Application of Remote Sensing and GIS Technologies with Physiological Crop Models

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Abstract
This study investigates how remote sensing and geographic information system (GIS) technology can be used with a physiological crop model to examine spatial variability in county soybean yield. Remote sensing provided a means of classifying land cover and for identifying agricultural regions within the county, while the GIS allowed the spatial organization of soil and weather data inputs to the model. Results show that spatial variability in simulated county yield is often large and corresponds closely with soil moisture availability. This availability is influenced primarily by soil properties and by the timing and amount of precipitation, both of which vary greatly across space. Examination of the spatial patterns of simulated yield can improve production estimates and highlight vulnerable areas during droughts. While data acquisition for remote sensing, GIS, and physiological models can be costly, these tools allow analysis that is impossible through other means and that provides insight into the interacting variables influencing yield.

Introduction
Physiological crop models are an important tool that agricultural meteorologists use to examine the link between climate and crop production. While many of these models were originally designed for farm management, some have been used to measure the impact of climate variability and change on regional-scale crop yield (Hodges *et al.*, 1987; Curry *et al.*, 1990; Adams *et al.*, 1990; Rosenzweig, 1990). However, changing the spatial scale at which such models are used comes at a price. Because the models require detailed input values, one must either use databases with high spatial and temporal resolution, or generalize over relatively large areas. Unfortunately, generalization can obscure the spatial variability of environmental variables within the region. For example, the choice of a single soil type or meteorological data set could produce results that do not accurately represent the region being examined because of the sensitivity of physiological models to certain input variables. Most researchers adopting or evaluating this methodology recognize this limitation (Rosenberg, 1992). However, they have been constrained by the lack of an efficient means of incorporating the spatial variability of input variables into their models. Remote sensing and geographic information systems (GIS) can be used to derive data inputs for physiological models and overcome some of these constraints. Collectively, these tools should allow researchers to assess the impact of climatic variability and change on agriculture with greater detail and with regard to spatial patterns.

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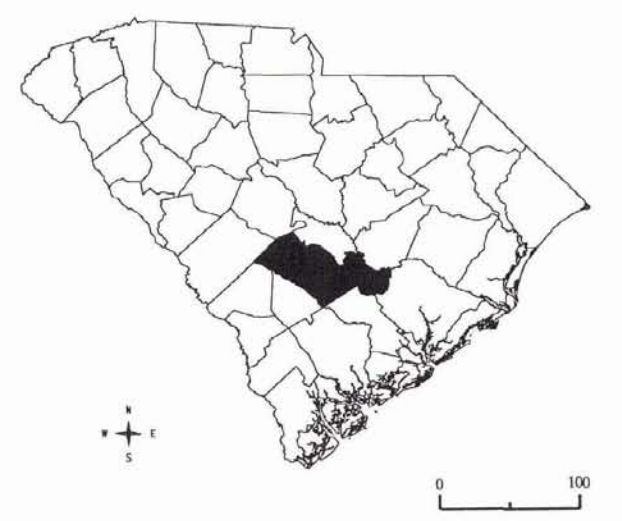

Figure 1. Location of Orangeburg County, South Carolina.

This research develops a methodology for using remote sensing and GIS techniques with the physiological soybean growth model, SOYGRO (Wilkerson *et al.*, 1983), to capture the spatial variability of input variables affecting yield estimates. Orangeburg County, South Carolina is used as the case study for demonstrating a procedure to identify agricultural regions, construct and manipulate spatial databases, and simulate soybean yield. There are three objectives to this research: (1) to describe the methodology for linking remote sensing and GIS data to physiological crop models; (2) to assess the sensitivity of simulated yield to spatial variability of input variables; and (3) to demonstrate the usefulness of the three tools for identifying spatial patterns of crop yield.

Study Area
Orangeburg County, South Carolina is located in the south-central portion of the state (Figure 1). It extends approximately 105 kilometres in the east-west direction and 45 kilometres in the north-south direction. The county is largely ru-

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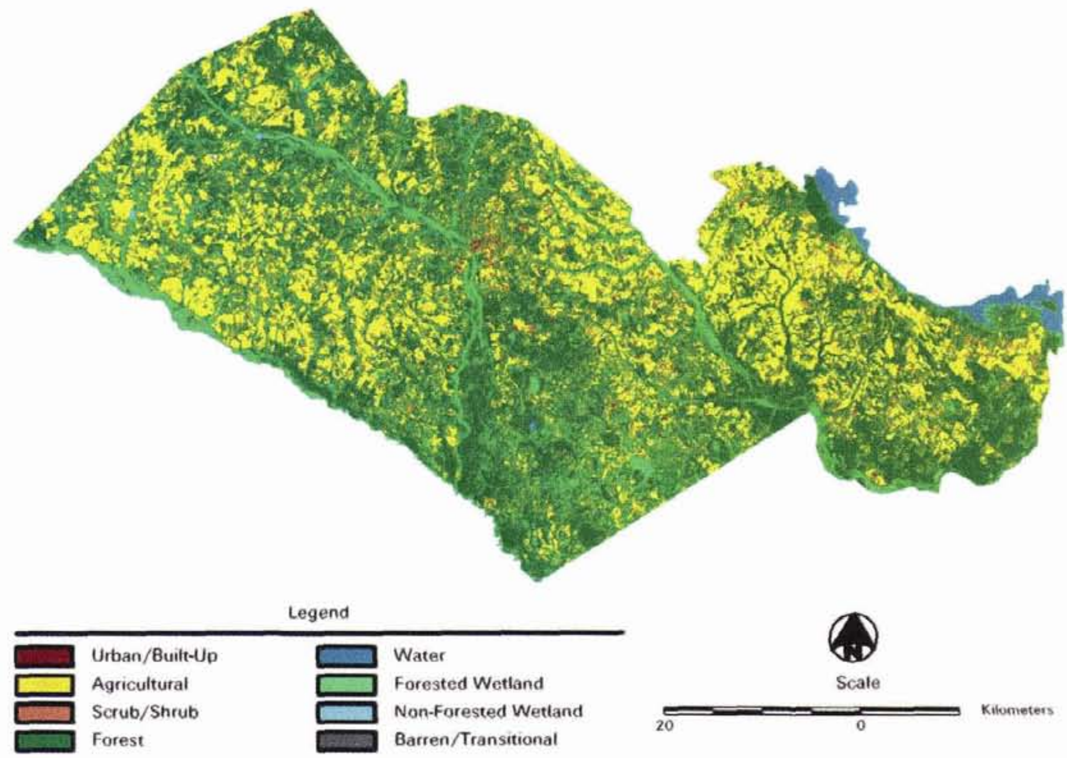

Plate 1. Remote-sensing-derived land-cover classes for Orangeburg County. SPOT XS data at 20m by 20m were used to classify the land cover.

ral and was selected because it is one of the most important agricultural counties in the state. It includes extensive soybean production and has a range of environmental conditions, including a wide variety of soil types. These factors allow tests of the sensitivity of simulated yield to spatial variability.

Methodology

Land-Cover Classification

The first step of the study was to identify agricultural regions in Orangeburg County. To accomplish this, a state-wide land-cover classification, recently compiled by the South Carolina Land Resources Commission (SCLRC), was used (Lacy *et al.*, 1991). The SCLRC used five scenes of SPOT satellite imagery from leaf-off periods in December 1988 and March 1989 to derive eight land-cover categories statewide. The land-cover classification was based on a combination of Anderson Level I and Level II data that adequately includes the state's major land-cover classes, including (1) Urban, (2) Agricultural, (3) Scrub/Shrub, (4) Forest, (5) Water, (6) Forested Wetland, (7) Non-Forested Wetland, and (8) Barren.

The SPOT data had been geometrically rectified to the Universal Transverse Mercator (UTM) coordinate system using the nearest-neighbor transformation. An unsupervised statistical clustering algorithm was used to derive 50 initial clusters from each image, based on original brightness values within the scene. An iterative "cluster busting" technique was subsequently applied to minimize the number of unclassified pixels (Jensen *et al.*, 1992; Narumalani *et al.*, 1993). The procedure involved developing a binary mask whereby successfully labeled clusters were recoded as "0" and the unclassified clusters as "1". The mask was subsequently applied to the original image to isolate the areas that could not be classified. The parameters of the statistical clustering algorithm were modified and it was re-applied to these "unclassified" areas, thus resulting in new statistically independent clusters. A total of three iterations of cluster busting were performed, resulting in 110 new clusters which were grouped into the respective eight land-cover classes to produce a final land-cover classification image map for the entire scene (Plate 1). The five classified image maps were merged to produce a composite land-cover map for Orangeburg County. Because all imagery was rectified to a standard coordinate system (i.e., UTM), the imagery could be geographically edge-matched. The procedure must be done so that geographic information from several adjacent images or maps can be represented as spatially contiguous data. Table 1 shows the total acreage of the respective land-cover classes. A mask was applied to delineate agricultural areas, recoding the agricultural class as "1" and non-agricultural classes as "0" (Figure 2).

SOYGRO

SOYGRO is a physiological soybean growth model developed at the University of Florida. Its mathematical structure relates major processes of soybean growth (e.g., photosynthesis, respiration, tissue synthesis, translocation of protein, and senescence) to environmental conditions (Wilkerson *et al.*, 1983). The model is part of a comprehensive software package that includes several crop-growth models sharing standardized data structure (IBSNAT, 1986). It has been tested under a variety of environments and has proven reliable in estimating yield under well-managed conditions (Curry *et al.*, 1990). SOYGRO requires meteorologic, soils, and crop management data as inputs.

Meteorological data inputs to the model include maximum and minimum temperature, precipitation, and solar radiation. Photoperiod, also required, is calculated from lati-

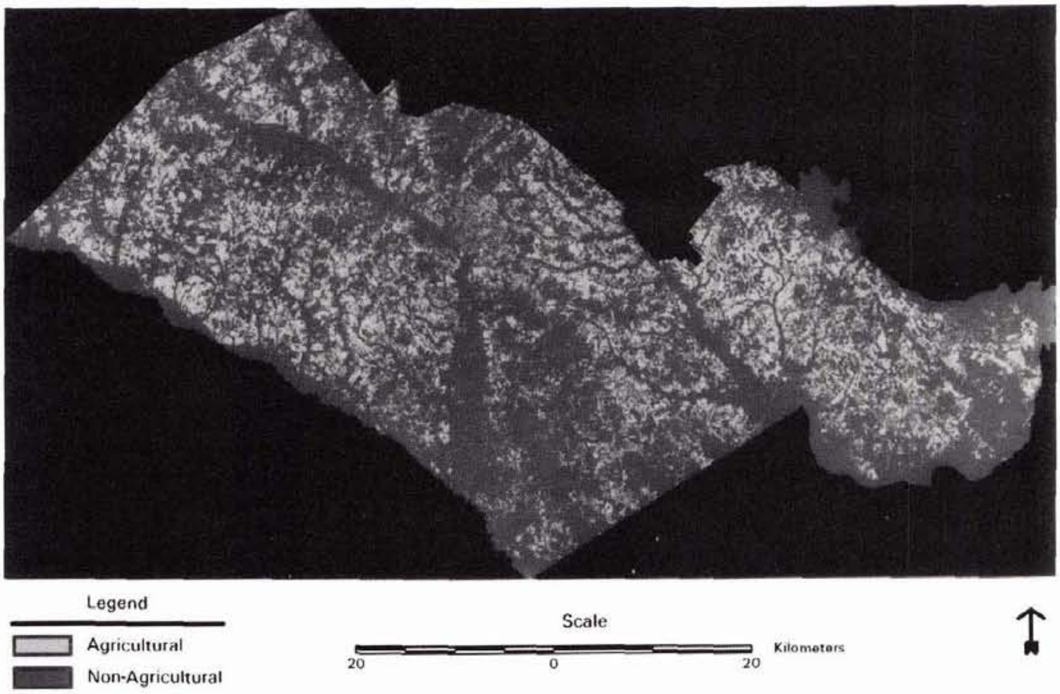

Figure 2. Distribution of agricultural land in Orangeburg County derived from remote sensing data.

tude and longitude. Daily temperature and precipitation data were obtained from five stations in the Orangeburg County region (Figure 3). While only two stations fall within the county (Orangeburg and Eutawville), three (Bamberg, Blackville, and Pelion) lie close to its borders. All stations are part of the National Weather Service cooperative network, except Eutawville, which is part of Clemson University's agricultural meteorology network. Solar radiation data were available from South Carolina State College in Orangeburg as part of the Solar Energy Research Institute (SERI) network.

SOYGRO requires soil variables related to water content, root growth potential, root water uptake, and nutrients. A value for each parameter is specified for several layers within the soil profile. Soils data were provided by the Pee Dee Research and Education Center, Florence, South Carolina, and the University of Florida's Institute of Food and Agricultural Sciences (Curry *et al.*, 1990).

Management data requirements include sowing date, plant population, row spacing, sowing depth, and irrigation strategy. These values were derived from experiment station reports and weekly crop and weather reports (Barefield and Chrestman, 1991).

Organizing, Manipulating, and Merging Model Inputs

Initially, all required data inputs were organized spatially using ARC-INFO, a vector-based geographic information system that stores and manipulates spatial data (Peuquet and Marble, 1990). SOYGRO is sensitive to soil moisture stress and is greatly influenced by the timing of precipitation. Unfortunately, the density of meteorological stations in the county is as sparse as in most parts of the United States, requiring the creation of a meteorological surface. Because present interpolation schemes often do not preserve important features of precipitation time series and because it is important to maintain internal consistency between variables, we constructed Thiessen polygons, centered on the location of five weather stations, to represent meteorological surfaces (Figure 3). Thiessen polygons (i.e., Voronoi polygons) are commonly used in analyzing climate data such as precipitation (Aronoff, 1993). While this method does not allow spatial variabil-

TABLE 1. LAND-COVER CLASSIFICATION AREAS DERIVED FROM SPOT IMAGERY

Class Id	Land Cover	Area (ha)
1	Urban	1,945
2	Agriculture	71,980
3	Scrub/Shrub	39,820
4	Forest	107,295
5	Water	5,276
6	Forested Wetland	58,321
7	Non-Forested Wetland	698
8	Barren	6,728

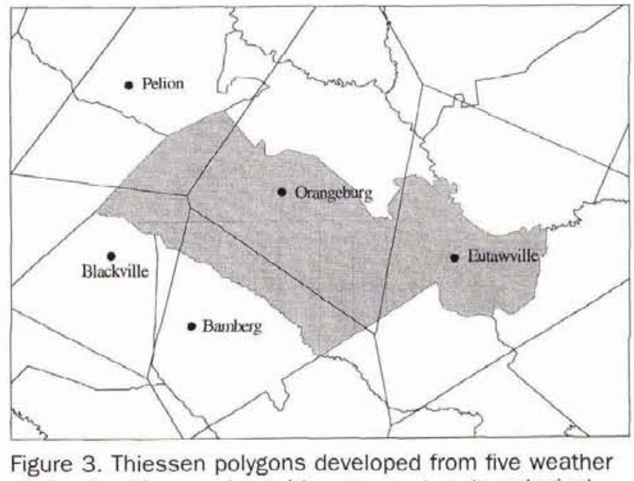

Figure 3. Thiessen polygons developed from five weather station locations and used to represent meteorological data inputs.

TABLE 2. DRAINED UPPER LIMIT (DUL) AND LOWER LIMIT (LOL) VALUES FOR EIGHT SOILS

Soil Type	Soil Layer Thickness (cm)	Lower Limit (LOL; cm³/cm³)	Drained Upper Limit (DUL; cm³/cm³)	Soil Type	Soil Layer Thickness (cm)	Lower Limit (LOL; cm³/cm³)	Drained Upper Limit (DUL; cm³/cm³)
Bonneau	12.	0.045	0.121	Fuquay	11.	0.042	0.118
Sand	13.	0.043	0.125	Sand	14.	0.041	0.120
	15.	0.047	0.142		15.	0.043	0.140
	21.	0.046	0.143		19.	0.043	0.140
	15.	0.133	0.244		16.	0.120	0.238
	21.	0.150	0.260		19.	0.135	0.260
	20.	0.150	0.260		20.	0.135	0.260
	27.	0.183	0.293		24.	0.174	0.280
	28.	0.183	0.293		30.	0.174	0.280
	28.	0.183	0.293		30.	0.174	0.280
Coxville	10.	0.137	0.254	Golds-	9.	0.062	0.162
Sandy	10.	0.132	0.254	boro	9.	0.058	0.168
Loam	13.	0.130	0.254	Sandy	10.	0.059	0.181
	25.	0.220	0.341	Loam	10.	0.058	0.182
	25.	0.220	0.341		33.	0.179	0.293
	25.	0.220	0.341		21.	0.232	0.346
	24.	0.221	0.342		27.	0.241	0.352
	30.	0.240	0.356		27.	0.241	0.352
	30.	0.240	0.356		27.	0.241	0.352
	30.	0.240	0.356		27.	0.241	0.352
Dothan	9.	0.060	0.124	Noboco	9.	0.052	0.125
Loamy	9.	0.061	0.167	Loamy	9.	0.059	0.165
Sand	13.	0.061	0.172	Sandy	13.	0.057	0.169
	15.	0.165	0.271		15.	0.159	0.271
	28.	0.173	0.275		28.	0.170	0.283
	23.	0.173	0.275		23.	0.170	0.283
	25.	0.173	0.275		25.	0.170	0.283
	25.	0.173	0.279		25.	0.170	0.283
	25.	0.173	0.279		25.	0.170	0.283
	28.	0.173	0.279		28.	0.170	0.283
Dunbar	10.	0.063	0.145	Orange-	5.	0.125	0.198
Sandy	10.	0.057	0.154	burg	10.	0.125	0.198
Loam	10.	0.100	0.208	Loamy	10.	0.125	0.198
	10.	0.100	0.208	Sand	9.	0.117	0.226
	11.	0.158	0.275		9.	0.117	0.226
	20.	0.228	0.342		10.	0.138	0.250
	32.	0.199	0.313		11.	0.138	0.250
	32.	0.199	0.313		38.	0.167	0.281
	32.	0.199	0.313		43.	0.182	0.291
	32.	0.199	0.313		30.	0.162	0.272
					28.	0.154	0.263

ity within each subregion of the county, it does preserve internal consistency between temperature and precipitation data. The same solar radiation times series was used for each polygon, because this variable was measured at only one location in the center of the county.

Soil series data make up the second data layer. The South Carolina Water Resources Commission (SCWRC) provided digital soils series data which were derived from 1:24,000-scale soil survey maps of Orangeburg County (USDA, 1988). Attributes for each soil series were stored in a relational database. The original data set consisted of 46 soil types, but was reduced to the eight dominant soils that were important for soybean production in the county. The characteristics of the eight soil types differ significantly (Table 2), and can result in yield variations for many crops.

To maintain consistency with remote-sensing-derived data, the meteorological and soils coverages were converted from vector to raster format. These data were merged with the land-cover image map to identify the specific meteorological and soils characteristics within agricultural areas. The five Thiessen polygons used for interpolating meteorological data for the county were subdivided according to soil type for agricultural lands.

Simulation

To evaluate the reliability of SOYGRO under a variety of conditions in Orangeburg County, simulated yield was compared to observed yield at the Edisto Research and Education Center, Blackville, South Carolina. Modeled yield values for different soybean varieties and planting dates were compared to those measured at the experiment station during six simulation years, 1986 through 1991. During most years, two soybean varieties were planted on two different dates. A total of 21 measured yield values allowed a detailed evaluation of model performance under relatively controlled conditions.

The next step was to simulate soybean yield under a range of environmental conditions representative of those found throughout the county. Each simulation serves as a yield sensitivity test to changes in meteorological, soils, and field management data, and, collectively, these tests measure how spatial variability in the input variables influences yield estimates. At one level, these simulations allow examination

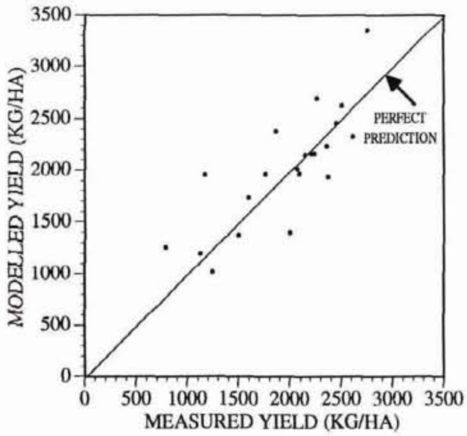

Figure 4. Modeled versus observed yield at Edisto Research and Education Center, Blackville, South Carolina.

into the causes of yield variations over time. At another level, they provide a means of identifying the spatial patterns of simulated yield across the county. Forty combinations of county-wide meteorological and soils data sets provided input values to SOYGRO, reflecting the eight dominant soil types in the five Thiessen polygons. Each of the 40 simulations offers a unique solution reflecting the interaction between a given meteorological time series and soil properties. In addition, it is possible to control for meteorology by examining the variability within a Thiessen polygon, and it is possible to control for soil type by examining yield on specific soil types between different Thiessen polygons.

Results and Discussion

Assessment of Model Accuracy

SOYGRO performed well in estimating soybean yield at the Edisto Research and Education Center, Blackville, South Carolina. The average simulated yield for 21 different input conditions during the six-year period was 2027.5 kg/ha as compared to the average measured yield under corresponding conditions which was 1963.4 kg/ha (Figure 4). Most modeled yield values are within 10 to 15 percent of field values, resulting in relatively low root-mean-square-error (RMSE) and mean-absolute-error (MAE) values of 339.3 and 259.7 kg/ha, respectively. These results suggest that SOYGRO adequately estimates yield under a variety of weather conditions, soil types, and soybean varieties at the Center. While there is always a risk when extrapolating such "point" tests to larger regions, the model has been tested extensively under a wide variety of conditions around the world (IBSNAT, 1986).

Range of Yield Variability

Forty simulations were run for each year between 1986 and 1991. In any individual year, yield ranged widely with the different input data sets and was very sensitive to soil type. The mean coefficient of variation of yield values within a given polygon (i.e., controlling for meteorology) ranged from 2.4 to 69.7 percent (Table 3). Such variability results largely from the difference in soil moisture-holding capacity. Two soil variables are particularly important in the model. The lower limit (LOL) measures the point at which soil moisture is low enough to cause plant dormancy, and the drained upper limit (DUL) measures a soil's highest water content after a thorough wetting and nearly complete drainage. Differences between DUL and LOL represent the amount of potentially extractable water. Simulated yield can vary among soil types either because DUL values are relatively low, preventing plants from taking advantage of precipitation, or because LOL values are high, causing the plant premature water stress. For example, 1990 simulations reveal regular soil moisture stress in the Eutawville polygon during the growing season for two soil types—Bonneau sand and Coxville sandy loam (Figures 5a and 5b). This stress reduced yield on these soils significantly (Table 4). Yields on the Bonneau sand are low because of very low moisture-holding capacity (low DUL values) through the soil profile. Yields on the Coxville sandy loam are low because its clayey nature restricts extraction of moisture by plant roots prematurely (high LOL values). Yields simulated using Goldsboro sandy loam and Noboco loamy sand are substantially higher because of greater moisture availability during the growing season (Figures 5c and 5d).

Table 3. Coefficient of Variation (CV) of Yield Values for the Five Meteorologically Defined Thiessen Polygons

Year	Bamberg	Blackville	Eutawville	Orangeburg	Pelion
1986	34.4	32.0	45.1	69.7	41.3
1987	51.5	55.1	51.7	42.9	39.5
1988	21.0	39.9	50.6	41.0	29.7
1989	56.7	45.9	13.6	2.4	13.7
1990	60.4	50.6	40.3	53.1	30.0
1991	45.4	52.7	43.8	16.6	48.0

Meteorological differences also account for yield variability within the county as shown with simulated yield values on Orangeburg loamy sand for each of the five Thiessen polygons during 1986 (Table 5). The large range in yield values during this relatively dry year results from the scattered nature of precipitation during the growing season. An examination of the daily precipitation time series shows the contrast between stations with relatively low yield—Blackville and Orangeburg—and one with relatively high yield—Eutawville (Figures 6a, 6b, and 6c). Regular precipitation in Eutawville during most of the growing season resulted in higher yield values. By contrast, precipitation fell less frequently in Blackville and Orangeburg, causing moisture stress, decreased photosynthetic activity, and reduced yield. A more significant difference between the stations is the number of days when precipitation exceeded 20 mm. Given the relatively low water-holding capacity of Orangeburg loamy sand, substantial rainfall is necessary to overcome drought stress. The minor precipitation events in Orangeburg and Blackville provided only brief plant recovery.

The contrast between meteorological stations is considerably less during years of ample precipitation such as 1989 and 1991 (Table 5). Precipitation over the region during these years is more uniform, resulting in a relatively equal levels of moisture availability at each station. Furthermore, maximum yield is constrained by the limits of moisture holding capacity which is reached during large parts of the growing season at all locations within the county.

Identifying the Spatial Variability of Yield

The greatest benefit of using SOYGRO with remote sensing and GIS technologies is the ability to detect spatial patterns of yield during individual growing seasons. During the 1988 growing season, for example, spatial variability in rainfall and soil type combined to produce a wide range of simulated yield values across the county (Plate 2). In general, growing season conditions were favorable for soybeans throughout the county. There were, however, some regional varia-

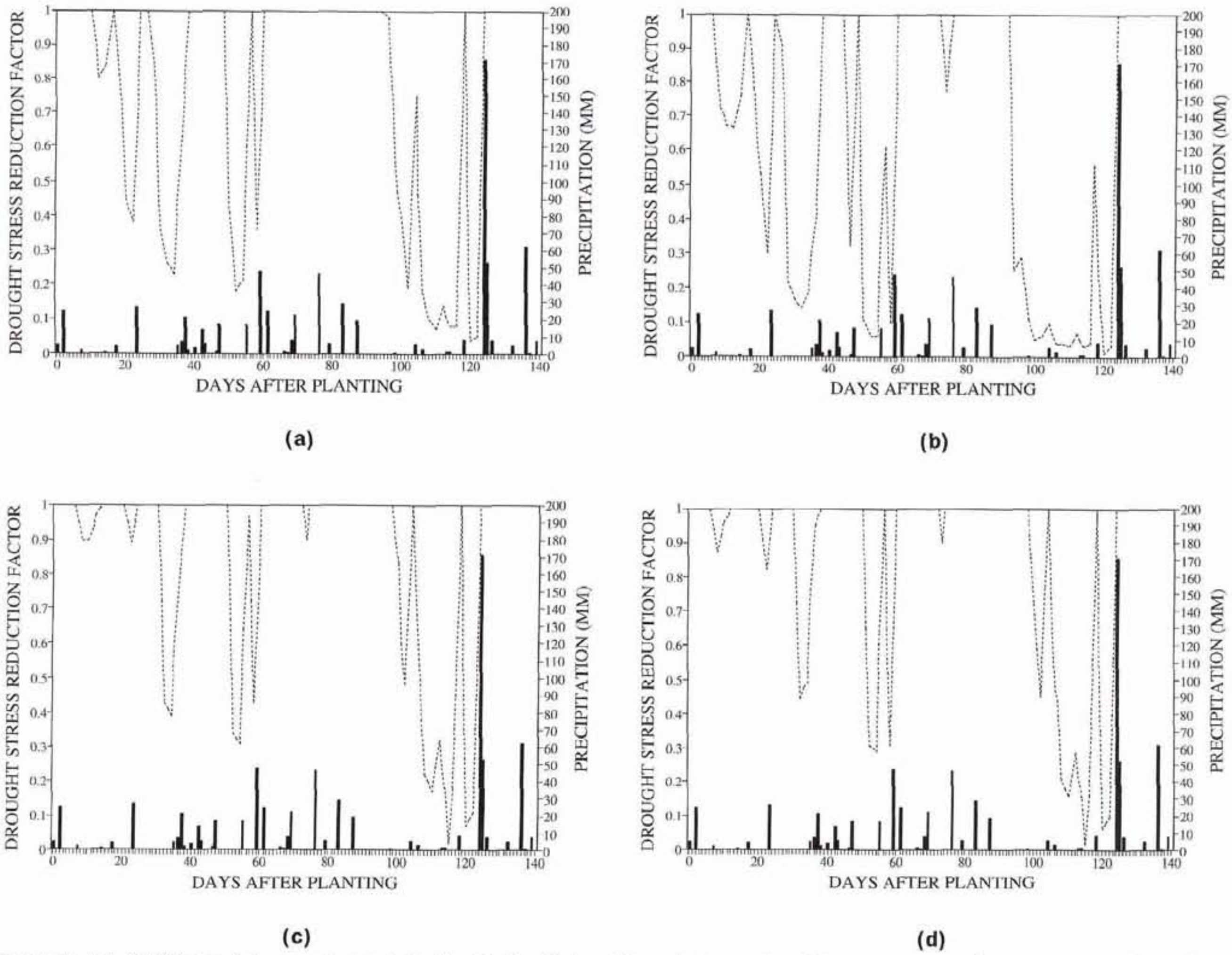

Figure 5. (a) 1990 growing season precipitation in the Eutawville polygon and moisture stress on Bonneau sand. Drought stress reduction factor values range from 1 (no stress) to 0 (complete stress) and measure the degree to which moisture deficiency reduces photosynthetic activity. (b) 1990 growing season precipitation in the Eutawville polygon and moisture stress on Coxville sandy loam. (c) 1990 growing season precipitation in the Eutawville polygon and moisture stress on Goldsboro sandy loam. (d) 1990 growing season precipitation in the Eutawville polygon and moisture stress on Noboco loamy sand.

Table 4. 1990 Simulated Yield in the Eutawville Thiessen Polygon

Soil Type	Yield (kg/ha)
Bonneau sand	1,382
Coxville sandy loam	616
Dothan loamy sand	2,076
Fuquay sand	1,499
Goldsboro sandy loam	2,073
Lynchburg fine sandy loam	2,899
Noboco loamy sand	1,980
Orangeburg loamy sand	2,947

Table 5. 1986, 1989, and 1991 Simulated Yields on Orangeburg Loamy Sand

	Yield (kg/ha)		
Location	1986	1989	1991
Bamberg	1,695	3,031	3,576
Blackville	1,145	3,061	3,693
Eutawville	2,979	3,083	3,708
Orangeburg	966	3,101	3,626
Pelion	1,756	3,150	3,653

tions. Simulated yields were highest within the two southernmost Thiessen polygons, referenced by the Bamberg and Blackville stations, because rain fell more regularly during important stages of crop growth at these two stations than at the three northern stations. The relative uniformity of yield in the Bamberg and Blackville polygons suggests that the timing of precipitation provided sufficient soil moisture to all soils. By contrast, precipitation at Orangeburg was not sufficient for producing high yields on all soils, and the greatest spatial variability of yield is found in the central portions of the county. In the western portions of the county, simulated yield values are low because of the prevalence of a particular soil type, the Fuquay sand, which has relatively low water-holding capacity. Precipitation falling at both the Pelion and Orangeburg stations was not adequate to sustain high yields on this soil.

During extremely dry years, the spatial representation of

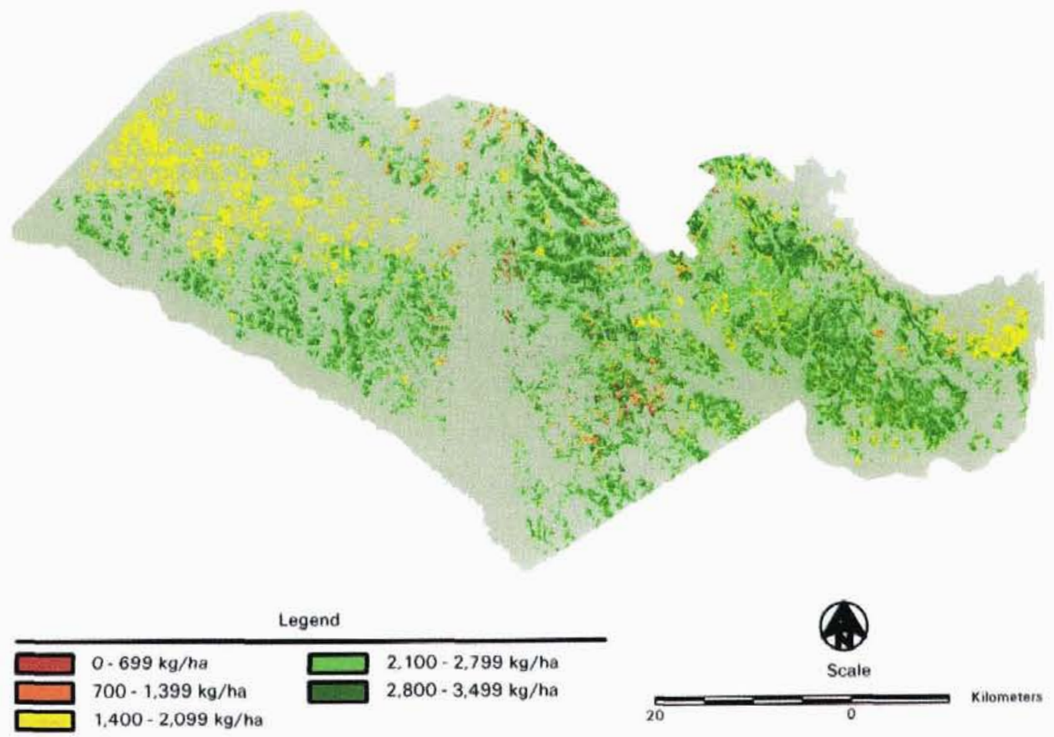

Plate 2. Spatial patterns of simulated yield during 1988 growing season.

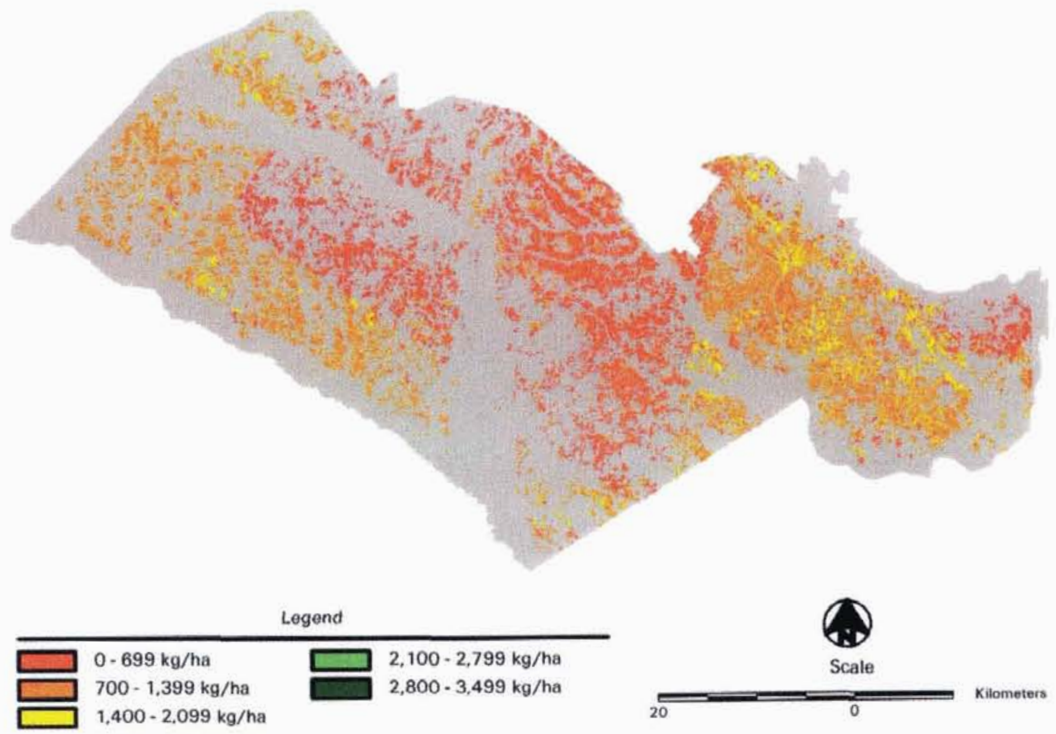

Plate 3. Spatial patterns of simulated yield during 1986 growing season.

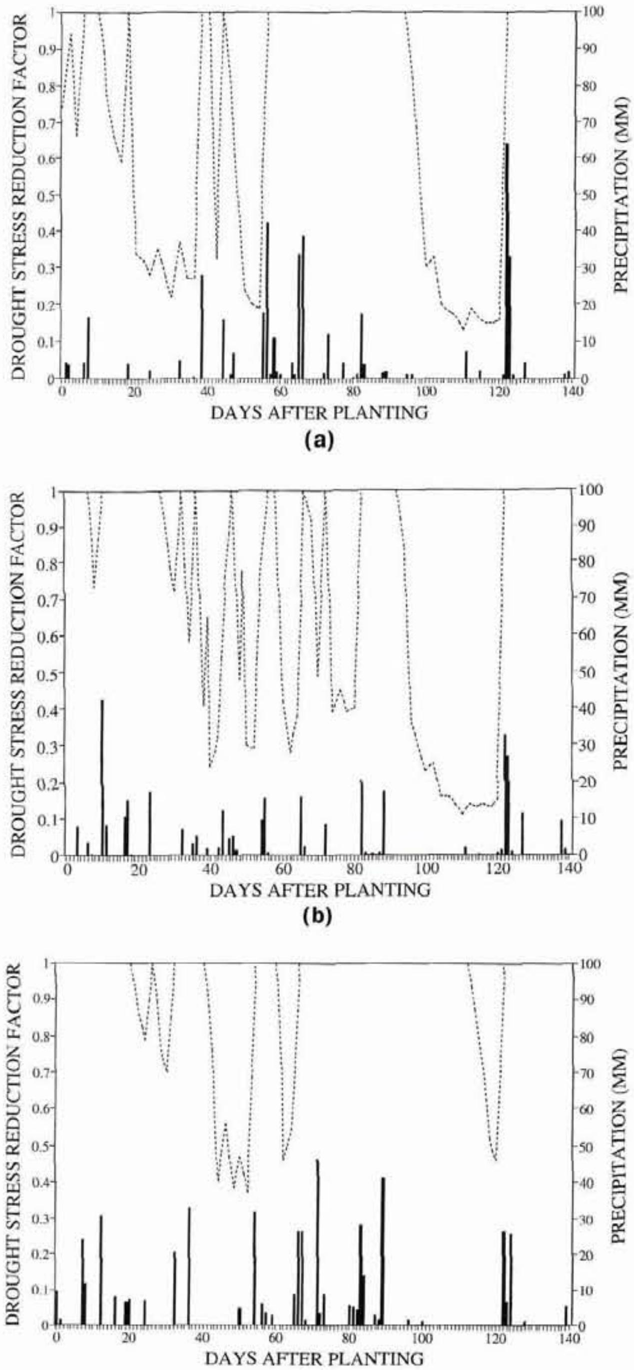

Figure 6. (a) Precipitation and drought stress during 1986 growing season, Blackville polygon, using Orangeburg loamy sand. (b) Precipitation and drought stress during 1986 growing season, Orangeburg polygon, using Orangeburg loamy sand. (c) Precipitation and drought stress during 1986 growing season, Eutawville polygon, using Orangeburg loamy sand.

yield can identify those regions most severely affected. The year-end county estimate of soybean yield during 1986 was 1,007 kg/ha, approximately 25 percent below the 5-year running mean for the period. Much of the southeastern United States experienced intense drought between December, 1985 and August, 1986, adversely affecting crops (Karl and Young, 1987). SOYGRO simulations with remote sensing and GIS data for 1986 successfully captured the impact of dry conditions on soybean yield (Plate 3). The spatial patterns of yield show that the drought was most significantly felt in the central portion of the county, as precipitation deficit was greatest at the Orangeburg station. The only large portion of the county spared by the intensity of the drought occurred in the east where slightly more regular precipitation caused higher simulated yields on the most favorable soils.

Conclusions

The study of Orangeburg County, South Carolina provides an example of the steps required to link remote sensing and GIS with physiological crop models. These procedures would be applicable to other regions within the constraints of data availability. Some of the data sets used in this study are widely available, while others are not. Meteorological data including maximum and minimum temperature and precipitation are available for all regions of the United States. The spatial density of precipitation stations is not always sufficient to capture convective precipitation that may be important to regional yield values. It is possible that the implementation of doppler radar will improve precipitation estimates over space (Klazura and Imy, 1993). Given that interpolation schemes do not adequately resolve daily precipitation surfaces, doppler radar products could provide the best means for expressing growing season precipitation at high resolution. While the network of solar radiation stations is relatively sparse, there exist reliable methods of estimating solar radiation from other meteorological parameters (Hodges *et al.*, 1985). Availability of digital soils data is more limited than meteorological data. At present, several efforts have been made to build digital soils databases for most U.S. counties, but it is an expensive and time consuming process (Reybold and TeSelle, 1989; Reed and Whistler, 1990). Finally, landcover data can be acquired at reasonable costs, but must be updated regularly in order to monitor shifting agricultural regions.

In principle, a comparison of the costs and benefits of linking remote sensing, GIS, and physiological models would be justified. The problem lies in defining and quantifying many of the intangible costs and benefits. For example, it is relatively easy to place dollar amounts to several data acquisition costs (e.g., SPOT images are presently available for $2,500/scene, and computer hardware and software required for image processing and GIS analyses while varying in price can still be quantified). However, there are intangible costs associated with applying these technologies. Examples of these include the cost of shared resources, personnel training, unexpected hardware and software failures or glitches (including "down-time"), etc.

Quantifying benefits is even more difficult. The results presented here, however, suggest that the costs involved in linking remote sensing, GIS, and physiological models are warranted. This link allows one to examine spatially complex, non-linear, interacting environmental variables and their influence on crop yield. The ability to identify spatial patterns of simulated yield encourages further examination of the physical causes of these patterns. Because these causes are seldom explained by a single variable, the ability to merge interactive variables spatially is vital. In addition, consideration of the spatial variability of model inputs should enhance research that investigates the impact of future climatic variability and change on agricultural production. Traditionally, such research has lacked any spatial detail as single, dominant soil types, and single meteorological data sets are often used to estimate regional-scale changes. The analysis presented in this study shows that simulated yield values can vary significantly over space when local data sets are used. Because climate impact studies often must deal with unpredictable future scenarios, it seems prudent to exploit data sources that are more certain. This study also shows that a soils database alone could help to improve estimates of crop yield changes by providing a more realistic range of possible changes. It is possible that regional-scale analysis could be improved through spatial data manipulation, whereby weighted averages are computed using simulation and overlays of meteorological and soils databases.

The research presented here could be expanded to include different regions and environmental conditions, longer time periods, and a variety of crops and models. Rapid growth of new technologies may improve the methodology described here. Perhaps the main constraint pertains to the derivation of areal estimates for the meteorological point data. While present interpolation schemes do not produce precipitation fields that can be used with physiological models, output from doppler radar could provide an alternative to Thiessen polygons which assume a uniform precipitation surface. The integration of remote sensing, GIS, and physiological crop models should evolve with the quality and availability of digital data bases necessary to drive the models.

Acknowledgments

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