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Methodology for the use of DSSAT models for precision agriculture decision support

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ABSTRACT

A prototype decision support system (DSS) called Apollo was developed to assist researchers in using the Decision Support System for Agrotechnology Transfer (DSSAT) crop growth models to analyze precision farming datasets. Because the DSSAT models are written to simulate crop growth and development within a homogenous unit of land, the Apollo DSS has specialized functions to manage running the DSSAT models to simulate and analyze spatially variable land and management. The DSS has modules that allow the user to build model input files for spatial simulations across predefined management zones, calibrate the models to simulate historic spatial yield variability, validate the models for seasons not used for calibration, and estimate the crop response and environmental impacts of nitrogen, plant population, cultivar, and irrigation prescriptions. This paper details the functionality of Apollo, and presents the results of an example application.

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1. Introduction

Producers in the Midwestern US often use yield monitors to map spatial yield variability within their fields. These data have revealed that a tremendous amount of yield variability exists within most fields. Spatial yield variability results from complex interactions among factors including water stress, nutrients, rooting depth, soil physical properties, drainage, weather, pests, and management. Much of the variability in a field is caused by soil properties, a source of variability which naturally exists and cannot easily be altered. On the other hand, some variability exists due to factors that can be managed (e.g. pests, poor emergence, water logging).

Crop growth models integrate the effects of soils, weather, management, genetics, and pests on daily growth, and can be used to gain insight into spatial yield variability. Among the numerous crop growth models, the most widely used are the Decision Support for Agrotechnology Transfer (DSSAT) models, which were designed to simulate growth, development, and yield of a crop growing on a uniform area of land, as well as the changes in soil water, carbon, and nitrogen that take place under the cropping system over time (Jones et al., 2003). DSSAT has been in use for the past 15 years by researchers all over the world, for a variety of purposes, including crop management (Fetcher et al., 1991), climate change impact studies (Alexandrov and Hoogenboom, 2001), sustainability

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research (Quemada and Cabrera, 1995), and precision agriculture (Paz et al., 2001, 2003), and is well validated for a number of regions and crops. Included in the DSSAT family are modules which simulate the growth of 16 different crops, including maize, soybeans, wheat, rice, and others. DSSAT uses common modules for soil dynamics and soil–plant–atmosphere interactions regardless of the plant growth module selected. Data requirements include weather inputs (daily maximum and minimum temperature, rainfall and solar radiation), soils classification, and crop management practices (variety, row spacing, plant population, fertilizer and irrigation application dates and amounts).

While the DSSAT family of crop growth models provides many opportunities for critical analysis, it is tedious to use for precision agriculture studies and decision support because the model is built for simulation of a single homogeneous field unit. In order to facilitate the use of DSSAT for precision agriculture decision support, automated procedures and related tools are needed to implement crop growth simulations spatially across field-level management zones.

We have developed methods to use the DSSAT family of crop growth models to understand causes of spatial yield variability, conduct yield gap analysis for factors that limit yield, and estimate the economic consequences of moving from uniform to spatially variable management. We have also developed methodologies to automate the preparation of necessary input files for DSSAT to be used to simulate spatially variable crop development. These methods have been used successfully in several studies (Thorp et al., 2006, 2007; DeJonge et al., 2007; Miao et al., 2006) but have not yet been fully explained.

In this paper we describe these methods, combined into a prototype precision farming decision support system (DSS) called Apollo, which integrates several precision farming applications developed for the DSSAT crop growth models into a single interface. Specifically, we detail the development and utilization of Apollo to allow researchers to (1) build model input files for spatially varying parameters, (2) calibrate input parameters for the crop growth models in order to simulate historical yield variability within a field, (3) validate the calibrations for seasons not used for calibration, and (4) estimate the crop response and environmental consequences of precision prescriptions or other management decisions.

2. Development

2.1. Building model input files for spatially varying parameters

DSSAT simulations require a soil input file that details the physical and hydraulic properties of the soil. If comparison of model output yield to observed yield data is to be done, for example in order to calibrate the model to specific local conditions, formatted yield data is also required. When using DSSAT for precision agriculture applications, a challenge is to efficiently generate these files for each management zone. One function of Apollo, then, is to automate the generation of these files from standard or commonly available data sources: in the

case of soil files, from a digital soil survey, and in the case of yield files, from yield monitor data.

There are, of course, other required input files for running DSSAT, namely, cultivar, management and weather files. In our implementation of Apollo, we assume that spatially variable weather data are neither necessary nor available. We also assume that within a single field, crop genetics are spatially uniform. However, the general approaches detailed in this paper could be used to generate and utilize spatially variable cultivar and weather files as well, if desired. We also assume that management of certain field activities, such as planting date and tillage types and schedules, is uniform across the field. Simulation and analysis of spatially variable planting population, nitrogen management, and irrigation will be discussed in a subsequent section.

In the past, creation of input files for model simulation of spatially variable management zones has been accomplished by manually manipulating measured model parameters with geographic information system (GIS) software and preparing crop model input files in a text editor. For Apollo, we automated this process within ArcGIS (ESRI, Redlands, CA), which is a collection of software for building, manipulating, and maintaining a GIS. Included within ArcGIS are several software components, such as ArcMap, which provides functionality for creating, maintaining, editing, and analyzing maps of geospatial data; ArcCatalog, which provides data management tools for organizing geospatial data within a geodatabase; and ArcToolbox, which provides functionality for common data conversion and geoprocessing tasks. While these three components of ArcGIS offer many built-in functions for managing and manipulating geospatial data, when a complex series of data processing tasks must be performed or when certain processing tasks must be completed repetitively, the limitations of the built-in ArcGIS functions are quickly reached. In this case, it is essential to employ the Visual Basic for Applications (VBA) macroenvironment contained within ArcMap or ArcCatalog to customize geospatial data processing (Razavi, 2002).

ArcObjects is the software development platform and technological framework of ArcGIS, and it is based on Microsoft's component object model (COM). The COM is a methodology for software development that facilitates software reuse; it is a protocol for developing self-contained and reusable software components in binary language. Software components are typically stored in either dynamic link libraries (DLLs) or executable files. As a result, they offer two advantages: programming language independence and location transparency. Programming language independence means that the functionality of a software component can be accessed from a variety of different programming languages. Location transparency means the software components can be accessed regardless of their location. Because ArcObjects is based on COM technology, it can be used within any COM-compliant development language, such as VBA, Visual Basic, and Visual C++, to develop custom ArcGIS applications. By understanding ArcObjects coding, a third-party programmer can access the full functionality contained within ArcGIS without needing access to the program's source code. ESRI provides an object model diagram in the unified modeling language (UML) for visualization of the objects, classes, relationships

between classes, class interfaces, and interface details that are available within ArcObjects (Zeiler, 2001a,b). Familiarity with this UML diagram is essential for learning how to properly access ArcObjects software components for developing custom geospatial data processing algorithms within VBA in ArcMap.

The software tools developed in this work allow a user to establish a management zone grid over the field area, clip digital soil surveys and yield monitor data according to management zones, and print soil and yield information for each management zone in the proper format for use with Apollo.

2.2. Delineating management zones

Before input files can be generated for each management zone, the management zones themselves must be delineated. In some cases, management zones are delineated according to soil type, soil fertility, or topography. In other cases, a grid system is used. For the latter, Apollo includes an approach for subdividing a study area into a user-defined number of equally sized rectangular management grid zones (Fig. 1).

The user first selects the reference layer from the list of layers currently open in ArcMap, and the corresponding map projection and coordinate system is assigned to the grid layer that will be created. Second, the user is required to enter two integers to define the management grid dimensions, or the number of rows and number of columns of grid zones. The user must then define the upper left and lower right geo-

graphic coordinates of the management zone grid. There are several options for completing this task. By clicking “Get From Map”, the map window in ArcMap is prepared such that the user can draw a rectangle on the screen, and the required geographic coordinates are extracted from the rectangle drawn. By clicking “Get From Layer”, the user is allowed to select from the existing layers currently open in ArcMap, and the required geographic coordinates are extracted from the outer bounds of the selected layer. Also, the user can input the required geographic coordinates manually in the textboxes provided. Then, the “Draw Grid” command button implements the user inputs for grid dimensions and corner coordinates to draw the management zone grid in the ArcMap window. After inspecting the management zone grid drawn in ArcMap, the user can click the “Create Shapefile” button to convert the grid to a polygon shapefile with separate polygons for each management zone. The polygon shapefile can then be added to list of layers in ArcMap and used for subsequent processing of geospatial data.

If a grid-based management zone scheme is to be used, one question of interest involves the optimum size and number of grid zones. Typically, in grid-based studies, the size and number of grid zones are assigned arbitrarily with no agronomic basis. Apollo can thus be used to facilitate studying the effect of management zone delineation on crop production, since it enables the user to change the size of management grid zones and recompute model input parameters accordingly.

If a grid-based management scheme is not to be used, the management zone grid creation tool is not necessary. Instead, the user must generate a polygon shapefile delineating the management zones according to whatever criterion the user chooses. This polygon shapefile could be based on digital soil survey polygons, a topographic contour, interpolations of the previous years’ yield monitor data, or any other data layer that can be expressed as a polygon shapefile.

2.3. Converting existing data to the management zone scheme

Generally, soils and yield data (or other field data) are available not by management zone but by some other scheme. A digital soil survey, for example, will delineate zones by soil type, and these zones may not be the same as the management zones for a given field. Similarly, yield data is often a series of georeferenced points collected in parallel swaths, and a management zone likely contains multiple points of yield data. Given that a large amount of information can be rapidly collected with modern crop sensing systems, the most practical method for obtaining data by management zone is to collect the data without regard to the management zone boundaries and to use post-processing techniques within a GIS to split the data by zone. For this reason, Apollo includes such tools to split input data by zone.

The field data-clipping tool allows a user to split polygon and point layers according to management zone boundaries, assuming the management zones are defined as a polygon layer in ArcMap. Upon initialization, this tool lists the available polygon and point layers currently open in ArcMap in a list box. The user selects the polygon and point layers to be clipped and clicks the “Setup Fields” command button. The user is asked

The screenshot shows a software window titled "Management Zone Grid Creation Tool". It is organized into four sequential steps:

- Step 1 - Select Reference Layer:** A dropdown menu shows "Mgsoil" selected, with a "Set Layer" button to its right.
- Step 2 - Define Grid Dimensions:** Two input fields are present: "Number of Rows" with the value "20" and "Number of Columns" with the value "5". A "Set Dimensions" button is to the right.
- Step 3 - Define Corner Coordinates and Draw Grid:** Four input fields for coordinates: "Upper Left X" (-94.073948399482), "Upper Left Y" (41.9347104232146), "Lower Right X" (-94.0711883474188), and "Lower Right Y" (41.926493474324). Buttons for "Get From Map", "Get From Layer", and "Draw Grid" are positioned to the right of their respective fields.
- Step 4 - Convert Grid To Shapefile:** A "Create Shapefile" button is centered. Below it is a progress indicator consisting of ten blue rectangular blocks. To the right are "Start Over", "Cancel", and "Finish" buttons.

Fig. 1 – The management zone grid creation tool user interface.

to select the name of the data set in the attributable, for example yield data or soil type, of the layer to be clipped. The tool loops through all layers selected for clipping until the user has selected data set of interest for each layer. Then, it advances the user to the next step, in which the user must select the polygon layer that defines the management zone boundaries to be used as a ‘cookie cutter’ for clipping. The user must then select the data set that defines unique zone identifiers for each management zone. This zone identifier is used within the crop model input files to associate model input data with the appropriate management zone, so the polygon layer used for clipping must contain a unique identifier for each polygon. For clipping polygon layers, Apollo computes the feature that covers the largest area within each management zone and assigns that feature to the entire zone. For example, when clipping a digital soil survey, the algorithm determines the soil type that covers the largest area within each management zone and assigns that soil type to the entire zone. For clipping point layers, the algorithm averages the values for all the points contained within management zone boundaries and assigns this value to the entire zone. For example, when clipping data from a yield monitor, all the yield measurements contained within a management zone are averaged, and this value is assigned as the final yield for the zone. In this way, crop model parameters can be defined such that the model’s limiting assumption of homogeneity is satisfied within each management zone. At the end of this process, Apollo will output the clipped layer of interest to a new polygon shapefile.

2.4. Creating model input files

The DSSAT family of crop models requires model input files that are written in a very specific format. Files necessary for operating crop model simulations using Apollo include the soil file (soil.sol), the yield files (*.mza for CERES-Maize), the management files (*.mzx for CERES-Maize), and the weather files (*.wth). For applications with Apollo, the soil file contains unique blocks of text in the specified DSSAT format to define the necessary soil properties for each management zone. Yield files for individual growing seasons contain the average measured yield for each management zone for use in model calibration and validation within Apollo, described in detail later.

After clipping a digital soil survey and yield monitor data according to management zones using the field data clipping tool, soil and yield files can be created. In the user interface for writing the soil file, the user is asked to select the layer corresponding to the soil survey delineated by management zone (for example, that created using the field data clipping tool). When this layer is selected, the available data sets within the layer are listed in a list box, and the user is asked to select the data sets containing the soil type information for each management zone. After selecting the appropriate data set, the user must define the relevant properties for each soil type respectively by manually entering them in Apollo. Most of the required values can be obtained from published soil surveys. However, some data not contained in typical county-level soil surveys, including values for drained upper limit and lower limit, are computed on the basis of the soil texture according to Ratliff et al. (1983). The soil properties for each soil type can

also be saved to and opened from a text file, such that the information does not have to be reentered when a soil type is reencountered in a different study.

Apollo also provides routines for creating the DSSAT performance files, FILEA and/or FILET, which include observed data that can be used in calibration and validation. The FILEA format is for average summary data (such as yield at harvest), and the FILET format is for time series data. First, the user is asked to select the layer corresponding to the performance data delineated by management zone (most likely created using the field data clipping tool). When this layer is selected, the available data sets within the layer are listed in a list box, and the user is asked to select the data set containing the desired information in each management zone for the growing season of interest. Our applications of Apollo have used yield data as the model performance indicator. Since the crop models must have yield information in units of kg ha^{-1} , Apollo includes the option to perform the appropriate conversion if yield data was not collected in these units.

2.5. Initializing a field

Upon first running Apollo for a particular field, the user must add the relevant information to the Apollo database. The user must provide Apollo with a field name and path pointing to the directory containing the crop model input files for the field, as well as the crop model management files (File Xs) that will be used in the analysis. When the user prompts Apollo to add this new field to the database, Apollo checks to determine if a corresponding yield file exists for each File X. If it does exist, Apollo copies numerous files, including the field database into the data directory. Next, the ASCII crop model soil database is loaded into the Apollo soil database. If the field has already been established in the Apollo database, the user can select that field and continue.

2.6. Model calibration and validation

DSSAT does not offer any automated procedures for calibration. Changes to parameters of the model in order to calibrate it for specific conditions must be done one-by-one, by hand, and making quantitative comparisons of model output to observations requires the data to be exported to an analysis package. In order to accomplish this in a precision farming simulation, this process must be repeated for every management zone. Apollo automates the process by optimizing multiple parameters of choice and identifying the best-performing parameter values for each zone individually. Likewise, to validate a calibrated model, running the model and analyzing the output quantitatively is a tedious exercise when more than one homogeneous unit are simulated. Apollo automates the process and provides quantitative results of the validation for each management zone.

2.7. Model calibration to simulate historical yield variability

As applied in Apollo, model calibration (Fig. 2) is the process of adjusting soil properties within their range of uncertainty to minimize error between simulated and observed yield for

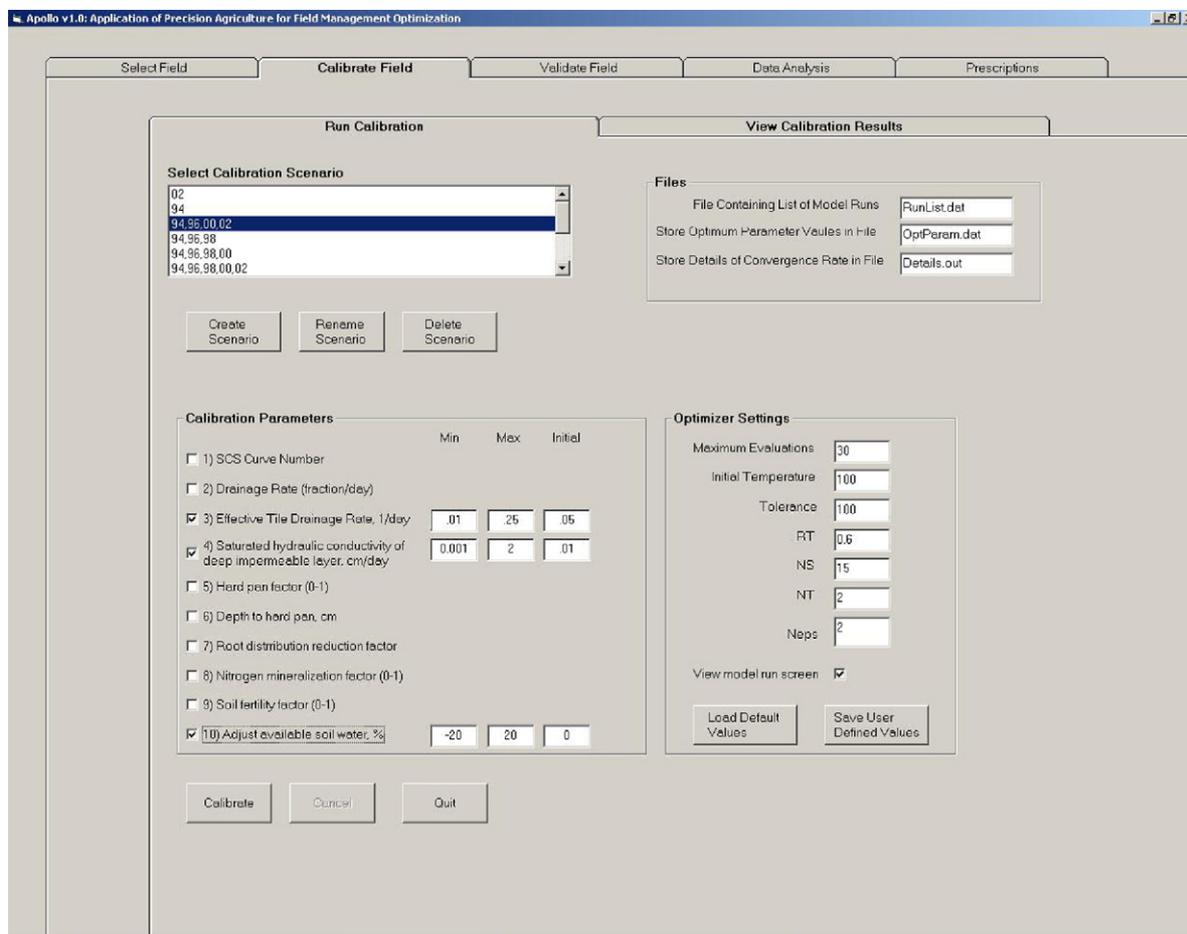


Fig. 2 – Calibration module in Apollo.

each grid over one or more years. The underlying methods are reported in Paz et al. (1998, 1999).

First, the user must define a calibration scenario by first selecting the years and grid zones to be used in the calibration. Once a calibration scenario is established or selected, the user can select one or more of 10 soil-related crop model inputs to calibrate. Selection of parameters to calibrate must be carefully considered based upon field-specific characteristics; not all parameters may be applicable in a given field. If the user selects too many parameters to calibrate, they may get excellent fit between simulated and observed yields for the calibration dataset, but get a poor fit for the validation dataset due to over fitting the model to the calibration dataset. When the user selects one or more soil parameters to calibrate, they can edit the default minimum and maximum search range for each parameter in order to customize it to the range of expected values for their soil types.

The user can also set several optimization parameters which dictate the termination criteria, such as the maximum evaluations (iterations), initial temperature, and convergence tolerance. There are two termination criteria for the simulated annealing algorithm (discussed below): (1) after a user specified number of function evaluations (i.e. number of crop model runs), or (2) if the root mean square error (RMSE) of successive optimum solutions is below a user-specified tolerance.

The maximum function evaluations should initially be set to a high value (i.e. 1000–4000) and can be reduced after experience with the dataset to reduce convergence time.

Apollo then uses the simulated annealing algorithm (Goffe et al., 1994) embedded in an optimization control program to search for parameter combinations that minimize RMSE between simulated and observed yield for the selected grid zones and years. Apollo provides a real-time visualization of the current simulated annealing solution (Fig. 3). It also provides the user with the current grid number being optimized, as well as the progress toward optimizing the current grid (iteration number), and the current RMSE between simulated and observed yield.

After the calibration is complete, the user can save the calibration results, which consists of the optimum soil parameter values for each grid, in the Apollo database. In this module, the user can also load a previously stored calibration scenario, obtain statistics about simulated and observed yield, and export the results to an ASCII text file.

2.8. Model validation

The purpose of the validation routine in Apollo is to compare simulated and observed yield for seasons that were not used for model calibration. The user must first load an existing cal-

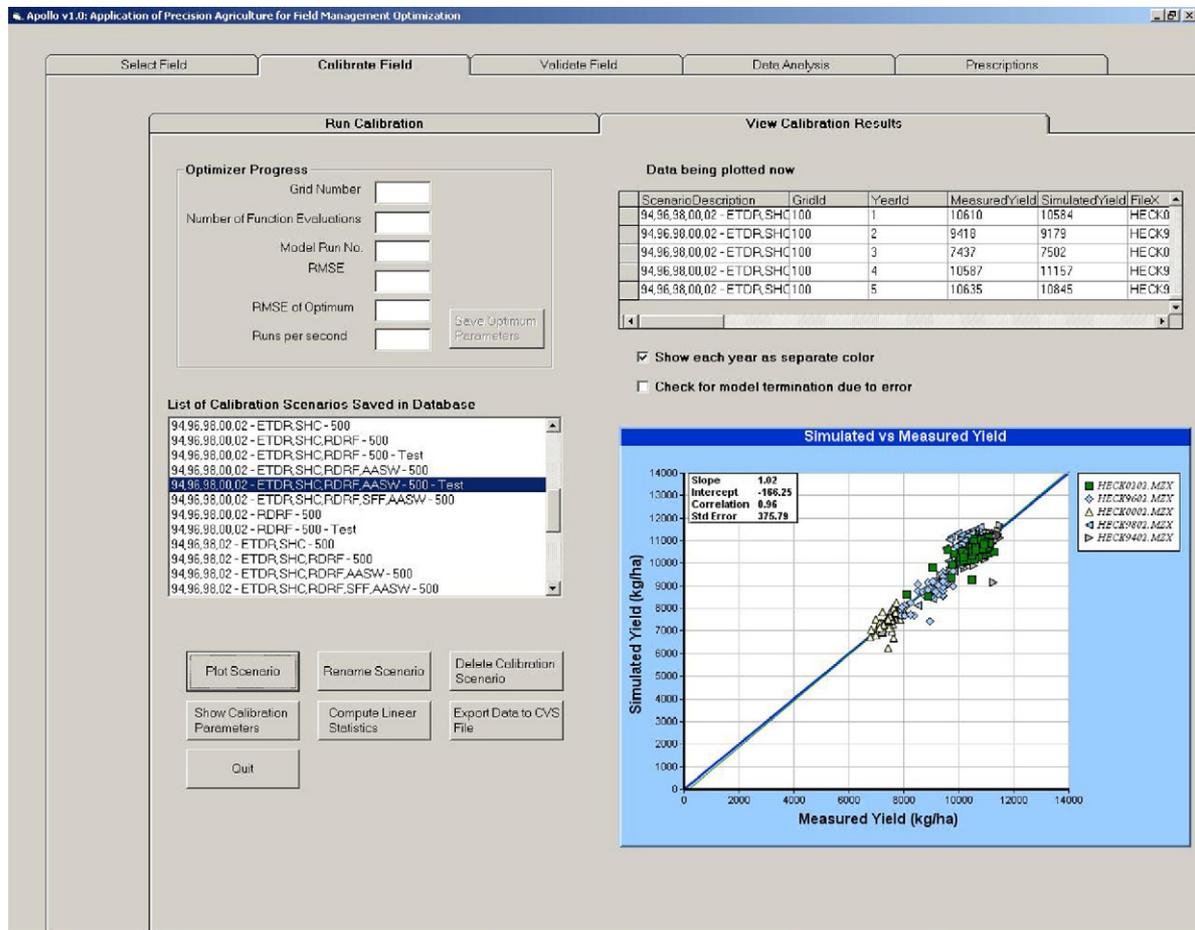


Fig. 3 – Real-time calibration results information provided by Apollo.

ibration scenario into Apollo by selecting a stored calibration scenario from a list box. Once the user selects a calibration scenario, a list of the File X(s) available (both calibration and validation) populates a list box, and the user can select the File X(s) to use for validation. Another list box displays the File X(s) and grid zones used for calibration as a reminder to the user. Apollo will then run the crop model for the selected File X(s) and display simulated and observed yields on a graph. The user can obtain statistics about the data, and export the simulated and observed yield to an ASCII or comma delimited file for analysis external to Apollo. The user can also run the WinGraf plotting package distributed with DSSAT, version 3.5 to examine many time series graphs of model state and rate variables for any File X and grid. It is often useful to try different combinations of calibration and validation years to obtain a better estimate of the error expected in simulated yield for years not used for calibration. This is especially helpful when using Apollo to evaluate performance of prescriptions.

2.9. Estimation of results of spatially variable management

2.9.1. Prescriptions

The purpose of the prescription module is to generate a family of yield or nitrogen loss curves for different years of his-

torical weather for each grid in the field. The idea behind prescriptions is to determine the optimum input that maximizes the long-term marginal net return or achieves a user defined environmental goal (i.e. nitrogen loss) over numerous years of weather (Paz et al., 1999; Batchelor et al., 2002; Thorp et al., 2006). Apollo currently generates yield and nitrate loss information necessary to compute optimum population and nitrogen rates over many years (i.e. 20–30) of historic weather.

The user must first set up a prescription by loading a calibration scenario into Apollo. The calibration scenario contains the site characteristics that will be used by the crop model to generate prescriptions. In order to generate prescriptions, the user must develop File Xs for many different years of weather (i.e. 20–30 years), and load these File Xs into the Apollo database using the “Add File Xs to List” button located on the Set Up Prescription tab. The user must select the File Xs desired for the prescription and add them to the appropriate list box.

After the prescription has been set up, the user is given the choice to run a population prescription, nitrogen prescription, or both. For each of the desired prescriptions, the user must specify a minimum, maximum, and increment that will be used for model runs. Apollo will then run the crop model for all combinations of selected File Xs, populations and nitrogen rates. Apollo stores the simulated yield for each combination in a user named file, along with the total soil ammonia, nitrate,

nitrate leached and nitrate lost through the tile drain for each combination of year, population, and nitrogen rate in the prescription. The user defined output file contains the necessary information for users to compute the optimum nitrogen and/or population rate to maximize marginal net return or to achieve a desired probability of N lost or left behind (Thorp et al., 2006).

2.9.2. Irrigation simulation

Using the same programming structure as the prescriptions, a module was created for Apollo to automate spatially variable irrigation scenarios. This module allows the user to assess scheduled irrigations or automatic irrigations based on the percent available soil water of each grid. Apollo obtains values from the prescription user interface and formats them into a data file, which is acquired by the crop model prior to any simulations. The user-chosen parameters then overwrite any parameters listed in the standard input files for the crop model.

Several input parameters are available in the Apollo visual interface. An option button allows the user to choose between several scenarios, including no irrigation, scheduled irrigation based on user-defined dates and amounts, and automatic irrigation with fixed irrigation amounts (simulating precision irrigation). The user can also adjust irrigation efficiency, application amount, and in the case of automatic precision irrigation, the management depth and percent of available soil water threshold used for automatic applications.

3. Case study: impacts of climate change on spatial yield variability

Previous investigations have detailed the use of Apollo for model calibration and validation (Thorp et al., 2007), development of precision nitrogen management strategies (Thorp et al., 2006), spatially variable-irrigation (DeJonge et al., 2007), etc. We will therefore conclude this paper by demonstrating the use of Apollo for a new application. We will use the system to simulate the potential effects of projected climate change spatial yield variability.

Future scenario climates for the mid to end of the 21st century as simulated by global climate models show a general warming over the United States. Large uncertainties accompany global model projection of future changes in global mean precipitation, but increase on an annual basis seems to be most likely. It is possible that the spatial responses and needs of a crop may differ under such changes in climate. In this case study, we used 9-year regional simulations of contemporary (current) and future scenario climates to provide a physically consistent set of climate variables for input to the Apollo system, in order to see what effect, if any, different climate patterns would have on the spatial response of the crop.

Regional climates consistent with global changes are created by downscaling global climate model results either by statistical or by dynamic (regional climate model) methods. Giorgi et al. (1994) showed that a nested regional model produces a more realistic simulation of precipitation over the United States than the driving global model alone, and also that the estimated changes in climate were different: pre-

cipitation changes differed locally in magnitude, sign, and seasonal details.

DSSAT requires daily precipitation, maximum and minimum air temperature, and solar radiation as standard weather inputs. These inputs were taken from a regional climate model that was driven by a global model. We used two sets of climate data: a contemporary scenario and a future. Results of the global climate model of the Hadley Centre (HadCM) were used to provide the basic climate information for these two scenarios. The HadCM (Murphy, 1995; Murphy and Mitchell, 1995) is a coupled atmosphere–ocean model that uses a finite difference grid of 2.5° latitude by 3.75° longitude (about 300 km in midlatitudes). This resolution does not provide enough spatial climate detail to represent realistic sub-regional climates. Thus, we nested a fine grid resolution regional climate model, HIRHAM, into the coarse grid global model to dynamically downscale global information to a sub-regional scale. HIRHAM (Christensen et al., 1996) simulations have a horizontal grid spacing of 0.5° latitude by 0.5° longitude, approximately 55 km in our study region. For this study, model simulations for the single grid box containing the study site were selected.

The contemporary climate scenario, represented by a 9-year window, corresponds roughly to the 1990s, selected from the HadCM simulations without enhanced greenhouse gas forcing, and has CO₂ levels of 360 ppm. The future climate scenario, represented by a 9-year window, corresponds roughly to the 2040s. This future scenario is from a transient HadCM simulation that assumed a 1% per year increase in effective greenhouse gases after 1990, and has CO₂ levels of about 500 ppm.

The 20.25 ha test field, near Perry, IA, USA (41.930808°N, 94.072548°W), was separated into 100 even management grid zones, each 45 m by 45 m. Five years of complete historical management, weather and spatially variable yield data for corn (*Zea mays* L.) were available (1994, 1996, 1998, 2000, and 2002). Yield data were processed using the Apollo DSS preprocessing routines described above. During the odd-numbered years in this sequence, soybeans were planted in this field. We used data for the even-numbered years to calibrate the model, using the process described above. A digitized soil survey, preprocessed for Apollo using the procedures outlined above, indicated five primary soil types present in the test field: Canisteo silty clay loam, Clarion loam, Nicollet loam, Harps loam, and Okobojo silty clay loam. Soil types were generally distributed topographically, with Clarion and Nicollet on hilltops and upper sideslopes, Canisteo and Harps on lower sideslopes, and Okobojo in bottom areas.

Initial soil water content and nutrient levels were not available for this field. Therefore, appropriate levels were assumed and assigned throughout the study area. Initial soil water content was set at 0.35 cm³ cm⁻³, a value near the drained upper limit for the soils of the field. Initial nutrient levels were set arbitrarily at 0.1 g elemental N, P, and K per Mg soil; this amount of initial nutrients was set to be negligible because it is assumed that spring fertilizer applications would supply nutrients for adequate growth. The plant population for each grid cell was collected during the 1996 growing season only, and the average population for this year was used in the calibration to eliminate any modeling error between grid cells due to population differences. Calibration model inputs for

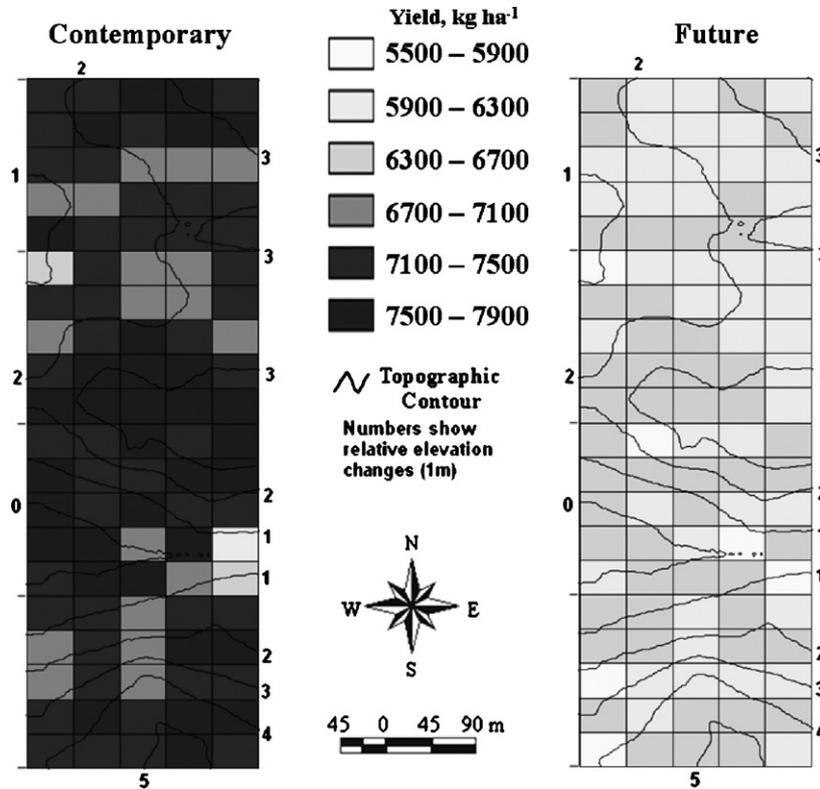


Fig. 4 – Average yields over 9 years of simulated contemporary climate (left) and future climate (right).

management practices (planting and harvest date, fertilizer application rate and dates) were set according to the producer’s actual practice in each of the five growing seasons. Management inputs for the simulation years were assumed by taking mean values from the calibration years. Calibration and validation of CERES-Maize for this field is discussed further detail in DeJonge et al. (2007) and Thorp et al. (2007).

Using the Apollo system, spatial yield predictions were made for both the simulated contemporary climate and the simulated future climate. These are shown in Fig. 4.

These results indicate that not only are average yields different between the two scenarios, but that the spatial distribution of higher and lower yielding areas is also different. In the contemporary scenario, average yields across the field

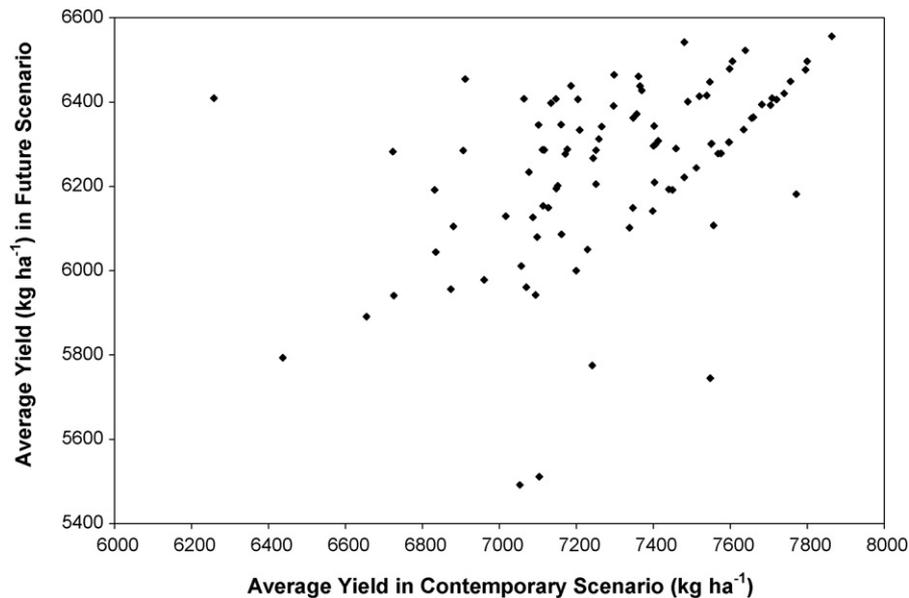


Fig. 5 – Comparison of average yields per management zone for contemporary and future simulations.

over all 9 years are approximately 7300 kg ha^{-1} with a standard deviation of approximately 300 kg ha^{-1} , whereas in the future scenario they are approximately 6250 kg ha^{-1} , with a standard deviation of approximately 200 kg ha^{-1} . While nearly every management zone shows a decrease in average yield from the contemporary to future scenarios, the locations of relatively higher and lower-yielding areas changes. In general, higher-yielding areas were more consistent than lower-yielding areas (Fig. 5).

That the future climate simulations result in lower yields overall is likely due primarily to differences in daily temperatures. The simulated future climate temperatures are notably warmer than the simulated contemporary climate, with the average daily maximum increased by an average of 1.95°C and the average daily minimum increased by an average of 2.56°C . This doubtless increased the evapotranspiration demand of the crop. Though the average annual rainfall in the simulated future scenario are higher (951 mm , as opposed to 722 mm), it is likely that the temporal distribution in the future scenario was not matched to the temporal distribution of crop demand. Moreover, the higher temperatures in the future scenario also caused a shorter grain-filling period, resulting in lower yields. The grain filling period is determined by accumulation of growing degree-days. Thus, if the daily temperatures are higher, the corn plant accumulates growing degree-days faster, and has fewer days to fill kernels. Corn adds weight to individual kernels at a very linear rate, approximately $6\text{--}8 \text{ mg/day}$, depending upon hybrid. Thus, yield is increased or decreased by the length of the grain-filling period, which is highly temperature dependent; higher temperatures shorten the filling period.

These results have several implications. That the yield response under the future scenario shows less spatial variability suggests that larger management zones would be just as effective. Furthermore, that the spatial distributions of yield in the two simulation sets were different indicates that optimal site-specific applications of fertilizer or irrigation would also be different between the two scenarios. Using the Apollo tool, the impacts of various management options can be fully investigated.

4. Conclusions

Crop models provide a mechanistic way to estimate the interaction of spatial differences in soil properties and pest populations with temporal stresses on yield variability within a field. This is possible because the models compute daily growth processes as a function of weather, stress, and pest damage. Once calibrated to simulate the historical yield variability within a field, crop models are a powerful tool to develop risk management strategies that can balance economic risk incurred by the producer with environmental risks that impact society. The Apollo system incorporates many procedures that crop modelers have developed to analyze causes of yield variability and to estimate economic and environmental consequences of prescriptions into a simple interface.

Because Apollo is designed essentially as a shell program to run the DSSAT model, it would be a useful methodology for

any spatially variable application of DSSAT, provided spatially variable input data (such as soils or yield data) is available. Thus, while the development and application presented in this paper was for simulation of corn production in central Iowa, the methodology is applicable for any location in which one wishes to use DSSAT for spatial simulation.

This paper presents a working beta version of Apollo. Because the code for the functions beyond automated generation of the spatially variable inputs and yield files were written to interface with DSSAT, version 3.5, some recoding will be necessary before the code can be used with DSSAT, version 4.0 and beyond, due to the change in structure of the cropping systems model. Among other benefits, compatibility with DSSAT 4.0 and beyond would allow for using Apollo in simulations and analysis of crop rotations, which is not supported in DSSAT 3.5. Code for the beta version of Apollo can be obtained free of charge from the corresponding author.

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REFERENCES

- Alexandrov, V.A., Hoogenboom, G., 2001. The impact of climate variability and change on crop yield in Bulgaria. *Agric. Forest Meteorol.* 104, 315–327.
- Batchelor, W.D., Basso, B., Paz, J.O., 2002. Examples of strategies to analyze spatial and temporal yield variability using crop models. *Eur. J. Agron.* 18 (1–2), 141–158.
- Christensen, J.H., Christensen, O.B., Lopez, P., van Meijgaard, E., Botzet, M., 1996. The HIRHAM4 regional atmospheric climate model. DMI Scientific Report 96-4. Copenhagen, 51 pp.
- DeJonge, K.C., Kaleita, A.L., Thorp, K.R., 2007. Simulating the effects of spatially variable irrigation on corn yields, costs, and revenue in Iowa. *Agric. Water Manage.* 92 (1–2), 99–109.
- Fetcher, J., Allison, B.E., Sivakumar, M.V.K., van der Ploeg, R.R., Bley, J., 1991. An evaluation of the SWATRER and CERES-Millet models for southwest Niger. In: Sivakumar, M.V.K., Wallace, J.S., Renard, C., Giroux, C. (Eds.), *Soil Water Balance in the Sudano-Sahelian Zone*. International Association of Hydrological Sciences, Wallingford, UK, pp. 505–513.
- Giorgi, F., Brodeur, C.S., Bates, G.T., 1994. Regional climate change scenarios over the United States produced with a nested regional climate model. *J. Climate* 7, 375–399.
- Goffe, W.L., Ferrier, G.D., Rogers, J., 1994. Global optimization of statistical functions with simulated annealing. *J. Econometrics* 60, 65–99.
- Jones, J.W., Hoogenboom, G., Porter, C., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P., Singh, U., Gijsman, A., Ritchie, J.T., 2003. DSSAT cropping system model. *Eur. J. Agron.* 18 (2003), 235–265.
- Miao, Y., Mulla, D.J., Batchelor, W.D., Paz, J.O., Robert, P.C., Wiebers, M., 2006. Evaluating management zone optimal nitrogen rates with a crop growth model. *Agron. J.* 98 (3), 545–553.
- Murphy, J.M., 1995. Transient response of the Hadley Centre coupled ocean-atmosphere model to increasing carbon

- dioxide, Part I: control climate and flux adjustment. *J. Climate* 8, 36–56.
- Murphy, J.M., Mitchell, J.F.B., 1995. Transient response of the Hadley Centre coupled ocean-atmosphere model to increasing carbon dioxide. Part II: spatial and temporal structure of response. *J. Climate* 8, 57–80.
- Paz, J.O., Batchelor, W.D., Colvin, T.S., Logsdon, S.D., Kaspar, T.C., Karlen, D.L., 1998. Analysis of water stress effects causing spatial yield variability in soybeans. *Trans. ASAE* 41 (5), 1527–1534.
- Paz, J.O., Batchelor, W.D., Colvin, T.S., Logsdon, S.D., Kaspar, T.C., Karlen, D.L., Babcock, B.A., 1999. Model-based techniques to determine variable rate nitrogen for corn. *Agric. Syst.* 60 (1999), 69–75.
- Paz, J.O., Batchelor, W.D., Tylka, G.L., 2001. Estimating potential economic return for variable rate management in soybeans. *Trans. ASAE* 44 (5), 1335–1341.
- Paz, J.O., Batchelor, W.D., Jones, J.W., 2003. Estimating potential economic return for variable rate soybean variety management. *Trans. ASAE* 46 (4), 1225–1234.
- Quemada, M., Cabrera, M.L., 1995. CERES-N model predictions of nitrogen mineralized from cover crop residues. *Soil Sci. Soc. Am. J.* 59, 1059–1065.
- Ratliff, L.F., Ritchie, J.T., Cassel, D.K., 1983. Field-measured limits of soil water availability as related to laboratory-measured properties. *Soil Sci. Soc. Am. J.* 47, 770–775.
- Razavi, A.H., 2002. *ArcGIS Developer's Guide for VBA*. Delmar Learning, Clifton Park, NY.
- Thorp, K.R., Batchelor, W.D., Paz, J.O., Steward, B.L., Caragea, P.C., 2006. Methodology to link production and environmental risks of precision nitrogen management strategies in corn. *Agric. Syst.* 89 (2–3), 272–298.
- Thorp, K.R., Batchelor, W.D., Paz, J.O., Kaleita, A.L., DeJonge, K.C., 2007. Using cross-validation to evaluate CERES-Maize yield simulations within a decision support system for precision agriculture. *Trans. ASABE* 50 (4), 1467–1479.
- Zeiler, M., 2001a. *Exploring ArcObjects. Volume 1: Applications and Cartography*. ESRI, Redlands, CA, USA.
- Zeiler, M., 2001b. *Exploring ArcObjects. Volume 2: Geographic Data Management*. ESRI, Redlands, CA, USA.