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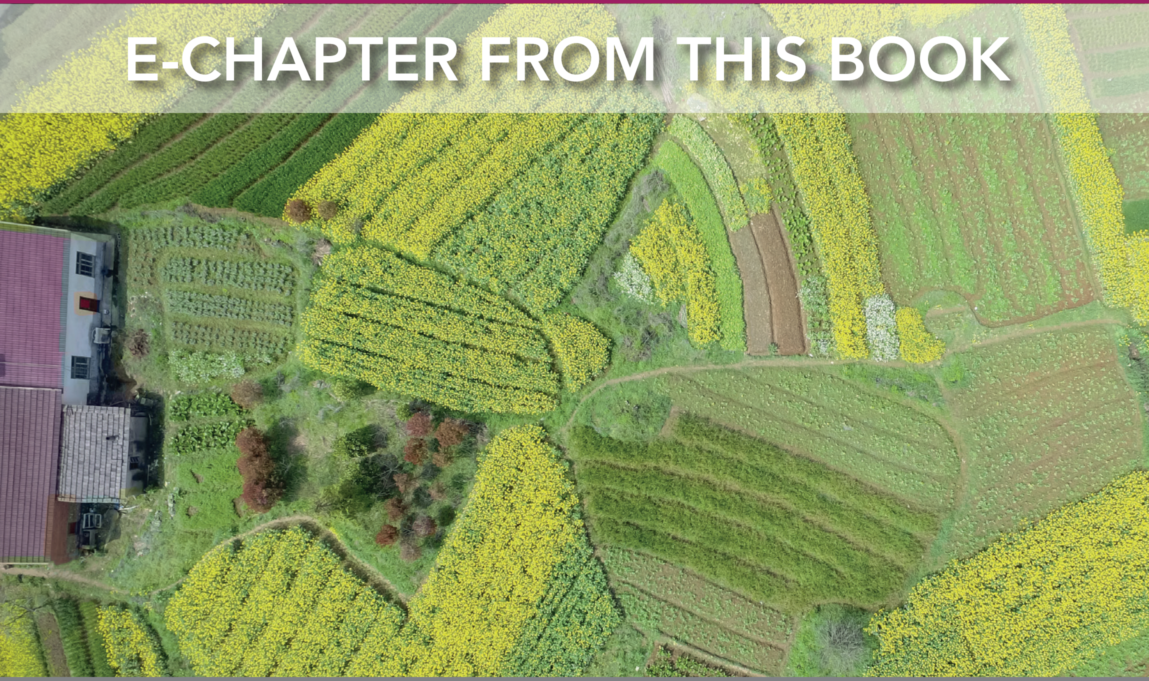

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The DSSAT crop modeling ecosystem

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1 Introduction

Traditionally, research for agricultural development and improvement is based on small plot experiments that are conducted for multiple years on a research station

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[1] This chapter is written in memory of Paul Wilkens, who passed away November 27, 2017, due to brain cancer. Paul was a key member of the DSSAT Development Team and his many contributions to the DSSAT community and his low-key humor are greatly missed.

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and, on occasion, in multiple locations. The outcomes of these experiments are then transmitted in the form of recommendations to farmers through state-wide and county-based extension services. Although this approach works well for the United States and Europe where farms are normally well managed with respect to fertilizer, irrigation inputs, and pests and diseases, in some countries funding and resource challenges make this approach less practical. In the early 1980s, the United States Agency for International Development (USAID) made a bold step to support a project that was based on systems analysis of agricultural production to address food security in developing countries. This project for improving agricultural production, called the International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT), was developed by Goro Uehara, a soil physicist and professor at the University of Hawaii. Uehara's previous work with the Benchmark Soils Project, which was also funded by USAID, showed that research only on soils cannot address food security in developing countries. The IBSNAT Project was funded from 1982 through 1992. In subsequent years, USAID and other funding agencies have not been as supportive of funding for basic model development and improvement as for providing funding for model applications.

The systems analysis approach of the IBSNAT Project was based on biophysical models that predict crop growth, development, and yield using daily weather data, local soil conditions, crop management, and genetics as input. At the start of the IBSNAT Project, crop modeling teams from the University of Florida (SOYGRO and PNUTGRO models) and from USDA-ARS in Temple, Texas (CERES-Maize and CERES-Wheat models) were invited to collaborate with scientists from the University of Puerto Rico, the University of Edinburgh (Scotland), the University of Guelph (Canada), and the International Fertilizer Development Center in Muscle Shoals, Alabama (Wilkerson et al., 1983; Boote et al., 1986; Ritchie et al., 1985; Jones and Kiniry, 1986). The early versions of these crop models were based on nonuniform and nonstandard input and output files, making it challenging for users to apply models for different crops to the same farming system. Therefore, the Minimum Data Set (MDS) system was developed to standardize the inputs required for these crop models as well as the file formats used (ICRISAT, 1984). This standardization facilitated the development of data utility programs for processing weather, soil, management input data, and experimental observation files, as well as tools for application and display of output data for the models, forming the basis for the Decision Support System for Agrotechnology Transfer (DSSAT) software. For further details of IBSNAT activities and outcomes, see IBSNAT (1993), Uehara and Tsuji (1998), and Jones et al. (2017).

2 The DSSAT ecosystem

The combination of different models, tools, utilities, and applications requires the development of a unique interface that provides easy access for a user who may not be familiar with crop models in general, especially with the challenges of formatting input and output files. Jim Jones conceptualized the design of DSSAT to be an integrated crop modeling platform (Jones et al., 1998). DSSAT provides tools to assist a user to prepare the different input files that are needed for running a model, to define the experiments and treatments or scenarios a user wants to simulate, and to conduct an analysis of crop model outputs from the simulations, including a comparison with observed data for model evaluation and strategic analyses for model scenarios (Fig. 1). In order to facilitate the interaction between the crop models, the data tools, the utilities, and the application programs, a very strict protocol is required for the file naming convention, specific file formats, and system settings that define the location and names of the model input and output files. This approach was first presented to DSSAT users in DSSAT Version 2.1 (IBSNAT, 1989) and DSSAT Version 3.0 (IBSNAT, 1993) at the end of the IBSNAT Project. The original design and concept are still viable in the most current version of DSSAT Version 4.7.5 (Hoogenboom et al., 2019) and in a proposed future implementation in jDSSAT (Resenes et al., 2019).

Over time, both the file formats and the file naming conventions have changed, but the approach is still the same. The same flat ASCII file structures

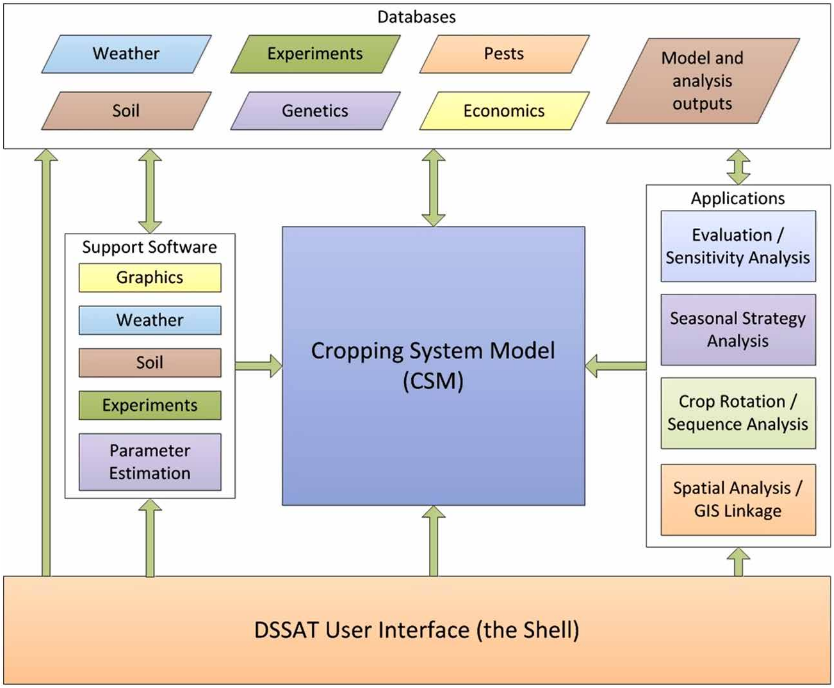

Figure 1 The DSSAT crop modeling ecosystem.

are used to provide ultimate portability, something learned after using early proprietary data base software that was no longer supported. As a result, a user can easily simulate crop growth, development, and yield for different crops for the same field while making only minor changes to the input files that are crop specific, such as variety selection, planting date, or plant density. The strict protocol also has allowed programmers to develop new tools and utilities that can be easily incorporated into DSSAT based on standard input and output formats. Examples include the graphics program EasyGrapher (Yang et al., 2014b), the genetic-specific parameter optimizer GLUE (He et al., 2010), and a platform-independent DSSAT shell (Resenes et al., 2019). The only challenge has been the use of two digits to represent a year, which will be resolved in the next release of DSSAT with the introduction of ICASA Version 2.0 file formats that were defined several years ago (White et al., 2013).

3 Minimum Data Set (MDS) for crop modeling

In order to run a crop simulation model, a minimum set of input data is required. The challenge is to define a MDS that is relatively easy to collect by crop model users and one that also provides reasonable simulation results. Unfortunately, the larger crop modeling community has never been able to come to an agreement on a standard definition for MDS (Hunt et al., 1994). One of the outcomes and successes of the IBSNAT Project was the definition of an MDS that was acceptable to all crop model developers for the CERES-Maize, CERES-Wheat, SOYGRO, and PNUTGRO models (Hunt et al., 2001). This MDS includes daily weather data, soil surface and soil profile information, crop management, and initial conditions at the start of the simulation. Although the MDS is specifically defined for crop model applications, the IBSNAT community also tried to emphasize that such data should include basic information collected for all agronomic experiments to fully understand the Genotype * Environment * Management interactions (Hoogenboom et al., 2012).

The minimum weather data include the metadata for the weather station, especially latitude, longitude, elevation, and sensor height, and daily maximum and minimum temperature, rainfall, and solar radiation. Although solar radiation is not commonly measured at many remote locations, it is a required input for the accurate simulation of photosynthesis and potential transpiration using the Priestley-Taylor equation (Priestley and Taylor, 1972).

The minimum soil data include the metadata for the location where the soil conditions were measured: soil surface color, slope, drainage, and permeability, as well as soil texture, bulk density, and soil organic carbon for each individual soil horizon. The DSSAT crop models simulate only a one-dimensional water balance with vertical flow to meet the requirements for relatively simple inputs for model users, especially for applications.

The crop management data include the crop and cultivar selection, planting date, plant density, row spacing, sowing depth, irrigation, and fertilizer inputs. For irrigated treatments and scenarios, the dates, amounts, and the type of irrigation system must be defined; for fertilized treatments and scenarios, the dates, amounts, and types of inorganic fertilizer must be defined, as well as depth of incorporation. For organic fertilizers using plant or animal material, the type and composition of the organic fertilizers have to be defined. If a crop, such as rice, tomatoes, or other vegetables, is transplanted, the initial weight of the transplant material, age, and the temperature of the nursery have to be defined. For potatoes, the weight of the seed-potato is an input, for cassava the weight and length of the stick and orientation of planting are defined, and for sugarcane the initial cane is defined. Although these inputs might seem complex, proper recording for all management activities will capture most of this information. For a few crops, including potatoes and cassava, the harvest date must be defined as well.

Boundary or initial conditions at the start of the simulation are also very important, especially for the soil environment, requiring initial soil moisture, nitrate, and ammonia for each horizon or soil layer, as well as the aboveground biomass residue and roots of the previous crop and their composition. Although these conditions can be challenging to measure unless equipment and personnel are available, they can be estimated using the tools and utilities that are provided with DSSAT.

The previously listed input data for weather, soil, crop management, and initial conditions are the MDS required for running the model. For model calibration, evaluation, and improvement, crop and soil measurements are required so that comparisons can be made between simulated and observed data. Depending on the research goals and objectives, measurements can include yield and yield components, detailed crop phenology, crop growth analysis, and soil profile measurements such as soil moisture, nitrate, and ammonia, organic carbon, and other information (Hoogenboom et al., 2012). The number of measurements needed should be based on the model application rather than requiring a researcher to collect as much data as possible. For example, variety trial data that are collected for multiple locations and multiple years for the same cultivars or hybrids can be very useful, but normally in these trials only yield, some yield components, and phenological events are recorded. Recently, there have been some discussions about a classification of experimental data sets for crop modeling (Boote et al., 2015; Kersebaum et al., 2015).

4 Input data tools

Most researchers have their own individual standard methodology for recording experimental data in field books, spreadsheets, and other electronic media. These individual differences make it somewhat challenging to convert the measured data into a format that can be directly applied in a crop modeling system. DSSAT, therefore, provides specific tools for entering weather, soil, crop management, and observational data.

4.1 XBUILD

XBuild is the tool for entering crop management data that are stored in a crop management file (Fig. 2). The tool is designed so that the user first enters information that defines the field, especially the weather station and soil profile that are associated with that experiment, followed by the crop and cultivar selection, and planting information. Initial conditions are defined in the Environmental Section of the tool. The user can enter different levels for each management scenario, such as multiple cultivars or hybrids, different planting dates, and different input levels and application dates for irrigation and fertilizer. Following the entry of all specific information, the user then defines the specifics for each individual treatment, including field location, crop and cultivar, planting details, initial conditions, and the appropriate irrigation and fertilizer level, similar to the way a researcher defines a treatment for an agronomic experiment.

4.2 WeatherMan

WeatherMan allows for the entry and formatting of weather data into DSSAT weather files (Fig. 2). A user can import weather data preferably from spreadsheets, but WeatherMan can also handle other formats including CSV and ASCII text files. Once the data have been imported into WeatherMan,

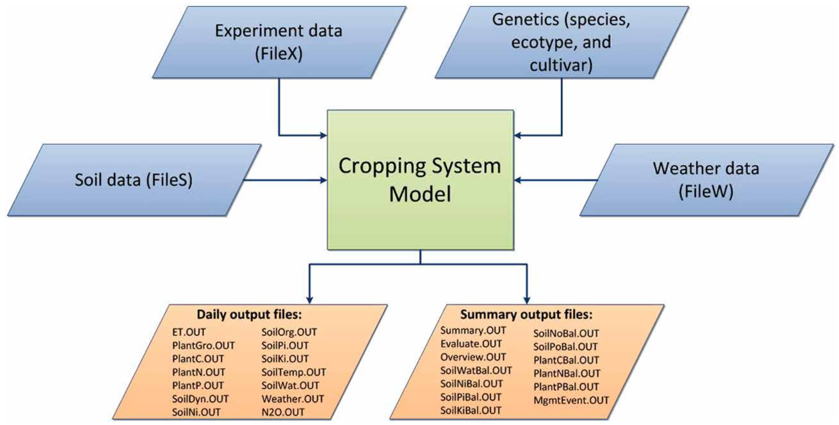

Figure 2 The DSSAT Input and Output file system.

quality control procedures can be applied to identify extreme values or extreme changes in values for two consecutive days and any missing values. A new internal database is created in WeatherMan with what is referred to as the 'corrected' data. The final procedure is to export the data back into DSSAT format weather files.

4.3 SBUILD

The soil water balance simulation in DSSAT is based on the tipping bucket approach with three key soil moisture variables, including Saturated Water Content (SAT), Drained Upper Limit (DUL), and the Lower Limit (LL) of plant extractable water. Although there are procedures for measuring these, they are not very common and require a significant amount of experimental resources. The SBUILD program of DSSAT allows a user to enter soil surface information, including soil color, slope, permeability, and drainage characteristics, and soil texture, bulk density, and organic carbon for each soil horizon. SBUILD then uses internal pedotransfer functions to calculate SAT, DUL, and LL for each soil horizon or layer, and it saves the information for that particular soil profile in the soil input file (Fig. 2).

4.4 ATCreate

Measurement data for model evaluation can be differentiated into two types in DSSAT. The first type is referred to as the summary data, and includes the key phenological stages, yield and yield components at final harvest, and other measurements that can be obtained at critical stages, such as maximum leaf area index (LAI) or grain nitrogen concentration. The summary data are stored in FileA as a single line per treatment. The second type of measurement data is referred to as time series data for growth analysis, soil moisture content, soil nitrogen measurements, and other relevant data that can be used for model evaluation. The time series data are stored in FileT and organized by treatment and then observation date. There is also the ability to store the observations for the individual replicates. The ATCreate program allows users to enter observations either manually or by importing a spreadsheet or text file, thereby creating the FileA and FileT for each experiment. It is important to select the appropriate header for each column of data so that the other programs within DSSAT are able to recognize the observed variables. The file called DATA.CDE holds the names of these variables (short name, long name, and units) so that header names are shared and are also readable by the graphics program and other programs in DSSAT.

5 The Cropping System Model (CSM)

The main engine of the DSSAT ecosystem is the Cropping System Model (CSM; Fig. 3). For most users, the model is run through the DSSAT Interface, but for power users, it can also be run through a command line interface on iOS, Linux, and Unix platforms. The original crop models in the first version of DSSAT were CERES-Maize, CERES-Wheat, SOYGRO, and PNUTGRO. These original models morphed over time from many independent models to a single agricultural systems model that encompasses all the original crop models as individual crop modules (Jones et al., 2003).

Development of models for new crops was initially based on creating new, stand-alone models, such as the model for dry beans BEANGRO, which was developed based on SOYGRO (Hoogenboom et al., 1994). In the early 1990s, the DSSAT developers realized that code modifications were often made redundantly for the separate SOYGRO (Jones et al., 1987), PNUTGRO (Boote et al., 1987), and BEANGRO (Hoogenboom et al., 1990) models. Therefore, we pulled all crop-specific parameters and relationships out of the FORTRAN code and placed them into external species files (per crop), thus allowing a single generic executable CROPGRO code to represent three crop species

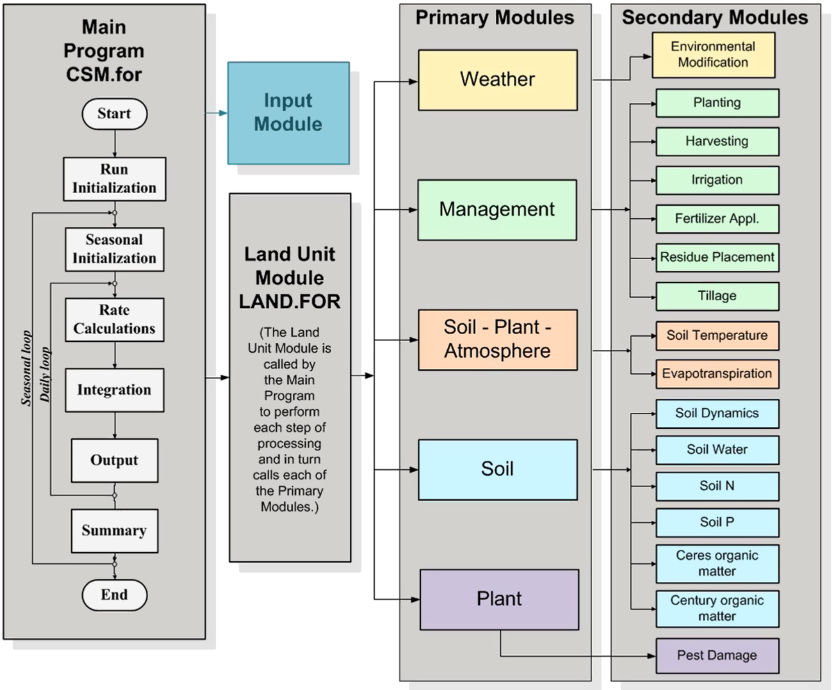

Figure 3 The structure of the Cropping System Model.

(Hoogenboom et al., 1991, 1992). These improvements were part of the DSSAT v3.5, a stable, well-used software system (Hoogenboom et al., 1999). This template approach allowed later adaptations of species files to represent many other crop species using the same source code.

During the 1990s, code improvements were made to the CROPGRO model to add mechanistic leaf-level photosynthesis coupled with hedgerow light interception to simulate leaf-to-canopy assimilation running on an hourly basis for sunlit and shaded leaf classes (Boote and Pickering, 1994; Pickering et al., 1995; Boote et al., 1998). The leaf-level photosynthesis captures the rubisco kinetics of Farquhar and von Caemmerer (1982) and mechanistically simulates photosynthesis response to CO_2, O_2, temperature, solar radiation, LAI, and leaf state (specific leaf mass and leaf N concentration). The simulated response to CO_2 is thus an outcome of this rubisco kinetics, rather than resulting from an externally prescribed CO_2 response curve often used in other models. The simulated leaf-level and canopy-level photosynthesis were tested against observed data and shown to be accurate by Alagarswamy et al. (2006). Since that time, this hourly leaf-level photosynthesis method has been the default for the CROPGRO model crops, in place of the older, but still available, daily canopy photosynthesis option. The CERES-based models in DSSAT are based on radiation-use efficiency (RUE), and they use an externally prescribed CO_2 response modifier based on observed CO_2 response data. See Boote et al. (2010) for a discussion of the CO_2 response curves for C3 and C4 crops simulated by the CERES-based models in DSSAT and for an evaluation of CERES and CROPGRO version crops against metadata on observed CO_2 response. A simple ozone impact routine was recently introduced in one of the wheat models in DSSAT (Guarin et al., 2019).

In the decade from 2000 to 2010, the DSSAT-CSM was created (Jones et al., 2003). This single executable program was able to simulate all the crop models, including the CERES models (Ritchie et al., 1998) and the CROPGRO models (Boote et al., 1998), that until this point were available only as individual models. With CSM, each crop module shares the same routines for the simulation of soil water dynamics, soil N dynamics, soil C dynamics, management operations, and daily weather processes. All input and output data use the same structure, naming conventions, and formats (see scheme in Fig. 2). This consolidation of the soil processes enabled the simulation of a true crop rotation, that is, a sequence of different crops grown in rotation in which the shared soil water, N, and C balances are run in a continuous simulation allowing carry-over of soil water, N, soil C from one cropping season to the next. During this same time period, the daily DSSAT-CENTURY soil C module was developed (Gijsman et al., 2002), providing simulation of surface residue decomposition and in-season contribution of senesced plant components, which are very important for long-term simulations of crop rotations and perennial systems.

5.1 Additional Crops in DSSAT

There are two methods for adding new crop modules into DSSAT. The first and easier approach uses the CROPGRO template and data from field experiments, journal articles, non-refereed publications and reports, and variety trials to calibrate the genetic parameters which control the growth and development characteristics of the new crop. This approach does not require any modification of the existing model software and computer code. The second approach is to add a completely new crop module into the CSM code, such as when growth or phenological characteristics of a new crop are very different from those described in the CROPGRO template. In this second case, both model coding and calibration of parameters are required. As an example, the CERES-Sugarbeet model was one of the most recent modules added to CSM (Anar et al., 2019).

During the past 20 years, a number of additional crops have been added to those originally available in the 1998 DSSAT v3.5 release. Figure 4 shows the crop models available in DSSAT v4.7, including a few models that are currently under development and will be released in a future version of DSSAT. Crops added since v3.5 that use the CROPGRO template include chickpea (Hoogenboom et al., 1997), tomato (Scholberg et al., 1997; Boote et al., 2012), cowpea (Boote, 1998, unpublished), mucuna or velvet bean (Hartkamp et al., 2002), faba bean (Boote et al., 2002), cotton (Boote, 2010, unpublished; Pathak et al., 2007), pigeon pea (Alderman et al., 2015), safflower (Singh et al., 2015), canola (Deligios et al., 2013), sunflower (Boote, 2014, unpublished), green bean (Boote, 2009, unpublished), cabbage, and pepper. All the CROPGRO type crops share the same source code, but they are facilitated by different species, ecotype, and cultivar files. The adaptation process for new CROPGRO template crops, as described for faba bean by Boote et al. (2002) and for pigeon pea by Alderman et al. (2015), makes use of available literature information for cardinal

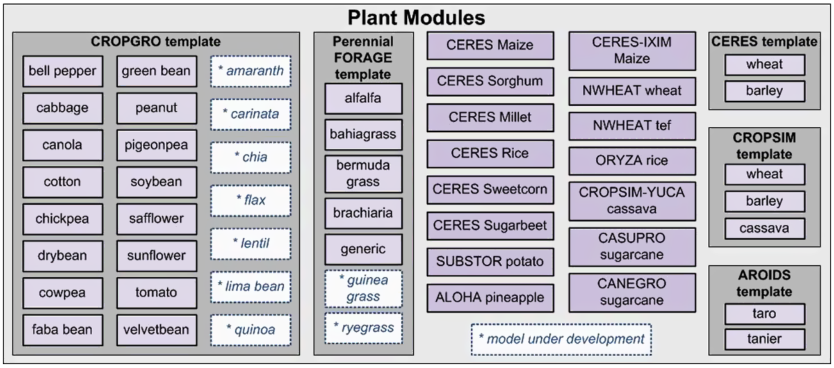

Figure 4 Plant modules of the Cropping System Model.

temperatures, composition, and so forth, along with observed time series growth analysis (LAI, total crop mass, reproductive mass) and subsequent inverse model optimization of parameters (in the species file). Crop models under development using the CROPGRO template include chia (Mack et al., 2019, paper submitted), quinoa, and carinata (Boote et al., 2019, in progress).

Sweet corn (Lizaso et al., 2007) and sugarbeet (Anar et al., 2019) were added as new crop modules following the style of CERES models. Other models in CSM were adapted from an existing model to use the modular format of CSM (Jones et al., 2003), such as CANEGRO sugarcane (Singels et al., 2008; Jones and Singels, 2018), ALOHA pineapple (Zhang et al., 1997), and NWheat (Asseng et al., 2000). NWheat was also used as a template for a new tef model (Paff and Asseng, 2019). The CROPSIM model (Hunt and Pararajasingham, 1995) was added to DSSAT-CSM as a template model for wheat, barley, and cassava. The CROPSIM template was also used to develop a new crop model specific for cassava called YUCA. The perennial forage model (Rymph, 2004; Pequeno et al., 2018) is based on the CROPGRO model, but it differs enough that it is a separate model. It is also a template model, allowing simulation of *brachiaria* and *cynodon* (Pequeno et al., 2014), and alfalfa (*Medicago sativa*; Malik et al., 2018). The SIMPLE modeling approach by Zhao et al. (2019) will also be included for the development of models for crops for which limited data are available.

6 Water balance processes

All the DSSAT models share the same soil water balance subroutine. On a daily basis, the soil water balance is computed by adding irrigation and rainfall and subtracting surface runoff, drainage, plant transpiration, and soil evaporation. Within a soil column, soil water is redistributed by vertical drainage, capillary rise, and tillage. Rainfall is supplied as a user input in weather files. Irrigation is specified in the experimental details input file which supplies information about the type of irrigation, the efficiency of water supply, and the amount of irrigation applied. Partitioning of rainfall to infiltration and surface runoff is based on the SCS curve number approach (Ritchie, 1998).

Drainage of soil water follows the tipping bucket approach for layered soils with only one-dimensional flow (Ritchie, 1998). Successive soil layers are defined by the LL (wilting point), DUL, and saturated volumetric soil water content. Downward water movement within the soil depends on a soil drainage factor (fraction per day), limited by the saturated hydraulic conductivity of soil layers.

Actual evapotranspiration (ET) depends on total ETo demand using either of two options: Priestley-Taylor (Priestley and Taylor, 1972), based on standard weather data input, or FAO-56 (Allen et al., 1998), which additionally requires wind speed and relative humidity as input data. After it is calculated, ETo is partitioned to the potential transpiration of the crop canopy (Ep) or potential evaporation of the soil (Es) as a function of the LAI and an energy extinction coefficient (Kep). Kep differs for each crop in CROPGRO, but it is more complex for the CERES crops where a 'mixed' function of extinction of photosynthetically active radiation is used. The actual soil evaporation depends on the potential Es and the soil water content, using either the older Stage 1 (square root of time method) or the Suleiman-Ritchie method (Ritchie et al., 2009). Actual transpiration of the crop is the minimum of the potential Ep or the root water uptake. Potential root water uptake from successive layers follows the approach described by Ritchie (1998), and it is dependent on root length density and the fraction of available soil water content in each layer. Total root water uptake is then integrated over all layers, and transpiration is reduced if potential root water uptake is less than potential Ep. The daily photo-assimilation is reduced as a function of actual transpiration (root uptake) over potential Ep, using a drought stress factor called SWFAC. Expansive processes are reduced somewhat sooner by a similar factor called TURFAC. See Boote et al. (2009) for a review of water balance, ET, and simulation of water stress effects in the CROPGRO model.

7 Nitrogen (N) balance processes

Soil nitrogen dynamics in CSM (Godwin and Singh, 1998) are handled in the soil inorganic N module and in two soil organic matter modules. In the inorganic N module, a mass balance accounts for all additions of inorganic N to the soil, all processes transforming N from one type to another, and all removals of inorganic N from the soil column. Additions of inorganic N are from fertilizer applications and from mineralized N resulting from decomposition of organic matter. Fertilizer applications are defined in the experimental details file and include the date applied, fertilizer type, amount of N applied, application method, and the depth and percentage of incorporation into the soil.

Daily transformations of nitrate, ammonium, and urea are computed based on process rates of nitrification, denitrification, ammonia volatilization, and urea hydrolysis. Removals of inorganic N from the system are based on plant uptake, immobilization due to decomposing organic matter, leaching, and N gas losses due to ammonia volatilization, denitrification, and nitrification. Gaseous emissions of N_2O, NO, and CO_2 are computed based on organic matter decomposition, nitrification, and denitrification processes. N gas emission algorithms are based on the DayCent model (Del Grosso et al., 2001). For flooded rice systems, in addition to the processes listed previously, the model simulates the chemical and biological processes occurring in the floodwater. These processes are discussed in more detail in Chapter 3 of this book.

Two options are available in DSSAT for computation of soil organic matter dynamics: the original CERES-based module (Godwin and Singh, 1998) and the CENTURY-based module (Gijsman et al., 2002). The main difference is the inclusion of surface fresh organic matter and three pools of soil organic matter in the Century model. The more complex CENTURY model allows more control over initialization of stable C pools and, therefore, overall decomposition dynamics, but it also requires additional input data which are difficult to obtain. These routines interact with the inorganic N and P modules by computing transformation of organic N and P into inorganic forms as a product of mineralization. Conversely, immobilization can remove inorganic N and P from the soil and reduce plant-available nutrients.

7.1 Plant nitrogen processes

The details of modeling plant N uptake in CSM vary between the individual crop modules listed in Fig. 4, but for all crop modules, N uptake is computed as the minimum of N demand and N supply. The potential N supply from the soil profile is a function of rooting density, nitrate and ammonium concentrations, and soil water in each soil layer (Godwin and Singh, 1998). Soil N supply is influenced by environmental factors such as soil temperature, soil moisture, soil pH, and management of N fertilizers and organic amendments. Root morphology, root architecture, and root length density may limit the ability of the crop to access the N supply.

Crop N demand differs with the growth stage of a crop, with higher critical N concentrations, and, therefore, higher N demand during early crop growth and development. N demand is driven by plant growth rate, growth stage, and tissue N status as a function of the growth stage (Godwin and Singh, 1998). Total crop N demand is the summation of all deficiency demands from various plant organs plus the demand by new growth. For legumes, simulated with the CROPGRO model, when the supply of N is less than the demand, carbohydrates are metabolized to meet the crop N demand via N-fixation (Boote et al., 1998). The N-fixation rate is influenced by soil temperature, soil water deficit, soil aeration, and plant reproductive age (Boote et al., 2008). For all other crops, when the N supply is less than N demand, vegetative tissues are grown at lower N concentrations. If this condition persists, N deficiency symptoms arise, resulting in a reduction in LAI, reduced photosynthesis (growth and yield reduction), and accelerated senescence.

8 Inorganic soil phosphorus (P) processes

The CSM inorganic soil P module maintains state variables for labile, active, and stable forms of phosphorus. Transformation between the pools assumes first-order kinetics with rate constants computed based on soil chemical and physical properties. Additions to the system are from fertilizer application and mineralization due to decomposition of organic matter. Removal of P from the system is from plant uptake and immobilization of P by microbes to meet decomposition demand. Tillage events will redistribute soil P in the layers affected.

Computation of plant-available P assumes that soil P is relatively immobile and that only soluble P in close proximity to roots is available for uptake. The soil column is partitioned into root and non-root volume zones using a species-dependent root radius parameter and dynamically varying root length density to define the root zone volume for P uptake. Pools of labile, active, and stable P are maintained separately for root and non-root soil zones. As roots proliferate, mass of soil and nutrients are transferred from non-root to root soil zones, making more P available to the plant with higher root density. Soluble P is a proportion of labile P calculated daily and dependent on soil water content, labile P, and soil texture in each layer. This soluble P in the root zone is the daily P supply available for potential root uptake.

Soil P initialization is critical to a successful simulation of P processes, but data are often difficult or expensive to obtain. Labile P is computed from the measured extractable P using an expert system that depends on the laboratory extraction method used and soil characteristics.

8.1 Plant P processes

Modeling P demand is similar to that of crop N demand. Each day demand for each plant part is calculated as the amount of P required to bring tissue concentration up to a stage-dependent optimal concentration, plus the demand for new growth. This demand can be met through the soil supply and by mobilization of P to grain from vegetative, pod, or root tissue. P uptake is defined as the minimum of supply and demand. The amount of P taken up by roots may be further limited by a species-dependent minimum vegetative N:P ratio, limiting P uptake with low vegetative N concentrations. When supply falls short of demand, P stresses occur affecting rates of photosynthesis, vegetative and reproductive growth, and senescence.

9 Modeling genetics in DSSAT

For the CERES-style crops, species genetic attributes are present in the source code (as allometric relationships of partitioning to growth stage) as well as in the species, ecotype, and cultivar files. The genetic attributes of the CROPGRO-style crops are contained in the species, ecotype, and cultivar files. For CROPGRO-style crops with its single generic source code, the species file contains all parameters and parameterized relationships for sensitivity of processes (leaf appearance rate, rate of reproductive progress, photosynthesis, respiration, leaf area expansion, protein mobilization, pod addition, and seed growth rate) to temperature, along with compositions, N effects on photosynthesis, and many other parameters. The species file and the ecotype file are reserved for the model developers, and model users should only modify the cultivar file to mimic different cultivars within a crop species. For example, the cultivar file contains critical photoperiod parameters, photothermal durations (or heat units) required to reach given growth stages, along with other traits affecting photosynthesis, determinacy, leaf appearance rate, seed size, seed fill duration, and seed composition. The number of cultivar coefficients varies, depending on the crop module that is being used. For instance, the CERES-Maize model includes six cultivar coefficients, while the CROPGRO model includes 18 cultivar coefficients.

9.1 Estimating genotype-specific parameters

The DSSAT modeling system defines genotype-specific inputs, normally referred to as the Genotype-Specific Parameters (GSPs), thus allowing a user to define differences among cultivars, varieties, hybrids, clones, and other seed material. Although the user has a lot of flexibility in evaluating different local management scenarios with respect to genotypic performance, there are also challenges. As model developers, the DSSAT group is unable to provide local cultivar-specific parameters beyond those with specific experiments included in DSSAT, which means that a model has to be calibrated first for local genetics, requiring some of the critical observations associated with the MDS described previously. Once the crop management and observational data have been entered, the specific cultivar then has to be calibrated, either manually or using optimization tools. The ultimate goal is to minimize the error between simulated and observed phenological dates, yield, and yield components. Within the DSSAT ecosystem, there are two tools that can be used for crop cultivar calibration, the *GLUE* tool and the *GENCALC* tool. In addition, the sensitivity analysis utility can also be used to improve the value of one or more cultivar coefficients by setting the range and increment for a particular cultivar coefficient and by comparing simulated with observed data. A comparison of the performance of these two tools for rice was conducted by Buddhaboon et al. (2018).

9.2 General Likelihood Uncertainty Estimation (GLUE)

The General Likelihood Uncertainty Estimation (GLUE) is a statistical approach that results in multiple sets of parameter values that are equally as likely as the final solution. This approach was first introduced by Beven and Binley (1992) for modeling hydrological processes. The initial evaluation of GLUE for DSSAT was made for the CSM-CERES-Sweetcorn model by He et al. (2009, 2010), which required defining the means and variances of all cultivar parameters for sweetcorn based on the existing cultivar database of DSSAT. The approach was successful and provided in DSSAT as a new tool for estimating GSPs.

To estimate the most likely values for the GSPs for a new cultivar, a user first has to provide the required input files associated with weather, soil, and crop management, and basic observations, especially for phenology, yield, and yield components. Although a user can estimate the GSPs for only one treatment, the results will normally not be very robust. Therefore, we recommend that at least two non-stressed treatments from different environments representing either different locations, planting dates, or years be used. Once the model runs properly, the GSPs can be estimated with GLUE, first for phenological GSPs, and then for the yield and yield component GSPs. For most of the crops in DSSAT, the means and variances for the GSPs are provided in an input file that is used by GLUE for estimating the uncertainty. The ultimate outcome of GLUE is a list of the most likely value for each individual GSP that is being estimated.

9.3 Genetic Coefficient Calculator (GENCALC)

The Genetic Coefficient Calculator or GENCALC uses a rule-based approach to determine the value for one or more GSPs (Hunt et al., 1993). In the input file for GENCALC, one or more GSPs are associated with one particular plant trait, as described in Section 9.2. During the calibration process, these GSPs are varied to minimize the error between the simulated and observed trait. GENCALC normally optimizes the phenological GSPs first, followed by growth, and then yield components and yield for final optimization. Most crop models do not have a specific GSP that controls only yield and most GSPs affect multiple yield components. GENCALC should be used by more advanced DSSAT users who are familiar with the GSPs of a particular model and are comfortable editing the GENCALC rules file (Anothai et al., 2008).

10 Model analysis utilities for performance evaluation

For performance evaluation of the model with experimental data, visualization tools that not only provide a visual comparison between simulated and observed data, but also statistical analysis, are critical (Yang et al., 2014a). The main tool in DSSAT for visualization and comparison of model simulations with observed data is GBuild. Another tool is EasyGrapher, originally developed by scientists associated with Agriculture and Agri-Food Canada (Yang et al., 2014b).

10.1 GBuild

GBuild is an analysis utility for visualization of simulated and experimental data (Uryasev et al., 2004). It gives a user the ability to easily plot graphs that are routinely used during crop model development and evaluation. The basic design of GBuild is based on a set of codes that are headers for each column of data that represent different variables. The file selection in GBuild allows a user to select one or more output files for plotting as well as any combination of the variables and runs/treatments, and then proceed to display the graph. The graphic-type selection options provide different views of the simulated results and include time series, for example displaying the simulated data as a function of date or days after planting (DAP), and simulated data versus experimental data. In order to compare the simulated results with observations from experiments, GBuild includes statistics for time series data with emphasis on the d-statistics (Willmott et al., 1985) and Root Mean Square Error (RMSE) and regression statistics for phenological and end-of-season data, such as flowering and maturity dates and yield and yield components. The graphic output of simulated and observed data can be visualized, printed, and exported into an Excel spread sheet with the statistics or exported to a text file with data only.

10.2 Sensitivity Analysis Tool

In addition to evaluating the model with real-world data, it is also important to understand the response of the model to one specific input, such as weather data, cultivars or hybrids, soil data, and values for individual GSPs. This approach, in which all inputs are kept constant except for one input or parameter, is called sensitivity analysis. A recently developed tool now available in DSSAT called SensitivityAnalysis enables the user to evaluate the model sensitivity to changes of cultivars, single GSPs, soil profiles, weather inputs for different location or year, plant and row spacing, and various other options. Variables that have numeric values, such as planting date, can be varied using a starting value, an increment value, and the number of iterations. The program automatically creates a new experimental file ready to run, with the selected sensitivity input variation. Following the simulations, the linked GBuild graphics program allows for a visual analysis of simulation results and associated statistics.

11 Application programs

Crop simulation models embedded in decision support systems are very powerful tools for scenario analyses. So far, this chapter has provided an overview of the structure and science of the crop simulation models that are included in DSSAT, as well as the tools and utilities for weather, soil, experimental and observational data entry, and crop model calibration and evaluation. Once a crop model has been calibrated, the most important and useful aspects are associated with the applications. DSSAT, therefore, includes several application programs. The seasonal analysis program is used for single-season scenario evaluations that account for both weather and economic uncertainties. The sequence analysis program is used for the analysis of crop rotation, and, in addition to weather and economic uncertainties, takes into account the effects of long-term cropping systems including changes in the soil system with respect to soil water, carbon, nitrogen, and other nutrient components (Fig. 5).

11.1 Seasonal analysis

The *'Seasonal Analysis'* application allows a user to explore the effects of weather variability and to evaluate the uncertainty and risk factors associated with various management and genetic inputs (Thornton and Hoogenboom, 1994). The DSSAT-CSM integrates the interaction of weather, soil, management, and genetic factors, enabling a user to simulate many hypothetical scenarios quickly

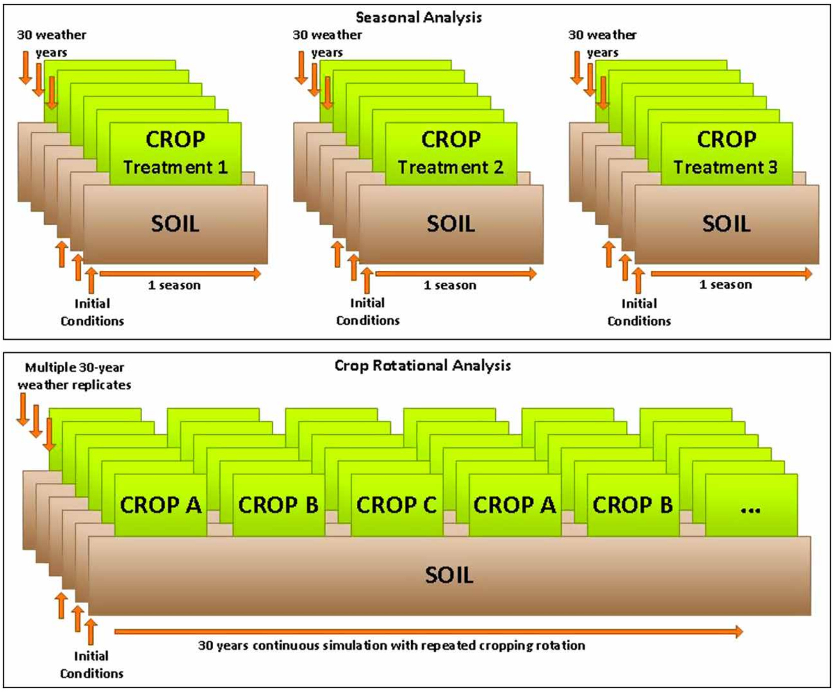

Figure 5 DSSAT scheme for the simulation of seasonal analysis scenarios (top) and crop rotational analysis scenarios (bottom).

and efficiently using long-term historical weather records or stochastically generated weather data. The model simulates a distribution of yields and other outputs, converting uncertainty in weather into uncertainty in yield for the specified management scenarios.

The seasonal analysis application works on a field scale and emphasizes weather uncertainty. Economic risks can also be estimated using costs of inputs and prices of products, including the variability associated with these costs and prices. The application can be used to select optimal crop and variety, planting options, irrigation options, application of fertilizer and other agrochemical inputs, marketing options, insurance risks, policy advisement, and investments in equipment, technology, and diversification of land use. Typically, one season of simulation per scenario per weather year is conducted (Fig. 5). For each scenario, a number of weather years are simulated, with re-initialization of soil variables done at the beginning of each simulation so that the results reflect the variation in model outputs due to interannual weather variability.

A graphical interface allows a user to explore distributions of outcomes for variables including crop yields, farm profits, and environmental factors such as nitrogen leaching and irrigation requirements. The application includes graphical options such as box plots, cumulative function plots, and mean-variance plots for biophysical and economic variables (Fig. 6). This feature allows the user to optimize management practices that will benefit the farmer and to select best management practices relative to maximum profit, minimum risk of low profit or yield, minimum degradation of the environment, or other criteria.

11.2 Crop rotation analysis

Crop rotation analysis (or sequence analysis) application allows a user to produce long-term simulations of a given cropping system for predictions of farming system sustainability such as soil carbon loss, soil fertility degradation, decreasing yields, and increased greenhouse gas emissions (Thornton et al., 1995). Users can explore the sustainability of various options over a long period of time and optimize options for managing the land to sustain productivity, soil health, and natural resources (Tsuji et al., 1998). Soil organic matter is related to crop nutrient availability and thus to yield, income, and food security. Organic matter also improves water- and nutrient-use efficiency and reduces losses and environmental pollution. The soil also provides a sink for atmospheric C, a potentially important climate change mitigation mechanism referred to as soil carbon sequestration.

Crop rotation analysis in DSSAT is generally used to explore cropping system options based on a pattern of crops planted in sequence. Figure 5 illustrates the process and shows how this analysis differs from the seasonal

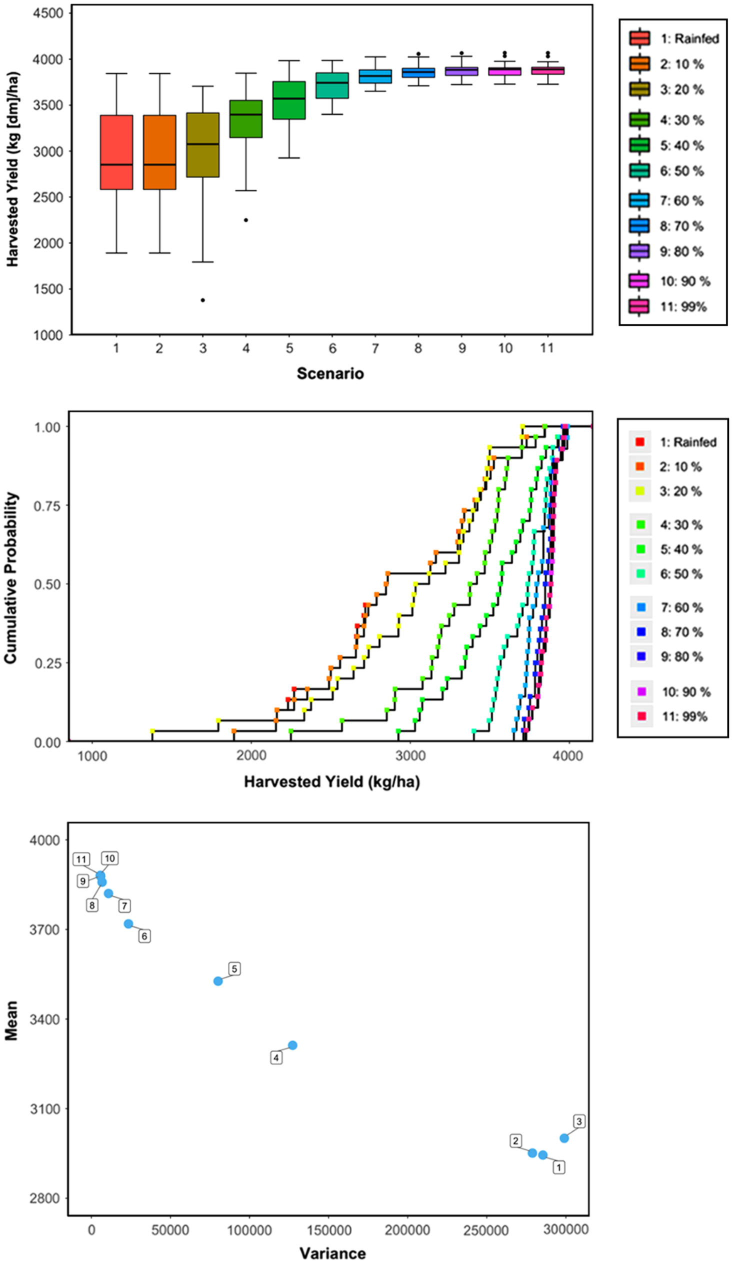

Figure 6 Box and whisker (top), cumulative probability (center), and mean-variance (bottom) plots a for scenario analysis of the impact of irrigation management on soybean yield in Gainesville, Florida, USA. The irrigation scenarios ranged from rainfed (scenario 1), a 10% threshold of extractable water (scenario 2), to a 99% threshold of extractable soil water (scenario 11) at 10% intervals for the top 30 cm of the soil profile.

analysis. In the crop rotation analysis, soil variables are initialized once at the beginning of a long-term, continuous simulation. A crop sequence kernel or pattern is defined. In the example in Fig. 5, the kernel is represented by Crop A, followed by Crop B, followed by Crop C. The kernel is repeated as many times as the user specifies for a given simulation. If the effects of weather variability are important to the analysis, weather data can be generated to allow multiple realizations of daily weather data associated with the climatology being analyzed. In the example of Fig. 5, 30 realizations of a 30-year period of simulation are generated, allowing a distribution of possible outcomes for each variable predicted and each year in the time series.

Dynamics of soil organic carbon are of prime importance in these long-term simulations. In a system with poor organic carbon management (e.g. low inputs and removal of all crop residues from the system), soil organic carbon can be rapidly depleted, especially in the tropics. In sequence simulations, soil organic carbon is 'carried over' from one season to the next and these long-term soil fertility dynamics can be analyzed. Initialization of soil organic carbon state variables is often difficult, but it is very important to the predictive accuracy of the model. Often data on soil organic carbon composition are not available. Methods have been developed to estimate the amount of stable, intermediate, and microbial soil carbon present in the system (Basso et al., 2011; Porter et al., 2010).

11.3 Spatial analysis

The crop models in DSSAT are point-based models, in that the inputs are based on site-specific information such as the weather data from a local weather station, the soil data from a local profile at the experimental site, and crop management for a plot or field. For many applications, there is significant interest in understanding the variability across space for crop growth and development. Therefore, the models can be operated at the spatial scale, providing all input data at a spatial level, either for a polygon in which the inputs are considered the same or for a grid that is evenly distributed across an area. One of the weaknesses of the current system is that the models do not allow for interaction across space. However, the strength of the CSM crop model is that it can simulate at a spatial scale as small as 1 m or less for precision agriculture to 1 arc-degree for global simulations. The current DSSAT software does not include a specific tool for preparation of input files and visualization of output files. However, the underlying crop model and associated input and output files with GPS coordinates can be easily integrated into other systems if the DSSAT file naming convention and system structure are maintained.

There have been many approaches for integration of the DSSAT crop models with various Geographical Information Systems (GIS) and spatial databases, starting with the Agricultural and Environmental Geographic Information System (AEGIS; Lal et al., 1993; Luyten et al., 1994) and AEGIS/WIN (Engel et al., 1997). Most of the spatial applications have been conducted external to the DSSAT Windows Shell due to the complexity of the GIS systems and there are various approaches to coupling or linking crop models with GIS (Hartkamp et al., 1999; Thorp et al., 2008). Due to the rapid changes in GIS technology and software, as well as costs associated with some of the GIS systems, recent spatial applications have concentrated on using scripting languages for pre- and post-processing of the input data as well as for visualization. One example is MINK for global gridded simulations, developed by the International Food Policy Research Institute (IFPRI; Robertson, 2017). Another example is pDSSAT that has been developed for global gridded climate change applications in agriculture (Elliott et al., 2014). One of the limitations of these systems is that all gridded spatial inputs have to be referenced to the same grid. A recent development is used for spatial simulations based on present coordinates, allowing for flexible input data with spatial different resolutions for crop mask, weather, soil, and crop management. This tool, called DSSAT-pythia, can be run on any platform, including Linux, Windows, and iOS. It does not require any GIS system for data preparation, and it can use open-source display systems for thematic mapping of crop model outputs.

12 Example applications

The current DSSAT ecosystem includes at least one real-world experiment per crop that was used either for model development, calibration, or evaluation. As model developers, we feel that it is important to show the performance of the model when making it available to the DSSAT modeling community. DSSAT as an application is used extensively for a range of applications from gene-based modeling for plant breeding to climate change impact assessment across the globe for policy decisions. An initial overview of the range of applications was presented by Jones et al. (2003), and published applications of DSSAT and CSM have increased exponentially during the past 15 years. Rather than providing a detailed literature review, we provide a few illustrative case studies here to demonstrate the approach that is normally used for developing a specific application.

12.1 Interaction of nitrogen and water management on performance of maize

An experiment was conducted at the University of Florida in 1982 to study the interaction of nitrogen and irrigation management on maize (Bennett et al., 1985). The experiment included three levels of irrigation, that is, rainfed, stress during early growth (vegetative stress), and irrigated, and two levels of nitrogen fertilizer, that is, 116 kg N/ha in three applications and 401 kg N/ha in six applications, for a total of six treatments. The maize hybrid McCurdy 84aa was planted on February 26, 1982, at a plant density of 7.2 plants/m^2. The crop was well managed; phenology was observed nondestructively and growth analysis samples were taken on a regular basis. The CSM-CERES-Maize model was calibrated for the non-stressed treatment, but over time some of the other treatments were used for evaluating the response to water and nitrogen. Because of the sandy soils, there was a strong difference between the irrigated and rainfed treatments (Fig. 7). The number of days to flowering and

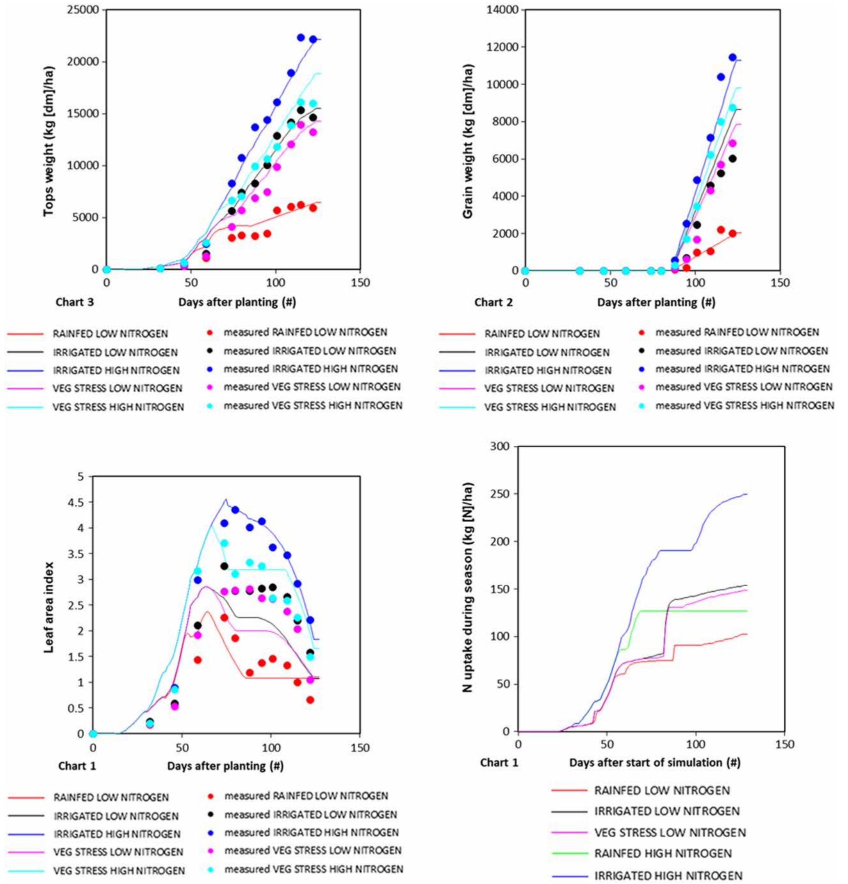

Figure 7 Simulated and measured tops weight (left top), grain weight (right top), leaf area index (bottom left), and N uptake (bottom right) for a maize experiment conducted in Gainesville, Florida, USA, in 1982. The experiment consists of three irrigation levels (rainfed, vegetative stress, and irrigated) and two nitrogen levels (low and high) for a total of six treatments.

physiological maturity were predicted well (RMSE for flowering duration: 1 day; RMSE for maturity duration: 1 day), and yield and yield components were also reasonable (RMSE for Tops Weight: 1280 kg/ha; RMSE for yield: 1087 kg/ha). No observations were available for the soil processes, but the model showed a clear response across the six treatments. Nitrogen uptake was highest for the irrigated-high nitrogen treatment and lowest for the rainfed-low nitrogen treatment (Fig. 7). Mineralization was slightly lower for the rainfed treatments compared to the irrigated treatments, but the differences were small. Nitrogen leaching was highest for the irrigated-high nitrogen treatment and lowest for the rainfed-low nitrogen treatment (Fig. 8). Inorganic nitrogen remaining

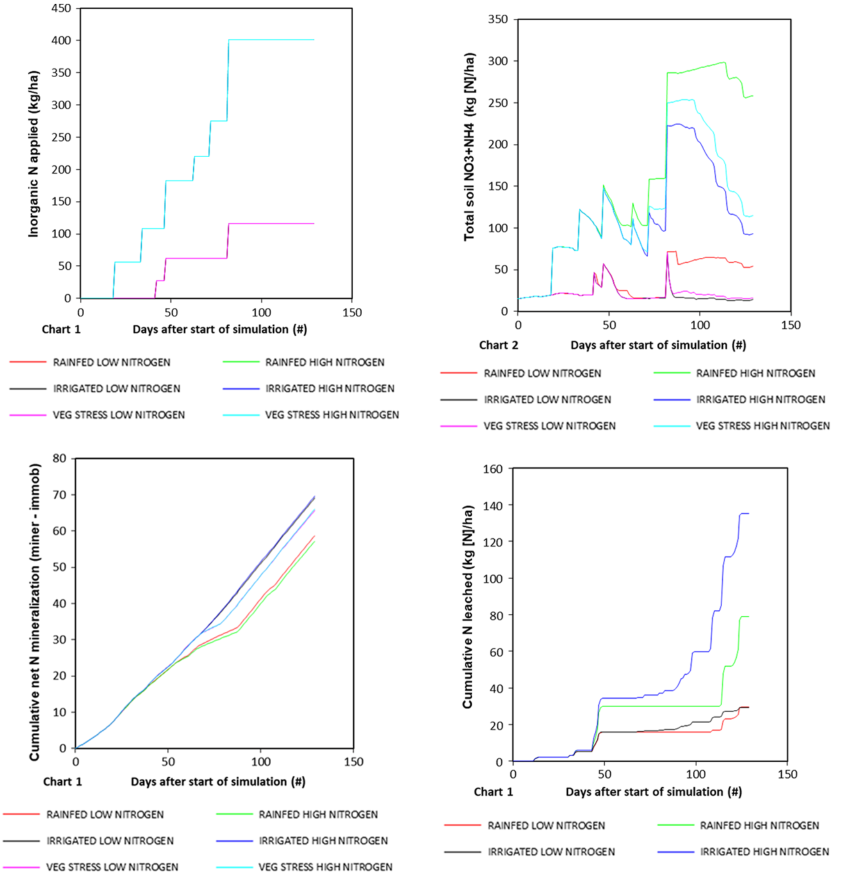

Figure 8 Simulated inorganic N applied (left top), total inorganic N in the soil profile (right top), cumulative N mineralized (bottom left) and N leached (bottom right) for a maize experiment conducted in Gainesville, Florida, USA, in 1982. The experiment consisted of three irrigation levels (rainfed, vegetative stress, and irrigated) and two nitrogen levels (low and high) for a total of six treatments.

at the end of the growing season was highest for the rainfed-high nitrogen treatment, with most of the applied nitrogen remaining in the soil, and lowest for the irrigated and vegetative stress-low nitrogen treatment (Fig. 8). Overall, the model was able to simulate a close interaction between nitrogen and irrigation management and the impact was not only on yield, but also on the environment.

12.2 Impact of irrigation management on performance of soybean

An experiment was conducted at the University of Florida in 1978 to study the impact of irrigation on soybean growth, development, and yield (Wilkerson et al., 1983). The experiment included two treatments, that is, rainfed and irrigated with 21 irrigation applications for a total of 206 mm of supplemental irrigation. Soybean is a nitrogen-fixing crop, so no nitrogen fertilizer was applied. The cultivar Bragg was planted June 29, 1978, at a plant density of 29.9 plants/m^2. The crop was well managed; phenology was observed nondestructively and growth analysis samples were taken on a regular basis. The CSM-CROPGRO-Soybean model had been calibrated for the Bragg cultivar grown in the treatments for this experiment, as well other prior experiments conducted on this cultivar at the same location. The number of days to flowering and physiological maturity were predicted well, and yield and yield components were simulated very well (RMSE for Tops Weight: 218 kg/ha; RMSE for yield: 157 kg/ha). Early during the growing season, there was no treatment effect on aboveground biomass and LAI (Fig. 9) due to the high amount of rainfall received during this period (Fig. 10). Around 60 DAP, rainfall ended dramatically, with a decrease in extractable soil moisture (Fig. 10). This resulted in severe drought stress for the rainfed treatment (Fig. 10), reducing dry weight gain in tops and seed, and accelerating LAI senescence for the rainfed treatment compared to the irrigated treatment (Fig. 9).

Following model evaluation, the same experiment was set up as a strategy analysis scenario, using the same input conditions for each year and long-term weather data. Because 30 years of continuous historical weather data were not available, the internal weather generator WGEN was used. However, for the irrigation management, the automatic irrigation option was selected with different threshold values to determine when to irrigate. When the soil moisture content in the top 30 cm of the soil profile drops below this threshold value, an irrigation event is triggered by the model. The irrigation thresholds ranged from 10% to 99% (remaining soil water at which to irrigate) for a total of ten irrigation scenarios and one rainfed scenario. Final results can be analyzed either as box and whisker plots, cumulative probability graphs, or a mean-variance graph (Fig. 6). Depending on the analysis question, these graphs provide different functionalities based on the overall objectives. A researcher

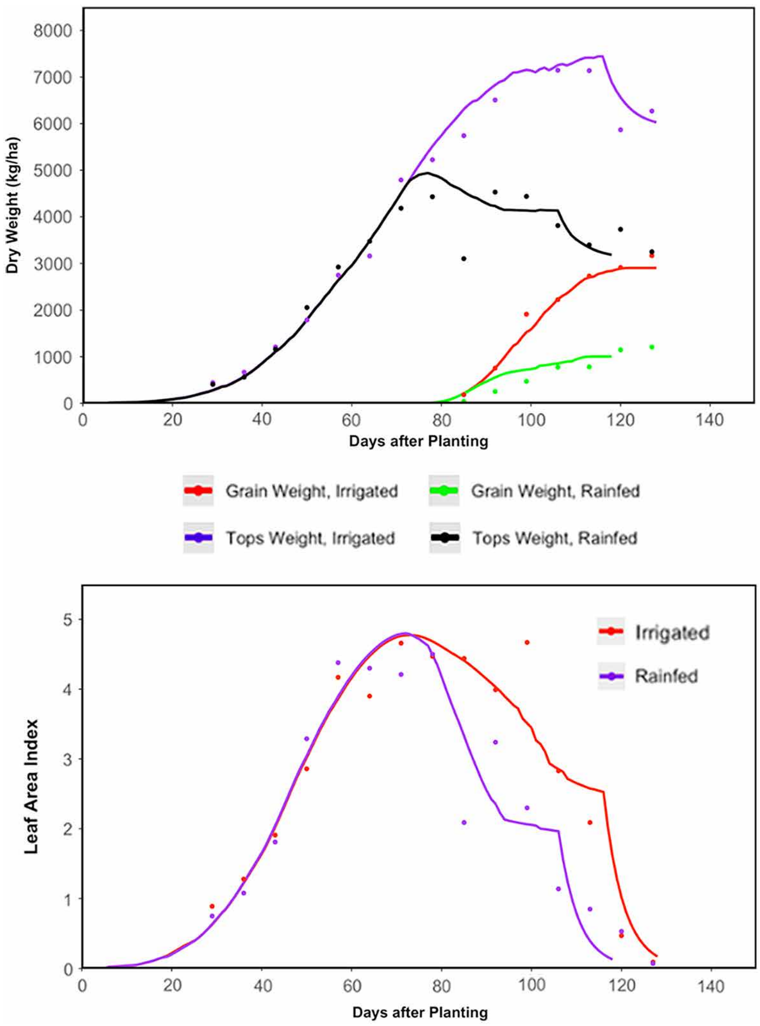

Figure 9 Simulated and measured tops and grain weight (left) and leaf area index (right) for a soybean experiment conducted in Gainesville, Florida, USA, in 1978. The two treatments were irrigated and rainfed.

might be interested in maximizing yield, maximizing water-use efficiency, or minimizing the impact on the environment or water use for irrigation.

The results show clearly that yield increased with an increase in the threshold value, while the variance and variability were reduced (Fig. 6). However, the amount of supplemental irrigation required also increased to over 300 mm for the highest threshold value with more than 30 irrigation applications (Fig. 11). In contrast, the amount of water applied upto a

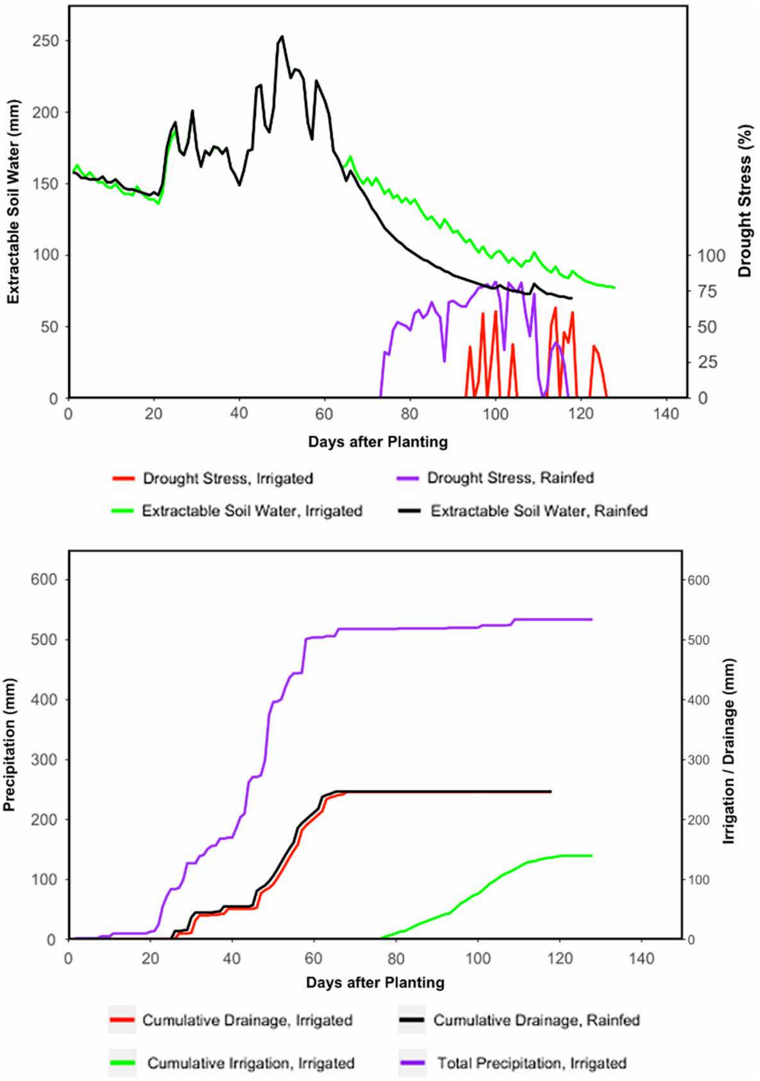

Figure 10 Simulated extractable water and drought stress (left) and cumulative irrigation, drainage and precipitation (right) for a soybean experiment conducted in Gainesville, Florida, USA, in 1978. The two treatments were irrigated and rainfed.

threshold value of 50% was less than 100 mm. The scenario with a threshold value of 50% showed the best water-use efficiency taking into consideration the associated uncertainty as well as yield (Fig. 6) and total water use (Fig. 11). If ground or surface water are limited due to governmental restrictions, water rights, or a drought, the model can be used to help determine the best

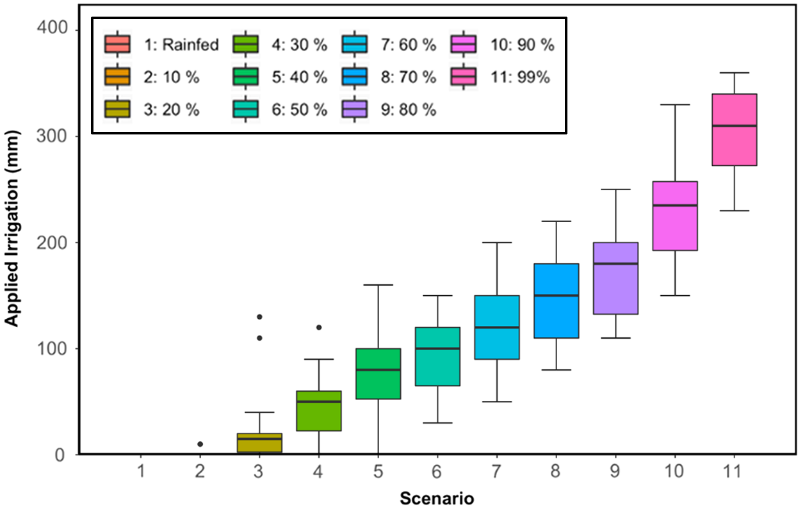

Figure 11 Total irrigation applied for a scenario analysis of the impact of irrigation management on soybean yield in Gainesville, Florida, USA. The irrigation scenarios ranged from rainfed (scenario 1), a 10% threshold of extractable water (scenario 2) to a 99% threshold of extractable soil water (scenario 11) at 10% intervals for the top 30 cm of the soil profile.

scenario that maximizes yield while at the same time optimizing water use for irrigation.

12.3 Residual soil moisture for crop rotations

In many regions around the world, crop production is restricted to the rainy season when sufficient moisture is available to grow a crop. However, in many instances, some soil moisture might be remaining at the end of the rainy season to allow for a second crop that requires less water. In India, soybean has become a dominant crop as a source for cooking oil, but it has to be grown during the rainy season due to the crop's water requirements. Chickpea is an important pulse crop that requires a lot less water. A soybean-chickpea rotation, therefore, has become quite common (Singh et al., 1999a,b). We defined a scenario to simulate this crop rotation using the different components described previously (Fig. 5). The location was Hyderabad, India, using a local soil. The soybean variety PK-472 (maturity group 8) was planted on June 25 and the chickpea crop was planted immediately following harvest of the soybean crop. The period between the harvest of the chickpea crop and planting of the soybean crop was considered to be a fallow period. For long-term weather, we used the WGEN weather generator, starting in 1978 and ending in 2020 for a duration of 42 years. Please note that these weather years are hypothetical years and do not represent the real weather conditions. The weather sequence from 1978 through 2020 was repeated 30 times.

Total seasonal precipitation for soybean ranged from 500 mm to 800 mm with some outliers, while seasonal rainfall for chickpea was less than 80 mm (Fig. 12). The median for plant extractable soil moisture at final harvest of

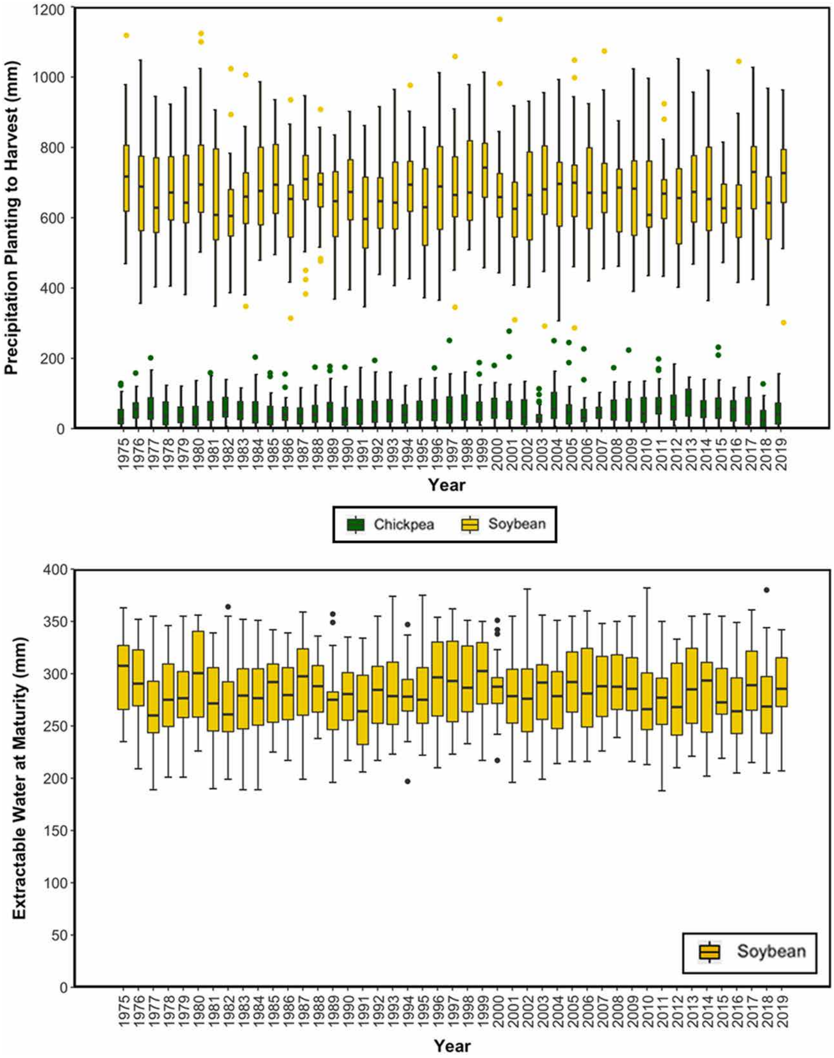

Figure 12 Seasonal precipitation from planting to harvest (top) and extractable soil moisture at soybean harvest (bottom) for a soybean-chickpea rotation in Hyderabad, India. Soybean was planted on June 25 and chickpea was planted immediately following the soybean harvest.

soybean ranged from 250 mm to 310 mm and was rather variable (Fig. 12). Yield for soybean was fairly constant, varying between 2.8 t/ha and 3.3 t/ha, while chickpea yield was much more variable, ranging between 0 t/ha (crop failure) and 0.4 t/ha (Fig. 13). Water-use efficiency based on total yield over precipitation was fairly constant for soybean ranging between 4 kg/mm and 5 kg/mm (Fig. 13), while for chickpea it ranged from 0 kg/mm to 8 kg/mm, with the outliers not even shown in the analysis (Fig. 13).

For a proper cropping systems analysis, one should consider not only a single growing season, as discussed previously, but also other crops that might be grown or the fallow period between harvest of one crop and planting of the following crop. The physical, chemical, and biological processes in the soil are continuous, and, therefore, they should be simulated. In the example for the soybean-chickpea rotation, we analyzed the impact of residual soil moisture of the rainy season for growing a second crop during the dry season. Boote (Chapter 17) analyzed the impact of a continuous corn sequence/rotation on yield for the same Hyderabad location, showing a decrease in yield over time for an unfertilized crop associated with soil C decline, whereas an N-fertilized maize treatment did not decline in yield. Basso (Chapter 8) analyzed long-term soil C dynamics for a crop rotation. Overall, simulation models can be very powerful tools to analyze long-term crop rotations, especially when good experimental data for long-term crop rotations in general are lacking.

12.4 Yield forecasting

The application of crop simulation models for in-season yield forecasting has been of interest to many in the agriculture community, but so far it has been challenging due to the complexity and access to current weather data, weather forecasts, and climate outlooks (Georgiev and Hoogenboom, 1999; Hoogenboom, 2000). A new tool was recently developed external to DSSAT but based on the DSSAT crop model engine and associated input files and DSSAT system setup. The Climate Change, Agriculture and Food Security (CCAFS) Regional Agricultural Forecasting Toolbox (CRAFT) is a Windows desktop application that provides relatively easy access to gridded crop modeling and yield forecasting along with risk analysis and climate change impact assessments at spatial resolutions of 5 arc-minutes (0.083° or 10 km) and 30 arc-minutes (0.5° or 50 km; Shelia et al., 2019). The input data are prepared based on the GIS shape files of the region, weather files, and soil profile(s) data for each grid cell, masked data for crop and management, including organic and inorganic fertilizer, irrigation, and other inputs, and then uploaded into a MySQL database.

The toolbox can generate and conduct multiple simulation scenarios, maps, statistics, and interactive visualizations for a region and for each grid cell

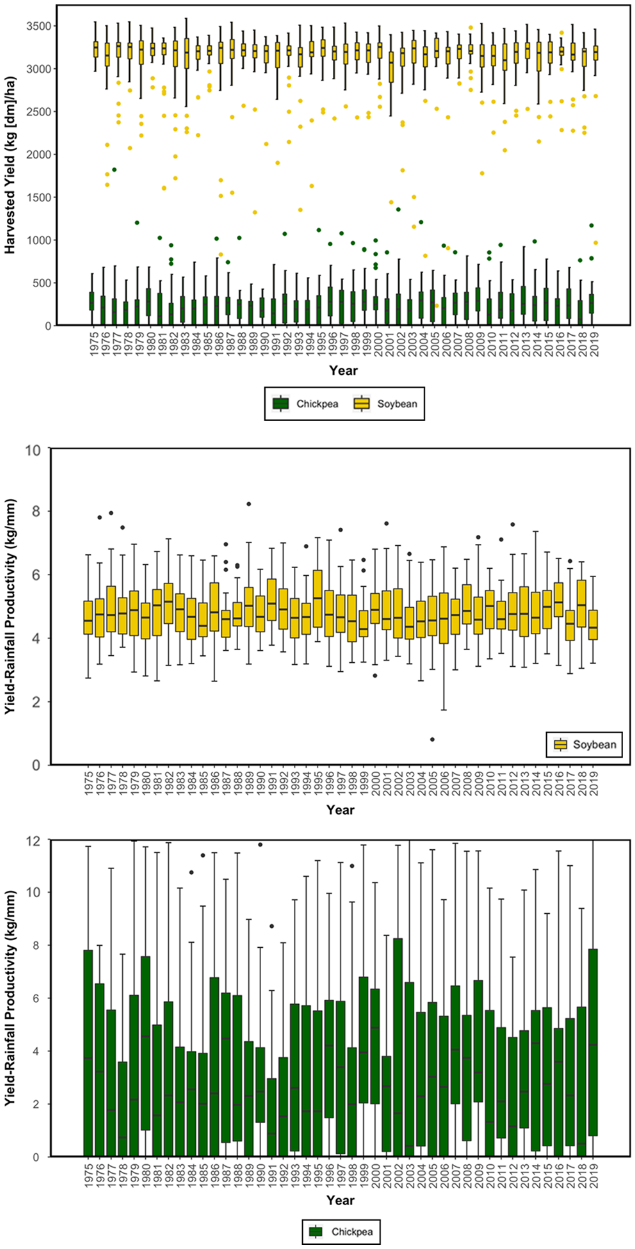

Figure 13 Final yield for soybean and chickpea (top) and water-use efficiency for soybean (center) and chickpea (bottom) for a soybean-chickpea rotation in Hyderabad, India. Soybean was planted on June 25 and chickpea was planted immediately following the soybean harvest.

of the selected region. The core of CRAFT is the crop engine that can run the crop simulation models not only for DSSAT, but also for other crop models such as APSIM and SARRA-H based on the Agricultural Model Intercomparison and Improvement Project (AgMIP) data tools (www.agmip.org). Gridded simulations can be conducted for any region for up to three different spatial scales such as a country, a state/province, or a district. CRAFT also has the embedded Climate Predictability Tool (CPT) for obtaining probabilistic seasonal climate forecasts (Mason and Tippett, 2016), and it uses a statistical approach to integrate the seasonal climate forecast with the crop yield forecast (Hansen et al., 2004, 2006; Mishra et al., 2008). Spatial aggregation from yield to production can be performed to account for the heterogeneity of environment and management of spatial data sets.

13 Developing a global modeling network

13.1 Software development

One of the unique aspects of the original IBSNAT Project was its participatory approach that encouraged scientists from different disciplines and different organizations to collaborate in support of the development of one unique DSSAT ecosystem. This network of model developers has expanded since the end of the IBSNAT Project in 1993 to include many scientists from Brazil, China, South Korea, France, Nigeria, South Africa, Kenya, and many other countries across the globe. The mutual support and collaboration are facilitated using an Open-Source approach, in which the source code of the crop simulation models along with the tools and utility programs are freely available. Currently, the source code for the CSM can be obtained from GitHub (https://github.com/DSSAT) upon request. We are planning to make CSM completely Open Source using the 3-Clause BSD License (BSD-3-Clause) once a few minor intellectual property rights have been resolved. Since 2014, the DSSAT Development Team has also facilitated biannual DSSAT Development Sprints, which are hackathons for crop modelers. During this 1-week, hands-on ‘working’ workshop, the emphasis is on crop model improvement and the advancement of application programs, tools, and utilities.

13.2 Software distribution and website

Previously, the DSSAT software had been sold to cover some of the administrative and development costs. In 2011, the distribution of DSSAT was changed to a free download system from the DSSAT portal (www.DSSAT.net) and since then the interest in DSSAT has exponentially increased. There have been 6630 downloads of DSSAT Version 4.5, 6500 downloads of DSSAT Version 4.6, and over 7100 downloads of DSSAT Version 4.7 from November 2017 through September 2019. For dissemination of information to the DSSAT user network, a DSSAT Listserv is used, and currently there are over 15000 unique e-mail addresses. User support and documentation are also provided through the DSSAT portal (www.DSSAT.net).

13.3 Training

Because DSSAT is a comprehensive software program, it requires training of agricultural scientists who traditionally specialize in single disciplines and who may not be very familiar with the systems approach that encompasses multiple disciplines. The first workshop sponsored by the IBSNAT Project was held in Venezuela in 1984, followed by a more extensive crop modeling training workshop at the University of Florida in 1985. Annual crop modeling training workshops have been held in the United States since then, initially as 2-week workshops and then condensed to intensive, 6-day training programs. Since 2002, these workshops have been hosted at the University of Georgia's Griffin campus, with an average of 50 international participants from universities, governmental organizations, and private industries. The rapid expansion of the DSSAT user network has also resulted in requests for international training programs across the globe, and recent workshops were held in Argentina, Australia, Indonesia, Nigeria, the Philippines, South Africa, Tanzania, Thailand, Tunisia, and Vietnam. In addition, some of our expert users are now DSSSAT trainers, facilitating workshops in Pakistan, Indonesia, Turkey, Brazil, China, and other countries. Ideal capacity building requires multiple workshops, starting with the basics of crop modeling and data requirements, followed by data collection for model evaluation, and finishing with model applications, the most critical part of crop modeling and decision support (Kihara et al., 2012).

14 The future of DSSAT

14.1 Collaboration

One of the challenges of maintaining and developing scientific software platforms in agriculture is the limited availability of resources for software development. Most grant agencies, both domestic and international, are not as interested in advancing scientific models as in applications. In addition, many agricultural scientists are not good programmers, especially in computer languages such as Fortran, Delphi, and Visual Basic that are currently used in DSSAT. Since the start of the development of DSSAT and the crop models, the emphasis has been on scientists developing the crop models, rather than relying on professional programmers who develop the code based on input provided by the scientists. However, this development model is not sustainable, especially when financial resources are limited. Therefore, collaboration is required among programmers who can code in scientifically sound code and scientists with state-of-the-art expertise. With the migration to Open Source and the sharing of the source code, the DSSAT Development group hopes to expand the community of those interested in advancing and improving the DSSAT ecosystem, including the models as well as the tools and utility programs. The DSSAT Development Sprints are part of this collaboration and so far the sprints have resulted in crop model improvement for irrigation management (Lopez et al., 2017), a new tool for soil data retrieval from the internet (Kim et al., 2018), and a new modeling engine for different operating systems (Resenes et al., 2019).

14.2 Mixed languages

The current source code of the CSM is Fortran. Although Fortran is computationally very efficient, it is not commonly taught in computer science courses. We are, therefore, evaluating a mixed-language approach, in which different programming languages can be combined into one that can be executable. The initial application for alternate languages will focus on the Input and Output file system of CSM, referred to as flexible I/O, to handle the Y2K issue with the current DSSAT input files and to provide a mechanism that facilitates adding or removing new parameters to the cultivar, ecotype, or species files.

14.3 Insect pests, diseases, and weed modeling

One weakness of the DSSAT ecosystem and many other crop modeling systems, is the limited capability for handling the impact of biotic stresses caused by insect pests, diseases, and weeds. DSSAT currently has a static system that allows a user to define biotic stressors based on field damage observations. However, there is no coupling with dynamic pest and disease models. We are currently evaluating using Docker containers and images that allow for the coupling of two or more models in order to provide opportunities for running multiple instances of two models in parallel.

14.4 Gene-based modeling

One of the most challenging aspects of the DSSAT crop models are the GSPs, which, for all models, must be estimated for local cultivars and hybrids prior to any real-world application. There have been efforts to bridge the gap between biotechnology, genetics, plant breeding, and crop modeling using either genes or quantitative trait loci (QTLs). The first, simple, gene-based model, GENEGRO, was developed by White and Hoogenboom (1996) more than 20 years ago, linking several genes to the GSPs of the dry bean model, BEANGRO. Predictions for phenology were as accurate as the original model, while final yield and biomass predictions were more challenging. A similar gene-based approach was applied for soybean by Messina et al. (2006). More recent developments are based on QTLs that are directly or indirectly linked to GSPs or plant traits (Wallach et al., 2018). As the cost of mapping QTLs/genes becomes cheaper, it is expected that rapid advances can be made in this area. A future model would have QTLs/genes linked to one or more growth and development processes via modules that would allow for the input of gene maps directly into crop models (Hoogenboom and White, 2003; White and Hoogenboom, 2003). If successful, this improvement would then reduce the requirements for calibration of a new cultivar for local conditions, assuming that QTL knowledge is public and proper phenotyping of QTL actions has been done (Hoogenboom et al., 2004).

15 Summary

The current agricultural production system is challenged with weather and climate extremes and variability and economic risks. There is pressure to grow more and healthy food using sustainable practices. At the same time, technology is rapidly improving with new sensor technologies, the Internet of Things, edge computing, and remote sensing. The amount of data that are being collected for agricultural production system is exponentially expanding, providing opportunities for data analytics for strategic and actionable decisions. The DSSAT ecosystem can play a major role in helping to understand the interaction between Genotype, Environment, and Management (G * E * M) and to provide alternative management options that increase crop yield and quality, optimize resource use, and minimize environmental impact for long-term sustainable agricultural production.

The DSSAT crop modeling ecosystem is one of the oldest and most widely used crop modeling platforms across the world. The success of DSSAT is based on the inclusiveness and participatory approach that has been used since the original development of the CERES and CROPGRO family of models and the emphasis on sharing data and model code. DSSAT is not just a software program, but an ***ecosystem*** of:

- Crop model users;
- Crop model trainers;
- Crop model developers;
- Models for the most important food, feed, fiber, and fuel crops;

- Tools and utilities for data preparation;
- Minimum data for model calibration and evaluation; and
- Application programs for assessing real-world problems.

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