4 Modeling Crop Yield for Site-Specific Management

E.J. Sadler and G. Russell

The basic premise underpinning precision farming is that variation in crop growth observed within a field can be explained in terms of measurable growing conditions. A wide variation in crop growth within farmers' fields has now been observed in numerous maps of yield, determined both by stop-and-weigh techniques and by on-the-go yield monitors. This phenomenon, however, is not new, having been observed 70 yr ago (Anonymous, 1926, Linsley & Bauer, 1929). Further, remote sensing techniques have shown within-field variation in crop response to water or other stresses for some time, although no reliable link has been established between these measurements and final yield. Farmers have recognized variability but until recently lacked the technology to manage it. Verhagen and Bouma (1997, this publication) have addressed how to model the variation in soils and soil characteristics considered important to crop growth and yield (e.g., water, fertility, pests). The purpose of this chapter is to describe the state of the science of modeling crop yield for use in site-specific farming.

In spite of extensive literature on models in agriculture, ecology, and related disciplines, many of which have clearly defined spatial capabilities or applications, there exist few examples of models that have been applied to, or are directly applicable to, site-specific farming. Consequently, we have broadened our perspective to include models that appear easy to adapt to site-specific farming and for which input data are potentially obtainable.

TYPES OF MODELS

Appropriate models of crop yield would integrate the effects of input levels to predict the final yield at a point in a field. We use appropriate because the required accuracy remains to be defined. For now, let us consider appropriate to mean accurate enough for the purpose for which the model is used. We will return to this general topic later. Crop models could be used to run simulations to support planning at scales from strategic (what to grow, or interpretations of yield maps), tactical (when to perform cultural tasks), logistical (labor and other resource allocation), to operational (how to control variable rate equipment). Issues important to transporting models between scales and objectives were addressed for bio-economic models of crop productions systems by King et al. (1993), who classified model objectives into the four broad categories: theory building, model tool development, technology and policy assessment, and management decision support. They observed that the original objective places important constraints on model structure, so that although many concepts and methods can migrate across objectives, models developed specifically for one objective may be difficult to adapt to another.

Whatever the scale or modeling objective, models written to support decisions generally contain complexity corresponding to the level of detail embodied in the operation being controlled. For example, at one end of the spectrum, models commonly used at long-term (annual or longer), broad-scale (county-wide or crop reporting district) levels have usually been based on empirical, often regression-based, relationships between yield and other factors such as rainfall or soil water storage (e.g., Leeper et al., 1974a,b; Runge & Benci, 1975). At the other end of the spectrum, models consist of complex descriptions of subcanopy-level crop processes on a time scale measured in seconds that require dynamic inputs and parameters numbered in dozens (e.g., Lemon et al., 1971). Between these extremes, many models operate on daily time steps and balance mechanistic rigor against data demand and computer time (e.g., IBSNAT, 1990). For such models, the choices of approach and of scale are not trivial, as witnessed by heated debates at modeling workshops for the past two decades.

Recent developments in spatial data acquisition and management, using remote sensing, digital terrain analysis, computerized cartography, and Geographic Information Systems (GIS), have lent themselves to a new type of model that does not fit the above descriptions. These models, which use rule-based logic, operate on both qualitative and quantitative characteristics of discrete parcels of land. An extension of rule-based models does not operate with discrete land use boundaries, but on gradual transitions across a border zone. This technique is based on fuzzy set theory, wherein points in the border zone belong to both areas, to a degree depending on proximity to the boundary. Rule-based models have been used to model the spatial distribution of soil attributes for ecological (Environmental Monitoring and Assessment Program, 1993) and agricultural (Ambuel et al., 1994; Cook et al., 1996) applications. This approach has particular utility for data-intense spatial applications. The usefulness of a GIS-based approach is enhanced if operations on individual points are simple enough to be handled within the GIS itself, and if the data are structured to permit families of points to be treated similarly, with characteristics of data layers pertaining to each point being varied simultaneously.

Authors of several conventional models have developed them into more general systems by nesting them within controlling structures (e.g., GOSSYM [Baker et al., 1983] within COMAX [Lemmon, 1986]), by rewriting the model structure to allow multiple runs (e.g., CERESV2.10 [Ritchie et al., 1989]), or by starting from scratch (e.g., EPIC [Williams, 1995]). Others have taken an original model and made multiple runs for scenarios describing variability in space. We will discuss such uses of these models later.

From the beginning of modeling, researchers have attempted to make use of all available data. Accordingly, when data are available to evaluate a model, provisions have sometimes been made to calibrate parameters, or to correct a model's state variables that have accumulated too much error. Soil water content is one common candidate for such user feedback because soil water balance has been both historically difficult to match and extremely important to crop models (e.g., SORGF [Maas & Arkin, 1978]). A number of approaches have been used. In the cited example, a state variable was adjusted to match in-season observations. Others have used in-season data to manually calibrate parameters for a test data set (e.g., most IBSNAT models), or used remotely-sensed crop data to objectively re-parameterize a model (Maas, 1988, 1993). A further adaptation involved the use of observations as direct inputs to drive a model. For instance, crop phenology can be either simulated or input to the CERES-Maize model (V2.1; Ritchie et al., 1989). The ultimate combination of models, data, and controller equipment will probably stretch the imagination of a current modeler. For example, one could envisage a model that uses a combination of previously measured spatial data (for instance, soil maps or last year's yield) combined with data from one or more on-the-go sensors (organic matter, texture) or from visual observations by the farmer to control a variable rate technology (VRT) applicator in real time.

TRENDS IN MODELING

The advent of increased computing power has allowed the development of more complex models and their application to longer-term scenarios and broader spatial scales. Realism is increased by adding the effects of factors such as pests (weeds, insects, diseases), fallow seasons, severe weather (frost, hail, wind, flood), crop rotations, and alternative cultural practices. Longer-term scenarios require that processes considered negligible in the short term, such as effects of cultivation on soil characteristics, need to be accounted for. Broader spatial scales require the incorporation of landscape feature interactions, including transport across area boundaries, such as runoff, erosion, and migration of pests. Modifications of existing models as well as new models that begin to account for these changes have been reported, and will inevitably continue to be developed. Lessons from long-term global climate change modeling and landscape ecology modeling may be useful to the agricultural modeling community (Fedra, 1993; Goodchild et al., 1993).

Although a specific objective of models such as the DSSAT/IBSNAT group is to describe the effects of varying soils on crop yield, there are few cases where crop models have been used to contribute to site-specific crop management. Such limited application appears to be caused by lack of data on within-field variability of soils, although existing models do not necessarily represent the complex interactions between soil, weather, and crop growth sufficiently accurately for VRT decision support purposes. Most models were developed for homogenous soils, such as research plots. Evaluations usually consisted of making runs for widely contrasting soils, such as are mapped at the county level (map scale of less than 1:12 000), and calculating the amount of variation explained. In cases where data resolution for within-field variation has been studied, the soil map resolution has been at a scale an order of magnitude finer (greater than 1:1 700; Sadler et al., 1997). It remains to be seen how arduous it would be to collect the data needed to parameterize and test models on scales meaningful to precision farming. Some applicable work has been published. Table 4–1 lists cases where models have been combined with GIS applications at scales ranging to the farm or field level, and where models have specifically examined variation at levels corresponding to soil map unit-level.

In all cases in Table 4–1, the models used were wholly deterministic, i.e., they were built to provide a single average prediction based on specific input values. Models were run once for each map unit or grid square and outputs were aggregated. For a limited subset of models, some researchers have provided an estimate of the variance as well as the mean. While not fully analogous, this methodology is similar to uncertainty analysis, in which uncertainty in inputs is propagated through the system of equations *via* partial differentials with respect to pertinent input variables (Morel-Seytoux, 1993). This procedure can be helpful for simple models, especially analytical ones with few inputs. Since optimization procedures often require some partial differentials, techniques could perhaps be acquired from differential equations. One drawback is that logistical difficulties associated with essentially doubling source code limits this approach for many complex models. A second drawback is that uncertainty analysis presumes independent stochastic variation in inputs, whereas in real fields there is likely to be systematic spatial correlation. Further, most complex models produce conditional results, meaning that because some input or state variable crossed a threshold, a different algorithm was employed. Such results would then be from multiple distributions, which violates assumptions implicit in uncertainty analysis, and for that matter, Monte-Carlo procedures as well.

Statistical techniques for analyzing spatial data, including variography, kriging, spatial regression, and applied time series analysis, have so far been used primarily to describe variation. It might be useful for a model to predict a mean and variation. For instance, if the degree and spatial distance of autocorrelation were found to depend on some weather, crop, or soil parameters, then a model could be developed to predict them. Such information could be very useful in a micro-economic production analysis of site-specific methods. For the time being, however, it appears that research in this area will continue to use deterministic models in multiple-run scenarios with varying inputs.

RESEARCH NEEDS

Input Data

Site-specific management may require extensive data not previously available and potentially very costly to acquire. Consequently, research is critically needed on how to obtain cost-effective information for input to VRT controllers, models, and other decision support tools. Traditional point-sampling techniques may not fulfill this need at an affordable cost, although such techniques may be supported in the future by expert systems. Methods that allow data to be collected in bulk, such as remote sensing and aerial photography, or during field operations, such as on-the-go sensors and monitors, will be the ones most likely to satisfy the demand for data.

Table 4–1. Model/Geographic Information System (GIS) combinations and uses of models for site-specific studies.

Citation	System name: Model with GIS name, if used†	Scale used
Berti et al., 1986	n/a: CERES-Maize V1.0, no GIS	soil map unit, 1:1 200
Sadler et al., 1988	n/a: CERES-Maize, CERES-Wheat, SORKAM, no GIS	soil map unit, 1:1 200
Ritchie and Amato, 1990	n/a: CERES-Maize, no GIS	classed by plant extractable soil water
Calixte et al., 1992	AEGIS V1.0: DSSAT V2.1 with PC Arc/Info, dBaseIV	region
Papajorgi et al., 1993a	AEGIS_2: more generic version	region
Lal et al., 1993	AEGIS: DSSAT-BEANGRO V1.01 with PC Arc/Info	region, 1:20 000
Hoogenboom et al., 1993	IAEGIS: DSSAT V2.1 with PC Arc/Info V3.41	soil map unit, ~0.5 ha min
Papajorgi et al., 1993b	AEGIS_2.5: DSSAT V2.5 with PC Arc/Info	farm
Wei et al., 1994	IAEGIS: DSSAT V2.1 with Unix Arc/Info V6.1	field
Papajorgi et al., 1994	AEGIS +: DSSAT V3.0 with Unix Arc/Info V6.1	field, map unit
Munster et al., 1994	n/a: SOYGRO, no GIS	soil map unit, 1:20 000
deJong and Reynolds, 1995	n/a: LEACHM with ILWIS V1.3 (objective was atrazine loading)	watershed
McCauley et al., 1995	unnamed: GOSSYM/COMAX with GRASS	grid in field
Engel et al., 1995	AEGIS/WIN: DSSAT with ArcView 2.0	field
Verhagen et al., 1995	n/a: SUCROS87, no GIS	50-m grid
Verhagen, et al., 1995	n/a: WAVE, GIS not stated	50-m grid
Han et al., 1995	unnamed: SIMPOTATO with PC Arc/Info	12.2-m grid in 50-ha center pivot
Verhagen and Bouma, 1997	n/a: WAVE, GIS not stated	50-m grid

†Mention of trade names is for information only. No endorsement implied

Modeling

Scale issues and accuracy

The most critical research need for the modeling community is to recognize the special needs of the scale involved in site-specific farming. Soil maps are usually drawn at scales from 1:12 000 to 1:24 000, which probably mask economically important variability. Beckett and Webster (1971), for example, reviewed the literature on soil variability and found that most within-field variation was already present within an area of one hectare. Moreover, boundaries on soil maps are generally drawn using pedological rather than agronomic criteria. Variation within map units is likely to be important if the full return on VRT investment is to be realized. Such variation increases demands for field data, no matter what model is used. Models themselves must be sensitive to all factors that limit yield in the particular circumstances of interest. This issue is critical for the accuracy of a model, which cannot be stated in general, because it depends on the task considered;. however, to be useful, for instance, in controlling a VRT N spreader, a model must at least be qualitatively accurate. Qualitative accuracy means that if a model simulates an increased yield (for some majority of likely weather scenarios) for an increment of applied N, one must assume beforehand that the real response is also an increase, otherwise the application would be optimized counter to the real response. Qualitative accuracy is often exploited by comparing ratios between model outputs or between observed and predicted values; however, operating a VRT application with such information would still be subject to quantitative inaccuracies in the marginal response to inputs if it were used for an optimization. The next higher level of accuracy would be where the model is absolutely accurate (within some limits), which means that it predicts the average well. This provides a better estimate for comparisons with other, nonmodeled options. Practical, quantitative accuracy would require that both the mean and the differential with respect to all inputs of interest were predicted within bounds suitable for the task at hand.

Several processes appear to require greater quantitative accuracy than that commonly obtained by modeling. These include water relations (rainfall partitioning, soil water holding capacity, crop water use, root growth), fertility (chemical transformations, pH effects, cation-exchange capacity), effect of stratified soils (water relations, root growth and distribution), organic matter balance and its effect on the physical and chemical properties of soil, other soil effects (consider a yield map that showed a wheat yield depression where the field had been disked while too wet), and temperature and daylength effects on phenology (consider spatial variation in maturity for field crops, or long-maturing crops such as pineapple (*Ananas comosus* (L.) Merr.)). In some circumstances, the importance of soil variability can obscure the problem of obtaining appropriate meteorological information. Many meteorological variables can be extrapolated over distances of tens of kilometers without introducing serious errors, provided the terrain is reasonably homogeneous; however, soil temperature and air minimum temperature are sensitive to small differences in topography and soil type while solar radiation and evapotranspiration rate can be influenced by aspect or by shade cast by topography or woodland. Many models do not contain the structures to account for the processes outlined above.

Perhaps the trend toward modular models will accelerate the process of adding these important components.

Discrete Effects

In addition to the quantitative factors mentioned above, many discrete choices are made by managers and planners, and many external factors affect crop yield with discrete, sometimes extreme, results. Examples of choices made by managers include cultivar, tillage type, and pest management method. Many choices have corresponding quantitative inputs as well, such as population, depth of tillage, and pesticide application rate; but these are generally handled if the structure exists in the model. Examples of external factors with potential for extreme effects include weather (hail, wind, frost, or flooding), pests (weeds, insects, disease, or animals), and accidents (spills, or spray drifting onto a sensitive crop). While the simulation of these effects must be deterministic, the stochastic information (probability of occurrence and severity of outcomes) should be useful to long-term planning. In addition, many of these processes and factors are distinctly spatial in nature, sometimes in predictable fashion, sometimes not. Therefore, information about their spatial extent would be useful.

Input/Output Formats and Standards

Standardization of inputs and outputs in terms of both the attributes required and methods used to evaluate them has been occurring for some time, both formally, as in the IBSNAT project objectives, and informally, as a natural consequence of models needing similar inputs and predicting similar outputs. There is a clear long-term, overall benefit to the standardization process, in that data may be transported more easily. There is a short-term, project-specific cost in that a standard is not always optimal for the model in question. Also, expansion of the use of data often brings with it expansion of data needs beyond those anticipated during standards development. Perhaps agricultural modelers can follow the lead of the microcomputer software industry, where most of the general word processing and spreadsheet applications can read others' files, either directly or via a conversion utility supplied with the software. This allows data transport, but does not force complete standardization on the industry. Whatever route is taken concerning data format, there will be a massive amount of data that will be difficult to manage unless new and better data management tools are developed. This issue is currently being addressed for storage and communication of yield and soil fertility data between monitors, controllers, and equipment by the Ag Electronics Association (A*E*A, mailing address: 10 So. Riverside Plaza, Suite 1220, Chicago, IL 60606-3710). Data documentation, database indexes, central archives, file transport tools, and conversion routines must evolve as the quantity of data grows.

Landscape Integration and Planning Horizon

We see a need for the continued integration of farm scale models to allow complex studies of whole landscapes. This must include the possibility of transport among landscape components, with a critical need for capability to account for runoff–run on of rainfall. We also see a need for continued increase in time scale, to allow multiple-year scenarios for calculating probabilities of occurrence, and for predicting long-term effects on properties currently input as constants.

Geographic Information Systems

We expect continued integration of traditional modeling with geographic information systems, global positioning systems, on-the-go sensors, and variable rate technology in general. This integration has been and will continue to be achieved using both altered model structure and model controllers that feed varied inputs to the models.

Project Management Tools

A topic not extensively developed but one that shows potential is the integration of models into project management tools. These are used extensively in the construction and manufacturing industries to schedule tasks and allocate resources. Farming practice is a collection of tasks, and should be amenable to classical techniques for project management. Integrating models (if appropriately accurate) into tools for management decisions regarding scheduling and resource allocation should contribute to enterprise-level tactical and strategic planning.

Model Documentation and Distribution

Our final topic is the documentation and distribution of the models themselves. Beyond the data management needs discussed above, there is also a need for ensuring fidelity of versions and for requesting, making, and documenting changes. Validation, or if one does not like that term, building confidence in the model, should be built into the model storage and distribution system so that all users can find and understand the tests. Electronic journals, Internet sites, and other techniques for publishing and maintaining models should be investigated.

CONCLUSIONS

The state of the science of modeling crop yield to contribute to site-specific crop management can best be described as developing – not yet mature, but showing potential. This is not to say that there is nothing that can now be done; rather, the range of decisions that can now be supported with models is somewhat more limited than the range of those that can be controlled with current technology. Demonstrating ability of models to predict effects of soil variations on a finer spatial scale than yet achieved would strengthen confidence in modeling for these purposes. While not absolutely required in current-year decisions for VRT controllers, demonstrating appropriate sensitivity to longer-term effects of management would also be beneficial. We support continued emphasis on using modular model structures, on increasing the quality and quantity of documentation, and on building confidence through wide distribution and user feedback. When modelers recognize the need, they will respond with answers to the questions pertinent to site-specific farming. The challenge for the site-specific farming industry is to pose the correct questions.

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