Journal of Pharmacognosy and Phytochemistry

Available online at www.phytojournal.com

E-ISSN: 2278-4136
P-ISSN: 2349-8234
JPP 2017; 6(4): 1006-1009
Received: 08-05-2017
Accepted: 10-06-2017

K Manikandan
Ph.D Scholar, Department of Vegetable Crops, Horticultural College and Research Institute, TNAU, Coimbatore, Tamil Nadu, India

P Irene Vethamoni
Professor (Hort.), Department of Vegetable Crops, Horticultural College and Research Institute, TNAU, Coimbatore, Tamil Nadu, India

Correspondence
K Manikandan
Ph.D Scholar, Department of Vegetable Crops, Horticultural College and Research Institute, TNAU, Coimbatore, Tamil Nadu, India

A review: Crop modeling in vegetable crops

K Manikandan and P Irene Vethamoni

Abstract
Vegetables are an important supplement to the human diet as they provide the essential minerals, vitamins and fibre required for maintaining health. Large number of land throughout the world cannot be used for food production because of the limitations imposed by natural or man made environmental stresses. This creates a major problem for agriculture. Production must be increased to meet rapidly growing demands with improved production techniques. 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. Modeling techniques applied to agriculture can be useful to define research priorities and understanding the basic interactions of the soil-plant-atmosphere system. As a research tool, model development and application can contribute to identify gaps in our knowledge, thus enabling more efficient and targeted research planning. Using a model to estimate the importance and the effect of certain parameters, a researcher can notice which factors can be most useful. 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.

Keywords: Crop model, Simulation, Calibrate, Validate, Vegetables

Introduction
A crop model can be described as a quantitative scheme for predicting the growth, development, and yield of a crop, given a set of genetic features and relevant environmental variables [1]. Crop Simulation Models (CSM) are computerized representations of crop growth, development and yield, simulated through mathematical equations as functions of soil conditions, weather and management practices [2]. Although crop models have great potential for practical use in agriculture and horticulture, their use is still limited [3]. 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.
Before a model can be used it must be validated, i.e. model output, after running the model on historical input data recorded for the real system, has to be compared with the real system output. Models are often validated with all or some of the data used for model development or calibration [4, 5]. Whereas independent data, not used in model development, should be used [6]. 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 e [7]. 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.

Uses of models
Modeling helps us to understand, predict and control a system in a more organised or methodological manner because models provide a quantitative description of the system and a way of bringing together knowledge about the parts to give a coherent and holistic view of the system. Models can help to identify areas where knowledge is lacking, and can help to stimulate new ideas or approaches for research.

Models can be used to identify interesting and stimulating areas of research, and those short-listed can later be implemented in actual experiments. Models can complement and add value to actual experiments. Interpretation of results from experiments can sometimes be aided using a model. In special circumstances, models can replace experiments to study the effects of certain factors or conditions that otherwise cannot be studied in actual experiments due to high costs, great length of time, high risks or technical difficulties. Modeling encourages collaboration among researchers from various fields of expertise because a system consists of various components, where the study of these different components often requires separate fields of study.

Crop modeling in vegetable crops

A dynamic simulation model for tomato crop growth and development, (TOMSIM) was validated for four glasshouse experiments with plant density 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 [8].

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 [9].

A mechanistic crop growth model for glasshouse tomato (TOMSIM) has been developed [10, 11], and the following of its submodels (modules) validated greenhouse transmissivity [12], photosynthesis [13], dry matter production [14, 10] and truss appearance rate, fruit growth period and dry matter partitioning [15, 11]. Sensitivity analyses for the modules for dry matter production and dry matter distribution were presented previously [14, 15].

In the area of greenhouse operation, yield prediction still relies heavily on human expertise. Automatic tomato yield predictor to assist the human operators in anticipating more effectively weekly fluctuations and avoid problems of both over demand and overproduction if the yield cannot be predicted accurately. The parameters used by the predictor consist of environmental variables inside the greenhouse, namely, temperature, CO2, vapour pressure deficit (VPD), and radiation, as well as past yield. Greenhouse environment data and crop records from a large scale commercial operation, Wight Salads Group (WSG) in the Isle of Weight, United Kingdom, collected during the period 2004 to 2008, were used to model tomato yield using an Intelligent System called “Evolving Fuzzy Neural Network” (EFuNN). There results showed that the EFuNN model predicted weekly fluctuations of the yield with an average accuracy of 90%. The contribution suggests that the multiple EFUNNs can be mapped to respective task-oriented rule-sets giving rise to adaptive knowledge bases that could assist growers in the control of tomato supplies and more generally could inform the decision making concerning overall crop management practices [16].

At high radiation levels, the diurnal canopy transpiration rate in cucumber was four times higher than at low radiation levels and the night transpiration rate reached values between 120 and 200 g m^{-2} d^{-1} in both cases. The leaf transpiration rate decreased during crop ontogeny and was higher in the afternoon than in the morning for the same value of radiation, whereas a linear relationship with the VPD was found even for values greater than 3 kPa. The results showed that the fitted simplified Penman Monteith formula accounted for more than 90% of the measured hourly canopy transpiration rate, signifying that this formula could be used to predict water requirements of crops under Mediterranean conditions and improve irrigation control in a substrate culture. However, the model coefficients will have to be adjusted for specific climate and crop conditions [17].

When using multiple regression equations, it is very much likely to predict the yield as related to temperature and light intensity with high probability. According to the statistical results, the equations of parameters were affected by the light intensity directly. Nonlinear regression models including light intensity, temperature and SPAD value may estimate yield of cucumber cultivars [18].

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 CO2 exchange. The canopy was described as a series of parallel rows with pseudo-rectangular 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 CO2 concentration in addition to energy and mass exchange [19].

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 [20].

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 [21].

Good description of leaf initiation data (R2 values of 0.9) was achieved when a gradual increase in the leaf initiation rate with increasing leaf number and increasing temperature. The end of the juvenile phase was estimated to occur on average when the plant had 12 leaves initiated. The duration of the curd induction phase in the model was described by using linear responses to temperature that are symmetrical below and above an optimum temperature [22].

A crop model and evapotranspiration model for lettuce. Field validation of the Etc model showed agreement with Etc measurements taken at four different locations using the water and energy balance methods. This model improved the estimation of exposed bare soil evaporation, which depends on irrigation frequency and soil hydraulic properties. The model requires only eto as a one input parameter, so it has a high potential to be adopted and used by lettuce growers. This can lead to water conservation and reduced nitrate contamination [23].

Evaluation of AquaCrop model which showed that the well simulated tuber yield, total biomass and WUE. Alternative irrigation application showed that four to six early irrigation applications after cessation of rainfall was enough to obtain good yield and biomass. From this finding the most critical stage of physiological water stress of the crop to be supplied with deficit irrigation was preferable method, and then, the additional water used in full supplementary irrigation should be saved and invested in additional land productivity [24].

Model EPOVIR is integrated in the decision support system TUBERPRO which forecasts tuber yields graded by size and the infection of the tubers by PVY and PLRV. It supports optimization of haulm killing dates in the seed potato production. The system calculates expected seed yield and the probability that virus infection remains below the tolerance limit used in seed certifIcation. The combination of the two factors gave the expected certifIed seed yield, which can subsequently be optimized [25].

Data from a field experiment carried out on growth of onion was used to fit logistic, gompertz, expolinear and scaife and jones functions using time, day degrees and effective day degrees and to test a mechanistically based that combines the effects of potentially limiting variables such as temperature and light and allows for plant zone area in light interception. The expolinear function seemed the most reliable function in estimating the early relative growth rate which is the crucial value in all the modification for canopy senescence in onion [26].

Two approaches for modelling in growth and development of cassava (*Manihot esculenta* Crantz). The two models differ only in the hypotheses accounting for storage root growth. In model one assimilate allocation to storage roots was governed by the combined Chanter's growth equation and in model two the *spill-over hypothesis* for assimilate allocation to storage root governs storage root growth. In both models, canopy photosynthesis generated the carbon substrate required for all growth processes. The growth rates of leaves, stems and storage roots were defined by growth equations subject to substrate saturation kinetics. A key feature of both models was that the growth demands of the stem, fibrous roots and storage roots were related to leaf demand rates. Allocation to stems and branches was modeled by means of a modified logistic growth equation which includes all the parameters and variables (number of nodes, internode lengths, stem density, stem modulus of elasticity and branch tensile strength) that define the limits of the load bearing capacity of the shoot's supportive structures. For a growth season of 290 d (after which leaf area index equals zero and crop growth ceases), both models simulate the sigmoidal transition from the lag to exponential phase of crop growth [27].

Limitations in crop modeling

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 [28]. 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 [29].

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. Sampling errors also contribute to inaccuracies in the observed data [30].

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 [31]. 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 crop model is closely linked to the end use of the model and the precision required.

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 [32]. In terms of designing decision support systems, specialists in agricultural engineering, farming systems and computer sciences.

For this integration to be effective, efforts have to be made towards a more professional practice of building and maintaining crop models [33]. 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.

References

1. Monteith JL. The quest for balance in crop modelling. Agron. J. 1996; 88:695-697.
2. Hoogenboom GJ, White JW, Messina CD. From genome to crop: integration through simulation modelling. Field Crop Res. 2004; 90:145-150.
3. Challa H. Crop growth models for greenhouse climate control in R. Rabbinge, J. Gourdian, H. Van keuden, F.W.T. Penning devries and H.H. Van laar (des.) theoretical production ecology: reflections and perspectives, simulation monographs 34, PUDOG wageninger, 1990, 125-145.
4. Jones JW, Dayan E, Allen LH, van Keulen H, Challa H. A dynamic tomato growth and yield model _TOMGRO.. Trans. ASAE. 1991; 34:663-672.
5. Bertin N, Gary. Evaluation d'un modele dynamique de croissance et de development de la tomate (*Lycopersicon esculantum* Mill) TOMGRO, pour different niveaur d'offrent de demande en assimilats. Agronomite, 1993; 13:395-405.
6. Mc carl BA. Model validation an overview with some Emphasis on Risk Models" Review of marketing and agricultural Economics. 1984; 52(3):153-173.
7. Jones JW. Decision support systems for agricultureal development. In: F.W.T. Penning de Vries, P. Tengand K. Metsellaar, eds. Systems approaches foragricultural development. Kluwer Academic Publishers, Dordrecht, The Netherlands. 1993, 459-471.
8. Heuvelink E. Evaluation of a dynamic simulation model for tomato crop growth and development. Annals of Botany. 1999; 83:413-422.
9. Maldonado AJ, Mendoza AB, Romenus K, Morales B. Dynamic modeling of mineral contents in greenhouse tomato crop. Agricultural Sciences. 2014; 5(2):114-123.
10. Heuvelink E. Dry matter production in a tomato crop: measurements and simulation. Annals of Botany. 1995a; 75:369-379.
11. Heuvelink E. Dry matter partitioning in tomato: validation of a dynamic simulation model. Annals of Botany. 1996a; 77:71-80.
12. Heuvelink E, Batta LGG, Damen THJ. Radiance transmission of a multispan Venlo-type glasshouse: validation of a model. Agricultural and Forest Meteorology. 1995; 74:41-59.
13. Heuvelink E. Tomato growth and yield: quantitati.e analysis and synthesis. PhD Thesis, Wageningen Agricultural University, Wageningen, The Netherlands. 1996b.
14. Bertin N, Heuvelink E. Dry-matter production in a tomato crop: comparison of two simulation models. Journal of Horticultural Science. 1993; 68:995-1011.
15. Heuvelink E, Bertin N. Dry-matter distribution in a tomato crop: comparison of two simulation models. Journal of Horticultural Science. 1994; 69:885-903.
16. Qaddoum K, Hines EL, Iliescu DD. Yield prediction for tomato greenhouse using efunn. Hindawi Publishing Corporation. ISRN Artificial Intelligence. Volume 2013, Article ID 430986, 2013, 9.
17. Medrano E, Lorenzo P, Guerrero M, Montero J. Evaluation and modelling of greenhouse cucumber-crop transpiration under high and low radiation conditions. Scientia Horticulturae. 2005; 105:163-175.
18. Kurtar ES, Odabas MS. Modelling of the yield of cucumber (C*ucumis sativus* L.) using light intensity, temperature and spad value. Advances in Food Sciences. 2010; 32(3):12-15
19. Yang X, Short TH. Fox RD, Bauerle WL. Dynamic modeling of the microclimate of a greenhouse cucumber row-crop: Theoretical model. Transactions of the ASAE. 1990; 33(5):1701-1709.
20. Chamont S. Modelling dry matter allocation in cucumber crops -competition between fruits and roots. Acta Hortic. 1993; 328:18-21.
21. Song W, Qiao X. A Regression Model of Dry Matter Accumulation for Solar Greenhouse Cucumber. In: Li D. (eds) Computer And Computing Technologies In Agriculture, CCTA 2007. The International Federation for Information Processing, Springer, Boston, MA. 2008, 2:259.
22. Grevsen K, Olesen JE. Modelling cauliflower development from transplanting to curd initiation. Journal of Horticultural Science. 1994; 69:755-766.
23. Gallardo M, Snyder RL, Schulbach K, Jackson LE. Crop growth and water use model for lettuce. Journal of irrigation and drainage engineering. 1996; 354:24-28.
24. Gebremedhin Y, Berhe A, Nebiyu A. Performance of aquacrop model in simulating tuber yield of potato (*Solanum tuberosum* L.) under various water availability conditions in mekelle area, northern ethiopia. Journal of Natural Sciences Research. 2015; 5:5-7.
25. Nemecek T, Derronl JO, Fischlin A, Roth O. Use of a crop growth model coupled to an epidemic model to forecast yield and virus infection in seed potatoes. 2nd international potato modelling conference, Wageningen. paper for session vii: application of models in crop production. 1994.
26. Tei F, Aikman DP, Scaife A. Growth of lettuce, onion and red beet. Growth modeling, Annals of botany company. 1996.
27. Gray VM. A Comparison of Two Approaches for Modelling Cassava crop growth. Annual Botany. 2000; 85(1):77-90.
28. Shewmake S. Vulnerability and the Impact of Climate Change in South Africa's Limpopo River Basin. *IFPRI Discussion paper.* 00804. 2008. http://books.google.com.gh/books?id Accessed 1st August 2012.
29. Grotch SL. Regional Intercomparison of General Circulatory Model Predictions and Historical Climatic Data. U.S. Dept of Energy, Office of Energy Research Report, DOE/NBB-0084 (TR041). 1988, 291.
30. Patricia Oteng- Darko, Yeboah S, Addy SNT, Amponsah S, Owusu Danquah E. Crop modeling: A tool for agricultural research – A review. E3 Journal of Agricultural Research and Development. 2012; 2(1):001-006.
31. Jame YW, Cutforth HW. Crop Growth Models for Decision Support systems. Canadian J. Plant Sci. 1996; 76(1):9-19.
32. Gary C, Jones JW, Tchamitchian M. crop modelling in horticulture: state of the art. Scientia horticulturae, 1998; 74:3-20.
33. Challa H, Heuvelink E. Photosynthesis driven crop growth models for greenhouse cultivation: advances and bottle-necks. Acta Hortic. 1996; 417:9-22.