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RESEARCH ARTICLE

Estimation of Maize Yield at Spatial Level Using DSSAT Crop Simulation Model

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Abstract

Crop simulation models are often used to characterize, develop and assess field crop production practices. The present study was carried out to estimate the yield of maize under Ariyalur and Perambalur districts. A method has been developed to use DSSAT (Decision Support System for Agro-technology Transfer) models to estimate maize yield spatially. In this study, one of the DSSAT crop simulation model, CERES-Maize was employed to estimate maize yield during *kharif* 2017 under Ariyalur and Perambalur districts. To simulate the yield, DSSAT required datasets of crop growth and management, daily weather data and soil data. The simulated yield was validated using the observed data from farmers' fields. The agreement between DSSAT simulated and observed yield was 90.4 per cent with R^2 and RMSE of 0.502 and 538.6 kg ha^{-1} respectively. These results indicate that maize yield can be estimated spatially using the DSSAT crop simulation model.

Keywords: *Maize, DSSAT, Yield, Crop simulation model*

Introduction

Crop simulation models are key components to test the advances in agricultural technology and to predict crop responses to present and future climate forcing. These models are being used widely to estimate the crop production potential, transfer of agro-technologies, assist strategic decisions and forecast real-time yields (Bannayan and Crout, 1999). DSSAT models are simulating growth and development of a crop by integrating soil, crop phenotype, weather, and management options (Jones *et al*., 2003). DSSAT has modules that allow users to build model input files for spatial simulations across predefined management zones, calibrate the models to simulate historic spatial yield variability and crop response to environmental and management variations (Thorp *et al*., 2008).

Crop simulation models involve the mathematical function of various crop physiological factors such as photosynthesis, respiration and relative growth rate to describe the crop growth changes under various climatic and environmental conditions. The model at times becomes complicated as it needs several detailed inputs for simulation and makes the calibration process tedious to perform (Sivarajan, 2011). The capability of the DSSAT model in simulating crop responses and the sensitivity of the model output to input parameters with spatial attention to the determinants of the model response to the practice of conservation agriculture was analyzed. The results showed that the phonological cultivar parameters were the most influential model parameters. The correlation between the input parameters and output variables were stable over a wide range of seasonal rainfall conditions (Corbeels *et al*., 2016). DSSAT CERES-Maize model was used to analyze the gap between the actual and potential yield of maize cultivated in Eastern Canada. The yield of seven different maize cultivars grown in the region was simulated and after the simulation, the cultivars are grouped based on their yield potential *viz.,* low, medium and high. The yield potential of selected cultivars are greater than the simulated or actual yield observed (Jing *et al.,* 2017).

The evaluation of model adequacy is an essential step of the modeling process because it indicates the level of accuracy of the model estimations. This is an important phase either to build up confidence on the current model or to allow selection of alternative models (Oreskes, 1998). Validation is a more robust, reliable method of measuring prediction accuracy. It is the process of determining whether the conceptual model is an accurate representation of the actual system being analyzed and deals with building the right model. In practice, model validation aims at increasing confidence in model accuracy as much as possible, which is partially determined by the intended uses of a specific model and project objectives. In the present investigation,

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we used the DSSAT CERES-Maize model was used to simulate yield of maize spatially and validated it by comparing with observed data.

Material and Methods

Study area

Ariyalur and Perambalur are inland districts of Tamil Nadu with an area of 1949 sq.km and 1757 sq.km, respectively. Black and red loamy are the predominant soil types in Perambalur district. Annual rainfall of the district is 908 mm. Red sanding with scattered packets of black soil is the predominant soil type in the district. The study area is one of the major maize cultivation regions in Tamil Nadu. Ground truth data on LAI (Leaf Area Index), crop management practices and yield data has been collected for 35 monitoring locations in the study area for generating input files for DSSAT crop simulation model

Crop yield simulation using DSSAT model

DSSAT is a microcomputer software product that combines crop, soil and weather databases into standard formats for assessment by crop model and application programs. The user can then simulate multi-year outcomes of crop management strategies for different crops at any location in the world and hence the DSSAT was used in the present study. The methodology is presented in Fig. 1.

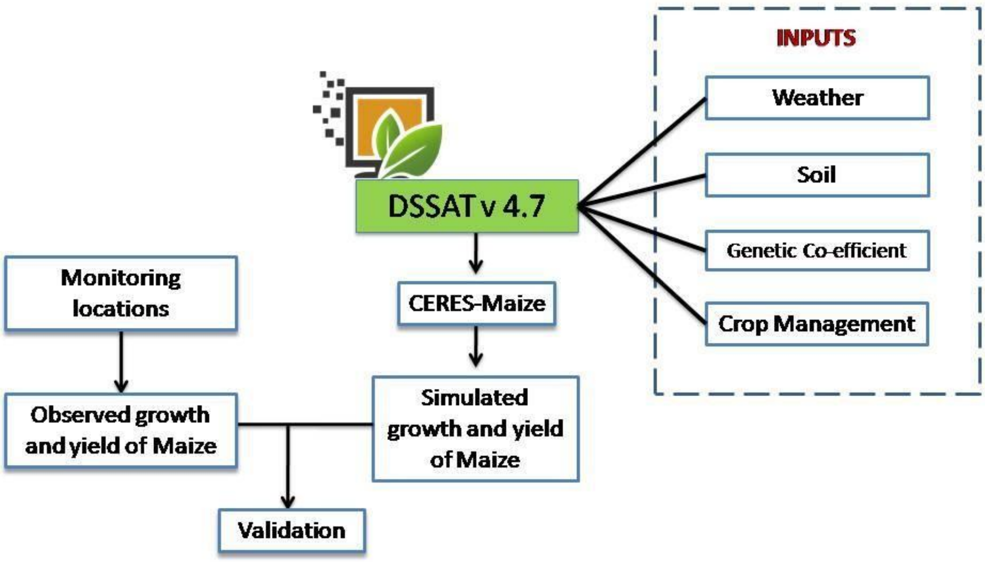

Fig. 1. Flow chart depicting the methodology of DSSAT CERES-Maize crop simulation model

The daily weather data on minimum and maximum temperature (^{O}C), solar radiation ($MJm^{-2}day^{-1}$) and rainfall (mm) were collected for the study area. The weather input files for crop simulation was generated using weatherman tool in DSSAT for monitoring locations. Soil information for creating soil files was obtained from the Department of Remote Sensing and GIS, TNAU. The profile details as required in DSSAT were extracted from the above database using QGIS (GIS tool) and were fed into 'S' build tool in DSSAT to create soil file.

This file documents the inputs to the model for the monitoring fields from the study area to be simulated. The details of the experimental conditions and field characteristics such as weather, soil and field description details, planting geometrics, irrigation, fertilizer management, si mulation controls and output options are given in the experimental file. The genetic coefficients required in the CERES-Maize model were simulated by entering the varietal character as incorporated in the model in the form of genetic coefficients for cultivars. The genetic coefficients determined in the model using identical management and other conditions were used insubsequent validation and application. The description of the genetic coefficients used was given in Table 1.

Model validation

Three input files were created to run the DSSAT model using collected data.

Weather file: 'Weatherman' program in DSSAT and collected weather data.

Soil file: 'S Build' program in DSSAT and soil data.

Experimental data file: 'X Build' program in DSSAT and crop management data

The model was calibrated using collected data during the maize crop growing season of 2017 through determination of genetic coefficients for COH (M) 6 with spatial analysis mode in DSSAT. The model was validated by comparing the observed results with simulated results. Yield data collected from farmers' fields in the study area were considered as observed data.

Results and Discussion

Crop simulation model is a simple representation of a crop in relation to growth as influenced by different factors *viz.,* variety, soil weather, management, etc., The CERES-Maize model was calibrated, tested and validated to simulate crop yield as influenced by these factors spatially. The validation results showed that the growth processes and final yield were significantly correlated with the observed data.

Table 1. Genetic co-efficient (GC) of maize used in DSSAT CERES-Maize model for COH(M)6

GC code	Description	Genetic co-efficient
P1	Thermal time from seedling emergence to the end of the juvenile phase (expressed in degree days above a base temperature of 8°C) during which the plant is not responsive to changes in photoperiod.	295
P2	The extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 hours).	0.510
P5	Thermal time from silking to physiological maturity (expressed in degree days above a base temperature of 8°C).	840
G2	Maximum possible number of kernels per plant.	635
G3	Kernel filling rate during the linear grain filling stage and under optimum conditions (mg day^{-1}).	8.30
PHINT	Phylochron interval; the interval in thermal time (degree days) between successive leaf tip appearances.	39.0

DSSAT does not offer any automated procedures for calibration. Changes to parameters of the model in order to calibrate it for specific conditions must be done one-by-one, manually. Quantitative comparison of model input to observations required the data to be exported to an analysis package. In order to accomplish this in a yield simulation, the process was repeated for every monitoring location. The data collected from the farmers' fields were used for model evaluation. Model calibration and validation were described as different ways of model evaluation by Otter and Ritchie (1985). Specific cultivar coefficients for the genotypes used in this experiment was not in the list of genotypes available with the model. The cultivar coefficients were adjusted until the main growth and development stages were simulated within 10 per cent of the measured values. Simulated observed comparisons were made for growth and development parameters, the purpose being sensitivity analyses of the model and improvement of the coefficients. Models were tested by validation using RMSE (Root Mean Square Error) and R^2 which allow comparative assessment of model performance at particular location whereas, linear regression line expressed model stability across variable field conditions. The DSSAT model formed well to simulate maize growth and yield. The simulated maize yield for the monitoring locations was found to be in the range of 4653 to 6371 kg ha^{-1} whereas the observed yields were at 4100 to 6250 kg ha^{-1} (Table 2) The mean agreement between simulated and observed yields was 90.4 per cent (Fig. 2). The R^2 and RMSE values of the regression between the simulated and observed yield were 0.502 and 538.6 kg ha^{-1}.

Crop simulation models provide a mechanistic way to estimate the interaction of spatial differences in soil properties and weather parameters on yield variability within field. Once calibrated to simulate the spatial yield variability between different fields, crop models are powerful tool to develop risk management strategies that can balance economic risk incurred by the producer with environmental risks that impact society. The CERES-Maize model that has been calibrated and validated for many maize growing regions of the world, was found to estimate the spatial responses to various genetic and agronomic management practices under different weather and soil conditionsprecisely as indicated fromthe higher agreement (90.4%) between simulated and observed yields.

Table 2. Validation of DSSAT yield

Village	Latitude	Longitude	DSSAT yield (kg ha^{1})	Observed yield (kg ha^{1})	Agreement (%)
Ilanthankuzhi	11.180278	79.034444	5159	4820	93.0
Asur	11.245165	78.996026	4841	4650	95.9
Ladapuram	11.238021	78.743007	5835	5500	93.9
Perumathur	11.331586	79.022150	4824	5600	86.1
Thiruvalandurai	11.430585	78.919179	6038	5438	89.0
Valikandapuram	11.321989	78.927099	6371	5760	89.4
Bommanapadi	11.152815	78.770031	6181	5400	85.5
Siruvachur	11.196521	78.864086	6015	5640	93.4
Siruganpur	11.160373	78.948133	6038	5750	95.0
Ottakovil	11.193665	79.113665	4824	5180	93.1
Anandavadi	11.184330	79.175580	4983	4600	91.7
Ranjangudi	11.336230	78.939840	6371	6000	93.8
Veppankuzhi	11.041121	79.015731	4841	4730	97.7
Sengunam	11.264990	78.908371	6015	5600	92.6
Ezhumur	11.297697	78.974900	6015	5400	88.6
Keelapuliyur	11.297692	78.971728	6181	5700	91.6
Perali	11.236883	78.959052	6371	5450	83.1
Illupaiyur	11.215297	79.138867	4653	5000	93.1
Pottaveli	11.231587	79.130514	4841	4100	81.9
Sirugudal	11.301942	78.946015	6371	5800	90.2
Thaikkal	11.391010	78.947166	6181	5420	86.0
Veppanthattai	11.324930	78.822930	6371	5730	88.8
Poolambadi	11.402260	78.707810	5835	5520	94.3
Vengalam east	11.368920	78.785460	6015	5615	92.9
Alagapur	11.308914	78.921944	6371	5830	90.7
Vilagam	10.973769	78.979581	6371	5490	84.0
Kadambur	11.432410	78.722950	6038	5740	94.8
Kadugur	11.196525	79.169407	6181	5250	82.3
Rayampuram	11.270803	79.168151	6015	5150	83.2
V Kalathur	11.409561	78.914313	6371	5430	82.7
Mangalamedu	11.362194	78.960164	5835	5580	95.4
Vengalam	11.372030	78.775010	6015	5760	95.6
Esanai	11.291660	78.832800	6371	6250	98.1
Vellur	11.297136	79.128580	4653	4170	88.4
Nallur	11.352415	78.997050	4841	5370	90.1
Mean			5778	5400	90.4
			R Square	0.502	
			RMSE (kg ha^{-1})	538.629	
			NRMSE (%)	9.790	

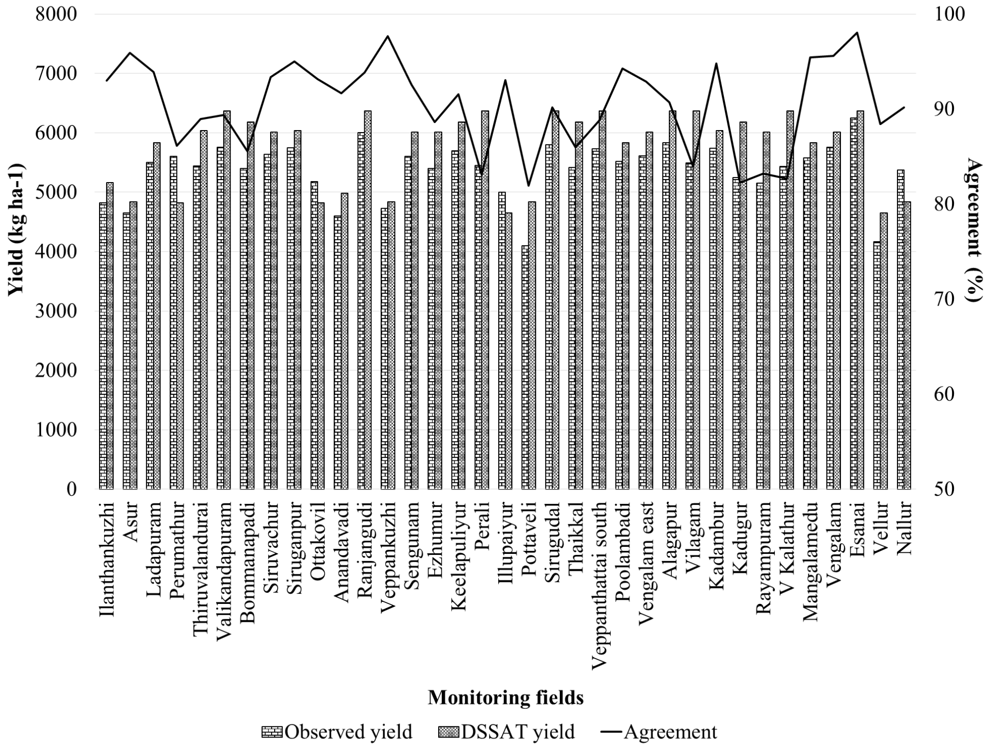

Fig. 2. Agreement between observed and DSSAT simulated yield

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