for the weaknesses of the other. The technique takes advantage of the dependence of model performance on growth-related parameters that can be evaluated using infrequent satellite observations and numerical analysis procedures. Through re-parameterization, within-season satellite observations of crop canopy development constrain the response of a relatively simple growth simulation model to bring it in line with what is happening in the field. The technique has a number of advantages with respect to its use in an operational yield estimation program, including,

(1) The same model can be used for both foreign and domestic applications
(2) The same model can be used for many different crops
(3) The model is relatively simple, and requires weather data that can be routinely obtained from existing sources
(4) The model requires infrequent (as few as one) observations of crop canopy development, which can be easily obtained by satellites for a large number of fields in a region
(5) The model can be used to produce probabilistic predictions of yield during the growing season

Figure 1. Summary of the strengths and weaknesses of the remote sensing and growth modeling technologies with respect to crop yield estimation.

	STRENGTHS	WEAKNESSES
REMOTE SENSING	Provide a quantification of the actual state of the crop during the growing season Information on crop status can be obtained for many fields more economically than by field sampling	Observations are discrete time events that tell little about how the crop got to the observed state Growth and yield must be inferred through empirical methods with questionable general application
GROWTH MODELING	Provide a continuous description of crop growth over the growing season Growth and yield are determined from environmental conditions based on physiological principles	Must contain a considerable amount of detail Must have detailed on-site observations of environmental inputs

Figure 2. Schematic diagram of how remotely-sensed observations are used to constrain the growth model simulation.

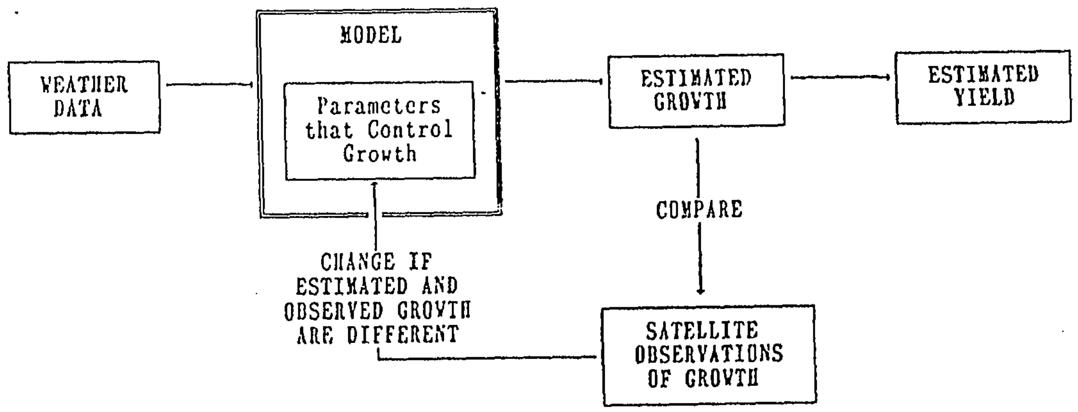


Figure 3. GRAMI simulation of leaf canopy development (GLAI) and biomass growth (AGDM) for corn (maize). Circles represent observations, while the solid lines are the respective model simulations.

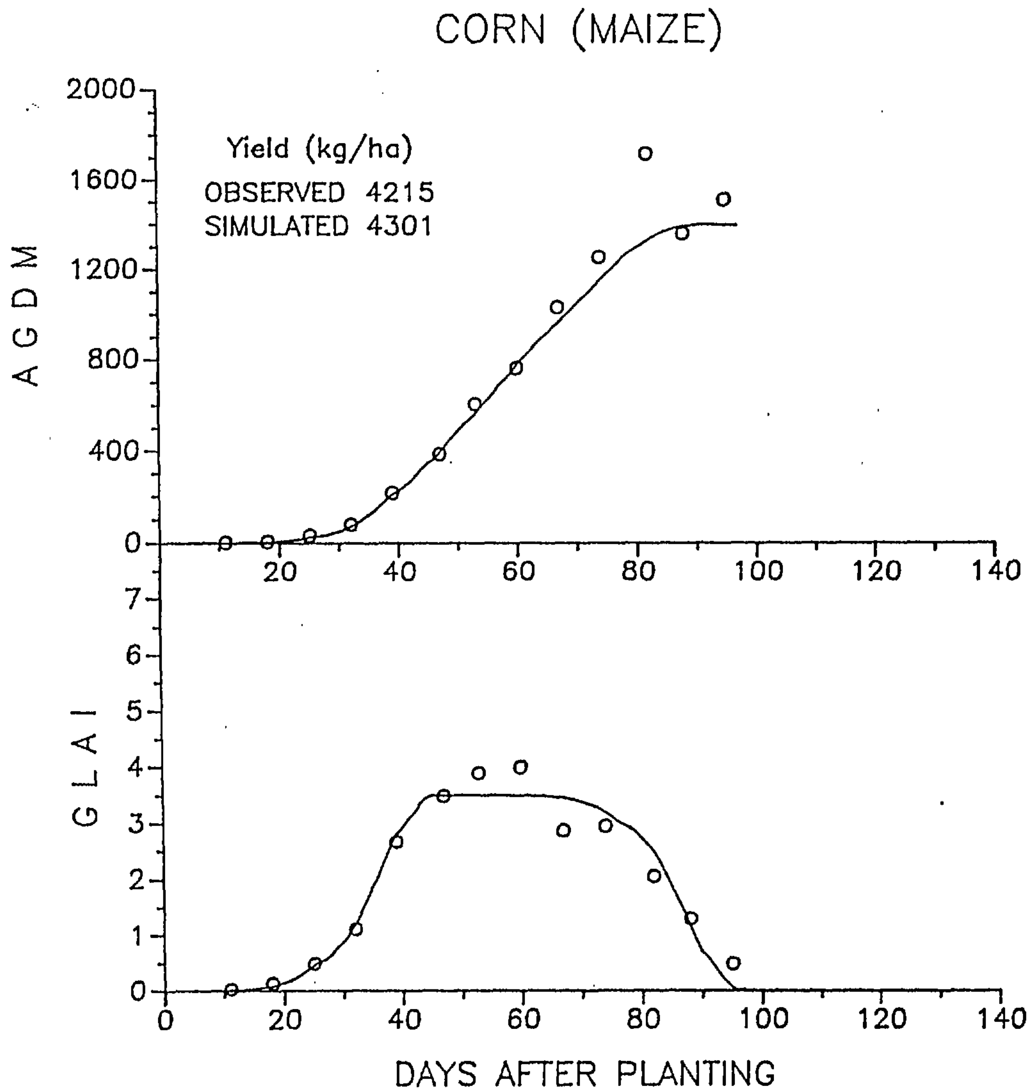


Figure 4. GRAMI simulation of leaf canopy development (GLAI) and biomass growth (AGDM) for grain sorghum. Circles represent observations, while the solid lines are the respective model simulations.

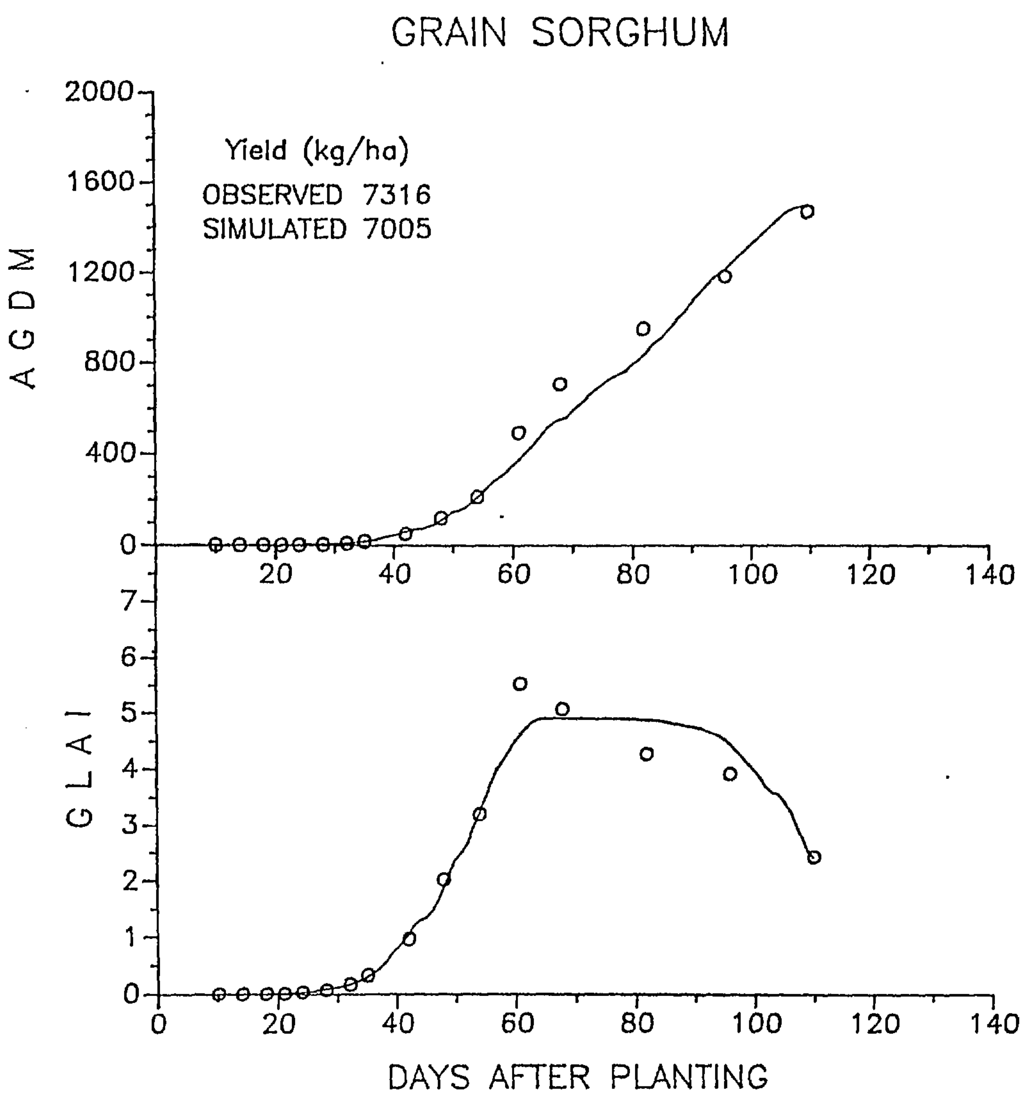


Figure 5. GRAMI simulation of leaf canopy development (GLAI) and biomass growth (AGDM) for spring wheat. Circles represent observations, while the solid lines are the respective model simulations.

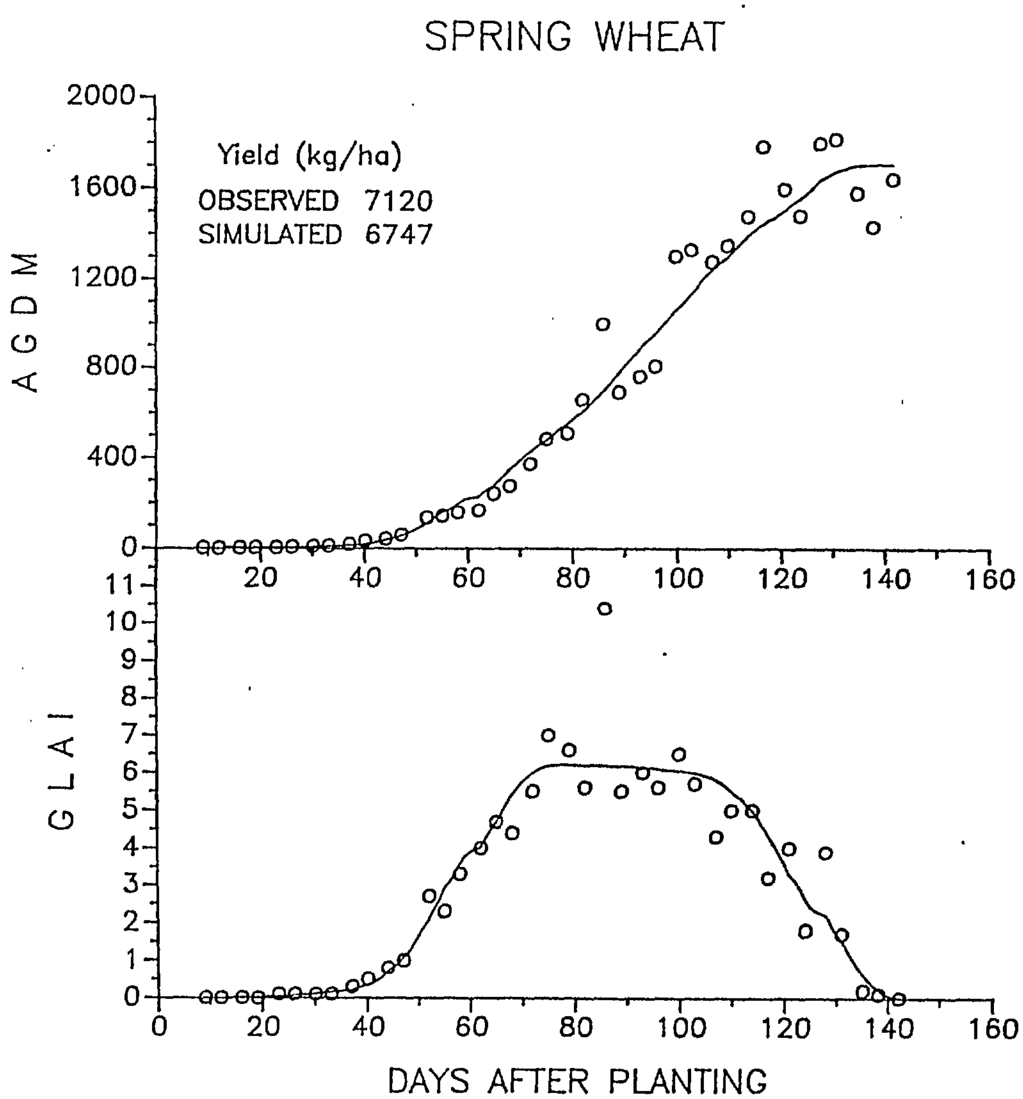


Figure 6. GRAMI simulation of leaf canopy development (GLAI) and biomass growth (AGDM) for winter wheat. Circles represent observations, while the solid lines are the respective model simulations. Solid circles indicate growth that occurred during autumn. "Days after planting" are actually days after the start of the simulation in mid-winter.

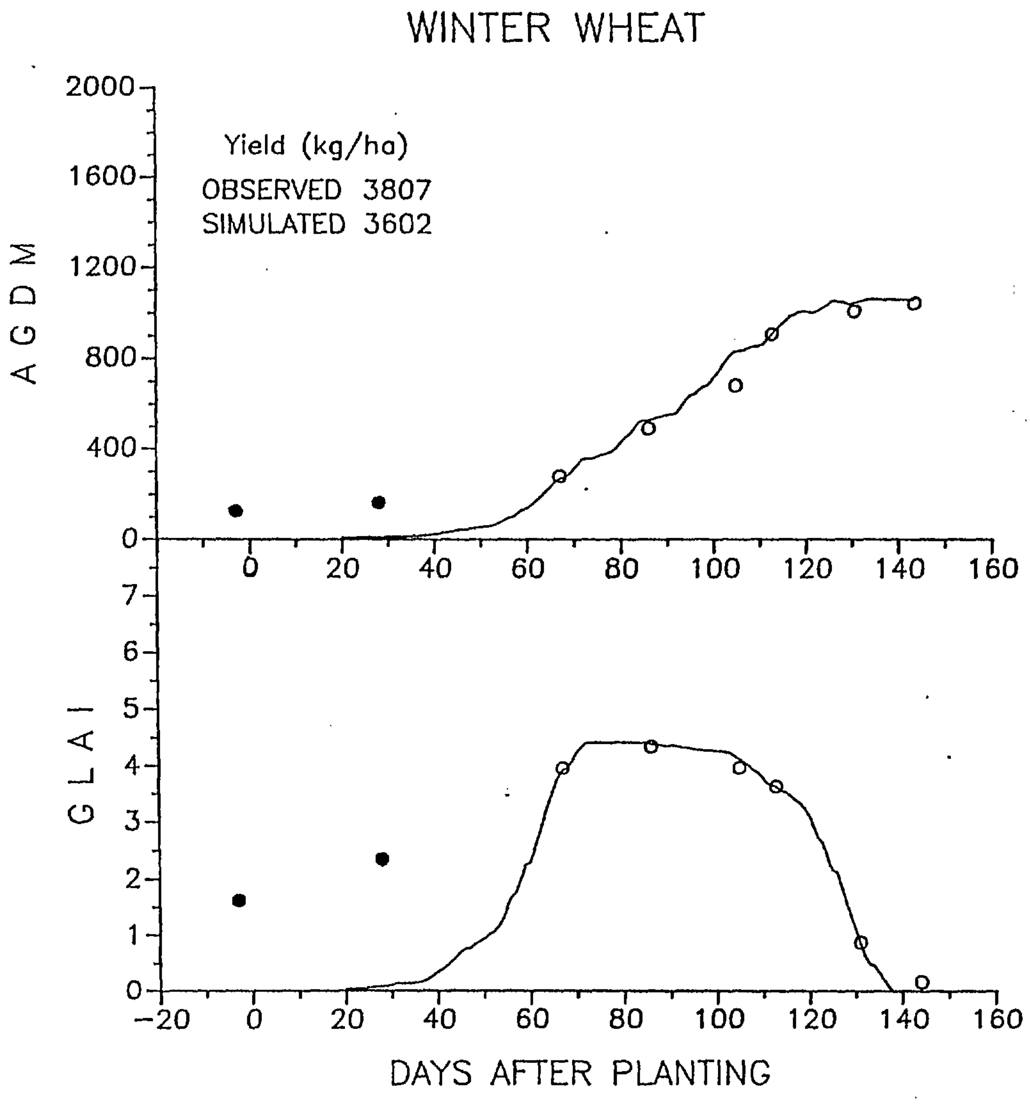
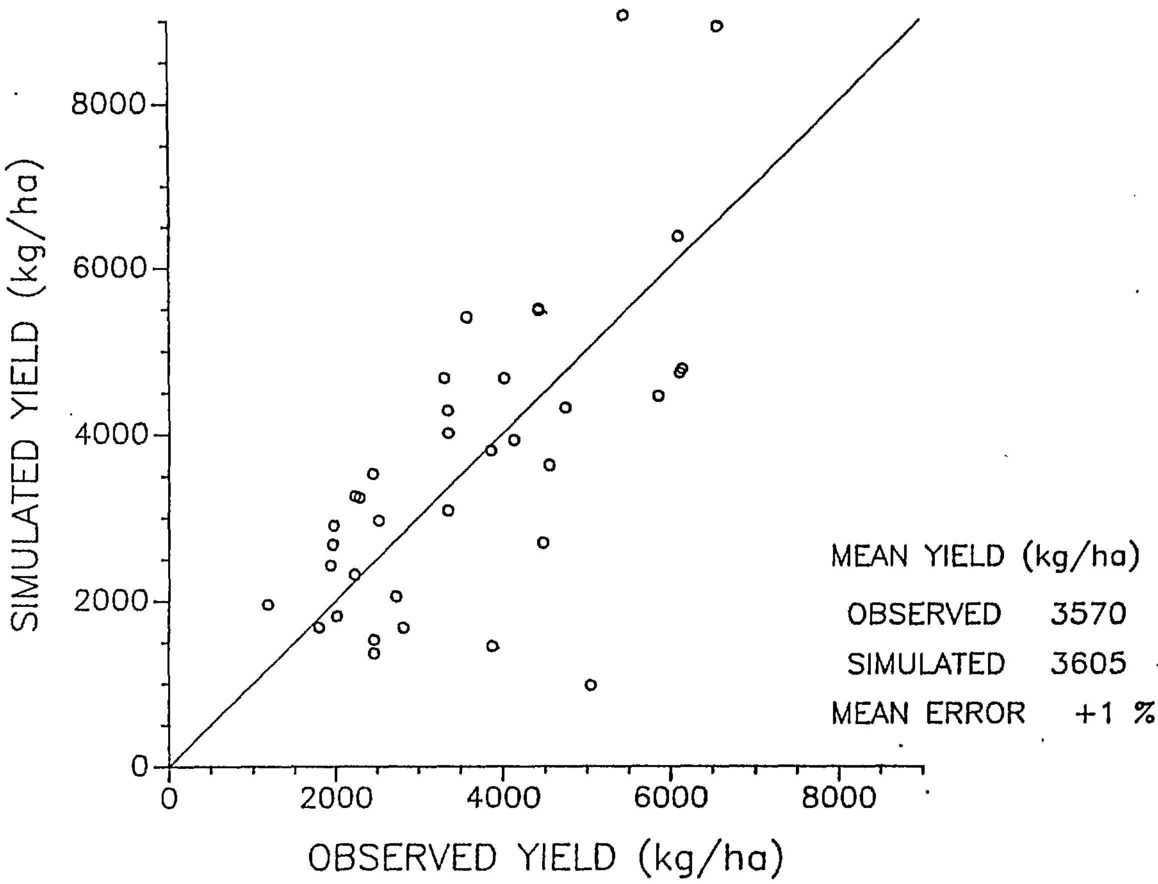


Figure 7. Results of the initial validation of GRAMI using 37 grain sorghum fields in Hidalgo County, Texas.



<u>Figure 8</u>. Same as Fig. 7, except that yield estimates based on only one Landsat observation are indicated by crosses.

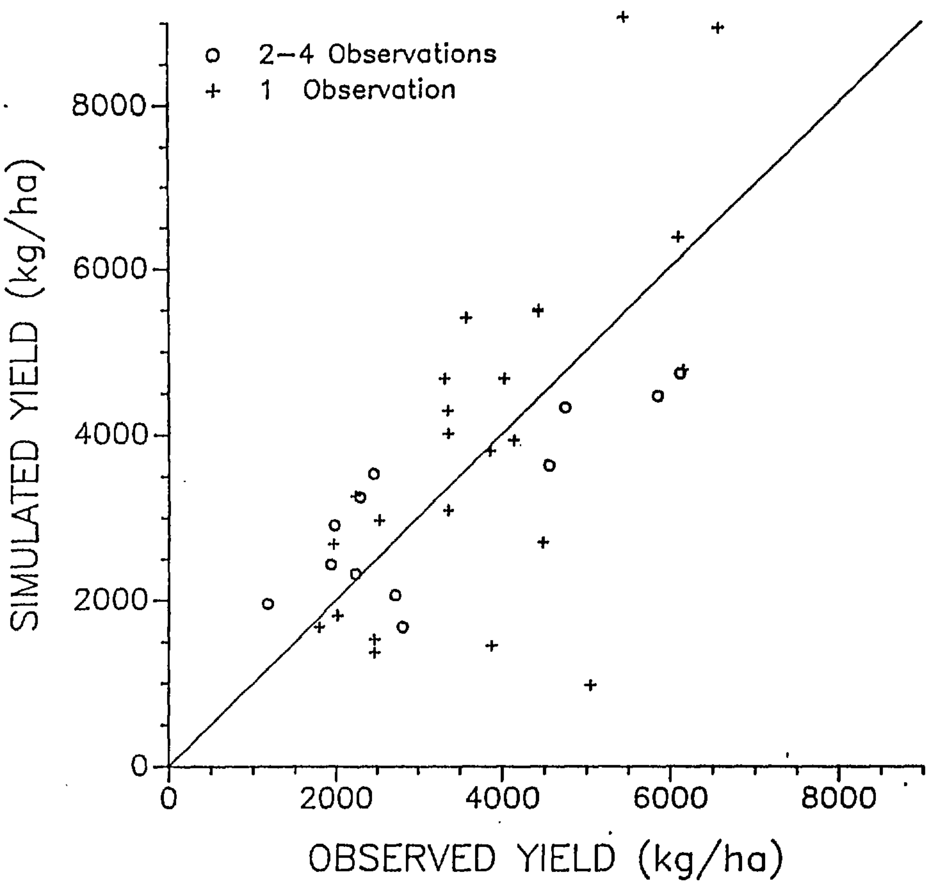


Figure 9. HYDRO simulations of CWSI for the six spring wheat varieties grown at Phoenix, Arizona.

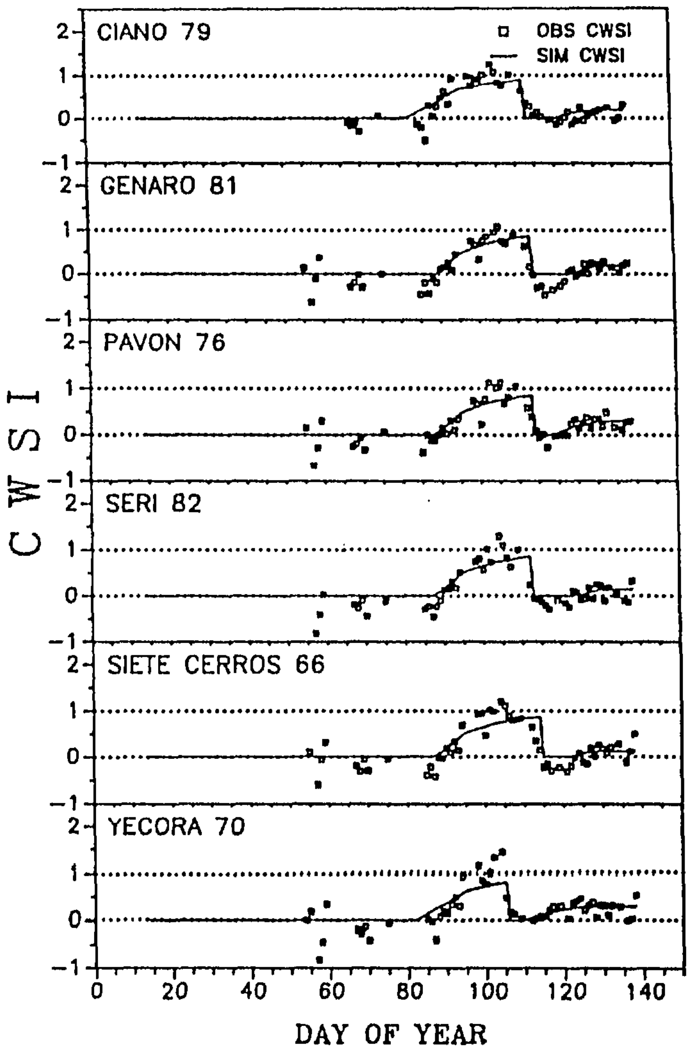


Figure 10. HYDRO simulations of leaf canopy development (GLAI) and biomass (dry mass) for the six spring wheat varieties grown at Phoenix, Arizona. Dotted curves represent biomass simulations that incorporate the stress effect on photosynthesis, while dashed curves represent biomass simulations that do not incorporate the effect.