E3 Journal of Agricultural Research and Development Vol. 2(1). pp. 001-006, March, 2013
Available online http://www.e3journals.org
ISSN: 2276-9897

Review

Crop modeling: A tool for agricultural research – A review

Patricia Oteng-Darko*, S. Yeboah, S. N. T. Addy, S. Amponsah and E. Owusu Danquah

CSIR-Crops Research Institute, P. O. Box 3785, Kumasi, Ghana

Accepted 7 December, 2012

The Earth's land resources are finite, whereas the number of people that the land must support continues to grow rapidly. This creates a major problem for agriculture. Production (productivity) must be increased to meet rapidly growing demands while natural resources must be protected. New agricultural research is needed to supply information to farmers, policy makers and other decision makers on how to accomplish sustainable agriculture over the wide variations in climate around the world. In this direction the use of crop models in research is being encouraged.

Keywords: policy, simulate, climate, decision, management

INTRODUCTION

Studies on crop production are traditionally carried out by using conventional experience-based agronomic research, in which crop production functions are derived from statistical analysis without referring to the underlying biological or physical principles involved. The application of correlation and regression analysis has provided some qualitative understanding of the variables and their interactions that were involved in cropping systems and has contributed to the progress of agricultural science (Kumar and Chaturevdi, 2009). However, the quantitative information obtained from this type of analysis is very site specific. The information obtained can only be reliably applied to other sites where climate, important soil parameters and crop management are similar to those used in developing the original functions. Thus, the quantitative applicability of regression based crop yield models for decision making is severely limited. In addition, because of the unavoidable variability associated with weather, more than 10 years is required to develop statistical relationships that are useful in agricultural decision making. Ref Statistical evidence based on long-term studies generally show that more than 40% of the total variation is usually associated with experimental error (Jame and Cutforth, 1996).

As knowledge is accumulated, results obtained from observation change from being qualitative to being quantitative and mathematics can be adopted as the tool to express biological hypotheses. Advances in computer technology have made possible the consideration of the combined influence of several factors in various interactions. As a result, it is possible to quantitatively combine the soil, plant, and climatic systems to more accurately predict crop yield. Thus, with the availability of inexpensive and powerful computers and with the growing popularity of the application of integrated systems to agricultural practices, a new era of agricultural research and development is emerging (Jones *et al*, 1993). In crop growth modeling, current knowledge of plant growth and development from various disciplines, such as crop physiology, agrometeorology, soil science and agronomy, is integrated in a consistent, quantitative and process-oriented manner.

Computerized decision support systems that allow users to combine technical knowledge contained in crop growth models with economic considerations and environmental impact evaluations are now available. DSSAT (Tsuji *et al.* 1994) is an excellent example of a management tool that enables individual farmers to

Corresponding author. Email: patamankwaa@yahoo.com

match the biological requirement of a crop to the physical characteristics of the land to obtain specified objectives. In the Ghanaian research sector, modeling is a new discipline and basic background information on the application of models in research is not easily available. Lack of awareness about model structure, possibilities and limitations have been identified as hindrance to model application in our society.

What is crop modeling?

Modeling is the use of equations or sets of equations to represent the behaviour of a system. In effect crop models are computer programmes that mimic the growth and development of crops (USDA, 2007). Model simulates or imitates the behaviour of a real crop by predicting the growth of its components, such as leaves, roots, stems and grains. Thus, a crop growth simulation model not only predicts the final state of crop production or harvestable yield, but also contains quantitative information about major processes involved in the growth and development of the crop. Reactions and interactions at the level of tissues and organs are combined to form a picture of the crop's growth processes.

Brief history of crop modeling

The development of crop growth simulation models has been a natural progression of scientific research. Jame (1992) reviewed the history of attempts to quantify the relationships between crop yield and water use from the early work on simple water-balance models in the 1960s to the development of crop growth simulation models in the 1980s. Two decades ago, it was not certain whether the complex physical, physiological and morphological processes involved in the growth of a plant could be described mathematically, except perhaps in some controlled environments. Thus, the relevance of crop growth simulation models in crop agronomy was challenged (Passioura 1973). However, during the past 40 years, crop growth modeling has changed dramatically.

In the sixties, the first attempt to model photosynthetic rates of crop canopies was made (de Wit, 1965). The results obtained from this model were used among others, to estimate potential food production for some areas of the world and to provide indications for crop management and breeding (de Wit, 1967; Linneman *et al.,* 1979). This was followed by the construction of an Elementary Crop growth Simulator (ELCROS) by de Wit *et al.* in 1970. This model included the static photosynthesis model and crop respiration was taken as a fixed fraction per day of the biomass, plus an amount proportional to the growth rate. In addition, a functional equilibrium between root and shoot growth was added (Penning de Vries *et al*., 1974).

The introduction of micrometeorology in the models (Goudriaan, 1977) and quantification of canopy resistance to gas exchanges allowed the models to improve the simulation of transpiration and evolve into the Basic Crop growth Simulator (BACROS) (*de* Wit and Goudriaan, 1978).

To help resource poor farmers in the tropics and sub tropics IBSNAT (International Benchmark Sites Network for Agrotechnology Transfer) began the development of a model in 1982. This was under a contract from the U.S. Agency for International Development to the University of Hawaii at Manoa, USA. IBSNAT was an attempt to demonstrate the effectiveness of understanding options through systems analysis and simulation for ultimate benefit of farm households across the globe. The purposes defined for the IBSNAT project by its technical advisory committee were to understand ecosystem processes and mechanisms, synthesize from an understanding of processes and mechanisms, a capacity to predict outcomes and enable IBSNAT clientele to apply the predictive capability to control outcomes.

The major product of IBSNAT was the Decision Support System for Agro- Technology Transfer (DSSAT) which is currently being used as a research and teaching tool. As a research tool its role is to derive recommendations concerning crop management and to investigate environmental and sustainability issues. The DSSAT products enable users to match the biological requirements of crops to the physical characteristics of land to provide them with management options for improved land use planning. The package consists of: data base management system for soil, weather, genetic coefficients, and management inputs, Crop simulation models, series of utility and weather generation programs and strategy evaluation program to evaluate options including choice of variety, planting date, plant population density, row spacing, soil type, irrigation, fertilizer application, initial conditions on yields, water stress in the vegetative or reproductive stages of development, and net returns. In effect, DSSAT has the potential to reduce substantially the time and cost of field experimentation necessary for adequate evaluation of new cultivars and new management systems.

Types of models

Depending upon the purpose for which it is designed the models are classified into different groups or types. A few of them are:

Empirical models: These are direct descriptions of observed data and are generally expressed as regression equations (with one or a few factors) and are used to estimate the final yield. This approach is primarily one of examining the data, deciding on an equation or set of equations and fitting them to data. These models give no information on the mechanisms that give rise to the response. Examples of such models include those used for such experiments as the response of crop yield to fertilizer application, the relationship between leaf area and leaf size in a given plant species and the relationship between stalk height alone or coupled with stalk number and/or diameter and final yield.

Mechanistic models: A mechanistic model is one that describes the behaviour of the system in terms of lower-level attributes. Hence, there is some mechanism, understanding or explanation at the lower levels (eg. Cell division). These models have the ability to mimic relevant physical, chemical or biological processes and to describe how and why a particular response occurs. The modeler usually starts with some empirism and as knowledge is gained additional parameters and variables are introduced to explain crop yield. The system is therefore broken down into components and assigned processes.

Static and dynamic models: A static model is one that does not contain time as a variable even if the end-products of cropping systems are accumulated over time. In contrast dynamic models explicitly incorporate time as a variable and most dynamic models are first expressed as differential equations

Deterministic models: A deterministic model is one that makes definite predictions for quantities (e.g. crop yield or rainfall) without any associated probability distribution, variance, or random element. However, variations due to inaccuracies in recorded data and to heterogeneity in the material being dealt with are inherent to biological and agricultural systems (Brockington, 1979).

In certain cases, deterministic models may be adequate despite these inherent variations but in others they might prove to be unsatisfactory e.g. in rainfall prediction. The greater the uncertainties in the system, the more inadequate deterministic models become.

Stochastic models: When variation and uncertainty reaches a high level, it becomes advisable to develop a stochastic model that gives an expected mean value as well as the associated variance. However, stochastic models tend to be technically difficult to handle and can quickly become complex. Hence, it is advisable to attempt to solve the problem with a deterministic approach initially and to attempt the stochastic approach only if the results are not adequate and satisfactory.

Simulation models: These form a group of models that is designed for the purpose of imitating the behaviour of a system. Since they are designed to mimic the system at short time intervals (daily time-step), the aspect of variability related to daily change in weather and soil conditions is integrated. The short simulation time-step demands that a large amount of input data (climate parameters, soil characteristics and crop parameters) be available for the model to run. These models usually offer the possibility of specifying management options and they can be used to investigate a wide range of management strategies at low costs.

Optimizing models: These models have the specific objective of devising the best option in terms of management inputs for practical operation of the system. For deriving solutions, they use decision rules that are consistent with some optimizing algorithm. This forces some rigidity into their structure resulting in restrictions in representing stochastic and dynamic aspects of agricultural systems.

Crop model applications

Simulation modeling is increasingly being applied in research, teaching, farm and resource management and policy analysis and production forecasts. They can be applied, namely, research, crop system management, and policy analysis.

Research understanding: Model development ensures the integration of research understanding acquired through discreet disciplinary research and allows the identification of the major factors that drive the system and can highlight areas where knowledge is insufficient. Thus, adopting a modeling approach could contribute towards more targeted and efficient research planning

Integration of knowledge across disciplines: Adoption of a modular framework allows for the integration of basic research that is carried out in different regions, countries and continents. This ensures a reduction of research costs (e.g., through a reduction in duplication of research) as well as the collaboration between researchers at an international level.

Improvement in experiment documentation and data organization: Simulation model development, testing and application demand the use of a large amount of technical and observational data supplied in given units and in a particular order. Data handling forces the modeler to resort to formal data organization and database systems.

Site-specific experimentation: Specific site selection can be using the model Crop models can be used to predict crop performance in regions where the crop has not been grown before or not grown under optimal conditions.

Yield analysis: When a model with a sound physiological background is adopted, it is possible to extrapolate to other environments. Simulation models are used to climatically-determined yield in various crops.

Through the modeling approach, quantification of yield reductions caused by non-climatic causes (e.g., delayed sowing, crop spacing, soil fertility, pests and diseases) becomes possible. Simulation models have also been reported as useful in separating yield gains into components due to changing weather trends, genetic improvements and improved technology.

Climate change projections: The variability of our climate and especially the associated weather extremes is currently one of the concerns of the scientific as well as general community. The application of crop models to study the potential impact of climate change has been widely used across the continents. The increased concentration of carbon dioxide and other greenhouse gases are expected to increase the temperature of earth. Crop production is highly dependent on variation in weather and therefore any change in global climate will have major effects on crop yields and productivity. Elevated temperature and carbon dioxide affects the biological processes like respiration, photosynthesis, plant growth, reproduction, water use etc. Proper understanding of the effects of climate change will therefore help scientists to guide farmers to make crop management decisions such as selection of crops, cultivars, sowing dates and irrigation scheduling to minimize the risks.

Scoping best management practices: Simulation can be done to determine the best management practices under a certain cropping system. In the past, the main focus of agronomic research has been on crop production. Recently, in addition to profitable crop production, the quality of the environment has become an important issue that agricultural producers must address. Agricultural managers require strategies for optimizing the profitability of crop production while maintaining soil quality and minimizing environmental degradation. Solutions to this new challenge require consideration of how numerous components interact to effect plant growth. To achieve this goal, future agricultural research will require considerably more effort and resources than present research activity. Models having chemical leaching or erosion components can be used to determine the best farming practices over the long-term. Investment decisions like purchase of irrigation systems can be taken with an eye on long term usage of the equipment when irrigation schedules are done using the modeling approach.

Yield forecasting: Reasonably precise estimates of crop yield over large areas before the actual harvest are of immense value to both the researcher and the farmer in terms of planning. In this approach the model is run using actual weather data during the cropping season for the geological region of interest. Weather years for typical years are used to continue simulations until harvest.

Breeding and introduction of a new crop variety: Development and release of a variety is a complex process that may extend over a period of 5 – 15 years. Since the modeling systems approach integrates different components of agro ecosystems, it can be used to conduct multi-location field experiments to understand genotype by environment (G x E). Such studies can help in reducing the number of sites/seasons required for field evaluation and thus increase the efficiency of the process of variety development.

Again, by modeling a range of probable genotypes and selected environments known to discriminate between the genotypes, it is possible that the crop parameter determining the specific interaction could be identified. Hypothetical values could then be modeled combining the crop parameters conferring the most advantage as an indication of suitable traits and breeding target.

A modeling approach can also provide estimates of yield probability in target environments based on the understanding of the G x E.

Crop model applications in crops research

Amissah-Arthur and Jagtap (1995) successfully assessed nitrogen requirements by maize across agroecological zones in Nigeria using CERES-maize model. Hammer *et al*. (1995) using local weather and soil information correlated peanut yields with estimates from PEANUTGRO, a model in the CERES family and gave a regression with high coefficient (r^2 = 0.93) of variation. Clifford *et al* (2000) tested the effects of elevated CO_2, drought and temperature on the water relations and gas exchange of groundnut.

Hammer and Muchow (1994) used the modeling approach to quantify climatic risk to sorghum in Australia's semi arid tropics and subtropics.

The EPIC, ALMANAC, CROPSYST, WOFOST, ADEL and CERES-Maize models are being successfully used to simulate maize crop growth and yield.

The SORKAM, SorModel, and SORGF models are being used to address specific tasks of sorghum crop management. CERES – pearl millet model, CROPSYST, PmModels are being used to study the suitability and yield simulation of pearl millet genotypes across the globe. Similarly, the two most common growth models used in application for cotton are the GOSSYM (Mckinion *et al*, 1989) and COTONS models. On the same analogy the PNUTGRO (Boote *et al,* 1989) for groundnut, CHIKPGRO for chick pea, WTGROWS for wheat, SOYGRO for soybean, BEANGRO (Hogenboom *et al,* 1994) for beans QSUN for sunflower are in use to meet the requirements of farmers, scientists, decision makers, etc., at present.

The APSIM, GROWIT added with several modules are being used in crop rotation, crop sequence and simulation studies involving perennial crops.

Model Parameterization (calibration, evaluation and validation)

Model calibration involves the modification of some model parameters such that data simulated by the error-free model fit the observed data. In many instances, even if a model is based on observed data, simulated values do not exactly comply with the observed data and minor adjustments have to be made for some parameters. Non-compliance may arise from sampling errors as well as from incomplete knowledge of the system. Alternatively, it may arise when the model is used in a situation that is markedly different from the one under which it was developed.

The model validation stage involves the confirmation that the calibrated model closely represents the real situation. The procedure consists of a comparison of simulated output and observed data that have not been previously used in the calibration stage. However, validation of all the components is not possible due to lack of detailed datasets and the option of validating only the determinant ones are adopted. For example, in a soil-water crop model, it is important to validate the extractable water and leaf area components since biomass accumulated is heavily dependent on these. Evapotranspiration also becomes a determinant to validate.

Crop model limitations

Crop models are not able to give accurate projections because of inadequate understanding of natural processes and computer power limitation. As a result, the assessments of possible effects of climate changes, in particular, are based on estimations. Moreover, most models are not able to provide reliable projections of changes in climate variability on local scale, or in frequency of exceptional events such as storms and droughts (Shewmake, 2008). General Circulatory Models (GCMs) have so far not been able to produce reliable projections of changes in climate variability, such as alterations in the frequencies of drought and storms, even though these could significantly affect crop yields.

As different users possess varying degrees of expertise in the modeling field, misuse of models may occur. Since crop models are not universal, the user has to choose the most appropriate model according to his objectives. As a result, the assessments of possible effects of climate changes are based on estimations. Moreover, most models are not able to provide reliable projections of changes in climate variability on local scale, or in frequency of exceptional events such as storms and droughts (Shewmake, 2008). General Circulatory Models (GCMs) have so far not been able to produce reliable projections of changes in climate variability, such as alterations in the frequencies of drought and storms, even though these could significantly affect crop yields. GCMs do a reasonable job in simulating global values of surface air temperature and precipitation, but do poorly at the regional scale (Grotch, 1988).

Furthermore, biological and agricultural models are reflections of systems for which the behaviour of some components is not fully understood and differences between model output and real systems cannot be fully accounted for. Crop models are therefore not able to give accurate projections because of inadequate understanding of natural processes and computer power limitation. Again, methodology of model validation is still rudimentary.

The main reason is that, unlike the case of disciplinary/traditional experiments, a large set of hypotheses is being tested simultaneously in a model. The validation of models at present is further complicated by the fact that field data are rarely so definite that validation can be conclusive. This results from the fact that model parameters and driving variables are derived from site-specific situations that ideally should be measurable and available. However, in practice, plant, soil and meteorological data are rarely precise and may come from nearby sites. At times, parameters that were not routinely measured may turn out to be important and they are then arbitrarily estimated.

Measured parameters also vary due to inherent soil heterogeneity over relatively small distances and to variations arising from the effects of husbandry practices on soil properties. Crop data reflect soil heterogeneity as well as variation in environmental factors over the growing period.

Model performance is limited to the quality of input data. It is common in cropping systems to have large volumes of data relating to the above-ground crop growth and development, but data relating to root growth and soil characteristics are generally not as extensive. Most simulation models require that meteorological data be reliable and complete. Finally, sampling errors also contribute to inaccuracies in the observed data.

An ultimate crop model would be one that physically and physiologically defines all relations between variables the model reproduces and universally real-world behaviour. However, such a model cannot be developed because the biological system is too complex and many processes involved in the system are not fully understood (Jame and Cutforth, 1996). Even if an ideal crop model could be produced, the collection of the highly precise system parameters and of the input data for the crop environment would be a formidable task in itself. Thus, the level of detail involved in a crop model is closely linked to the end use of the model and the precision required.

Even when a judicious choice is made, it is important that aspects of model limitations be borne in mind such that modeling studies are put in the proper perspective and successful applications are achieved.

CONCLUSION

As a research tool, model development and application can contribute to identify gaps in our knowledge, thus enabling more efficient and targeted research planning. Models that are based on sound physiological data are capable of supporting extrapolation to alternative cropping cycles and locations, thus permitting the quantification of temporal and spatial variability.

Most models are virtually untested or poorly tested, and hence their usefulness is unproven. Indeed, it is easier to formulate models than to validate them. Many agronomists have been confused by the situation. They are discouraged by the complexity of the models, the lack of model testing, and the inevitable inaccuracies that arise when such testing is done. Consequently, they have seriously doubted the usefulness of crop models in agronomy. Unfortunately, this confusion is caused partly by those who are naively optimistic that crop modeling is the panacea for agricultural problems and apply crop models indiscriminately. Because most agronomists do not fully understand the concept of crop growth modeling and systems-approach research, training in this area is required. An intensely calibrated and evaluated model can be used to effectively conduct research that would in the end save time and money and significantly contribute to developing sustainable agriculture that meets the world's needs for food.

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