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in Field Research and Technology Transfer

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CHAPTER 12

Addressing Spatial Variability in Crop Model Applications

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INTRODUCTION

The topic of this chapter, addressing spatial variability in crop model applications, comes from the logical combination of two trends in agricultural research. The first trend dates to the 1950s when Monsi and Saeki (1953) published the first known application of physical models to explain processes important to agricultural production. During the succeeding years, many models have been developed for research purposes, including those discussed later in this chapter. The second trend is the more-recent development of site-specific or precision agriculture, the formal start of which is often attributed to the granting of a patent for a device to apply dry granular fertilizer on a site-specific basis (Ortlip, 1986), followed soon by the development of combine-mounted yield monitors (Vansichen and De Baerdemaeker, 1991).

The ability to custom-apply fertilizer immediately generated the need for site-specific fertilizer recommendations, and the yield variation observed in yield maps immediately suggested a need for explanations of causes of variation. For both theoretical and empirical reasons, however, traditional statistical methods are not well-suited to address spatial problems. Seeking new tools to meet both these needs, researchers logically embraced process-oriented crop models, although for reasons discussed below, applying existing models proved not to be a simple task. Handling spatial variability in models, which were usually one-dimensional (1-D) in the vertical soil profile direction, embodied accounting for two additional horizontal dimensions. This added at least an order of magnitude greater complexity than simply increasing the resolution in the vertical dimension.

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The remainder of this chapter describes the current state of the art in applying models to site-specific agricultural problems, using three approaches. The first is an extension of conventional methods, the second applies remote sensing tools to provide input data, and the third employs inverse modeling to generate spatially distributed inputs that produce the best description of the spatially distributed yield. Before starting on the spatial modeling, a discussion of temporal variability and how it is handled in dynamic models is useful.

During development, a model's structure depends upon the modeler's compromises between the objective and what knowledge can be encoded into the model. In simple terms, these are what can be predicted and what can be described. Although lack of suitable input data can constrain the choices, for the most part, the objective defines the time basis for the prediction. For example, predicting canopy temperature during cloud passage requires a time basis ranging from seconds to minutes, while predicting organic matter contents under decades or centuries of conservation tillage may require a time basis ranging from months to years. Common examples of several varying temporal scales include the Root Zone Water Quality Model (RZWQM, Ahuja et al., 2000) at sub-hourly time steps (for hydrology), the CERES (Jones and Kiniry, 1986) and CROPGRO models (Hoogenboom et al. 1994; Boote et al., 1998a) at daily time steps, and the CENTURY model (Parton et al., 1992) at monthly time steps. The remainder of this chapter discusses daily time step models, often using the CERES-Maize or CROPGRO-Soybean models as examples.

If one concludes that increasing the temporal resolution of a model requires a smaller time step, then it is possible that this will eventually require alterations in the model structure. This happens if empirical approximations break down under a smaller time step. For instance, a daily time step model cannot, by definition, handle diurnal patterns except by using approximations based on daily averages, ranges, or other statistical descriptions. In most such cases, the empirical approximation must be replaced by a module somewhat more mechanistic in nature to describe the time-sensitive processes at the smaller time step.

Often, temporal and spatial problems, and the programming solutions to them, are linked. In the case of the soil water balance, many models, including the DSSAT suite, currently use the SCS Curve Number method (USDA-SCS, 1972) to compute runoff and infiltration, which is desirable because the temporal scale is daily, corresponding to widely available daily total rainfall data. In order to adequately simulate runoff and redistribution within a field in a two- or three-dimensional (2-D or 3-D) soil water balance model, more accurate predictions of runoff and surface flow are needed. Better methods are available, but require shorter time steps and intra-day (or even sub-hour) rainfall data. As described in the next section, this topic poses yet another challenge to spatial modeling.

SPATIAL MODELING

Prior to widespread use of spatial tools, models were (usually)

1. Dynamic, meaning they accounted for temporal variability
2. One-dimensional in the vertical soil profile dimension
3. Sensitive to large differences in cultivars, soils, and weather
4. Validated with plot averages

To apply to spatially variable applications, however, they must retain their dynamic nature, as well as:

1. Add two horizontal dimensions.
2. Account for subtle differences in, primarily, soils, with secondary differences in weather.
3. Predict the variance as well as the mean.

These additional requirements deserve considerable thought. Within a field, the soil texture and chemical component (nutrients, salinity, etc.) variation might be significant, but certainly less so than differences across states, countries, or continents. Weather variability is very much reduced (and in some models, not a spatial input at all at the field scale, despite many meteorological parameters being known to have significant spatial variation), and cultivar characteristics are usually constant across a field. Despite the apparent reduction in these known sources of variation, the yield variability within a single field can be as large or larger than the yield variability measured between fields or counties within a state. Even though the soil types may not vary as much within a field as from field to field or county to county, there is still tremendous variability within the field that these models must address. Furthermore, if these models are to be reliable for evaluating variable rate decisions within a field, they must not only be able to provide good predictions of mean yield, but also of within-field variation in yield, as a response to highly spatially variable factors that affect yield. Mathematically stated, to use the results in an optimization algorithm, not only must the mean be predicted well, but also the partial differential with respect to all the important inputs. These criteria for success are severely stringent.

For a model to be successful, all important variations must be reflected in the model processes and associated variables established as model inputs. For some situations where mixed results have been obtained, variations in the observed data may not have been reflected in either one or both of the model's processes or of the model's inputs. For instance, if a model predicts phenology as a function of air temperature collected at a weather station several kilometers away, it is not likely that the observed spatial variation in canopy temperature, and hence energy balance and associated processes, will be modeled correctly within the field. Another example comes from the use of plot averages during model validation — observed high-yield spots within a field have been observed to exceed the model-allowed limit for harvest index, which had been chosen based on plot averages (Paz et al., 2001). These are clearly cases where simply adding finer-scale input data will not guarantee success. On the other hand, if a model were to have sufficient detail, but require correspondingly higher resolution of spatial soils data, then increasing the resolution of inputs might be productive, but it will almost certainly be expensive. The increase in expense can be easily proven — doubling the spatial resolution of a measurement means that the number of samples is doubled in both directions, with four times the cost for sampling.

One can speculate on what model processes and inputs would be necessary to fully characterize spatial yield variation in typical cropped fields, but both the availability of data and knowledge of the basic processes are usually quite severely limited (e.g., Robert, 1996). For instance, high-resolution spatial and temporal variation in soil physical and chemical properties would be prohibitively expensive to characterize. Some progress has been made in using terrain analysis and hydrologic modeling to predict within-field redistribution of runoff (e.g., Simmons et al., 1989; Moore et al., 1993; Kaspar et al., 2001), although transient effects of spatially variable evapotranspiration on soil water content and the several feedbacks into crop water stress, future infiltration, and eventual crop yield appear to be significant (Sadler et al., 2000a). Beyond these effects within the framework of the isolated monoculture are an entire litany of "external" factors including weeds, insects, nematodes, diseases, and other landscape-level ecological factors that so far have not been integrated completely into many crop models.

In our collective experiences, we have modeled spatially variable crop growth using three general approaches. The first approach is essentially a brute force method, acquiring inputs and running the model conventionally at multiple points in space (e.g., Sadler et al., 1998, 1999, 2000b). A second approach (e.g., Barnes et al., 1997, 2000; Jones and Barnes, 2000) used remote sensing to either augment inputs or test outputs and change state variables iteratively. The third approach (e.g., Irmak et al. 2001; Paz et al., 2001) employed objective parameterization, using optimization routines or database searches, to solve for spatially variable inputs that minimize errors between simulated and measured yield across seasons. In all three cases, the models used were 1-D models repeated in space rather than fully 3-D models of crop growth and yield. These latter, although desired, are not yet available.

Conventional Method

The conventional method approach was designed simply to acquire input data at more points than in an otherwise traditional way, either on grids or in management zones, and then to run the model conventionally at each point. The state of this art in 1995 was catalogued by Sadler and Russell (1997), who described approximately 20 such efforts, including AEGIS (Papajorgji et al., 1993; Engel et al., 1995) and other model-running shell programs (e.g., Han et al., 1995). Depending on the circumstances and how far removed the simulation was from typical conditions, these efforts suggested two things. First, success was mixed. Some of the work provided acceptable results, but other results were disappointing (see Sadler and Russell, 1997; Sadler et al., 1998, 1999, 2000b). Second, acquiring the extensive input data encouraged the search for more efficient procedures.

The usual procedure has been to obtain input values for soil parameters from soil surveys and typical pedon descriptions at the county level (~1:24000) or from similar techniques employed at a fine scale (~1:1200 – 1:5000). These have been supplemented occasionally with physical property measurements for profiles on transects and grids. In nearly every case, however, there existed additional variations not captured in the soil data collected (e.g., Sadler et al., 1998, 1999, 2000b). Despite the amount of data employed, it did not appear to be sufficient. Increasing the resolution using standard survey techniques appeared to be neither feasible nor productive, because even the finer scale approaches have not met with unambiguous success. Making the extensive measurements deemed necessary has been attempted at considerable effort in research settings, but it is not generally considered economically feasible in production settings.

The foregoing has dealt with traditional data that has had location added to it. There exists a data type that is acquired literally *en masse* (such as via photography), or practically so (such as with a scanning sensor in remote sensing or an on-the-go yield monitor). One characteristic that distinguishes such data from the traditional data mentioned above is that where the above is usually data-starved, these inherently spatial data sets are data-rich. This distinction allows several additional uses, some of which are worthwhile either in isolation or as a contribution to other spatial modeling efforts.

Spatial sensors were cited as one of the primary research needs to help solve the lack-of-data problem at several of the early Precision Agriculture Conferences (Schueller, 1993; Robert, 1996), and this may still be the primary bottleneck. Where such data have been obtained, they have been applied in modeling applications in one of three general ways. The first use has usually been to define areas where variation occurs in soil properties and crop development, illustrating areas that need to be managed or, in this context, modeled separately. Where one is fortunate enough to have spatial data for outputs of models, using them for validation of models is quite valuable. Where the observations are intermediate or state variables in models, in-season adjustments can improve the performance of models under certain conditions. Where the observations correspond to model inputs, these can be considered traditional data collected much more efficiently in space. Examples of such data include depth to clay layer, organic matter, plant population, and topography and terrain attributes (see review by Sudduth et al., 1997). One particular type of such data is the basis of the second approach for modeling spatial variation.

Remote Sensing Methods

The particular example of inherently spatially variable data is by remotely sensed (RS) observations, usually corresponding to intermediate variables. One of the most commonly cited uses of RS to provide a linkage with crop models has been to estimate leaf area index (LAI; Weigand et al., 1979). One method is to relate LAI and RS data with a radiative transfer model (RTM; e.g., Asner and Wessman, 1997) used in either direction. An RTM can be used to calculate LAI based on the radiometric characteristics of the field for comparison to the model, or the LAI output from the model can be used to calculate the scene reflectance for direct comparison to the RS data (Guérif and Duke, 2000). An advantage of this method is that it is not extremely dependent on site-specific relationships between the crop and RS data. A disadvantage is that the input data requirements for some RTM models are themselves quite severe. A second method is to use a locally determined, empirical relationship between the RS data and variable of interest (e.g., a simple linear regression with LAI as the independent variable and vegetation index, as in Jones and Barnes, 2000). Other crop parameters that have been estimated from RS data and incorporated into crop models include crop water status (Barnes et al., 2000), evapotranspiration rates (Moran et al., 1995), and canopy chlorophyll content (Weiss et al., 2001).

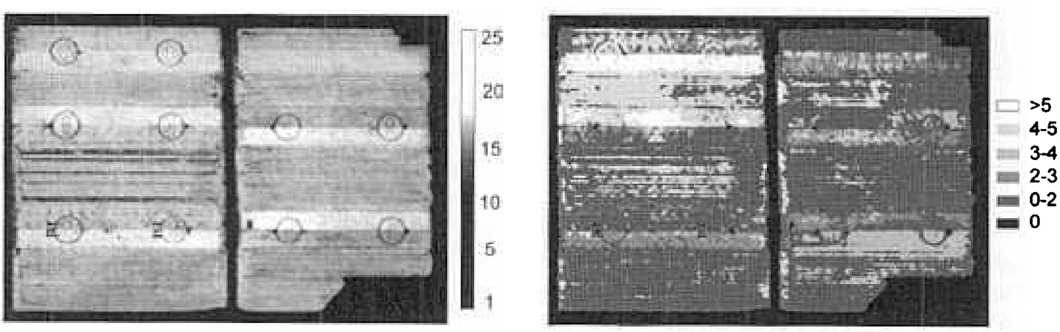
Exactly how the link is made between RS data and a model has varied according to the objectives of the researchers involved, but can be grouped by method. In a review on the topic, Moulin et al. (1998) placed methods to integrate RS data and models into four categories:

1. Inputting a variable estimated from RS data
2. Updating a state variable in a model from an RS estimate
3. Adjusting model's initial conditions
4. Calibrating parameters to produce better agreement between RS estimates and model predictions during the season

A fifth category uses remotely sensed data to identify areas where crop development is significantly different from surrounding areas and, thus, requires independent simulation (Jones and Barnes, 2000).

For category 1, it is theoretically possible to build a model that accepts the state variable as an input rather than as a computation from other inputs. This requires that a sufficiently intensive time series of spatial data could be obtained for a state variable. There are no known practical examples of such an application using remotely sensed data directly at daily time steps; however, estimates of state variables have been interpolated between image acquisitions to derive daily values to drive a model (examples cited in Moulin et al., 1998).

An example of updating a state variable (category 2) in CERES-Wheat is taken from Barnes et al. (1997), who modified the LAI predicted by the model based on remotely sensed estimates. LAI was replaced by a RS estimate when an estimated LAI was available for a particular day and the model's predicted LAI was outside of a predefined tolerance from the RS estimate. If the prediction was outside of the tolerance, the model's predicted LAI was set to the RS estimate by adjusting the model's prediction of accumulated green leaf area and leaf weight to match the RS estimate. The simulation then would continue until the next RS observation or end of the simulation. This approach is illustrated in Figure 12.1a, which shows a ratio vegetation index (RVI = ratio of



a) Ratio vegetation index images (RVI)

b) LAI classification map

Figure 12.1 Maps of a wheat field derived from March 31, 1966, image data (a) RVI and (b) LAI classification.

Table 12.1 Predicted and Observed[a] Wheat Yields Corresponding to the LAI Classes of Figure 12.1b

LAI Class in Figure 12.1b	Yield ($kg\ ha^{-1}$) Observed	Yield ($kg\ ha^{-1}$) Predicted	% Difference
>5	8000	7454	
4–5	7500	7417	
3–4	7000	7366	
2–3	6500	7008	
0–2	5700	6045	

[a] Observed is the approximate yield determined for the various treatments during the 1995–1996 experiment, which has been assigned to an LAI class based on the LAI of that treatment during the time the image was acquired.

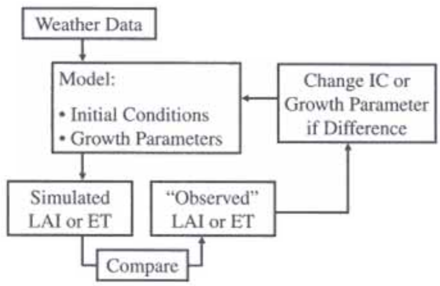


Figure 12.2 Schematic of approach developed by Maas. (*Agron. J.*, 85:354-358, 1993.)

near-infrared to red reflectance) image acquired from an aircraft on March 31, 1996, near the time of anthesis. In the image, the bands of increased RVI running left to right correspond to a high nitrogen treatment. The circles apparent in the image were from pipes that were used to inject carbon dioxide (see Kimball et al., 1999, for a description of the experiment). CERES-Wheat was used to simulate the field conditions, assuming adequate nitrogen and water were present. On the date the image was acquired, the LAI classes from the RVI image (Figure 12.1b) were input to the model and then the simulation was resumed, still assuming adequate nitrogen and water. Reasonable yield predictions were obtained with this particular image, because it was near the time of anthesis (see Table 12.1); however, this approach is subject to several limitations. Accuracy decreased for LAI modifications more than ~10 days before or after anthesis. This method also did not work as well if the "base" model run was underpredicting LAI (i.e., it was easier to lower the model's predictions than to raise them). Difficulties obtaining near-real-time data limit the application of this particular technique for real-time farm management, and the need for data near the time of anthesis significantly limits the amount of corrective action available to a farm manager.

An example that uses a combination of categories 3 and 4 is the approach used by Maas (1988, 1993) to calibrate model parameters initially based on LAI. This approach was later expanded by Moran et al. (1995) to consider RS estimates of evapotranspiration (ET). A flow diagram of their approach is illustrated in Figure 12.2. The model's initial condition of water content and field capacity were adjusted based on the difference between RS-estimated and model-predicted ET. To match RS estimates of LAI, leaf span or biomass partitioning was changed through adjustments of the model's calibration parameters. The approach provided accurate simulation for growth and yield of grain sorghum, corn, spring wheat (Maas, 1993) and alfalfa (Moran et al., 1995).

Objective Parameterization Methods

The third approach described in this chapter uses an inversion of modeling, which was developed more recently, and which, because of the complexity of the method, requires somewhat more explanation than the prior two approaches. It uses the relationships embodied in models to simultaneously derive the spatial array of input values that produces the best match to the observed data. The impetus to this work is that specific values for some critical spatial model inputs, especially soil properties and rooting depth, are not available at the desired spatial resolution within a field to adequately predict yield variability. Often, these properties are available only at the soil type scale, estimated years ago using techniques that provide typical ranges of values within the soil type. Using values estimated or measured at this larger resolution introduces unacceptable error for precision farming applications.

To refine the spatial estimates of the selected critical inputs, this approach uses the model with a range of the chosen critical inputs to predict yield or some other factor of interest, such as temporal soil water content, and minimizes the error between the set of predicted and measured values. The idea is that, if these critical parameters are estimated correctly, the model should perform well across seasons (temporally). Typically, this approach is applied to small homogeneous areas within a field, and the analysis is conducted independently for each area.

This method, objective parameterization, has been approached in two ways. Both require an objective function be defined, usually to minimize error between simulated and measured yield. One method links a classical optimization algorithm, such as Simulated Annealing (Goffe et al., 1994) or the AMOEBA method (Nelder and Mead, 1965; Press et al., 1992), to the model. Then, the optimizer runs the model multiple times while incrementally varying the chosen critical inputs within a reasonable range, and searches for the values of the input parameters that satisfy this objective function. The second approach constructs a database by running the model with the selected spatial inputs varied in a linear fashion over the expected range of variation and searching the database for combinations of inputs that minimize error according to the objective function.

The result from both approaches is a field of spatial inputs calibrated, or fine-tuned, to improve model performance. The key to success for both is to correctly identify a limited number of key spatial inputs that are uncertain, and calibrate those inputs within a realistic range. All other important inputs must be known with reasonable certainty.

The first example of objective parameterization is outlined in Paz et al.(2001). The goal of this work was to use the CROPGRO-Soybean model (Hoogenboom et al., 1994; Boote et al., 1998b) to determine causes of spatial soybean yield variability and to estimate the impact of different yield-limiting factors on yield variability for a field in Central Iowa. In this example, they identified water stress, soybean cyst nematodes (SCN), and weeds as the major yield-limiting factors. They built on previous work with modifications of the model to account for SCN damage (Fallick et al., 2001), incorporated the effects of tile drainage and nutrient movement (Shen et al., 1998), and then added the effects of weed damage using a separate model. They divided the 50-ha field into 77 grids and developed the appropriate model inputs for each grid for three seasons. Next, they linked the simulated annealing algorithm (Goffe et al., 1994) to the model for parameter estimation. Finally, they solved for the values of tile spacing, saturated hydraulic conductivity of the impermeable layer, and root depth distribution using the simulated annealing process. They were able to explain approximately 80% of the spatial yield variability over the 3-year period (Figure 12.3) caused by water stress, weeds, and SCN.

Once calibration was completed, the model could be used to study the relative effects of the different yield-limiting factors. They used the calibrated parameters in the model to calculate the yield loss caused by SCN, weeds, and water stress for one year. Figure 12.4 shows the predicted yield potential for each grid when all stresses were turned off. Each data point represents the

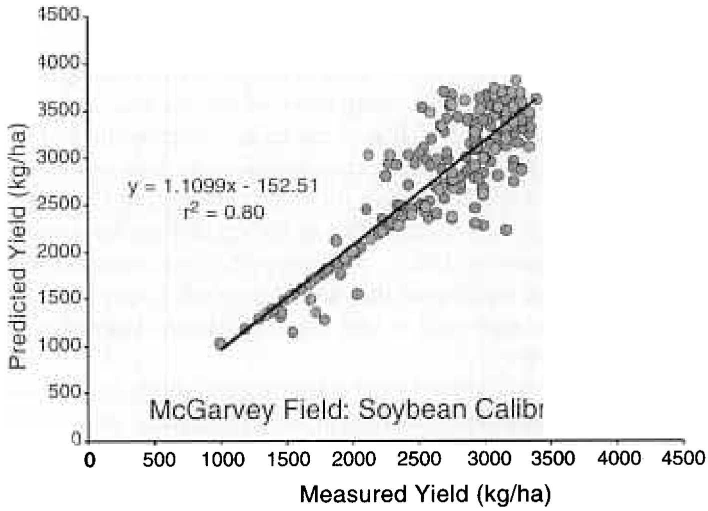


Figure 12.3 Predicted vs. measured yield calibrated for 3 seasons for the McGarvey field near Perry, Iowa. (Paz et al. 2001. A modeling approach to quantify the effeds of spatial soybean yield-limiting factors. *Trans. of the ASAE* 44(5):1329–1334. With permission.)

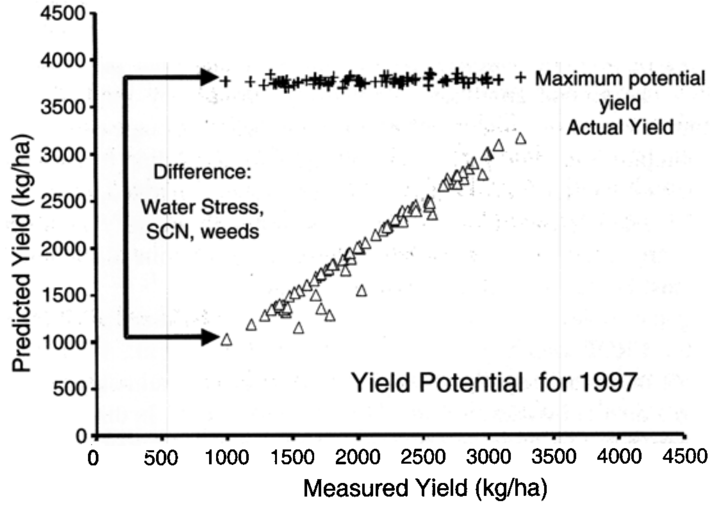


Figure 12.4 Example for effect attributed to water stress, weeds, and soybean cyst nematode, using 1997 yield data. (Paz et al. 2001. A modeling approach to quantify the effeds of spatial soybean yield-limiting factors. *Trans. of the ASAE* 44(5):1329–1334. With permission.)

predicted yield potential for a grid. The yield potential differs in each grid because of differences in measured soybean plant population for this season. A sequence of model runs was made by turning off each stress individually to predict the yield reduction due to water stress, SCN, and weeds in each individual grid. Table 12.2 shows a summary of the results when averaged over all grids. Water stress caused approximately 709 kg ha^{-1} in yield loss averaged over all grids. Some grids had large yield reductions due to water stress, while other grids experienced small yield reductions. Similarly, SCN and weeds caused average yield reductions of 119 and 20 kg ha^{-1}, respectively. The interaction among the three yield-limiting factors caused an additional 93 kg ha^{-1} of yield loss over the field.

Table 12.2 Predicted Yield Loss Due to Water Stress, Soybean Cyst Nematodes and Weeds for the Mcgarvey Field in 1997

Stress	Yield Loss (kg ha^{-1})
Water stress	709
SCN	119
Weeds	20
Interactions	93
All stresses	941

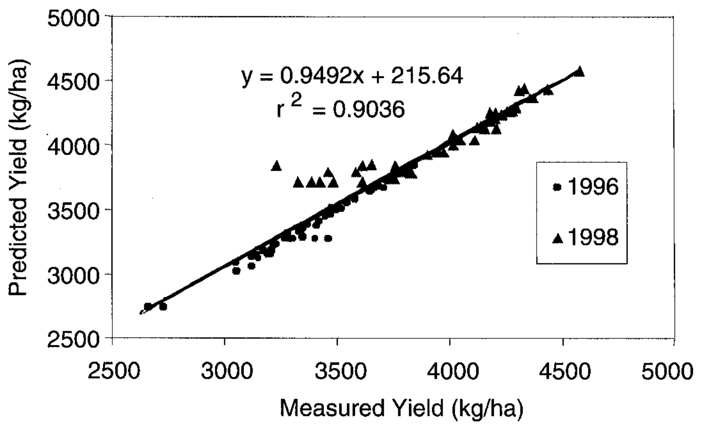


Figure 12.5 Results of case 4 scenario. (Irmak et al., 2001, Estimating spatially variable soil properties for application of crop models in precision agriculture, *Trans. of the ASAE* 44(5):1343–1353. With permission.)

The second example used the database search method outlined by Irmak et al. (2001). The goal of this work was to use the CROPGRO-Soybean model to determine causes of yield variability in a 30-ha field in eastern Iowa. Similar to the previous method, they divided the field into 48 grids, and developed the appropriate crop model input files for each grid for a 2-year period. Upon analyzing the data, they concluded that water stress and soil fertility were the likely causes of yield variability. Thus, their focus was to calibrate several uncertain model inputs dealing with the soil water balance and soil fertility for each grid. They used the same modified version of the CROPGRO-Soybean model used by Paz et al.(2001), adapted for tile drainage conditions found in the Midwest. They ran the model for all possible combinations of saturated hydraulic conductivity of the impermeable layer, a soil productivity factor that reduces yield based on soil fertility and other unknown factors (Paz et al., 2001), maximum rooting depth, tile spacing, and SCS runoff curve number, all within accepted ranges of values for each parameter. They conducted this analysis for each of the 48 grids and two seasons of data, totaling nearly 75,000 model runs. Each combination of model parameters and corresponding predicted yield was entered into a large database. An objective function was developed and the database was searched to determine the combination of parameters that minimized the error between predicted and measured yields in each grid over the 2-year period. The database search procedure took about half the time required by the simulated annealing approach.

Figure 12.5 shows the predicted and measured yield for the five-parameter calibration for 1996 and 1998. Each data point represents yield in a single grid. Using this approach, they were able to explain more than 90% of the yield variability within the field. Figure 12.6 shows the spatial pattern

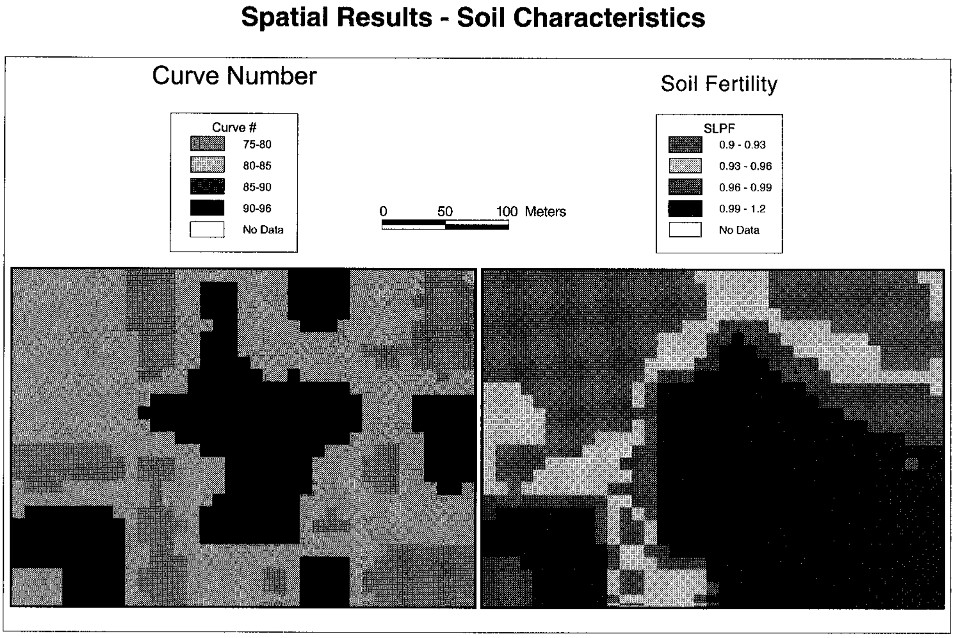


Figure 12.6 Example of spatial inputs from the database search routine. (Irmak et al., 2001, Estimating spatially variable soil properties for application of crop models in precision agriculture, *Trans. of the ASAE* 44(5):1343–1353.

for the SCS curve number and soil fertility factor produced by this technique. The model estimates of these five parameters consisted of a realistic spatial structure, further adding credibility to this approach.

CONCLUSIONS

Several conclusions can be drawn from the foregoing. First, the three approaches, both individually and collectively, contributed significantly to the body of knowledge about applying models to spatial applications. Conventional methods have helped define both strengths and critical gaps in basic knowledge to be incorporated into models. Remote sensing methods have employed high-resolution data to refine model estimates and in some cases, to reset the model during a season's run. Objective parameterization has shown how multiple years of data can be analyzed to provide the best set of spatial inputs for a field, and also to calibrate the model for those conditions. In all cases, the success of the models illustrated the potential for either further use or refinement of the models.

The choices of critical inputs to be measured, evaluated, or solved for in these approaches collectively illustrate the opinions and the conclusions reached by the researchers involved. These critical variables included plant population, LAI, fertility, rooting depth, and several soil physical properties, particularly surface runoff characteristics, water holding capacity, and hydraulic conductivity. One case, the simulated annealing example, also included tile spacing, weeds, and soybean cyst nematode infestation. These latter studies indicate one modeling need — pests are known to affect yield, and spatial variation in pests would then need to be accounted for. Nonetheless, for all examples, the importance of soil water and crop water stress is evident.

Extending that thought suggests future directions for improvement in spatial modeling might profitably concentrate on implementing 3-D modeling of water flow, particularly runoff and lateral subsurface flow. Such transfers of water in the horizontal directions are well known to occur under common weather, soil, and terrain conditions. As such, they are difficult to handle with 1-D models, even used at multiple points in space as described herein. Judging from the importance attributed to water-related soil parameters in the several modeling studies described here, the additional effort to implement and the additional computer resources to run 3-dimensional models may be justified.

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