Kapitel 5

Chapter 5

Ertragspotentiale

Yield-potential

5.1 Application of Crop Models in precision agriculture

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5.1.1 Background and rationale

Agronomic research has focused for a long time on single discipline studies in the field of plant nutrition, physiology of plant growth and development, plant breeding and crop protection. Dose-effect relations were determined to derive optional fertilization rates, irrigation rates, varieties yield response. However, it has been shown that single factor efficiency is strongly affected by other production factors. Indeed, traditional trial and error agronomic research leads to results that are limited to the weather, time and space of the experiment. Crop simulation models have been developed to transfer site and weather specific experimental results to other space and time by taking into account the relevant management, weather, soils, and genotype characteristics used in connection with any experiment. Simulation models integrate knowledge from different disciplines and provide researchers with capabilities for conducting computer experiments to supplement field experiments Site specific results are used to test the accuracy of crop models in different soil, weather, management, and genotypes. When sufficiently tested under a wide range of such of such conditions, user of models can have confidence that the outcome of simulations for untested sites will be reasonable accurate for specified soil, weather management, and genotypes and used for various decision making scenarios. Crop growth simulation models are increasingly used to support field research, extension, and teaching. The number of costly, multi-treatment, time-consuming field trails can be substantially reduced by crop simulation as crop models can quantify the magnitude and variability in response to treatments (Ritchie *et al*., 1989; Ritchie 1991; Jones and Ritchie, 1991). The efforts of several research groups around the world for the last 30 years (Day and Atkin, 1985; Uhera and Tsuji, 1993; Ten Berge, 1993; and Tsuji, Hoogenboom and Thorton, 1998) have resulted in considerable progress in the development and widespread testing and use of crop models.
Agricultural production systems are inherently variable due to spatial variation in soil properties, topography, and climate. To achieve the ultimate goal of sustainable cropping systems, variability must be considered both in space and time because the factors influencing crop yield have different spatial and temporal behavior (Pierce and Nowak, 1999). Advances in technologies such as Global Positioning Systems (GPS), Geographic Information Systems (GIS) and remote sensing have created the possibility to assess the spatial variability present in the field and manage it with appropriate site-specific practices (Verhagen et al., 1995). Site-specific management (SSM) strategies may be able to optimize production, but their potential benefits are highly dependent on the accuracy of the assessment of such variability (Pierce and Nowak, 1999).
Traditional analytical techniques, such as regression of static measurements against yield, have failed to explain the reasons for yield variability because the dynamic, thus temporal, interactions of stresses on crop growth and development cannot be accounted for (Jones and Ritchie, 1991; Cambardella et al., 1996; Sudduth et al., 1996). Process oriented crop simulation models, such as the CERES and CROPGRO models (Ritchie et.al, 1985; Boote et al., 1998), integrate the effects of temporal and multiple stress interactions on crop growth proc-

esses under different environmental and management conditions. Even though crop models have shown high potential for optimizing production and minimizing environmental impact (Ritchie, 1987), their application for SSM has been limited thus far (Sadler et al., 2000). Crop models can be used for understanding yield variability in both space and time, leading to a more sustainable environment (Sadler and Russell, 1997, Cora et al., 1999; Paz et al., 1997, 1999; Boolting et al., 2001; Batchelor et al. 2002). Clearly, the goal of crop simulation in precision agriculture is to explain the spatial variability of crop performance mapped with grain yield monitoring systems and to help guide in management decisions related to the site-specific management of crop inputs. It is also clear that crop simulations cannot be performed everywhere given that the cost and the availability of detailed inputs would be prohibitive. A more balanced approached to the application of crop simulation models to precision agriculture would be to delineate zones within the field of similar crop performance.
The purpose of this paper is to review present strategies of crop models application for :

1. assessing spatial and temporal yield variability over different environmental conditions,
2. analyzing economic return of prescriptions,
3. estimating environmental consequences of prescriptions.

5.1.2 Spatial application of crop models.

5.1.2.1 Case study I. Applying crop models on small scale grids within a field.

One method of overcoming spatial limitations in the DSSAT crop models is to run the point-based models for small, homogeneous areas within a field. Results from each homogeneous area can then be aggregated at the field level for analysis. The DSSAT models require point estimates of soil inputs including soil water holding capacity at 15-30 cm depth increments, hydraulic conductivity, tile flow characteristics, rooting depth, and initial soil water and nitrate conditions. All of these inputs are highly spatially variable. Point-based management inputs include planting date, row spacing, fertilizer applications, population and genetic traits. Population is the only management input that typically has a spatial component.
This concept is demonstrated for a 20 ha field in central Iowa using a modified version of the CERES-Maize model (Garrison et al., 1999). The McGarvey field has rolling topography and is in the Clarion-Nicollette-Webster soil association. The field is drained by subsurface tile lines to reduce the impact of high water tables that normally occur during the spring. Maize was planted in 1994, 1996 and 1998. The 20-ha field was divided into 100 grids 0.2 ha in size, and yield was measured for each grid by aggregating point measurements from a calibrated yield monitor. Model inputs were measured, calculated or estimated for each grid in different ways. Soil water holding capacity was estimated for different depths using measured soil particle size and the methods outlined in Ratliff et al. (1983). The field was managed for maximum yield, and thus, nitrogen was assumed to not be a limiting factor. Plant population was measured in each grid and other management-related inputs to the model were available (ie. planting date, row spacing, and genetic traits). Daily weather data including rainfall, maximum and minimum temperature and solar radiation was measured on site using an automated weather station.
Several spatial inputs including root depth and tile drainage characteristics required by the model were not available. Thus, the strategy was to calibrate these spatial properties for each grid by minimizing the root mean square error (RMSE) between predicted and measured yields over the three seasons in a grid. The CERES-Maize model was linked to an optimization program that searched for the optimum combination of these parameters that minimized

the RMSE over 3 seasons. This resulted in a unique set of values for these parameters for each grid. Figure 1 shows the predicted and measured yield over the 3-year period. The model explained 76 % of the yield variability (r^2 = 0.76) and gave a RMSE of 407 kg ha^{-1}. The source of the remaining variability is unknown.

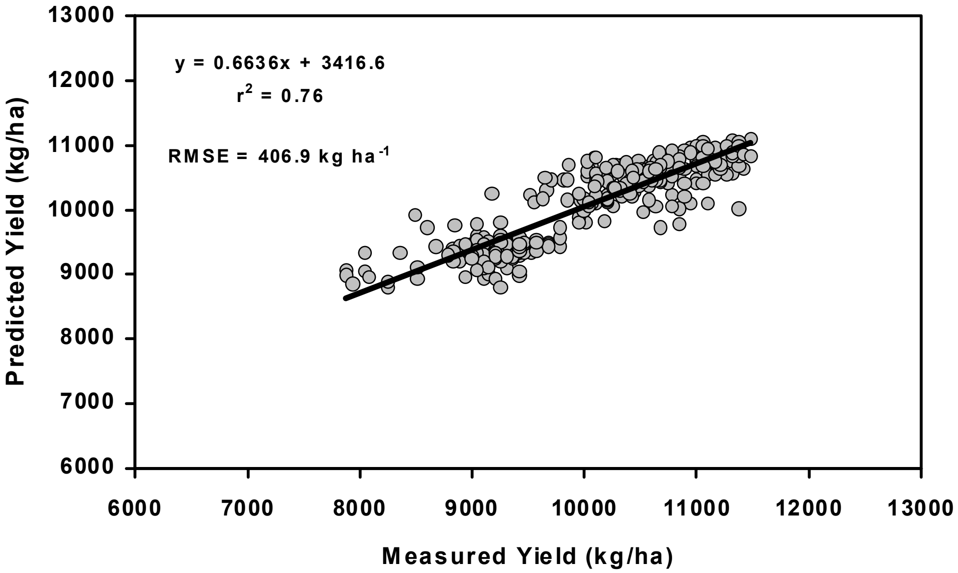


Fig. 5.1-1: Comparison of measured and predicted yield for the McGarvey Field using 3 years of data (1994, 1996, and 1998) and calibrating two parameters (SLPF and RHRF).

The idea behind this approach is rather naïve. The model is used as a complex, non-linear regression function and is forced to fit measured final yield data by assuming that water stress and population are the yield-limiting factors in each grid (this follows the findings of Paz et al., 1999). If the model can be calibrated to fit the temporal behavior of yield over several seasons, it is assumed that population and water stress are indeed the predominant yield-limiting factors. In grids where the model does not fit the observed temporal yield behavior, other factors must have been limiting. In this sense, the model can be used as a rapid screening tool to determine the relative impact of population and water stress versus unknown stresses on yield (Paz et al., 2001a). The problem with this approach is that there is not hydrologic connection between grids, thus, the model does not account for surface run-on. There is also a danger of obtaining the right answer for the wrong reason. For instance, water stress can mimic low pH effects on maize yield. The advantage of this approach is that the models can be implemented without modification, or coupling to complex spatial water balance models, and the inputs are relatively easy to measure or estimate.

This simple approach can be expanded when additional spatial information regarding yield-limiting factors is available. If appropriate spatial inputs are measured in small, relatively homogeneous areas within a field, point-based models can prove useful in estimating the spatial and temporal yield loss due to yield limiting factors.

5.1.2.2 Case Study II. Applying crop models on imagery derived zones within a field.

Clearly, the goal of crop simulation in precision farming is to explain the spatial variability of crop performance mapped with grain yield monitoring systems and to help guide in management decisions related to the site-specific management of crop inputs. It is also clear that crop simulations cannot be performed everywhere given that the cost and the availability of detailed inputs would be prohibitive. A more balanced approach to the application of crop simulation models in precision farming would be to delineate zones within the field representing areas of similar crop performance. One approach may be to obtain vegetation indexes derived from remote sensed imagery during critical times during the growing season, classify the images for target sampling, delineate spatial patterns and use the results of the target sampling as inputs for the models. Model validation can be then be performed at selected sites within these delineated management zones. Such an approach would facilitate the challenge of using crop models in precision farming by obtaining spatial inputs to simulate variations of crop yields across the field, as well as to decide where to use field averages for some factors along with spatially variable inputs for others.

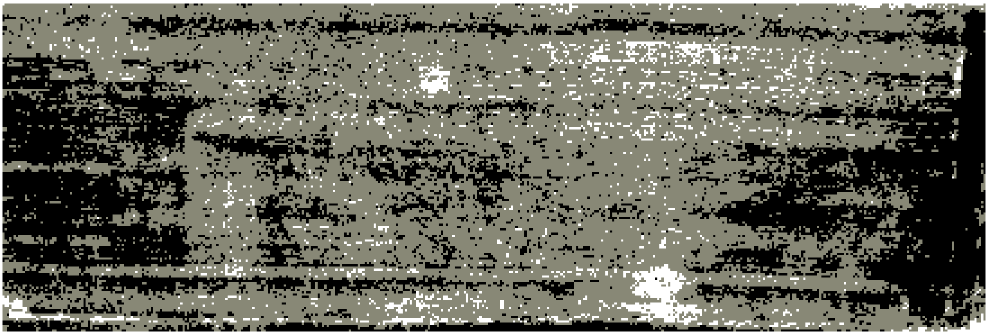
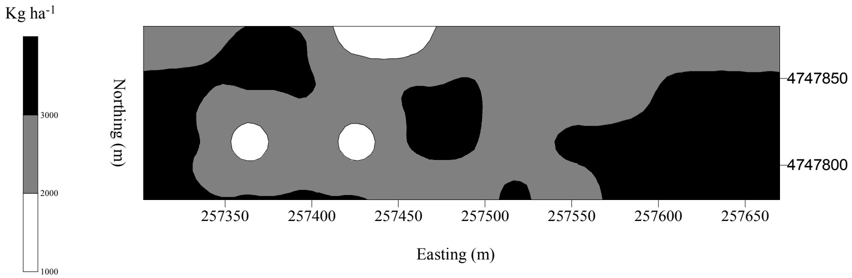


Fig. 5.1-2: Reclassified NDVI image showing three NDVI classes for a soybean field (image acquired during late vegetative stage on July 18).

Basso et al. (2001) conducted a study to examine a new procedure for spatial validation of crop models for use in precision farming. This procedure used the CROPGRO-Soybean model to validate management zones across the field that were delineated using a NDVI classification procedure. Airborne false color composite images in the blue, red, green and NIR portion of the spectrum were taken at selected time during the season at 1 meter pixel resolution. The images provided spatial information about the condition of the crop throughout the season. Each image was used to generate NDVI maps of the field and to identify spatial patterns across the field. The false color composite image taken on July 18 was selected for quantifying areas with similar reflectance by grouping areas into classes of similar NDVI values using supervised classification technique. Pixels of similar reflectance were queried across the field after trying various ranges of values able to reproduce the spatial patterns visible in the original false-color composite image. The reclassified NDVI map from 18 July image clearly showed spatial variability in soybean performance (Fig.2). Classification of the NDVI image indicated three classes of importance in this field. Soil properties (soil depth, soil texture, soil organic carbon, soil nitrogen, soil water limits) and plant population were measured in each of the zones with a target sampling procedure and measured data were used as inputs necessary to execute the model. The model was then run without calibration for the season, and comparisons were made between predicted and measured

yields in each zone. Figure 3 shows the kriged map of measured and simulated yield for the three NDVI classes. The model was able to simulate well the yield for the three NDVI classes (RMSE = 101Kg ha^{-1}). The model performance indicated that the NDVI reclassification procedure was appropriate and with multi-year simulation should allow for the characterization of management zones for this field.
The use of site specific model inputs obtained with the NDVI-reclassification procedure has a major advantage since the power and application of simulation models in precision farming has been limited by data requirements at the sub-field scale. The site-specific inputs approach is scale-independent because the scale is controlled by the observed variation in the field and that is the scale at which the model is applied.



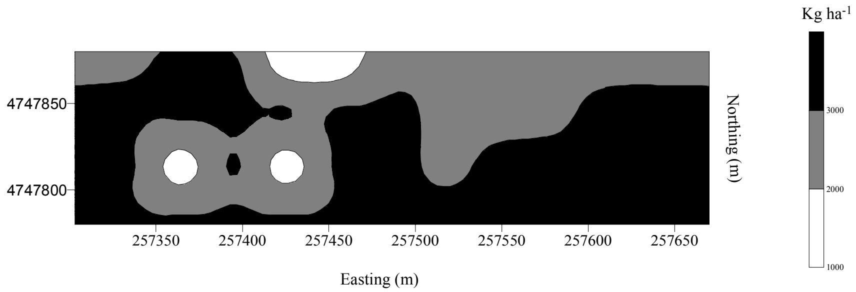


Fig. 5.1-3: Kriged map of measured soybean yield for the three NDVI classes (upper); Kriged map of simulated yield for the three NDVI classes (lower).

5.1.3 Analyze Economic Consequences of Prescriptions

The ultimate goal of precision farming technology is to apply precise amounts of inputs to management zones within the field to achieve a management objective, such as maximizing net returns. Producers in the Midwestern US have identified plant population, variety, irrigation and fertility as primary management practices that could be applied in variable rates to improve net return. Other prescriptions may achieve environmental objectives such as decreasing edge of field losses of nitrogen, phosphorus, or antibiotics (from manure sources) or reduction in erosion.
Determining the optimum prescription for a location within a field is challenging. The biggest challenge is that the plant response to variable management levels is often highly dependent upon the weather that occurs during the season. For instance, a high population may be optimal for maximizing net return for a hilltop within a field in a wet year, while a

very low population may be optimal in a dry year. The producer, however, must make a decision about population level at planting time, without knowledge of the weather that will be encountered during the season. Since future weather is unknown, a risk management strategy must be employed to determine the prescription that satisfies the objective function over a sufficiently long period of time (ie. 30 years) to represent the diversity of environments that may be encountered for the prescription in the field. The biggest challenge to this strategy is the development of an appropriate yield response function that can represent the plant's response to the variable rate management and represent the response to other interactions that may affect the plant response to management. Simple statistical functions that relate yield response to nitrogen rate or population does not sufficiently account for temporal interactions of weather and stress on yield response to management to be of much use for this complex problem.

Paz et al. 1998; 2001 proposed to use process-oriented crop growth models as a yield response function to evaluate the economic response of crop growth and yield to different management levels. Process-oriented crop growth models have proven useful as a yield response function for estimating economic consequences of various prescriptions. The DSSAT crop models are superior to simple one or two-factor yield response functions because they were designed to account for many temporal stresses imposed by weather patterns and interactions of stresses on plant growth and yield. Simple regression-oriented yield response functions for single management factors do not adequately capture the complex interactions of weather and management on yield response. Thus, the authors proposed process-oriented crop model based techniques to estimate the yield response to variable rate management. In this section, we outline a procedure through a case study to demonstrate the use of the CROPGRO-Soybean model to estimate the optimum variety prescription to be planted within a field.

The goal of this case study was to determine the optimum prescription for soybean varieties that maximize the 3-year marginal net return in each grid in the McGarvey field described above. The field 20 ha field was divided into 100 grids and the crop model was calibrated to minimize error between predicted and measured yields in each grid over a 3-year period (Fig. 1). Genetic coefficients required by the model were available to simulate the yield of 70 public soybean varieties adapted to the area. The model was then run for each variety and 34 years of historical weather data to generate a variety by weather yield response curve for each grid. The marginal net return was computed for each grid, year and prescription level by

$$MNR(v)_n^t \quad = \quad Y(v)_n^t * P \quad - \quad C \tag{1}$$

Where :

$MNR(v)^t_n$ = marginal net return for variety v, grid *n* and year *t* ($ ha^{-1})

$Y(v)^t_n$ = predicted yield for variety v, grid *n* and year *t* (kg ha^{-1})

P = selling price of soybeans ($ kg^{-1})

C = cost of inputs related to the variable rate decision (ie. fertilizer, seeds) ($ ha^{-1})

The break-even cost was computed by subtracting the net return using the producer's current variety from the marginal net return for each variety, averaged over all grids. A break-even curve was generated by making this calculation for several different selling prices for the crop.

Three prescriptions were considered. Prescription A was defined as the maximum potential return for a variable variety prescription for this field. It was computed by selecting the vari-

ety that maximized MNR in a grid for each specific year of weather. Thus, different varieties could be selected for a particular grid each year. This prescription assumes *a priori* knowledge of future weather. Prescription B was defined as the realistic expected return for a variable variety prescription for this field. It was defined by selecting the variety that maximized the MNR over 34 seasons of weather data for individual grids. Thus, a single variety was selected for all seasons for a particular grid. This prescription does not assume a priori knowledge of future weather, and is realistic with respect to the information available for the decision-making process. The third prescription (C) was to select the variety that maximized the field level MNR over 34 seasons. Thus, a single variety was selected for all grids and years. This prescription was developed to compare variable rate management to the best possible uniform management for the field.
Figure 4 shows the results of prescription B. Variety '395' was found to maximize the 34-year average MNR in 77 grids. Dwight was selected as optimum in 18 grids, followed by Trisoy 3252 in 5 grids. The distribution of varieties was somewhat correlated to position on the landscape, which indicates a selection, based on soil water holding capacity in this field. This is not surprising since many soybean varieties respond differently to water stress.

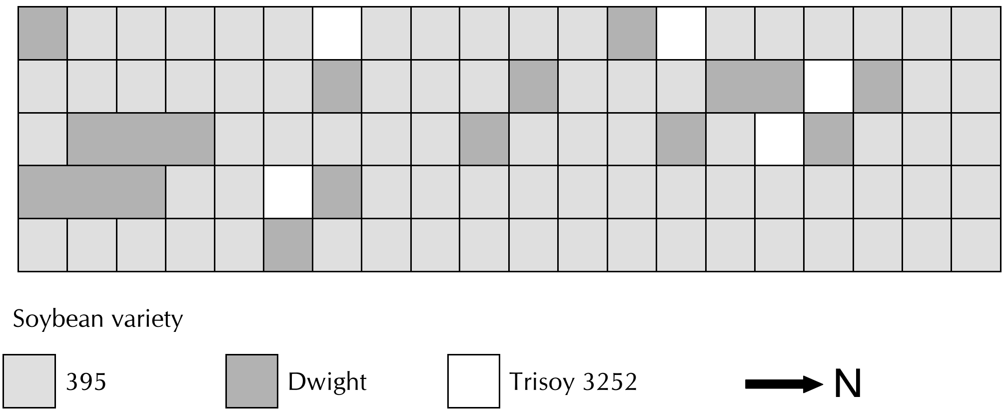


Fig. 5.1-4: Soybean variety prescription map showing the variety that maximized the marginal net return over a 34-year period for the McGarvey field.

Figure 5 shows the break-even cost for each of the three prescriptions. This set of curves reveals several interesting possibilities for uniform and variable variety prescriptions. First, by planting variety '395' uniformly across the field, the producer would realize a significant increase in net return over his existing variety. For instance, if soybeans are valued at $\$225\ t^{-1}$, the producer would realize an increase of approximately $\$30\ ha^{-1}$ over his current variety choice. If the producer has perfect knowledge of future weather information (prescription A), the break-even cost of implementing prescription A is approximately $\$55\ ha^{-1}$ over the producer's current costs when soybeans are valued at $\$225\ t^{-1}$. This means that the producer could afford to spend $\$55\ ha^{-1}$ to collect appropriate information and implement prescription A to break even with his current practice. If he spent less, the variable variety prescription would lead to an increase in MNR. This prescription estimates the maximum potential economic value on variable variety prescriptions for this field, because it assumes that the producer has perfect information regarding future weather, which is the primary factor that influences variety performance. Finally, the break-even cost of implementing prescription B, assuming a soybean value of $\$225\ t^{-1}$ would lead to a break-even cost of approximately \$33 ha^{-1}. This is still superior to the producer's current practice, but is only marginally better (\$3 ha^{-1}) than planting the best variety uniformly across the field (prescription C). The difference in break-even costs for prescription A and B indicates the sensitivity of this decision to the weather that occurs during the season. It is a direct estimate of the value of *a priori* knowledge of future weather.

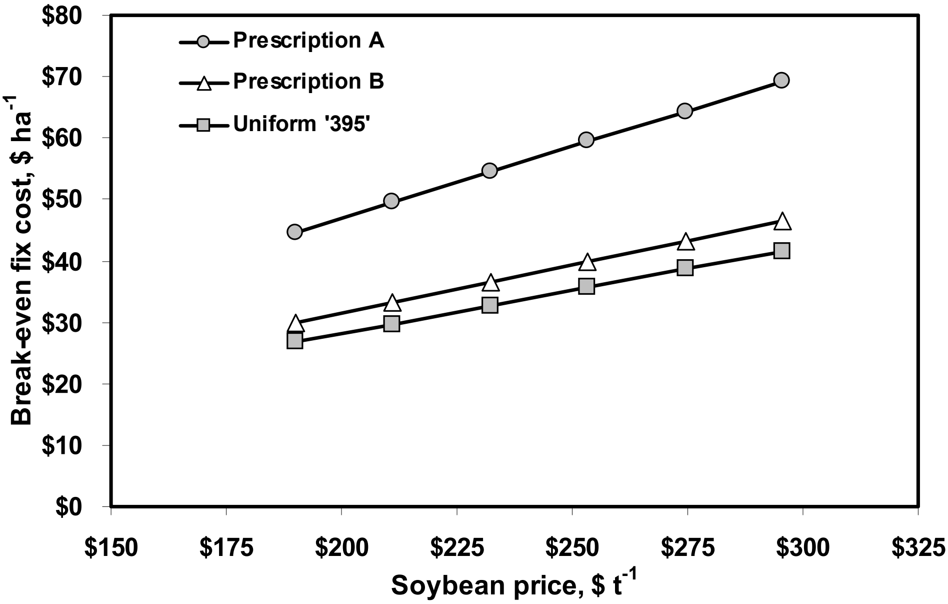


Fig. 5.1-5: Break-even cost comparisons for the different soybean variety prescriptions in the McGarvey field.

This same strategy can be employed for a vast array of variable rate decisions. Paz et al. (2001c) used this strategy to estimate the economic consequences of variety selection for disease management and variable populations. They found that the decision to plant a disease resistant variety in the presence of a disease is not influenced by future weather. However, the decision of optimum population is highly sensitive to future weather, thus eroding the economic return for variable population management.

5.1.4 Estimating Environmental Consequences

One of the emerging issues driving the future of precision agriculture is environmental protection. The ability to manage the landscape in a variable way is a new tool that opens new opportunities in the area of environmental policy and protection. Variable rate management, such as variable nutrients, tillage, population, and pesticide application rates, offers the possibility of managing small units within a field to achieve environmental policy objectives.

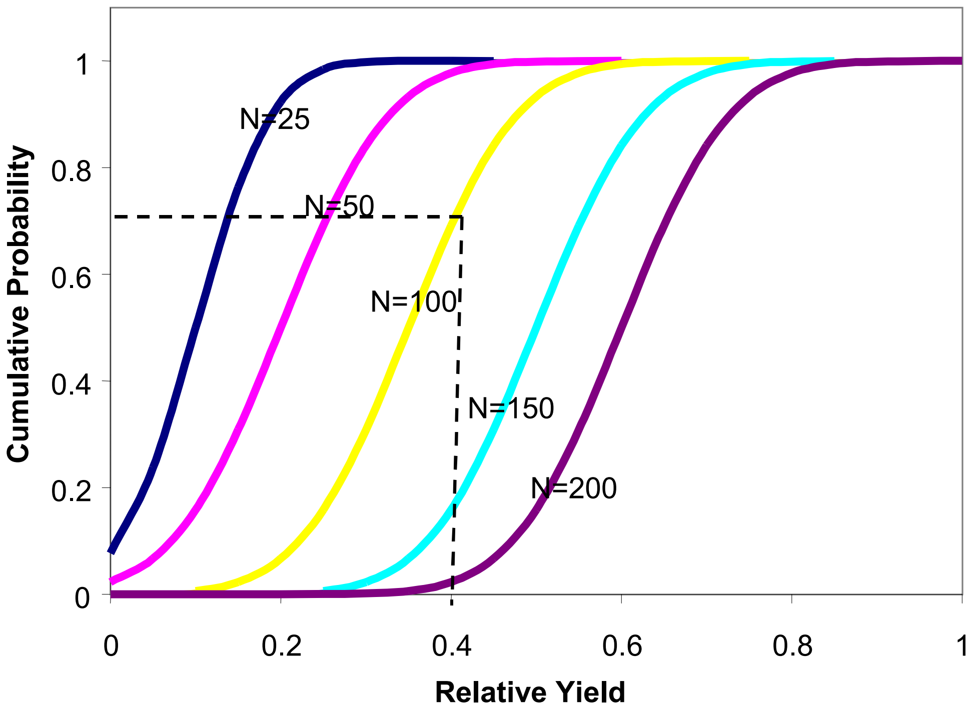


Fig. 5.1-6: Probability distribution of yield to different nitrogen application rates (kg ha^{-1}) over 30 seasons.

Process-oriented crop growth models can play an important role in linking environmental policy with producer economics. This can be demonstrated with the following example. Consider the trade-off between nitrogen application rate and nitrogen loss to the edge of a field. Figure 6 shows a typical probabilistic yield response to nitrogen application rate over 30 seasons in a field. In this case, the model is run for multiple nitrogen application rates for 30 seasons of historic weather data to develop a family of yield response curves. The yield is then normalized to the maximum yield that is predicted over the 30-year period for the field. A cumulative probability distribution curve is then generated for each nitrogen rate. The family of cumulative probability distribution curves represents the risk the producer incurs due to different nitrogen management strategies. Figure 7 shows the cumulative probability of nitrogen loss (surface runoff, leaching, and tile flow) as a function of the different nitrogen application rates for the same field and seasons of weather. This relationship represents the environmental impact of different nitrogen management strategies. The two figures together can be used to link environmental policy and economic consequences to the producer. For instance, an environmental policy may state that 80% of the time the nitrogen loss from a field cannot exceed 50 kg ha^{-1}. From Figure 7, this policy dictates that the nitrogen rate cannot exceed 100 kg ha^{-1}. This nitrogen rate, dictated by the environmental policy can be used in conjunction with Fig. 6 to determine the economic risks the producer incurs by following this policy. For instance, in this example, there is a 70% chance that the yield associated with the 100 kg ha^{-1} nitrogen application rate would be less than 40% of the maximum yield the producer would achieve in the best year at the highest nitrogen application rate (Fig. 6). This directly links environmental policy to economic consequences and aid policy makers in determining how to provide incentives for environmental policies.

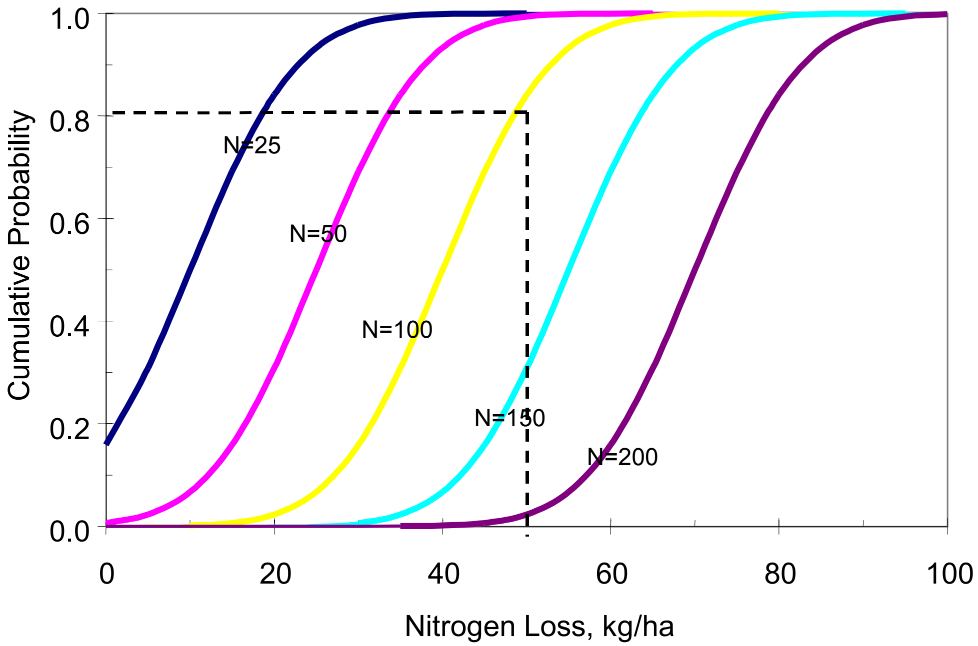


Fig. 5.1-7: Probability distribution of nitrogen loss to different nitrogen rates over 30 seasons.

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