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# A MODELING APPROACH TO QUANTIFY THE EFFECTS OF SPATIAL SOYBEAN YIELD LIMITING FACTORS

J. O. Paz, W. D. Batchelor, G. L. Tylka, R. G. Hartzler

**ABSTRACT.** *Spatial yield variability is a complex interaction of many factors, including soil properties, weather, pests, fertility, and management. Crop models are excellent tools to evaluate these complex interactions and provide insight into causes of spatial yield variability. The goal of this study was to use a soybean crop growth model to determine the contribution of three factors that cause spatial yield variability and to test several calibration and validation strategies for yield prediction. A procedure was developed to calibrate the CROPGRO–Soybean model and to compare predicted and measured soybean yields, assuming that water stress, soybean cyst nematodes (SCN), and weeds were the dominant yield-limiting factors. The procedure involved calibrating drainage properties and rooting depth over three seasons for each grid. These procedures were tested on 77 grids (0.2 ha in size) in the McGarvey field in Perry, Iowa, for 1995, 1997, and 1999. Predicted soybean yields were in good agreement ( $r^2 = 0.80$ ) with measured yield after calibrating three model parameters. The calibrated model was used to quantify the effects of three yield-limiting factors on soybean. The maximum soybean yield potential in 1997 was estimated by running the calibrated model with no water, SCN, or weed stress. The model was then run for 1997, turning each yield-limiting factor off to assess its relative impact on yield reduction. Average estimated yield loss due to the combined effects of water stress, SCN, and weeds in each grid was 842 kg ha<sup>-1</sup>. Soybean yields were significantly reduced by an average of 626 kg ha<sup>-1</sup> as a result of water stress. The presence of SCN in several grids accounted for an average yield reduction of 105 kg ha<sup>-1</sup>. The effects of weeds on soybean yield were not significant.*

**Keywords.** *CROPGRO–Soybean model, Yield-limiting factors, Spatial yield variability.*

**S**patial yield variability is a complex interaction of many factors including water stress, rooting depth, soil and drainage properties, weather, pests, fertility, and management. The challenge for farmers is to identify the factors that they can control and manage and to make appropriate management decisions to increase profits. Recent improvements in farm technology have given farmers the tools and capabilities to effectively map their fields, record yield histories, and even vary inputs/management strategies in response to variations in soil and environmental factors in the field. Research advancements in the field of precision agriculture (PA) have provided opportunities for farmers to further increase the productivity of their agricultural lands. Still, both farmers and researchers must work with the problem of significant yield variability within a field.

Process-oriented crop models such as CROPGRO–Soybean (Hoogenboom et al., 1994) were designed to study the interactions of weather, soil, management, and genetics on yields. In precision farming, crop models can be used to: (1) identify yield loss due to interacting factors, (2) evaluate consequences of management prescriptions, and (3) forecast spatial yields during the season. Recently, researchers have demonstrated the use of crop models to identify spatial yield-limiting factors for both corn and soybeans (Batchelor and Paz, 1998; Fraisse et al., 1998; Paz et al., 1998; Paz et al., 1999). Paz et al. (1998) used a modified version of the CROPGRO–Soybean model and evaluated the role of spatial water stress in causing spatial yield variability in a single field utilizing multiple years of yield data. Soil parameters related to rooting depth and hydraulic conductivity were calibrated in the model in each of 224 grids in a 16-ha field in Iowa using three years of yield data. They concluded that water stress explained 69% of the variability in yield for all grids over three years. Paz et al. (1999) implemented similar procedures to evaluate the interaction of corn population and water stress on spatial yield variability. Fraisse et al. (1998) used the approach developed by Paz et al. (1998) to examine water stress effects on corn yield variability in Missouri. Their calibration procedure involved adjusting the soil water upper and lower limits, saturated hydraulic conductivity, and root hospitality factor.

From the previous work, and from much anecdotal evidence, water stress is a dominant soybean yield-limiting factor. Very little can be done to control this problem in the non-irrigated Midwest. However, other stresses such as soybean cyst nematodes (SCN) and weeds can also create significant spatial yield variability and can be controlled

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through proper management. There has been no published effort extending crop-modeling procedures to evaluate more complex interactions among these factors and to determine their relative impact on spatial soybean yield variability.

In order for the models to be adopted by farmers and industry, an assessment needs to be made to determine the ability to predict spatial yields in independent environments. To date, all published work has focused on calibrating the models to predict within-field yield variability and evaluate yield-limiting factors. The objective of this study was to extend the use of crop models to study the effects of water stress, SCN, and weeds on soybean yield variability.

## PROCEDURES

### MODEL DESCRIPTION

The CROPGRO-Soybean crop model (Hoogenboom et al., 1994) was developed to compute growth, development, and yield on homogeneous units (either plot, field, or regional scale) and has been demonstrated to adequately simulate crop growth at a field or research plot scale. This model requires inputs including management practices (variety, row spacing, plant population, fertilizer and irrigation application dates and amounts) and environmental conditions (soil type, daily maximum and minimum temperature, rainfall, and solar radiation). From this information, daily growth of vegetative, reproductive, and root components are computed as a function of daily photosynthesis, growth stage, and water and nitrogen stress. Soil moisture and nitrogen balance models are used to compute water and nitrate levels in the soil as a function of rainfall and soil moisture holding properties. Because the model is process-oriented, it is relatively simple to couple additional processes, such as impact of pests, to daily calculation of state variables.

### YIELD-LIMITING FACTORS

Soybean cyst nematode (SCN), *Heterodera glycines* Ichinohe, is the single most damaging pest of soybeans in the United States. It is responsible for significant economic losses in soybean production throughout the United States (Wrather et al., 1997). SCN may decrease yields substantially without inducing obvious symptoms. In determining the effects of SCN, this study used the SCN damage routine proposed by Fallick (1999). The CROPGRO-Soybean model calculates photosynthesis as a function of photosynthetically active radiation (PAR). The relationship is of the form:

$$PTS_{\max} = PHT_{\max} \cdot \left( 1.0 - e^{-\left(\frac{PAR}{PAR_{\max}}\right)} \right) \quad (1)$$

where

- $PTS_{\max}$  = potential photosynthesis based on PAR
- $PHT_{\max}$  = constant defining the maximum possible photosynthetic rate
- $PAR_{\max}$  = light saturation constant.

Gross photosynthesis ( $P_g$ ) is calculated using the following equation:

$$P_g = PTS_{\max} \cdot \prod_i^N RFAC_i \quad (2)$$

where  $RFAC_i$  are a series of reduction factors ( $i$  = leaf nitrogen factor, canopy factor, leaf age factor, etc.).

Fallick (1999) used a constant damage factor that was calculated as a function of the initial population density of SCN eggs in the soil and applied to the CROPGRO-Soybean model. SCN damage was coupled to photosynthesis through RFAC.

A computer-based weed management system, WeedSOFT (Mortensen et al., 1999), was used to estimate the effects of weeds on soybean yield. Information regarding weed species and weed density rating in each cell was used as input to WeedSOFT, which then estimated the amount of yield loss. To simplify weed damage, yield loss was added after calibration and was not integrated into model runs.

### SITE DESCRIPTION

In 1996, a project was initiated to study causes of corn and soybean yield variability at three sites in Iowa. One of those sites, the McGarvey field near Perry, Iowa, was selected for this study. The field was divided into 100 grids 0.2-ha in size for studying the effects of soil and pest variability on yields.

Yield data were collected from 1994 to 1999 (1994 and 1995 data were collected by the farmer prior to the initiation of the project). Relevant crop management (e.g., plant population and fertilizer rate) and soil information were collected in 1996-1999. In addition, soybean cyst nematode (SCN) spring egg counts and weed species and density data were obtained from each grid in 1997. Weed data were collected when the soybean plants were at VE/V1 (emergence/1st leaf node) and V7/V8 (7th/8th leaf nodes) stages. This information allowed us to identify specific areas within the field where SCN and weed infestation were high and may have significantly affected soybean yield. Furthermore, information on SCN and weed population allowed us to identify causes of yield variability other than water stress.

Seven soil types were identified in the McGarvey field (fig. 1). Basic soil layer information, such as soil texture and bulk density, was obtained from the county soil survey report (Soil Conservation Service, 1981). In the absence of field-measured soil water limits, values for lower limit (LL), drained upper limit (DUL), and saturated upper limit (SAT) were determined by using a database (Ratliff et al., 1983) of soil water limits for different textural classes. Soil nutrient (nitrogen, phosphorus, and potassium) data were obtained from analysis of soil samples taken from each grid in 1997.

### METHODS TO COMPUTE YIELD-LIMITING FACTORS

For this exercise, we developed a method designed to calibrate the model for each grid across three seasons of yield data. The idea was to calibrate the model with all available seasons of data in order to obtain the best description of the interactions. The model databases were populated with soybean final yield and crop management and soil data obtained in each of the 100 grids at the McGarvey field for model calibration. However, only 77 out of 100 grids had three years (1995, 1997, and 1999) of yield data. Thus, analysis was focused only on grids that had complete sets of data. However, there is a lack of hydraulic information in the field (i.e., tile flow characteristics and water table characteristics), which is a primary factor in creating yield variability. Paz et al. (1998, 1999) demonstrated that several

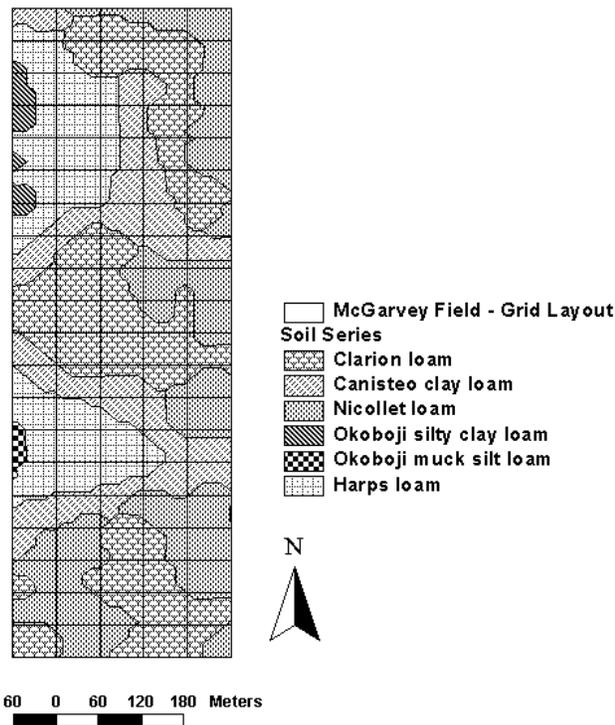


Figure 1. Map showing the dominant soil type for each grid-cell in the McGarvey field.

model parameters related to tile drainage can be estimated by minimizing error between predicted and measured yields over several seasons of data. Based on the work of Paz et al. (1998) and Shen et al. (1998a), we elected to calibrate three model parameters in each grid to minimize error in predicting yields over three seasons. Those parameters were:

- FLDS – effective tile drain spacing (m)
- KSAT – hydraulic conductivity of the bottom soil layer (cm day<sup>-1</sup>)
- RHRF – root depth and distribution (cm).

Paz et al. (1998) developed methods to adjust RHRF to fit spatial yield data. However, they ignored spatial tile flow and water table dynamics in their analysis. Shen et al. (1998b) developed methods to adjust FLDS and KSAT to fit measured cumulative tile drainage flow and soil water content data. In this exercise, we combined the results of the two previous studies to obtain a better representation of water table and rooting depth interactions. The saturated hydraulic conductivity of an impermeable layer and effective tile drain spacing were adjusted to force the soil to saturate early in the season and allow the water to slowly drain from the soil between the tile and impermeable layers. In combination, these parameters create water stress conditions by simulating a perched water table. In addition, root growth is favored or limited, corresponding to an increase or decrease in root hospitality factor.

We calibrated the CROPGRO–Soybean model by adjusting the values of three model parameters (FLDS, KSAT, and RHRF). A control program containing the simulated annealing algorithm was linked with the CROPGRO–Soybean model. Simulated annealing is a very robust algorithm (Goffe et al., 1994) and is used in solving complex combinatorial optimization problems. This study

used a simulated annealing routine as described by Corana et al. (1987) and implemented by Goffe et al. (1994). Model parameters were optimized in each of the 77 grids to minimize the sum of square error between predicted and measured yield for 1995, 1997, and 1999. The objective function established for the model simulations was written as:

$$\text{Min: } SSE = \sum_{i=1}^3 (Y_{m_i} - Y_{p_i})^2 \quad (3)$$

where *SSE* is the sum of square error between *Y<sub>m</sub>* (measured yield) and *Y<sub>p</sub>* (predicted yield), and *i* is the *i*th year. In each case, the effect of SCN population was coupled directly to the model, and the estimated yield loss due to weeds was subtracted from the predicted yield prior to computing the *SSE*.

## RESULTS AND DISCUSSION

### MODEL CALIBRATION

Calibration of the CROPGRO–Soybean model using three years of yield data resulted in high *r*<sup>2</sup> (0.80) and low root mean square error (RMSE = 346.2 kg ha<sup>-1</sup>) after adjusting three model parameters (fig. 2). This result implies that water stress, SCN, and weeds could account for approximately 80% of the variability in yield. Furthermore, this reflects an improvement in model calibration compared to a previous study (Paz et al., 1998), which found that 69% of soybean yield variability was attributed to water stress alone. Errors in soybean yield prediction for 1997 were very low (±5%) in most grids in the McGarvey field (fig. 3). Interestingly, grids that were grossly underpredicted (–20% to –30%) have poorly drained (Harps) or very poorly drained (Okoboji) soils that are predominant in depressions or potholes.

### YIELD-LIMITING FACTORS

The effects of three yield-limiting factors were then computed for 1997 using the calibrated model. Figure 4 shows a comparison of predicted and measured yield under different conditions of yield-limiting factors. The maximum potential soybean yield (+ symbol) in 1997, determined using

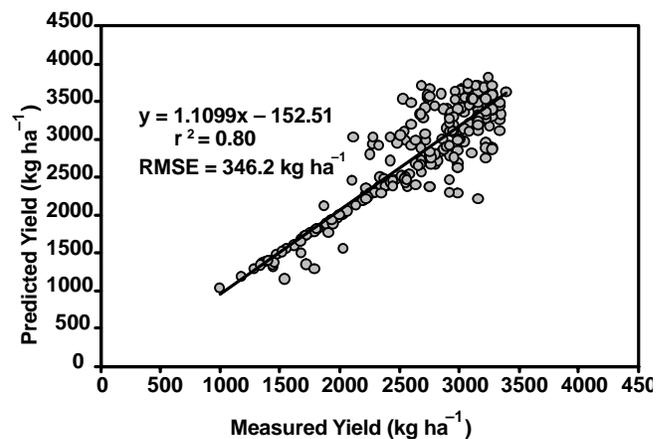


Figure 2. Comparison of measured and predicted soybean yield after calibrating three model parameters (FLDS, KSAT, RHRF) and using three years of yield data.

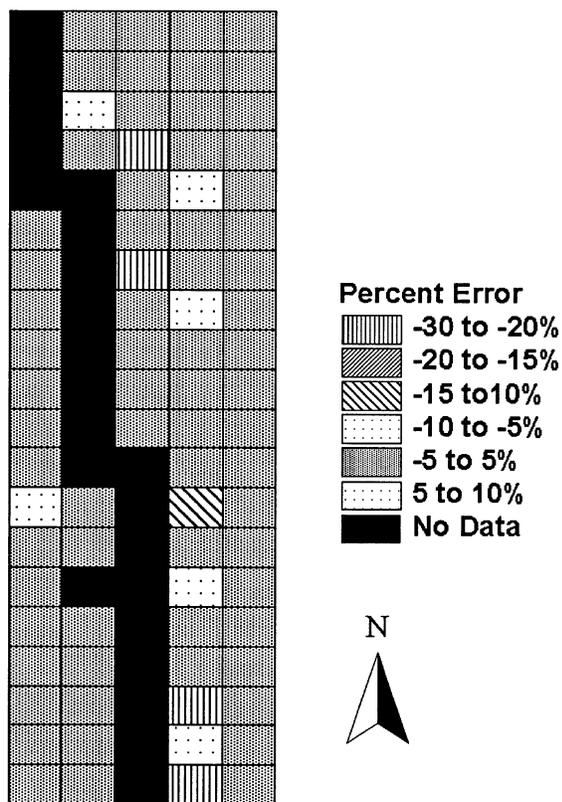


Figure 3. Error in soybean yield prediction in 1997 for McGarvey Field

the 3-parameter calibrated model, ranged from 3700 to 3800 kg ha<sup>-1</sup>. The values vary slightly from grid to grid because of differences in plant population. Predicted yields using the calibrated model for 1997 with all of the stresses

(water stress, SCN, and weeds) taken into account are indicated by the dark triangles. For a specified grid, subtracting the dark triangle value from the + value indicates the estimated yield loss due to the combined effects of water stress, SCN, and weeds.

A similar approach was taken in determining the effects of each yield-limiting factor. For example, yield reduction due to water stress in a grid was determined by subtracting the dark triangle value from the white diamond value (labeled “no water stress” in fig. 4). Average estimated yield loss (over all grids) due to the combined effects of water stress, SCN, and weeds in each 0.2-hectare grid was 842 kg ha<sup>-1</sup> (table 1). A significant number of grids had high yield reduction of greater than 1170 kg ha<sup>-1</sup> (fig. 5).

Among the yield-limiting factors examined, water stress had the greatest impact on soybean yield. Soybean yields were significantly reduced by an average 626 kg ha<sup>-1</sup> as a result of water stress condition. Eight grids had high yield losses ranging from 877 to 1461 kg ha<sup>-1</sup> (fig. 6). Grids with poorly drained (Harps) and very poorly drained (Okoboji) soils tended to have higher yield loss due to water stress.

In 1997, the presence of SCN in several grids accounted for an average yield reduction of 105 kg ha<sup>-1</sup>. Yield loss due to SCN ranged from 30 to 410 kg ha<sup>-1</sup> (fig. 7). Weeds did not have any significant adverse effect on soybean yield (table 1), primarily because of effective weed control. This outcome does not, however, rule out the possibility of weeds having a significant effect in any other production year.

## CONCLUSIONS AND RECOMMENDATIONS

Three factors affecting soybean yield variability, namely water stress, soybean cyst nematode (SCN), and weeds, were

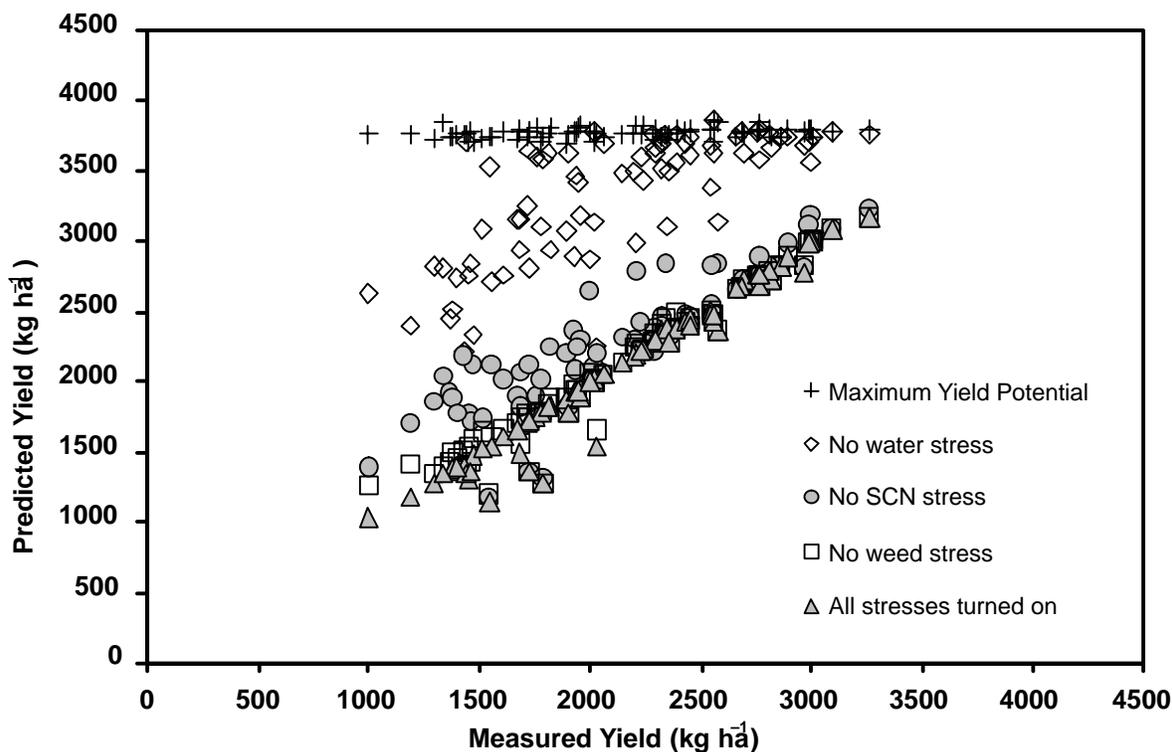
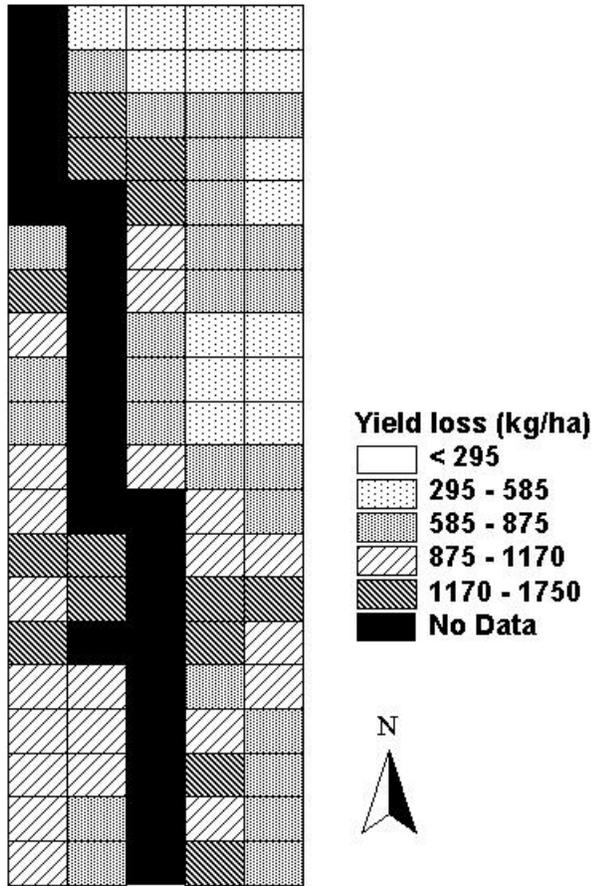


Figure 4. Maximum potential soybean yield in 1997 and variations in predicted soybean yield as affected by SCN, weeds, and water stress.

**Table 1. Average estimated soybean yield loss in 1997 due to the effects of water stress, SCN, and weeds.**

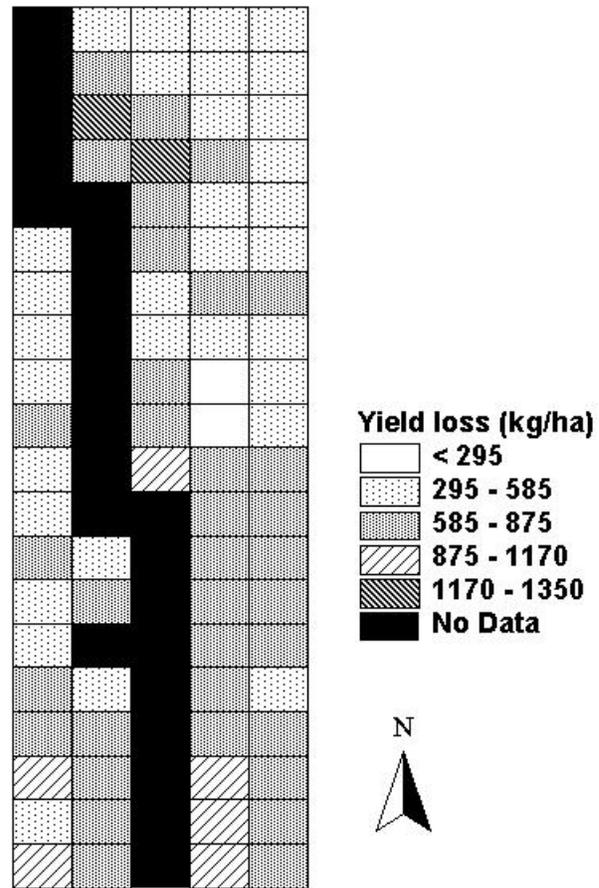
Yield reduction factors	Yield loss (kg ha <sup>-1</sup> )
Water stress	626
Soybean cyst nematode (SCN)	105
Weeds	18
Water stress + SCN + weeds	842



**Figure 5. Grid distribution of estimated yield loss in 1997 due to the combined effects of SCN, weeds, and water stress.**

examined in a central Iowa soybean field using the CROPGRO–Soybean model. We calibrated three parameters (FLDS, KSAT, and RHRF) that affect water stress and incorporated the other two yield variability factors (SCN and weeds). Calibration of three model parameters (FLDS, KSAT, and RHRF) using three years of data had better  $r^2$ .

Among the yield variability factors that were examined in this study, water stress clearly had a big impact on yield production. However, we cannot discount the effect of other factors, such as SCN and weeds. Information on SCN and weed population allowed us to identify causes of yield variability other than water stress and the degree to which these factors may have affected model prediction. The technique presented in this study shows the value of using a crop growth model in quantifying the individual as well as combined effects of yield variability factors. There is a need, however, to further test the model using another year of data and to examine the performance of the model at other sites.



**Figure 6. Estimated yield loss in each grid due to water stress in 1997.**

A bigger challenge is how to use a crop growth model to develop grid-level management prescriptions, and analyze the economic impact of such prescriptions.

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#### REFERENCES

- Batchelor, W. D., and J. O. Paz. 1998. Process-oriented crop growth models as a tool to evaluate spatial yield variability. In *Proc. First Int. Conf. on Geospatial Information in Agric. and Forestry*, Vol 1: 198–205. Ann Arbor, Mich.: ERIM International.
- Corana, A., M. Marchesi, C. Martini, and S. Ridella. 1987. Minimizing multimodal functions of continuous variables with the simulated annealing algorithm. *ACM Trans. on Mathematical Software* 13(3): 262–280.
- Fallick, J. B. 1999. Simulating soybean cyst nematode (*Heterodera glycines*) damage using the CROPGRO–Soybean crop growth model. MS thesis. Ames, Iowa: Iowa State University.
- Fraisse, C. W., K. A. Sudduth, and N. R. Kitchen. 1998. Evaluation of crop models to simulate site-specific crop development and

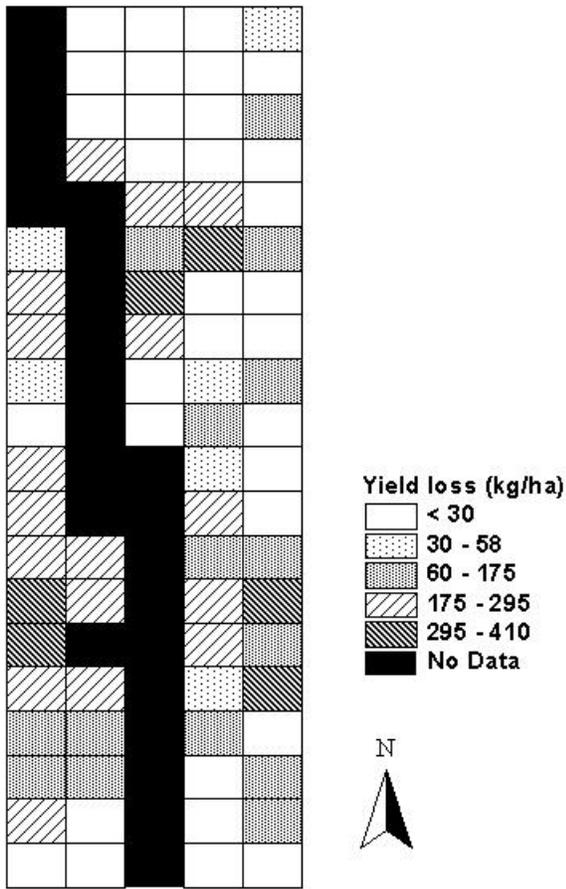


Figure 7. Estimated yield loss in each grid due to soybean cyst nematode (SCN) in 1997.

yield. In *Proc. Fourth Int. Conf. on Precision Agric.*, 1297–1308. Madison, Wisc.: ASA–CSSA–SSSA.

Goffe, W. L., G. D. Ferrier, and J. Rogers. 1994. Global optimization of statistical functions with simulated annealing. *J. Econometrics* 60(1): 65–99.

Hoogenboom, G. J., J. W. Jones, P. W. Wilkens, W. D. Batchelor, W. T. Bowen, L. A. Hunt, N. Pickering, U. Singh, D. C. Godwin, B. Baer, K. J. Boote, J. T. Ritchie, J. W. White. 1994. Crop models. In *DSSAT v3*, Vol. 2–2: 95–244. G. Y. Tsuji, G. Uehara, and S. Balas, eds. Honolulu, Hawaii: University of Hawaii.

Mortensen, D. A., A. R. Martin, F. W. Roeth, T. E. Harvill, R. W. Klein, M. Milner, G. A. Wicks, R. G. Wilson, D. L. Holshouser, D. J. Lyon, P. J. Shea, and J. T. Rawlinson. 1999. *WeedSOFT User's Manual*. Version 4. Lincoln, Neb: University of Nebraska, Department of Agronomy.

Paz, J. O., W. D. Batchelor, T. S. Colvin, S. D. Logsdon, T. C. Kaspar, and D. L. Karlen. 1998. Analysis of water stress effects causing spatial yield variability. *Trans. ASAE* 41(5): 1527–1534.

Paz, J. O., W. D. Batchelor, B. A. Babcock, T. S. Colvin, S. D. Logsdon, T. C. Kaspar, and D. L. Karlen. 1999. Model-based technique to determine variable rate nitrogen for corn. *Agric. Systems* 61(1): 69–75.

Ratliff, L. F., J. T. Ritchie, and D. K. Cassel. 1983. Field-measured limits of soil water availability as related to laboratory-measured properties. *SSSA J.* 47(4): 770–775.

Shen, J., W. D. Batchelor, R. Kanwar, J. T. Ritchie, and J. W. Jones. 1998a. Validation of the water balance model in CROPGRO–Soybean. *Trans. ASAE* 41(5): 1305–1313.

Shen, J., W. D. Batchelor, and R. S. Kanwar. 1998b. Prediction of spatial soil water balance in a soybean field. ASAE Paper No. 98–1109. St. Joseph, Mich.: ASAE.

Soil Conservation Service. 1981. Soil survey of Boone County, Iowa.

Wrather, J. A., T. R. Anderson, D. M. Arsyad, J. Gai, L. D. Ploper, H. H. Ram, and J. T. Yorinori. 1997. Soybean disease loss estimates for the top 10 soybean producing countries in 1994. *Plant Disease* 81: 107–110.