Crop modelling in agricultural crops

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With limited land resources and a growing population, agricultural output is under considerable strain. New technology is necessary for overcoming these issues and advising farmers, legislators and other decision-makers on adopting sustainable agriculture despite global climate variations. This has led to the crop simulation models that illustrate crop growth and development processes as a function of climate, soil and crop management. They also support agricultural agronomy (yield estimate, biomass, etc.), pest control, breeding and natural resource management. This study examines crop modelling for agricultural production planning and field-level management strategies. These can help researchers comprehend the significance of crop modelling for scenario-building and provide field-level suggestions by analysing future conditions and strategic activities to minimize the predicted negative influence and maximize the projected positive effect. The limitations and potential directions of crop modelling improvement have also been highlighted in this study.

Keywords: Climate change, crop models, management strategies, sustainable agriculture, yield estimation.

AGRICULTURE is India's economic backbone and is anticipated to continue so in the near future. The country has 51% of the world's agricultural land, compared to 11% globally (2018–19). Agriculture employs 58% of the workforce, down from 75% during independence (www.icar.org.in). Since the Green Revolution, Indian agriculture has experienced significant alterations and reached incredible achievements. Population increase enhances food security, whereas climate change limits inputs. In its Fifth Assessment Report (2014), the Intergovernmental Panel on Climate Change (IPCC) recorded a 0.85°C global average combined land and ocean surface warming between 1880 and 2012. Also, a 4.5–9.0% reduction in agricultural production was found between 2010 and 2039 (ref. 1), with an estimated 25% loss in the long run (2070–99). This necessitates an analysis of the impact of climate change on crop yield.

Due to its multiple uses, water is an important agricultural input. Given the changing weather, agricultural irrigation is problematic. Due to the water crisis, precise irrigation procedures must be established, measured or scheduled to optimize water consumption efficiency. In arid and semi-arid locations, eco-friendly irrigation research is popular[2].

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Traditional farming must be replaced by technology to boost agricultural output. Traditional crop yield functions were established through statistical analysis, with minimal attention to biological and physical elements[3]. This site-specific knowledge may be transferred to places with similar climate, soil and crop management practices. A model must handle these constraints and be flexible to crop, soil and climate factors. Due to the rising demand for agricultural commodities and pressure on cultivable land, groundwater and natural resources, agricultural decision-makers require more data. Crop modelling, which combines administrative and technological tools, may increase the quality and quantity of agricultural products. Regression-based agricultural yield models have little quantitative relevance for decision-making. Due to weather fluctuations, it takes over 10 years to develop relevant statistical linkages for agricultural decision-making.

With soil, weather, crop management and environmental parameters, including carbon dioxide, solar radiation and water, crop models are developed to predict crop growth, development, yield and water absorption. They reduce time, expenses and yield variations over field trials[4]. Since the beginning of crop modelling research 40 years ago, a wide range of crops with varied management practices are now applicable. Crop modelling will help study the influence of climate change and management on crop yield[5,6]. Crop models are effective tools for studying how crops respond to irrigation under different climates[7]. This study focuses on numerous crop model applications and findings.

Types of models

Based on the purpose for which they are designed, crop models have been classified into different types[8].

Type of models in agriculture

(i) Mathematical model.
(ii) Growth model.
(iii) Crop weather model.

Mathematical model: This explains relationships through a mathematical equation.

The three types of mathematical models are: (a) Linear programming models. (b) Empirical curves. (c) Mechanistic models or dynamic models.

Table 1. History of crop models

Year	Event	Crops
1958	Develop early computational analyses of plant and soil processes[9]	
1960	Pioneers in soil water balance modelling (WATBAL)[10]	All crops
1965–70	Early crop modelling pioneers developed photosynthesis and growth models[9,11,12]	
1969–75	Prompted development of several cotton models[11,13,14]	Cotton
1970	Elementary crop growth simulator construction (ELCROS)[15]	
1975–82	Developed soybean models SOYGRO and GLYCIM[16,17]	Soybean
1980	EPIC (environmental policy integrated climate model) – USA	All crops
1982	IBSNAT began the development of the DSSAT model – USA	All crops
1983	SOYGRO model and PNUTGRO model were developed[18] – USA	Soybean, groundnut
1984 – present	ORYZA model[19] – USA	Rice
1985	CERES model for wheat[20]	Wheat
1986	CERES model for maize and wheat[21]	Maize and wheat
1989	PNUTGRO model was developed[22]	Groundnut
1993	CERES-Rice[23]	Rice
1994	The ORYZA1 model was developed[24]	Rice
1994	India's first crop model WTGROWS was developed followed by InfoCrop[25]	Rice
1994	RICAM[26]	Rice
1990	Rice–weed competition model[27]	Rice and weeds
1991	Developed APSIM model (CSIRO – Australian Commonwealth Scientific and Industrial Research Organization)	All crops
1990	CROPSYST – Washington State University, USA	All crops

Growth models: The phenomenon of growth is explained by this model.

Crop weather model: This model describes the link between crop growth and day length.

Other models

Statistical models: They show the association between yield and weather parameters, e.g. correlation and regression.

Deterministic models: They predict the exact yield by generating definite forecasts for quantities without probability. More system uncertainty makes deterministic models less accurate.

Stochastic models: They assess output at a set rate and assign each output a probability. Since these models are complex, they are used only when the deterministic model fails.

Dynamic models: Time is a variable, and the outcome changes with time are considered in this model.

Static models: This model omits time. Variables with consistent values across time are considered.

Mechanistic models: They show system behaviour. These models describe the relationship between weather and yield.

Simulation models: These are real-world representations. The models predict agricultural productivity depending on weather and soil conditions. They use differential equations to compute rates and variables.

Descriptive models: They specify system behaviour.

Explanatory models: They describe the mechanisms and methods of system behaviour. These models are developed by independently quantifying the processes and mechanisms of a system.

The history of crop models demonstrates the significant efforts made by several disciplines to handle varied output systems at the field, research and higher levels (Table 1)[9–27]. Models are an integration of many disciplines that incorporate biological, physical, chemical and environmental factors for more reliable outcomes. History demonstrates that the development of agricultural system modelling is still increasing, and several research organizations and educational institutions are working on a worldwide and national scale to provide more intriguing findings.

Input data required by the models

Any crop model requires fundamental input data on weather, soil, crop and management variables. Table 2 lists some of the most typically necessary input data, i.e. crop model input parameters.

Steps in modelling

The processes necessary to develop a model are outlined below.

(1) Define goals: Agricultural system.
(2) Define the system and its boundaries: Choose the variables.

Table 2. Input parameters for crop models

Site data	Weather	Soil	Crop	Management
Country, altitude, latitude and longitude	Maximum temperature, minimum temperature, sunshine hours, rainfall, evaporation and wind speed	Type of soil, soil texture, soil structure, bulk density, soil moisture, soil pH and EC, soil N, P_2O_5, K_2O and soil infiltration rate	Name of the crop, date of sowing, date of harvesting, rooting depth, K_c value, critical depletion and leaf area index	Applied fertilizer dose, quantity and method of irrigation water and seed rate

State variables consist of measurable factors like soil moisture content, crop output, etc. Rate variables indicate the rate at which certain system processes take place, e.g. rate of photosynthesis and transpiration.

The factors that drive the system are those that are external to it but have an effect on it, e.g. sunlight and rainfall.

Auxiliary variables are intermediary molecules produced during the life cycle of a plant, e.g., dry matter partitioning, water stress, etc.

(3) Quantify relationships (evaluation).

(4) Calibration: Before using a model, it is essential to calibrate it. Calibration is the process of evaluating and fine-tuning a model for collection of data using a specified set of inputs.

(5) Validation: Using local field data different from calibration data, the accuracy of the model is tested.

(6) Sensitivity analysis: The model is then examined with various alterations to the input elements to determine its response.

Crop-based models

DSSAT

The University of Florida's Decision Support System for Agro-technology Transfer (DSSAT) simulates 42 crops, including CERES-barley, CERES-maize, CERES-rice, CERES-sorghum, CERES-sunflower and CERES-wheat. This architecture comprises databank management programs for soil, weather, crop management, experimental data, utilities and application[28,29]. Using Priestley–Taylor equations, DSSAT can determine evapotranspiration. The model assesses the effects of climate change and management on agricultural production[30,31]. It simulates evapotranspiration and soil moisture during drought, making it valuable for monitoring and forecasting drought. CERES (Crop Environment Resource Synthesis) model simulations have been validated for yield estimation across a wide range of climates[32], including monsoonal[33], semiarid[34–37], Mediterranean[38], continental and oceanic[39–41].

CERES-Rice is a variety-specific rice crop growth simulation model that estimates the relationship between plants and the environment. It is utilized locally and globally to model grain and biomass yields, and determining the influence of climate change on crop output[42,43]. Transpiration, soil evaporation, precipitation, soil surface run-off, irrigation and soil drainage are used to measure soil nitrogen balance and intake[30,44,45]. Rice growth has been analysed, and production with 11% difference between simulated and real grain yield was observed. It has been concluded that the CERES-rice model may be used under integrated management alternatives by resource-poor farmers in semi-arid conditions[45]. The DSSAT-CENTURY model forecasts soil nitrogen and organic carbon dynamics in low-input maize cropping systems[46,47].

CERES-Rice can predict grain yields, biological yields, and leaf area index (LAI) with model efficiency of 0.89, 0.75 and 0.38, respectively, under varied irrigation and nitrogen levels. ORYZA2000 was compared with CERES-Rice in 2010, and it was concluded that the simulated values provided by the farmer were more accurate[48,49].

CERES-Wheat optimizes wheat leaf and ear water use[50,51]. This model is used to study plant density and N fertigation on wheat yield[52,53]. It predicts biomass, actual evapotranspiration (ETa), which is defined as the quantity of water that is removed from a surface due to the process of evaporation and transpiration and grain output well[54–57]. Simulations and actual wheat phenological events differ by –9 to +6 days for anthesis and –6 to +3 days for 14 physiological maturities[58].

CERES-Maize assesses how varying planting dates and irrigation levels[59,60], nitrogen and irrigation levels[61] and mulching[62] affect maize yield and water productivity. The model has been used for three decades to simulate agricultural changes in a variety of meteorological settings[18,51,63–67].

CROPGRO can predict soybean production based on season, ideal sowing date, inter- and intra-spacing, weather and moisture[68,69]. The model predicts soybean seed yield, harvest index and LAI as 17%, 12% and 38% respectively[3,70,71]. CROPGRO-Pigeon pea effectively replicates seed yield under varied climatic conditions, with an error rate of less than 10% (ref. 72). The CROPGRO-Peanut model has been found a good relation between actual and simulated yield, and yield parameters in groundnut with low RMSEa, RMSEn and R^2 values[73].

Using the DSSAT model, the effects of climate change on growth, yield, water use efficiency and crop evapotranspiration of cotton and wheat in semi-arid climate were observed[74]. Due to a doubling of CO_2 levels, rice and soybean yields decreased by 10–20% (refs 75, 76). DSSAT has been used for yield simulation with the integration of remote sensing[77,78].

Advantages

DSSSAT is more exact than the simulation model for rice–weather relations (SIMRIW) because it incorporates more crop/soil/weather factors, whereas SIMRIW considers only a few crops and optimal irrigation strategies[79].

It requires a minimum dataset for simulation compared to other models.

Limitations

Accurate results can be produced only if the model is parameterized to take into account plough pan and soil structure under conservation agriculture[62].

ORYZA

The International Rice Research Institute (IRRI), the Philippines, Wageningen University, and the Oryza Research Center developed the ORYZA crop model. This model simulates rice crop growth and development, including water, C and N balance in lowland, upland and aerobic settings[80,81]. With good results, ORYZA (v3) has been evaluated and used to predict rice growth and development under diverse environmental situations[82–85]. ORYZA2000 has been utilized to explore the impact of varied nitrogen and irrigation levels on rice yield. The model can predict rice growth and yield under varied fertilizer and irrigation practices. ORYZA2000 helps determine the optimum rice-production tactics before field tests. The model was used to study the effect of different transplanting dates (i.e. late transplanting on 1 July and early transplanting on 16 May) on rice yield and evapotranspiration over time. It was concluded that late transplanting and two-day irrigation frequency with medium puddling in the coarse-textured soils of Punjab, India, resulted in a higher yield that was comparable to observed yields[86].

This model can assess the effects of climate change on rice yields, agricultural water use and water productivity[87]. ORYZA2000 was used to study the impact climate change on cold rice output[88,89]. Lu *et al.*[90] found that humidity will increase over the next 40 years, which will enhance cold rice farming. The model can replicate crop biomass and LAI for calibration and validation with a high R^2 and low RMSE. Auto-calibrated ORYZA2000 can simulate full and deficit irrigation and plan irrigation in deficit scenarios[91].

APSIM

The Agricultural Production Systems Simulator (APSIM), a modular modelling framework developed by Australia's Agricultural Production Systems Research Unit, which can be used for more than 20 crops, enables users to determine the effects of soil type, planting date, cultivar variety, fertilizer/irrigation management and climate on crop and pasture production. This model links to GIS for spatial studies[92]. APSIM was previously presented using data from ICRISAT, Patancheru, Telangana, India, under varied planting densities, photoperiods and growth conditions. The new millet tillering growth module identifies tillers as a cropping unit[93]. As a long-term decision-making tool for regulating nitrogen for pearl millet in the Sahel, the APSIM model could successfully forecast plant water availability and nitrogen stress with acceptable results[94]. It was used to explore the effect of planting dates on canola growth and yield response[95]. When long-term weather data are available, the model can predict yield with low error for varied cultivars, sowing dates and locations[96].

APSIM was tested for Asian cropping systems and could anticipate yields for a wide range of crops, types, conditions and management techniques across the continent[97,98]. The Pond module in APSIM can imitate biological and chemical processes in ponded rice fields and has been proven for wheat in a variety of soils and climates[99,100]. APSIM could forecast wheat growth, grain yield, water and N intake, soil water and soil N in Western Australia with an R^2 of 0.77 (refs 101, 102). In Punjab, the APSIM model was tested for its ability to simulate the effect of water management and mulching on wheat yield. An R^2 of 0.91 and 0.81, with and without mulch respectively, was observed[103]. The APSIM model has been used to predict the effects of shade on maize productivity. It can anticipate maize output in agroforestry systems with up to 50% shadowing, although caution is needed at higher levels[104]. The APSIM-wheat model was used to study the impact of nitrogen on grain production and protein content[105]. It was used to explore agroforestry alternatives for low-rainfall areas of Australia, assessing the possible advantages and dangers of planting trees as windbreaks on producing land[106].

Advantages

APSIM can be used for intercropping systems and crop rotations.

It has the capacity to combine models drawn from disparate research endeavours.

Limitations

APSIM cannot simulate greenhouse gases (GHGs) from rice fields. It is sensitive to nitrogen.

INFOCROP

InfoCrop was developed by researchers of the Brazilian Agricultural Research Enterprise in 1978. It can simulate crop development, biomass, grain yield, yield loss due to pests, long-term changes in soil organic carbon, and GHG emissions in rice and wheat crops farmed in a variety of agro-environments[107–109]. Irrigated treatments were more predictable than rainfed treatments[110]. The vulnerability of Indian mustard to climate change using the InfoCrop model was studied, and it was concluded that yield reduction would be the largest in eastern (67% and 57%), central (48% and 14%), and northern India (47% and 14%)[111]. Rice, wheat, potato, cotton, sorghum, soybean, peanut and coconut have all been effectively adapted, calibrated and verified. With the changing climatic scenarios during 2050, terminal heat stress will lower wheat yield by 18.1% (ref. 112). InfoCrop has been tested under alternate nitrogen fertilization[113–115]. Using this model, researchers have studied the impact of rising CO_2 and high temperature on rice[116], *kharif* maize[117], sorghum[118], and cotton[119] growth and yield.

Limitations

The model does not consider yield loss due to biotic parameters, leading to deviation in results compared to field data.

Water management models

AQUACROP

This is a Windows-based software application developed by FAO that models field crop yield, biomass and water productivity responses to changing amounts of water availability. It is a user-friendly program that combines accuracy, robustness and simplicity with a minimum of input data, bridging the gap between agricultural modelling professionals and end-users[120].

The AQUACROP model accurately predicts maize grain and biomass output, canopy cover, soil water content in the root zone, and water productivity under deficit irrigation scenarios[121–127]. Canola and sugar beet yielded similar results[128–130]. AQUACROP can simulate yields at different planting dates by maximizing biomass production, increasing water use efficiency, and establishing deficit irrigation programmes to reduce wasted run-off, drainage and soil evaporation. Transpiration and biomass growth rate are linearly related, requiring fewer input data[131]. The model forecasts maize grain and biomass yield with R^2 values of 0.95 and 0.9 t/ha and incorporates the bare minimum of input data under surface and drip irrigation settings respectively.

This model was used to regulate cotton irrigation, and simulated yields were similar to measured data[132]. AQUACROP may be used to estimate paddy crop yields and productivity[133]. The model has been employed to study the consequences of climate change on maize, sorghum and millet, and it was concluded that the model predicts a higher harvest index of 0.59 than in the experimental fields[134].

Advantage

AQUACROP is ideal for situations in which water is the primary factor restricting crop yield.

Limitations

AQUACROP can simulate daily biomass production and ultimate crop yield for herbaceous plants with only one growth cycle.

It is designed to determine crop yields for a specific field (point simulations).

Only vertical incoming (rainfall, irrigation and capillary rise) and outgoing (evaporation, transpiration and deep percolation) water flows are analysed; no changes in crop growth, transpiration, soil quality or management are considered.

CROPWAT

This is a computer-based software program developed by FAO based on the Penman–Monteith equation. It provides reliable values with actual crop water use data worldwide[135–137]. It contains numerous modules that measure crop water requirement, irrigation requirement, source evapotranspiration, etc.[138–149]. Crop water requirement was estimated for *kharif* and *rabi* groundnut in Andhra Pradesh, India, as 591.3 and 443.3 mm respectively[150]. Similar results are available for the Krishna western delta and Mahi right bank canal command[151,152]. Irrigation water requirement of major crops in the Balangir district of Odisha was estimated as 4524 mm/yr, and the net scheme water supply was 852 Mm^3/yr. Farmers can use this information to choose the amount and frequency of irrigation water for the main crops[153].

The CROPWAT model was used to study the influence of climate change on agricultural water demands in the arid regions of Saudi Arabia. A10°C hike in average temperature may increase the crop water needs by 2.9% (ref. 154). A 20% decline was estimated in rice production in North India due to CO_2 and increase in temperature[155]. Crop water demand for rice, coconut, banana, arecanut, vegetables, lentils, rubber, tea, coffee, and cotton in Kerala, India, and for various agro-ecological units was estimated[156–158]. CROPWAT has been used to estimate evapotranspiration and the water supply–demand gap in the Shipra river basin[159], Nawagarh distributary in Chhattisgarh[160], and the Khadakwasla dam irrigation project in Maharashtra, India[161]. Maize crop water requirements[162,163], maize intercropping with rice and soybean[164], wheat, potato and alfalfa[165], soybean and sorghum[166], rice[167–169], sugarcane and tobacco[170], cotton and sugarcane[171,172], sunflower[173], groundnut[174,175], banana, sweet pepper, onion, potato, rice, pulses and mango, etc.[176–178] were estimated using the CROPWAT model.

Advantages

CROPWAT outperforms other models, such as DSSAT, CERES-Wheat, etc., in estimating reference evapotranspiration[147].

Conclusion

Here we present an analysis of the findings of research done on crop models and the uses of such models in agriculture. Models, in their most basic form, are instruments that decision-makers employ to address problems which extend beyond the regional or farm-level. The development of crop models has been a continuing process for the past half a century. Even now, these models are constantly refined to include more inputs and outcomes. The robustness of the data and precision of calibration are the primary factors that influence the accuracy of the model. The results of several studies reveal that the models have been improved for usage in a wide variety of contexts in a short span of time. In the future, those models must consider abiotic stress, as this factor plays a significant role in yield reduction. To account for intensified climate change, the models will need to emphasize GHG emissions and losses due to pests and weeds, which also contribute to a decline in yield. Integration of crop models with remote sensing is becoming increasingly relevant as a result of the capacity to predict spatial yield[80]. Thus modelling is an improved method for synthesizing knowledge about a variety of system components, as well as for summarizing data and effectively presenting improved research findings to the users.

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