Environment and Ecology 40 (3A) : 1318—1324, July—September 2022
ISSN 0970-0420

A Review : Application of Crop Modeling in Horticultural Crops

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Received 21 April 2022, Accepted 19 June 2022, Published on 6 August 2022

ABSTRACT

The horticulture production process can be characterized as an open and highly complex system affected by weather, soil, insects, diseases, weeds, nutrition, prices and interactions of these many factors. At the moment, knowledge of the whole system is rather limited and models describing their behavior are incomplete approximations of the real system that they attempt to simulate. Nevertheless, it is possible to identify different types of problems, a grower might be confronted with in horticulture (operational, tactical, strategic decisions). In order to implement models for decision support, it is not sufficient to know the potential problems, it is also necessary to understand the decision making process which is described from a more theoretical point of view. A review of the evolution of computer-based systems for supporting decision making completes the preceding descriptions. In confronting the different types of real problems with the available technical possibilities, the discussion about implementation problems will be opened, including the question, who should or will apply models to derive answers to problems. It is concluded that the use of models in practice will only increase if the models deal with problems faced by the decision makers and if it becomes obvious to the farmers that they can derive answers to their problems on a more efficient way using specific models.

Keywords Crop modeling, Horticultural crops

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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 under lying 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 2012). 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 (Murthy, 2003). 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 Cut forth 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. (Van Ittersum ***et al***. 2003) 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, agro meteorology, soil science and agronomy, is integrated in a consistent, quantitative and process-oriented manner (Batchelor *et al.* 2002). 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 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 (Oteng-Darko *et al.* 2012). Lack of awareness about model structure, possibilities and limitations have been identified as hindrance to model application in our society. With remote sensing method, the form of crops developed in an area, crop state, and yield can be considered. Recording crop state by remote sensing can get the crop status in addition to the condition and progress of their development. Obtaining the crop situation data at early steps of crop development is still more significant than acquiring the fixed production after harvest period (Pinter *et al.*2003).

Modeling: Definition and concepts

Modelling is the use of equations or sets of equations to represent the behavior of a system. In effect crop models are computer programmes that mimic the growth and development of crops (USDA 2007). Modelling represents a better way of synthesizing knowledge about different components of a system, summarizing data, and transferring research results to users (France and Thornley 1984). Model simulates or imitates the behavior 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. Crop models can be used to understand the effects of climate change such as elevated carbon-dioxide changes in temperature and rainfall on crop development, growth and yield.

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 modelling 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).

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 (Jones *et al.* 2003). 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 (Roubtsova 2014).

Mechanistic models: A mechanistic model is one that describes the behavior of the system in terms of lower-level attributes (Johnson 2003). 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 (Challinor *et al.* 2009).

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 (Rauff and Bello 2015). 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 (Di Paola *et al*. 2016), 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 (Wallach *et al*. 2014).

Simulation models: These form a group of models that is designed for the purpose of imitating the behaviour of a system (Jones JW *et al.* 2017). 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 (Ewert *et al*. 2011).

Optimizing models: These models have the specific objective of devising the best option in terms of management inputs for practical operation of the system (Ramirez-Villegas *et al*. 2015). 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 (Challinor *et al.* 2014).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 (Palosuo *et al.* 2011). 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. (Olesen *et al.*2004). This ensures a reduction of research costs (e.g., through a reduction in duplication of research) as well as the collaboration between researchers at anointer national 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 (Clevers and Vonder 2002). 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 (Brisson *et al*.1998).

Crop modeling in fruit crops

Fruit producers have, over the last decades, been adopting a wide variety of new technologies to meet increased market demands and environmental standards, to improve production quantity, to avoid losses, and to reduce maintenance costs. Increasing fruit quality and uniformity requirements are met by breeding, post-harvest technology, better management practices and more intensive monitoring (Ladaniya, 2007). In recent years, fruit quality has become an increasingly important aspect of fruit production. Thus, a new field of science has been emerging that is loosely termed functional-structural plant modelling (Godin and Sinoquet 2005). Several authors (Behera and Panda 2009; Bojacá *et al.* 2009) have developed and used models that explain the effect meteorological variables have on the growth of different kinds of crops. As convincingly demonstrated by de Wit (1986), agricultural productivity depends primarily on the carbon assimilation and partitioning systems. Thus the backbone of crop models of this type involves modelling of plant photosynthesis, respiration and the allocation of the net photosynthate to the fruit or organs of interest. This includes, of course, annual crops as well as fruit tree crops. Nowadays, the interest in mathematical modelling about the quality changes during fruit maturation has been increased (Wegehenkel and Mirschel 2005). Fruit quality is a complex issue. It involves a set of traits such as fruit size, overall composition, taste, aroma, texture and proportion of edible tissue (Genard *et al.* 2007, Gruda 2005). The links between environmental control and quality traits have been extensively investigated (Wu *et al.* 2002, Challinor *et al.* 2004). Even though every process involved in fruit physiology cannot be integrated into a model, a real degree of complexity is needed since fruit exchanges energy and mass with its environment and it is composed of a large number of diverse components (different sugars, acids) which interact with each other non-linearly (Genard *et al.* 2007).Taste mainly results from the accumulation of sugars and acids in fruit cells. This accumulation can be controlled through the intensity of metabolic transformations. These processes are well known and have been extensively described in the literature (Ho, 1998, Wink 1993). On this basis, Genard *et al.* (2007) designed a mechanistic model called SUGAR to predict changes in sugar composition during each fruit development. In this model, sugars are either directly stored in the cells, transformed into other sugars, or used to synthesize other compounds. Lobit et al. (2006) designed two models predicting fruit acidity, the first one described citric acid production and degradation through the citrate cycle. In the second, malic acid content was modelled mainly on thermodynamic conditions of its transport from cytosol to vacuole. Fruit tree crops share an important number of commonalities with annual crops (Goldschmidt and Lakso 2005) most processes occurring in annuals will occur in fruit tree crops. Therefore knowledge gathered on the modelling of annual crops provides a first basis to develop more advanced models for perennial fruit crops. Photosynthesis-driven models are also common for perennial fruit trees. Such photosynthesis-driven models have been developed for apples (Baumgaertner Graf and Zahner1984, Seem *et al*. 1986), grapes (Gutierrez *et al*. 1985), kiwifruit (Buwalda 1991), olives (Abdel-Razik 1989) and peaches (Grossman and Dejong 1994). Pioneering work of C.T. dewit (Van Ittersum *et al*. 2003), most process-based fruit models have focused on carbon relationships leading to predictions of fruit growth in dry mass.

Crop modeling in vegetable crops

A dynamic simulation model for tomato crop growth and development, (TOMSIM) was validated for four glasshouse experiments with plant den sity and fruit pruning treatments and on data from two commercially grown crops. In general, measured and simulated crop growth rates from 1 month after planting onwards agreed reasonably well, average overestimation being 12%. However, crop growth rates in the first month after planting were overestimated by 52% on average. Final crop dry mass was overestimated by 0 - 31%, due to inaccurate simulation of LAI, resulting partly from inaccurate SLA prediction, which is especially important at low plant density and in a young crop(Heuvelink 1999). Rregression models were generated to mimic the behavior of minerals in tomato plants and they were included in the model in order to simulate their dynamic behavior. The results of this experiments showed that the growth model adequately simulates leaf and fruit weight (EF > 0.95 and Index > 0.95). As for harvested fruits and harvested leaves, the simulation was less efficient (EF < 0.90 and Index < 0.90). Simulation of minerals was suitable for N, P, K and S as both, the EF and the Index, had higher values than 0.95. In the case of Ca and Mg, simulations showed indices below 0.90. These models can be used for planning crop management and to design more appropriate fertilization strategies. A mechanistic crop growth model for glasshouse tomato (TOMSIM) has been developed (Heuvelink *et al.* 1995) and the following of its submodels (modules) validated greenhouse transmissivity (Heuvelink *et al.* 1996), photosynthesis (Heuvelink *et al*. 1996), dry matter production and truss appearance rate, fruit growth period and dry matter partitioning(Bertin and Heuvelink 1993). Sensitivity analyses for the modules for dry matter production and dry matter distribution were presented previously (Heuvelink *et al*. 1995).

Theoretical model of greenhouse microclimate was developed for describing heat and mass transport processes in a greenhouse row-crop stand, including radiation transfer, energy balance, transpiration and CO_2 exchange. The canopy was described as a series of parallel rows with pseudorectangular cross-sections and variable architectural parameters. Each of the individual submodels was parameterized from experimental data for a dense row cucumber crop. The general theoretical considerations were assembled into a dynamic simulator by applying energy and mass balances simultaneously over differential strata of plant leaves and greenhouse air. Outputs of the simulator included both diurnal courses and vertical profiles of leaf temperature, air temperature, humidity and CO_2 concentration in addition to energy and mass exchange(Yang *et al*.1990). Simple model of carbon distribution for the simulation of root development of a cucumber crop. Roots are an important sink and growth of small fruits (before flowering) may be strongly inhibited in the case of low photosynthetic activity. Root growth is an opposite function of the fruit load and there is a close correlation between the simulated rate of root growth and the root lengthening (Chamont 1993).

A regression model for cucumber dry matter production was established based on Logistic curve and the time state variable was expressed as a logistic function about effective temperature accumulation (ETA) and effective light intensity accumulation (ELIA). ETA was defined as the sum of the temperature that was higher than physiological zero point in certain period, and ELIA was defined as the sum of the light intensity that was higher than light compensation point multiplied with time in certain period. Temperature, light intensity and day length were synthetically considered. The model had less state variables, and provided the relationships between the cucumber dry matter accumulation (DMA) per plant and environmental data (temperature, radiation and day length). The result of simulation was satisfied, because RMSE value was less than 6, and the R2 value of the results was 0.99. It indicated that the regression model for cucumber dry matter production was reasonable and feasible (Song and Qiao 2008).

Limitations

As George E.P. Box Systems Science Professor reportedly said “All models are wrong. Some models are useful”. It is important to acknowledge the first statement for complex systems like fruit trees, but to strive for usefulness. 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 *et al.* 2012). 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. GCMs do a reasonable job in simulating global values of surface air temperature and precipitation, but do poorly at the regional scale(Grotch *et al*. 1988).

CONCLUSION

Model development can contribute to identify gaps in our knowledge, thus enabling more efficient and targeted research planning. Species diversity, crop nature, quality parameters and yield were decided the good decision making in the crop modeling. This will be possible only if cooperation among scientific disciplines develops. So that better crop modeling were involved between crop physiologists and geneticists, plant pathologists, entomologists, and food technologists. In terms of designing decision support systems, specialists in agricultural engineering, farming systems and computer sciences. The adoption of standard units, formation of inputs and outputs, selection of variables, the production of proper documentation, limitations and the use of procedures of software quality assurance would increase the portability of models and lower the risk of error or misuse. 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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