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Meta analysis on the evaluation and application of DSSAT in South Asia and China: Recent studies and the way forward

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ABSTRACT

The Decision Support System for Agrotechnology transfer (DSSAT) is a global modelling platform that encompasses crop models for more than 40 different crops. The models have been used extensively throughout the world, including South Asia and China. From the web of science database, we reviewed 205 papers that were published from January 2010 to February 2022 containing examples of the evaluation and application of the DSSAT crop simulation models. In South Asia and China, more than 50 traits and variables were analyzed for various experiments and environmental conditions during this period. The performance of the models was evaluated by comparing the simulated data with the observed data through different statistical parameters. Over the years and across different locations, the DSSAT crop models simulated phenology, growth, yield, and input efficiencies reasonably well with a high coefficient of determination (R^2), and Willmott d-index, together with a low root mean square error (RMSE), normalized RMSE (RMSEn), mean error (ME) or percentage error difference. The CERES models for rice, wheat and maize were the most used models, followed by the CROPGRO models for cotton and soybean. Grain yield, anthesis and maturity dates, above ground biomass, and leaf area index were the variables that were evaluated most frequently for the different crop models. The meta-analysis of the data of the most common simulated variables (Anthesis, maturity, leaf area index, grain yield and above ground biomass) for the four commonly used DSSAT models (CERES-Rice, CERES-Wheat, CERES-Maize and CROPGRO-Cotton) showed that the models predicted anthesis with an RMSE of ~2 (CERES-Maize) and -4 days (CERES-Wheat), a normalized RMSE of ~2.5 (CERES-Maize) and -3.8% (CERES-Rice), and a R^2 ~ 0.98-0.99. The maturity was predicted with an RMSE~ 3.0 (CERES-Maize)-6.1 days (CROPGRO-Cotton), normalized RMSE~2.3 (CERES-Wheat)-5.0% (CERES-Rice) and R^2 ~ 0.90-0.99. The leaf area index was predicted with an RMSE~ 0.3-0.7, normalized RMSE~6 (CROPGRO-Cotton)-16% (CERES-Maize) and R^2 ~ 0.75-0.98. The model performance for simulating grain yield was best with CROPGRO-cotton with a normalized RMSE of 4.4%, RMSE of 138.8 kg and R^2 of 0.99. The lowest R^2 and highest RMSEn was found for CERES-Wheat. Among all the variables that were evaluated, above ground biomass was least accurately simulated with a RMSEn as high as 18% and R^2 as small as 0.50 by CERES-Wheat. The models were used for studying the crop response under various soil, weather, and management conditions. The review will be helpful to identify the research gap in the use of crop models for different crops in South Asia and China. It can also aid scientists to target their research for specific applications to address food and nutrition security based on sustainable management practices.

Keywords: CERES, CROPGRO, CROPSIM, SUBSTOR, CANEGRO, OILCROP, simulation model

Agronomic experiments are location specific and subject to spatial and temporal variability (Basso *et al.,* 2016). It is, therefore, challenging to transfer new production technologies across locations where soils and climate are different (IBSNAT, 1993, Tsuji *et al.,* 1998). For understanding of the complex soil-crop-weather-management system and to facilitate the decision-making process, crop simulation models have been developed (Jones *et al.,* 1998; 2016). These models simulate the dynamic growth and

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development of the soil-plant-atmosphere system and ultimately predict crop yield and other traits (IBSNAT, 1993; Hoogenboom, 2000). Crop modelling had its early origins with scientists such as de Wit (1965), Monteith (1965), Duncan (1971), Duncan *et al.* (1967) and Loomis *et al.* (1979). By 1974, Duncan had developed crop models for cotton, peanut, soybean, and maize, and in 1978, de Wit and colleagues published a monograph describing the generic crop model BACROS (de Wit, 1978). During the early days of crop modeling, these models were mainly used in laboratories or the research groups where they were originally developed (Jones *et al.,* 2016).

With the start of the International Benchmark Sites Network for Agrotechnology Transfer Project in 1981 (IBSNAT, 1993; Tsuji, 1998; Uehara and Tsuji, 1998; Jones *et al.,* 1998), the Decision Support System of Agrotechnology Transfer (DSSAT) was conceptualized and developed. India played a key role in the early days of crop modeling and IBSNAT through a symposium organized at ICRISAT on minimum data (ICRISAT, 1984). DSSAT is an extensive crop modeling ecosystem that includes crop simulation models for more than 40 crops through the Cropping System Model (CSM) (Jones *et al.,* 2003; Hoogenboom *et al.,* 2019a). Models for new crops are continuously being added, such as strawberry (Hopf *et al.,* 2022a, b) for fruit crops, guinea grass (Brunetti *et al.,* 2021) for forages, and carinata as an oil crop (Boote *et al.,* 2021). The most recent versions of DSSAT are DSSAT Version 4.7.5 (Hoogenboom *et al.,* 2019b) that was released in 2017 as Version 4.7 and has been distributed to more than 17,275 users and DSSAT Version 4.8 (Hoogenboom *et al.,* 2021) that was released in 2021 and has been distributed to more than 3,400 users as of December, 2022. DSSAT can be obtained from the DSSAT web portal at www.DSSAT.net as a free software tool, while the source code is completely Open Source and available from GitHub.

DSSAT has been used for the past 30 years by researchers all over the world for a variety of purposes, including optimizing sowing dates (Halder *et al.,* 2017; Nouri *et al.,* 2017; Rahmani *et al.,* 2018; Phoncharoen *et al.,* 2021), fertilizer management (Gheysari *et al.,* 2009a, 2009b; Wajid *et al.,* 2021; Rizwan Shahid *et al.,* 2020; Khan *et al.,* 2022), manure management (Babel *et al.,* 2019), irrigation management (Zhou *et al.,* 2019, Dar *et al.,* 2017; Mompremier *et al.,* 2021), tillage management (Liu *et al.,* 2013), planting density (Zhang *et al.,* 2019; Zhang *et al.,* 2022), soil management (Yang *et al.,* 2013), cultivar selection (Chen *et al.,* 2021; Mall *et al.,* 2016), climate change impact studies (Anser *et al.,* 2020; Zhang *et al.,* 2019; Nasir *et al.,* 2020), in-season and long-term recommendations (Wang *et al.,* 2021; Chen *et al.,* 2020; Jha *et al.,* 2022), yield forecasting (Singh *et al.,* 2017; Shelia *et al.,* 2019; Choudhary *et al.,* 2021), climate change adaptation studies (Saddique *et al.,* 2020; Ahmad *et al.,* 2020), precision agriculture (Fu *et al.,* 2020; Bai and Gao 2021), and many others (Jones *et al.,* 2003).

Until recently, the review on the performance of the DSSAT models for different environmental conditions and crop management practices has been limited. Timsina and Humphreys (2006) and Basso *et al.,* (2016) reviewed the performance of the CERES-Rice, CERES-Wheat and CERES-Maize models, but a comprehensive review on the performance of these models and other crop models that are included in the DSSAT crop modeling ecosystem during the past decade is lacking. Moreover, there has been little quantitative and systematic evaluation on their performance using robust statistical criteria and there have been limited attempts to synthesize the results of these evaluations, especially for Asia. We, therefore, designed a research question to evaluate the performance of the DSSAT crop simulation models during the last decade from January 2010 to February 2022 in South-Asia, including India, Pakistan, Bangladesh, Nepal, Sri Lanka, and Bhutan, and in China. These countries represent some of the most popular countries for requests of the DSSAT software. For the period from 2019 through October, 2022, there were 3,182 requests from India, 1,937 requests from China, 1,570 request from Pakistan, 131 requests from Nepal, 130 requests from Bangladesh, 110 requests from Sri Lanka, and 38 requests from Bhutan.

Accordingly, the literature search was focused on (1) finding the different soil, crop and fertilizer related variables that were tested for the DSSAT crop simulation models under different conditions, and (2) compiling the statistical parameters used for testing the accuracy of the simulated results. The overall goal of this review is to provide a comprehensive study on the performance of the DSSAT crop simulation models and to provide an insight towards the priority areas for future research.

MATERIALS AND METHODS

We first started this study with defining the research question, and then we determined the search protocol on the ISI Web of Science database (https://www.webofscience.com/wos/). We used the following search strings to find the potential studies that included DSSAT and one of the crop modules of the Cropping System Model, including CERES, CROPGRO, CROPSIM, SUBSTOR, and CANEGRO: ["DSSAT[Topic) or DSSAT (All Fields) or CERES (All Fields) or CROPGRO or CROPSIM or CANEGRO or SUBSTOR or Cassava (All Fields). With respect to countries, we included Peoples R. China or India or Pakistan or Bangladesh or Nepal or Sri Lanka or Bhutan (Countries/Regions). For categories we used Agronomy or Environmental Sciences or Water Resources or Soil Science, which are Web of Science Categories. We then used Articles or Review Articles as Document types and Elsevier or Association of Agrometeorologists or MDPI or Springer Nature or Wiley or Taylor & Francis or American Society of Agronomy as Publishers. With respect to publishers and categories, we might have missed a few publications.

In total, 285 publications were found by the database using these search criteria. Once the relevant studies were read, they were selected and assessed using a set of selection criteria, i.e., availability of field data and/or availability of simulation results. Finally, 205 papers were selected for the study. We utilized a data extraction form to extract the selected papers to answer our defined research questions related to determine the different soil, crop and fertilizer related variables that were tested for the models under different conditions and compiling the statistical parameters used for testing the accuracy of the simulated results. Finally, we performed data synthesis and presented the results of the extracted data. A meta-analysis of the data was also done to check the overall performance of the model in simulating the anthesis date, maturity date, leaf area index (LAI), grain yield and biological yield. The statistical parameters used for determining the performance of the model or accuracy of the simulated results were calculated as per the procedures of Timsina and Humphreys (2006). A model reproduces observed data perfectly when the coefficient of determination, (R^2), Nash-Sutcliffe modelling Efficiency (NSME), or d-index is 1, while the Root Mean Square Error (RMSE), Normalized RMSE (RMSEn), Mean error (ME), or Standard error (SE) is 0.

RESULTS AND DISCUSSION

The results regarding the performance of the model in simulating the phenology, growth and yield of the different crops is presented separately for each individual module in the following sections.

CSM-CERES-Wheat

A total of 63 field studies tested the CERES-Wheat model. However, only 46 studies reported the evaluated variables, with the largest number of studies were from China (25), followed by India (15) and Pakistan (6). The model has been tested under the wide range of climatic condition ranging from arid to humid climate. The model has been evaluated for different phenological, growth, and yield variables (Fig.1). The variable that was evaluated by most of the studies was grain yield (41 studies), days to physiological maturity (23 studies), days to anthesis (21 studies), above ground biomass (16 studies), LAI (7 studies), crop evapotranspiration and unit grain weight (4 studies), days to flowering, leaf area/plant, number of grains/ear, forecasted yield, canopy N, grain protein, soil water content (2 studies) and sowing date, days from sowing-emergence, emergence-jointing, jointing to flowering, flowering-maturity, days to emergence, days to jointing days to emergence, days to jointing, No. of ears/m^2, straw yield, harvest index N, Biomass N, grain N, grain filling duration, days to harvest and N use efficiency (1 study). As shown in Fig. 1, it can be clearly noticed that most of the authors relied on evaluated the number days taken to anthesis and to physiological maturity, grain yield and above ground biomass, while less attention was given to other phenological events and growth attributes. There is, therefore, a need to evaluate other growth and yield variables for more reliable understanding of the performance of crop models. The research gap regarding simulation of soil and crop water balance, fertilizer and water use efficiencies and quality attributes needs to be fulfilled in the future.

The researchers have used different statistical procedures to determine the performance of CERES-Wheat model in simulating the different growth and yield attributes and other crop, soil and water related variables 9 (Table S1). A total of 43 studies reported the different errors for evaluating model performance, with 23 from China, 16 from India and 4 from Pakistan. For most of the studies, the difference between the simulated and observed date of anthesis was in the range of 2~4 days. However, a deviation as low as 0 days (Wajid *et al.,* 2021) and as high as 8.4 days (Ye *et al.,* 2020) were also reported. The relative error of 4.4% was reported by Zhong *et al.,* (2017) in China under different management scenarios; a mean absolute error of 4.6% was reported by Dar *et al.,* (2017) for different drip irrigation schedules. The difference for the number of

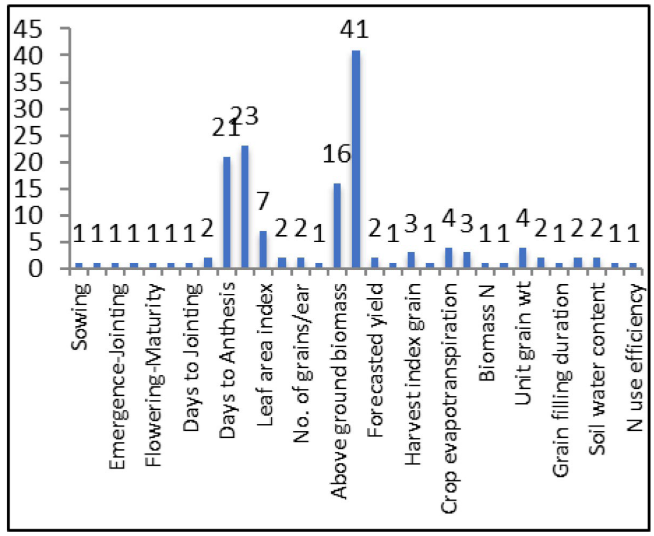

Fig. 1: The number of publications that evaluated different variables of the CSM-CERES-Wheat model.

days to physiological maturity was also less than 5 days for most of the studies. However, differences as large as 38 days (Kour *et al.,* 2013) under climate change studies in India or 10 days (Chen *et al.,* 2021) for evaluating spring wheat phenology of different cultivars in China were also reported. LAI was also evaluated by several authors (Table 1), with a RMSE as high as 1.99 (Wang *et al.,* 2020) and as low as 0.1 (Wajid *et al.,* 2021). The normalized RMSE and modelling efficiency in evaluating sowing-emergence, emergence-jointing, jointing-flowering, and flowering-maturity period was 44% & 0.36, 3.2% & 0.89, 12.4% & 0.45, 9% & 0.56, respectively (Wu *et al.,* 2017). The other parameters like grain number (Yao *et al.,* 2020), grain size (Liu *et al.,* 2016), evapotranspiration (Zeng *et al.,* 2021, Dar *et al.,* 2017), soil water content (Zhou *et al.,* 2019) and harvest index (Ishaque *et al.,* 2020) were less often evaluated.

The differences in grain yield were less than 2000 kg for most of the studies. However, some researchers reported a RMSE as large as 3550 kg (Patel *et al.,* 2010) or 2200 kg (Mall *et al.,* 2018). The model performance for simulating the grain yield was evaluated for a range of conditions such as irrigated and well fertilized (Lang *et al.,* 2020), rainfed (Wang *et al.,* 2020), drought (Yao *et al.,* 2020), water stress (Dar *et al.,* 2017), nutrient stress (Wajid *et al.,* 2021), heat stress (Liu *et al.,* 2016), different sowing dates (Shelia *et al.,* 2019), different cultivars (Wang *et al.,* 2020) and different management intensities (Zhang *et al.,* 2019).

From these studies, it can be concluded that the model performance was better under non- stress conditions as compared to under stress conditions (Patel *et al.,* 2010) or for yield forecasting with future climates. He *et al.,* (2013) conducted an experiment under different water stress levels and reported that the relative absolute error between simulated and observed grain yield ranged from 0.6-6.7% for different stress levels. Rizwan Shahid *et al.,* (2020) conducted experiment with different sowing dates and N levels and reported that the percent deviation between simulated and observed grain and above ground biomass was in the range of 14-24% and 11-18%, respectively. Wang *et al.,* (2020) conducted experiment with different sowing dates and cultivars of winter wheat

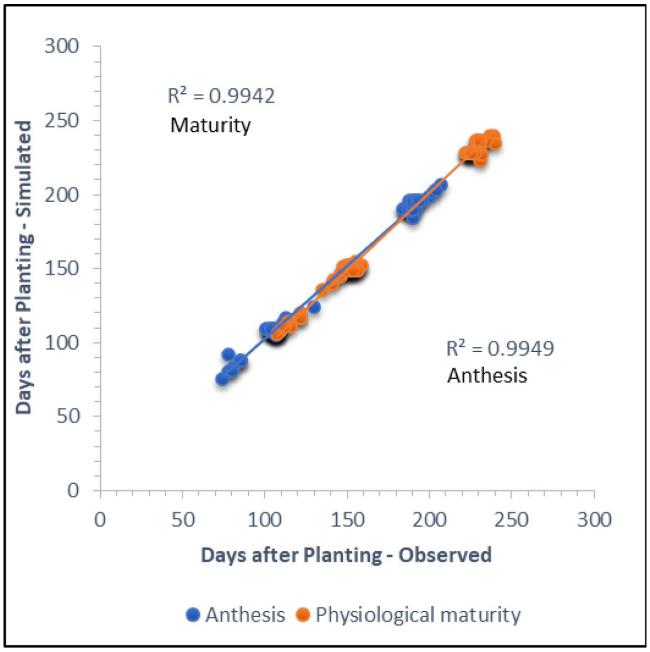

Fig. 2: Simulated and observed days to anthesis and maturity for wheat across a range of experiments conducted in south Asia and China.

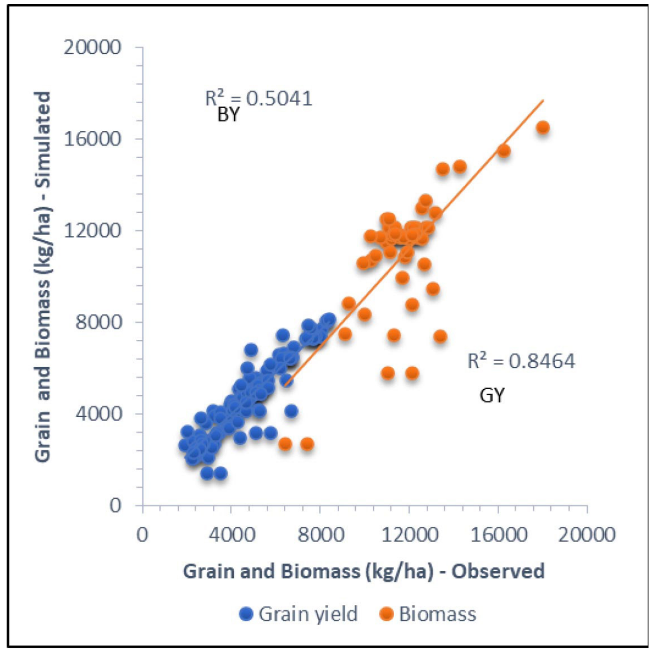

Fig. 3: Simulated and observed grain yield (GY) and above ground biomass (BY) for wheat across a range of experiments conducted in south Asia and China.

and reported a RMSEn of 5-8% for grain yield and 3-7% for above ground biomass. Zhou *et al.,* (2019) evaluated different irrigation management practices and cultivars and reported that RMSEn for grain yield ranged between 8-11%.

Soil water content was evaluated by Zhou *et al.,* (2019) and they reported a RMSEn of 5-73%, which is not really considered to be a good performance of the model. Water use efficiency and crop evapotranspiration were evaluated by Si *et al.,* (2021), Ji *et al.,* (2014), and Dar *et al.,* (2017) and they reported an error of 5-10% between the simulated and observed WUE and 8-14% between the simulated and observed ET. Ishaque *et al.,* (2020) reported normalized RMSE of 7% for harvest index of grain and 9% for harvest index of nitrogen.

The meta-analysis of the data revealed that the normalized RMSE for the variables that were evaluated with the CERES-Wheat model was 2.9% for anthesis (R^2~0.99), 2.3% for physiological maturity (R^2~0.99), 9.2% for LAI, 13.6% for grain yield (R^2~0.85), and 17.6% for above ground biomass (R^2~0.50) (Fig. 2 and 3). The number of days to anthesis and/or physiological maturity, grain yield and above ground biomass were evaluated with different statistical parameters to check the accuracy of the model (Table 1). However, there is a definite need for evaluation of other variables of the CERES-Wheat model.

CSM-CERES-Rice

The CERES-Rice model was evaluated for different phenological, growth, yield attributes, and yield in the different countries. The largest number of studies was reported for India (14), followed by China (7), Pakistan (4), and Sri Lanka (1). The variable that was evaluated by most of researchers (Fig. 4) was grain yield (22 studies), days to physiological maturity (19 studies), days to anthesis (13 studies), above ground biomass (9 studies), LAI (4 studies), panicle initiation and heading (3 studies), straw yield, harvest index, plant N uptake, soil moisture, evapotranspiration, soil water content, tops N, grain N, number of grains/m^2 and test weight (1 study). Based on Fig. 4, it can be stated that among the phenological events, anthesis and maturity remained the top choice for evaluation of the CERES-Rice model. Similarly, grain yield and biological yield were evaluated in most of the studies. However, researchers should also consider other phenological events, growth, and yield attributes for model evaluation. Special attention should be given on evaluation of the soil and plant water and nutrient balance in the irrigation and fertilizer assessment studies.

A total of 25 studies (Table S2) reported different statistical methods for model evaluation, with the largest number from India (15 studies), followed by China (7 studies), Pakistan (2 studies), and Sri Lanka (1 study). Most of the studies reported a RMSE of less than 5 between simulated and observed date of anthesis (Table S2). However, the differences were as small as 0.86 days (Kadiyala *et al.,* 2015) and as large as 11 days (Subba Rao *et al.,* 2016). The normalized RMSE was less than 5% for most of the studies. However, Zhou *et al.,* 2022 reported a RMSEn of 7.7% while evaluating the effect of elevation and precipitation under multiple planting dates and cultivars in China. The d-index for simulated date of anthesis ranged from of 0.16 (Kant *et al.,* 2018) to 0.99 (Kadiyala *et al.,* 2015). The number of days to maturity was less accurately predicted as compared to the number of days to anthesis. Although several studies reported a RMSE of less than 6 days (Anser *et al.,* 2020, Lv *et al.,* 2018; Vysakh *et al.,* 2016), but a RMSE greater than 10 was also reported for several studies (Subba Rao *et al.,* 2016; Guo *et al.,* 2019; Goswami *et al.,* 2016). The RMSEn ranged from

Table 1: Summary of the performance of the most commonly used DSSAT crop simulation models in south Asia and China during the last decade

Variable	CSM Model	RMSE	Normalized RMSE	R^2
Anthesis, days	CERES-Rice	3.2	3.8	0.98
	CERES-Wheat	4.0	2.9	0.99
	CERES-Maize	2.0	2.5	0.99
	CROPGRO-Cotton	3.0	3.4	0.99
Maturity, days	CERES-Rice	5.8	5.0	0.90
	CERES-Wheat	4.1	2.3	0.99
	CERES-Maize	3.0	2.3	0.99
	CROPGRO-Cotton	6.1	3.2	0.99
LAI	CERES-Rice	0.3	7.0	0.96
	CERES-Wheat	0.4	9.2	0.75
	CERES-Maize	0.7	16.0	0.98
	CROPGRO-Cotton	0.3	6.1	0.84
Grain yield, kg	CERES-Rice	514.8	10.5	0.93
	CERES-Wheat	658.2	13.6	0.85
	CERES-Maize	573.2	8.6	0.96
	CROPGRO-Cotton	138.8	4.4	0.99
Above ground biomass, kg	CERES-Rice	1078.3	10.8	0.84
	CERES-Wheat	2069.6	17.6	0.50
	CERES-Maize	1207.2	6.6	0.94
	CROPGRO-Cotton	576.3	6.2	0.96

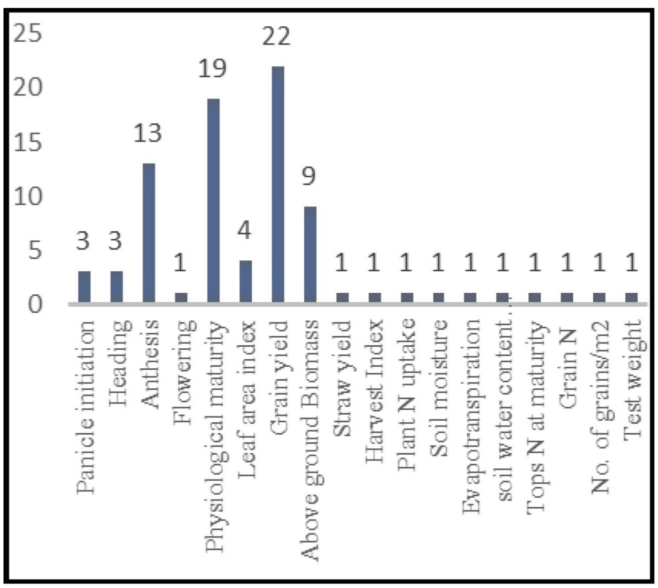

Fig. 4: The number of publications that evaluated different variables of the CSM-CERES-Rice model.

1% for a study utilizing different management strategies (Jha *et al.,* 2020) to 19% for a climate change study conducted by Goswami *et al.,* (2016). Some studies involving the simulation of date of heading revealed that the RMSE varied from 1.2 to 4.3 days (Zhang and Tao, 2013; Shamim *et al.,* 2012). A climate change study conducted by Zhang *et al.,* (2019) revealed that the heading date was simulated very well by the model, with a high d-index (0.98) and R^2 (0.94) and a low RMSEn (2.2%).

LAI is an important growth and yield contributing attribute and was evaluated by several researchers. The RMSE was reported in the range of 0.23 (Shamim *et al.,* 2012) to 1.29 (Ahmad *et al.,* 2013). A study conducted by Zhang *et al.,* (2018) in China involving different cultivars and N rates found a R^2 of 0.64 between the simulated and observed LAI. Kadiyala *et al.,* (2015) evaluated the effect of different establishment methods under rainfed, aerobic, and flooded conditions, found a poor performance of the model in simulating the LAI with a high RMSEn (51%), and low d-index (0.62), and poor correlation (r=0.68). However, Ahmad *et al.,* (2013) conducted an experiment with three planting densities and five irrigation regimes and found that the model performance in simulating the LAI was good with low a RMSE (1.1-1.3 and high d-value (0.96). Further studies are required to evaluate the model performance in this aspect under different management scenarios and environmental modifications. The yield attributes like number of grains m^{-2} and test weight were not evaluated in many studies. However, a study conducted by Shamim *et al.,* (2012) utilizing four cultivars and 3 planting dates of aromatic rice in India found that the model performance was poor in simulating the number of grains (RMSE=1822; MAE=1363; %error=12). However, the Student's t-test revealed that the difference was non-significant. Similarly, the test weight was underestimated by the model, but the differences were non-significant between the simulated and observed values.

Grain yield was the trait that was most frequently evaluated for the CERES-Rice model as all research efforts are ultimately directed to increase the grain yield. Most of the studies showed a good performance of the model in simulating grain yield. The coefficient of determination, R^2 was found to be as good as 0.99 (Sudharsan *et al.,* 2013), 0.97 by Debnath *et al.,* (2018), and 0.89 (Zhang *et al.,* 2019; Lv *et al.,* 2018) for simulating grain yield under varied irrigation and soil management practices. RMSE was the most used error to test the performance of the model. Anser *et*

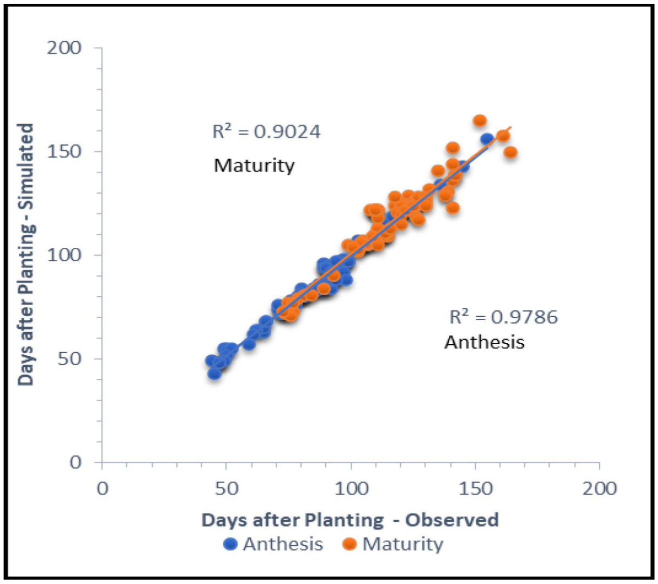

Fig. 5: Simulated and observed days to anthesis and maturity for rice across a range of experiments conducted in south Asia and China.

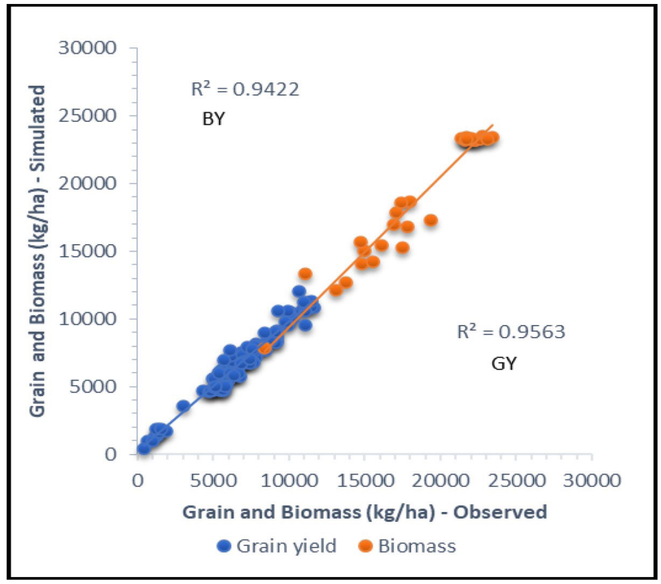

Fig. 6: Simulated and observed grain yield (GY) and above ground biomass (BY) for rice across a range of experiments conducted in south Asia and China.

al., (2020) used different adaptation strategies to study the impact of climate change and found a RMSE of 273 kg. To evaluate the effect of different rice cultivars and N management practices on yield and above ground biomass, Kant *et al.,* (2018) reported a RMSE of 197-499 kg and 1350-1778 kg, respectively. Medhi *et al.,* (2017) evaluated several planting dates and cultivars for the simulation of yield and found a close match between the simulated and observed grain yield (RMSE~245-387 kg). However, Kadiyala *et al.,* (2015) reported a RMSE as high as 700 and 1000 kg while evaluating the effect of different rice establishment methods under rainfed, aerobic, and flooded systems on grain and straw yield, respectively. Vysakh *et al.,* (2016) conducted an experiment with different planting dates and rice cultivars and found that the RMSE between simulated and observed grain yield varied between 1039 and 1186 kg/ha. Several researchers have reported a RMSEn between simulated and observed grain yield that varies from 4% (Jha *et al.,* 2020) to 18% (Kadiyala *et al.,* 2015). Poor performance of the model in simulating above ground biomass was reported by Debnath *et al.,* (2018), with high a RMSEn (35%). Soil moisture simulations were conducted by Kadiyala *et al.,* (2015) and Shrivastava *et al.,* (2018) under different management practices; they found that the RMSE for soil moisture ranged from 0.05 to 0.017 m^3 m^{-3}. For evapotranspiration, the RMSE of 60-100 mm was reported by Shrivastava *et al.,* (2018). Student's t-test was used by two researchers (Sudharsan *et al.,* 2013; Shamim *et al.,* 2012) to test the significance of the difference between the simulated and the observed results. However, they both found that it was non-significant, revealing the good performance of the CERES-Rice model in simulating the growth and yield under different management scenarios. The meta-analysis of the data revealed that the RMSEn for the variables that were evaluated by the CERES-Rice model was 3.8% for anthesis (R^2~0.98), 5.0% for physiological maturity (R^2~0.90), 7.0% for LAI, 10.5% for grain yield (R^2~0.93), and 10.8% for above ground biomass (R^2~0.84) (Fig. 5 and 6).

Although the different studies that were reviewed demonstrated that a well calibrated CERES-Rice model can be used effectively to simulate different phenological stages, growth and yield attributes, most researchers relied upon testing of the same variables (Table 1). There is a need to simulate other soil, water and nutrient related parameters and efficiencies, economics of the crop production technologies and management intensities. Moreover, the work on sensitivity analysis, sequential and rotation analysis, and climate change adaptation studies are lacking. Only a few studies reported on rotation and cropping system analysis, while none of the studies addressed the simulation of the impact of pests and diseases. This review may serve as the base for determining the research gaps in the use and application of the CERES-Rice model in South Asia and China.

CSM-CERES-Maize

A total of 35 studies simulated the different phenological, growth, and yield attributes to evaluate the performance of the CERES-Maize model (Fig. 7). The largest number of studies was from China (23), followed by India and Pakistan (5), Nepal and Bangladesh (1). The model has been evaluated for a wide range of environmental conditions and crop management practices. The variables that were evaluated in most of the studies was grain yield (32 studies), above ground biomass and anthesis (22 studies), maturity (20 studies), LAI (9 studies), soil water content and days to emergence (7 studies) and the number of grains/ear (3 studies). Two of the studies evaluated stover yield, harvest index, unit grain weight, end of grain filling, start of grain filling, time to harvest, and plant N uptake. Other attributes that were simulated in at least one study included test weight, soil total N, soil organic carbon, number of grains/m^2, silking, water use, grain N uptake, beginning of maturity, beginning of flowering, number of leaves, N leaching, days to jointing, days to tasselling, soil nitrate N, water use efficiency, beginning of grain filling and economic optimum dose of N. However, there is still a need to simulate other phenological

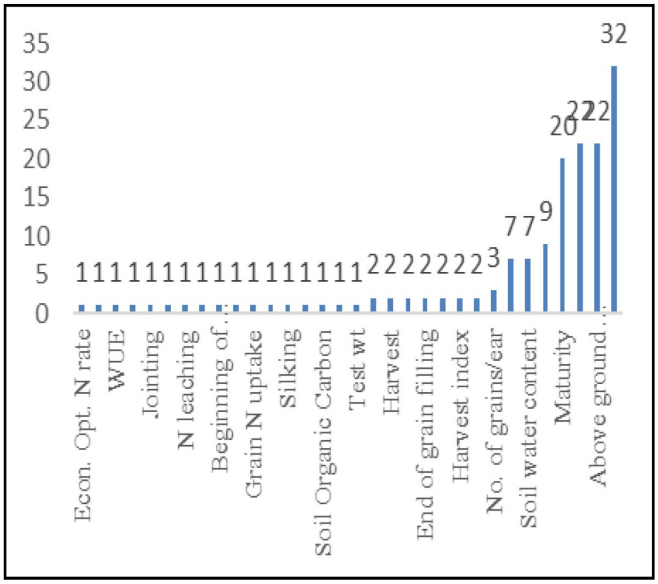

Fig. 7: The number of publications that evaluated different variables of the CSM-CERES-Maize model.

events and yield attributes for evaluation of the performance of the CERES-Maize model.

A total of 35 studies reported the different errors for evaluation of model performance. For most of the studies (Table S3), the difference between the simulated and observed date of anthesis was less than 5 days (Huang *et al.,* 2021; Choudhary *et al.,* 2021). However, the RMSE varied from 0 to 5.7 for a study evaluating the effect of different planting densities and cultivars in China (Zhang *et al.,* 2022). Abbas *et al.,* (2017) found a R^2 of 0.88 between simulated and observed date of anthesis while evaluating the potential impact of climate change and adaptation with different management practices such as planting depth, planting date, row spacing, and fertilizer application rates in Pakistan. An experiment conducted by Choudhary *et al.,* (2021) in Bangladesh for simulation of yield and forecasting with 5 sowing dates and 3 maize hybrids, showed that the CERES-Maize model simulated anthesis well (R^2~0.95, RMSE~0.63 days and d-value of 0.94). Rugira *et al.,* (2021) found a good performance of the model in simulating the maturity for different irrigation and sowing management practices in China, with a RMSEn of less than 1.2%. Zhang *et al.,* (2020) found a RMSE of six days between simulated and observed date of maturity under different Genotype x Management interactions for different agroecological zones in China. With respect to the emergence date, model performance was good with a RMSEn of less than < 1% (Rugira *et al.,* 2021; Bai and Gao, 2021).

Several studies found a much higher RMSEn for other variables. A study conducted by Shen *et al.,* (2021) for simulating summer maize under different mulch treatments, found that the differences were as large as 17%. The differences between simulated and observed LAI were large, with a RMSEn as high as 28% (Ran *et al.,* 2020), 17% (Rugira *et al.,* 2021) and 11% (Shen *et al.,* 2021). For an experiment conducted to evaluate the in-season N recommendation strategy for three planting dates, Wang *et al.,* (2012) found that the relative error was more than 20% between simulated and observed LAI and ranged from 6 to 12% for plant N uptake. Several studies evaluated model performance of CERES-Maize for simulating the soil water content of the top layers and most of them found that the RMSEn was more than 10%. An optimization study of irrigation and fertilization in drip irrigated corn conducted by Fu *et al.,* (2020), reported a RMSE of 12%. Similarly, Rugira *et al.,* (2021) and Bai and Gao (2021), reported RMSE of 2 to 25% and 11 to 18%, respectively.

Model performance in simulating the above ground biomass and grain yield was studied by most of the researchers. The RMSE for grain yield was reported to be as small as 20 kg with RMSEn of 0.2% by Zhang *et al.,* (2022) or more than 1000 kg (Yang *et al.,* 2013). However, most of the studies have reported a RMSE of less than 500 kg (Rugira *et al.,* 2021; Choudhary *et al.,* 2021; Ahmad *et al.,* 2020). An adaptation study conducted by Saddique *et al.,* (2020) in China reported a good match with a RMSEn and RAE of 5 % and 4%, respectively. Devkota *et al.,* (2015) conducted an experiment in Nepal to determine yield gaps and adaptation measures. They found that the model performed well in simulating grain yield with a RMSE less than 450 kg and a R^2 and d-value of 0.89 and 0.86, respectively. Similarly, a good performance of the model in simulating the grain yield (RMSE~400 kg, R^2~0.93, and d-value~0.99) was reported by Choudhary *et al.,* (2021) for a study the performance of three maize hybrids under three sowing dates conducted in Bangladesh.

Some researchers have used the Nash-Sutcliffe modelling Efficiency (NSME) to evaluate the performance of the CERES-Maize model. A study conducted by Geng *et al.,* (2018) reported that the model performance was good for simulating yield loss under drought stress with a NSE that ranged from 0.84 to 0.97. However, Ran *et al.,* (2020) reported that the NSE (0.05-0.19) was poor for simulating the water consumption and yield using the two different ET options in CERES-Maize. Model performance in simulating above ground biomass was comparable to grain yield, with a RMSE of less than 300 (Choudhary *et al.,* 2021) to more than 3000 kg (Zhang *et al.,* 2000; Ran *et al.,* 2020). To evaluate model performance for simulating plant N uptake and economical optimum dose of N, Wang *et al.,* (2021) conducted an experiment with three planting dates and six N rates in China; they reported that the model can be used for estimating the plant N uptake (R^2~0.96, RMSE~11.4 kg, RE~6%) and determining the economically optimum dose of N (R^2~0.71, RMSE~21 kg). Water use efficiency was simulated by Rugira *et al.,* (2021), who found that RMSEn ranged from 3 to 8%, while the absolute deviation ranged from 0.7 to 1.5%. Bai and Gao (2021) reported that the CERES-Maize model can effectively simulate the start and end of grain filling with a RMSE of less than 2 days and a RMSEn and MAE of less than 2%. The RMSEn and NSE for simulating the soil nitrate N ranged from 14 to 31% and from 0.79 to 0.96, respectively. Song and Jin (2020) conducted an experiment to simulate the grain weight under water stress conditions and reported that the model performed well in simulating the unit grain weight (ARE~3%, RMSEn~4%). The model performance was also found good in simulating the number of days to tasseling (Chen *et al.,* 2020), cumulative N leaching (Fu *et al.,* 2020), number of leaves on the main stalk (Babel *et al.,* 2019), the number of days to silking (Wang *et al.,* 2015), soil organic carbon (Yang *et al.,* 2013),

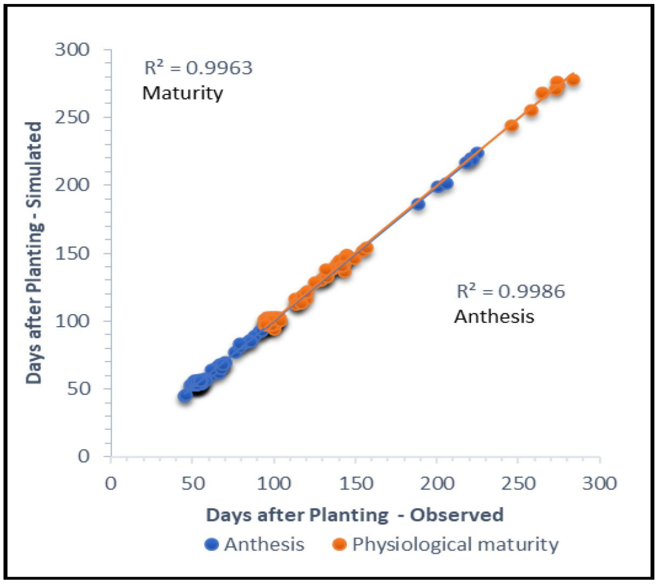

Fig. 8: Simulated and observed days to anthesis and maturity for maize across a range of experiments conducted in south Asia and China.

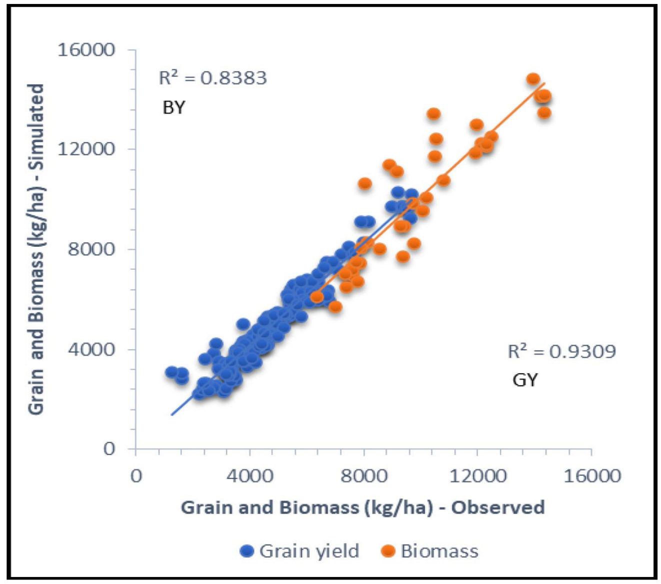

Fig. 9: Simulated and observed grain yield (GY) and above ground biomass (BY) for maize across a range of experiments conducted in south Asia and China.

the number of grains/cob and the number of grains/m^2 (Devkota *et al.,* 2015), and stover yield (Lone *et al.,* 2020). However, there are very few studies that reported all these traits at the same time. The meta-analysis of the data revealed that the RMSEn for the variables that were evaluated with the CERES-Maize model was 2.5% for anthesis (R^2~0.99), 2.3% for physiological maturity (R^2~0.99), 16.0% for LAI, 8.6% for grain yield (R^2~0.96), and 6.6% for above ground biomass (R^2~0.94) (Fig. 8 and 9; Table 1).

CSM-CERES-Sorghum

A total of five studies were carried out on sorghum using the CERES-Sorghum model. However, the model was only evaluated for three of the studies (Table S4a). Grain yield was evaluated in all three studies, while the anthesis and maturity dates were evaluated in only one study (Sandeep *et al.,* 2018), while phenological observations, and growth and yield attributes were not validated. There is, therefore, a need to conduct more research with the CERES-Sorghum modelling for grain sorghum in south Asia and China. A study conducted by Sandeep *et al.,* (2018) to evaluate the impact of climate change on sorghum productivity in India and its adaptation strategies, found that the CERES-Sorghum model was good in simulating the anthesis (RMSE<4 days), maturity (RMSE~4 days) and grain yield RMSE=320-755 kg). Chadalavada *et al.,* (2022) found that model performance was good in simulating grain yield (RMSE~300 kg and d-index~0.88) while evaluating the impact of climate change on post rainy season sorghum in India. Different plant spacings and N rates adaptation strategies were used by Singh *et al.,* (2014) to quantify the potential benefits of drought and heat tolerance for rainy season sorghum; he found that the model performed good in simulating the grain yield with a RMSE~370 kg and a d-index~0.9. However, there is a need to evaluate model performance for simulating other growth and yield associated traits.

CSM-CERES-Millet

The CERES-Millet model has been used to simulate the phenology and grain yield of pearl millet in two studies, one each in Pakistan and India (Table S4b). Asmat Ullah *et al.,* (2019) conducted an experiment to test the model performance in simulating the anthesis and maturity, LAI, biomass, and grain yield under arid and semi-arid environments of Pakistan. The model performance was found to be good as revealed by a low RMSE, a high d-index, and a high coefficient of determination. A multilocational trial with different cultivars conducted by Singh *et al.,* (2017) showed that the grain yield simulated with the CERES-Millets model was good with a RMSE that was less than 400 kg and d-index of 0.97. Pearl millet is an important crop for both semi-arid and arid environments, and, therefore, more studies are needed for evaluation and application of the model.

CSM-CROPGRO-Soybean

A total of three studies, including two from China and one from India used the CROPGRO-Soybean model to simulate phenology and grain yield. Grain yield was simulated in all three studies, while physiological maturity and soil water content were simulated in two studies (Table S4c). The remainder of the variables, such as the time of flowering (Wei *et al.,* 2021), soil temperature (Liu *et al.,* 2013), and total above ground biomass were evaluated in only one study (Walikar *et al.,* 2018). The performance of the CROPGRO-Soybean model was found to be good in simulating phenology and final yield. Wei *et al.,* (2021) found that the model performance was good in simulating the flowering and maturity dates for soybean under drought conditions with an absolute error of less than 5% and RMSEr of ~3%.

Model performance in simulating the soil water content varied between the two experiments conducted in China. Liu *et al.,* (2013) conduced an experiment on modelling crop yield, soil water content and soil temperature under conventional and conservation tillage and reported that the RMSEn for soil water content was in the range of 16-46% and the mean error was 0-0.8 cm3/cm3. However,

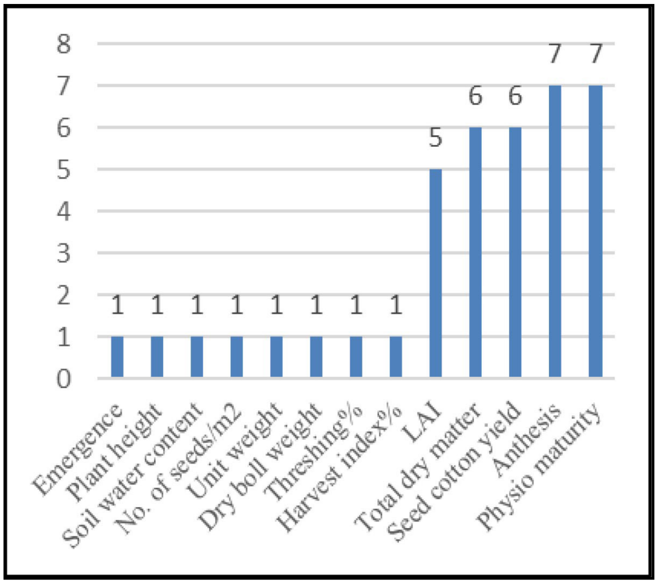

Fig. 10: The number of publications that evaluated different variables of the CSM-CROPGRO-Cotton model.

Wei *et al.,* (2021) found an absolute relative error of 2 to 8% and a RMSEr of 6% between the simulated and observed soil water content in a soybean drought risk quantification study. For studying the impact of projected climate on yield of soybean under different sowing dates, Walikar *et al.,* (2018), found the model performance was good in simulating grain and biological yield with a RMSE of less than 500 and less than 600, respectively. The d-index varied between 0.2-0.9 for grain yield and 0.7-0.9 for the above ground biomass. In a separate study, Liu *et al.,* (2013) reported that the simulated and observed yield differences ranged from -91 to 408 kg, both under and overestimating the grain yield under different tillage treatments. Modelling studies on soybean that involve different management intensities, cultivars and climate impact are lacking in the region, although it is a very important oil and protein crop. Therefore, more research is needed in the coming years.

CSM-CROPGRO-Peanut

There were only four studies that were reported that used the CROPGRO-Peanut model for simulation of phenology, growth, and yield of peanut. The pod yield was simulated by all four studies, followed by the flowering and first pod date (three studies). Biomass and shell weight were only evaluated by one study each while LAI, maturity date, first seed date, harvest index, and shelling percentage were only evaluated in one study (Table S4d). Different statistical errors were computed to quantify the performance of the CROPGRO-Peanut. A study conducted by Halder *et al.,* (2017) to evaluate the effect of different sowing dates and phosphorus fertilizer application, found that model performance was good for the simulation of the dates of anthesis, first pod, and first seed, harvest index, and shelling percentage. However, the error for the simulation of grain yield was higher (RMSE ~ 470 kg and RMSEn ~ 23%).

The relative error for the simulation of the different phenological stages such as dates for anthesis, first pod, first seed, and maturity were in the range of 5-13% for a study conducted by Parmar *et al.,* (2013) to evaluate the effect of sowing dates on different peanut cultivars. LAI, shell weight, and pod yield were also simulated well as indicated by low RMSE. Due to the lack of sufficient studies with the CROPGRO-Peanut model in south Asia and China, the performance of the model cannot be judged. Therefore, more studies are needed given the importance of the peanut crop in the region.

CSM-CROPGRO for other pulse crops: Pigeonpea, Chickpea, and Urd

Only one study was reported from India regarding the use of the DSSAT model for simulating the phenology and yield of different maturity groups of pigeonpea under the climate change. Yadav *et al.,* (2021) found that the RMSE for anthesis and maturity varied between one and eight days. The RMSEn was about 5% between the simulated and the observed phenology dates. Grain yield was well simulated with a RMSE of less than 300 kg and RMSEn of less than 7%. Although pigeonpea is an important Kharif pulse crop for India, crop modeling studies are very much limited and need to be increased in the near future.

One study each was conducted on chickpea by Yadav *et al.,* (2016) and one on urd by Kumar *et al.,* (2012) in India. However, the evaluation of model performance was not reported in these studies. ICRISAT was involved in the development of the original CSM-CROPGRO-Chickpea model based on the PNUTGRO model. This has resulted in several papers that were published prior to the period of this analysis (Singh *et al.,* 1999a, 199b).

CSM-CROPGRO-Cotton

A total of seven studies, including four in Pakistan, two in China, and one in India used the CROPGRO-Cotton for the simulation of cotton phenology, growth, and seed cotton yield. The dates for anthesis and physiological maturity were simulated in all studies, seed cotton yield and total dry matter in six studies, and LAI in five studies. Other parameters such as the number of days to emergence, plant height, number of seeds/m^2, unit weight, dry boll weight, threshing percentage, harvest index, and soil water content were simulated in one study each (Fig. 10). Different statistical errors were used to test the performance of the model (Table S5). The studies conducted by Arshad *et al.,* (2017) for simulation of cotton yield under different nitrogen levels and planting dates and Amin *et al.,* (2017) for optimizing the phosphorus use in two cotton cultivars in Pakistan, showed that the model performance was good in simulating the anthesis and maturity with a RMSE of less than 2 days. However, Arshad Awan *et al.,* (2021) found a higher percent difference and error between the simulated and observed anthesis (>9%) and maturity dates (>6%) while evaluating the impact of climate change on cotton. The model performed well in simulating LAI (RMSE~0.3), total dry matter (RMSE~960 kg), and seed cotton yield (RMSE~180 kg).

In a study conducted by Li *et al.,* (2019) regarding simulation of cotton growth and soil water content under plastic mulch drip irrigation, the simulation of LAI and soil water content by the CROPGRO-Cotton model was good with a high coefficient

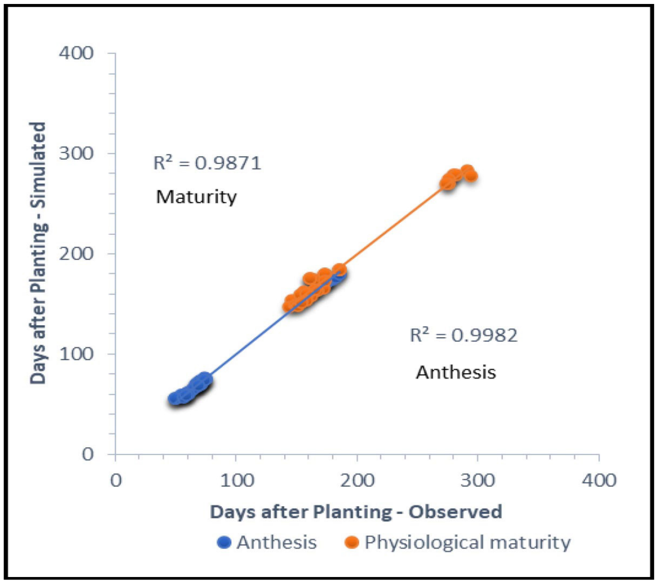

Fig. 11: Simulated and observed days to anthesis and maturity for cotton across a range of experiments conducted in south Asia and China.

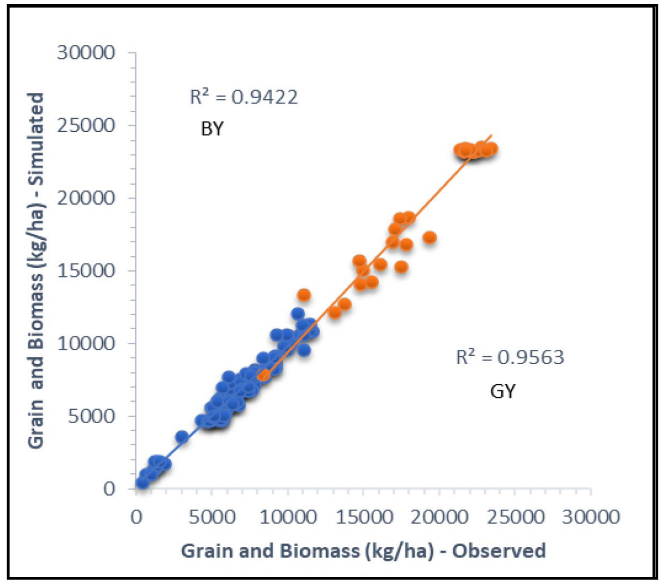

Fig. 12: Simulated and observed seed cotton yield (GY) and above ground biomass (BY) across a range of experiments conducted in south Asia and China.

of determination and d-index as well as a low RMSE. Mishra *et al.,* (2021) conducted a study on the effect of three different sowing dates on four cotton cultivars; they found that the fit between model simulated and observed seed cotton yield (RMSE<130 kg and d-index~0.97) and the total dry matter (RMSE~700 kg and d-index~0.98) were good. Habib ur Rahman *et al.,* (2018), found that the relative error for the simulated number of seeds/m^2, unit weight, dry boll weight and threshing percentage was 5, 3, 5 and 1 percent, respectively, with the overall conclusion that model performance can be considered good. The responses of cotton growth and yield to pre-planting soil moisture with the CROPGRO-Cotton model for a mulched drip irrigation system was studied by Wang *et al.,* (2020). This study found that the model did not perform well in simulating the phenology and yield of cotton. The RMSE for anthesis and maturity was more than 4 days, while for above ground biomass and seed cotton yield it was more than 2000 and 760 kg, respectively. The RMSEn between simulated and observed dry matter and seed cotton yield ranged from 10-31%.

The meta-analysis of the data revealed that the RMSEn for the variables that were evaluated for CROPGRO-Cotton model was 3.4% for anthesis (R^2~0.99), 3.2% for physiological maturity (R^2~0.99), 6.1% for LAI, 4.4% for seed cotton yield (R^2~0.99), and 6.2% for above ground biomass (R^2~0.96) (Fig. 11 and 12; Table 1). There is a need for more extensive crop modelling studies on cotton for different environmental conditions, crop management practices, and future climate scenarios because of its importance as the main fiber crop across the globe.

CSM-CANEGRO-Sugarcane

Two studies were found in the literature that were conducted during the past ten years and that used the CANGRO-Sugarcane (Table S6a). The studies included the simulation of days to emergence, the dates for peak tillering and physiological maturity, LAI, fresh cane yield, stalk fresh mass, and sucrose mass. A study conducted by Singh *et al.,* (2018) on the evaluation of the CANEGRO-Sugarcane model for phenology and yield attributes of four cultivars of sugarcane grown for three different sowing dates in India, found that the model performance was good in simulating the emergence date, peak tillering date, physiological maturity date, LAI, and fresh cane yield as indicated by the different statistical indicators including a low vale for RMSE and MBE and a high value for the d-index. However, the RMSE between the simulated an observed stalk fresh mass and sucrose mass reported by Bhengra *et al.,* (2016) for a study conducted with 10 sugarcane cultivars was much higher for both model calibration and evaluation. More studies are required to check the performance of the CANEGRO-Sugarcane model for simulating phenology, growth, and yield of sugarcane for different environmental conditions and management practices.

CSM-OILCROP-Sunflower

Two studies were found in the literature that evaluated the OILCROP-Sunflower model in Pakistan (Table S6b). The two studies included the number of days to anthesis and maturity, LAI, total dry matter, achene yield, oil content, soil water content, leaf N content, and crop ET. Awais *et al.,* (2017) conducted an experiment on simulating the water and nitrogen productivity of sunflower for four irrigation levels and three N rates. They reported that the mean error in simulating anthesis and maturity was less than 6%, while the error between the simulated and observed total dry matter and achene yield was up to 18%. LAI was underestimated by 25% or overestimated by 6%. The RMSE for soil water content was 0.05% and for crop ET was 33 mm. Nasim *et al.,* (2016) also found a good model performance for the evaluation of the performance of sunflower hybrids grown under different environmental conditions. The difference between simulated and observed anthesis and maturity dates, total dry matter and oil content was less than 7%, while achene yield (R^2=0.65-0.94) and LAI (d=0.55-0.97) were also well simulated by the model.

CSM-SUBSTOR-Potato

Two studies were reported (Table S6c) regarding the use of the SUBSTOR-Potato for simulating the tuber initiation, maturity, and yield. Naz *et al.,* (2022) reported a good performance of the model in simulating tuber initiation and maturity. Goswami *et al.,* (2018) found that the tuber yield was well simulated with a RMSE of 3800 kg and a d-index of 0.97. Although potato is one of the important commercial crops grown throughout Asia, studies that include crop modelling are very limited. Therefore, in depth research is needed to simulate and evaluate potato phenology, growth, and yield for different management and environmental conditions, as well as the impact of climate change and potential adaptation measures.

REFLECTION AND THE WAY FORWARD

During the last 11 years from 2010 to early 2022, many studies have been conducted in south Asia and China for evaluation and application of the different crop modules of the Cropping System Model of DSSAT under various environmental conditions and for many different management practices. In this Meta Analysis we reviewed a total of 206 publications that were published regarding the use of the DSSAT simulation models for different crops during this period and that are available in the Web of Science database. Most of the studies were conducted with the CERES modules for maize, wheat, and rice, as well as some for sorghum and pearl millet. Among the CROPGRO modules, most of the studies were conducted for peanut, soybean, and cotton. Other crops included sunflower, sugarcane, and potato. The number of days to anthesis and maturity, LAI, grain yield, and biological yield were the most common traits used for model calibration and evaluation. The models were tested for different environmental conditions, ranging from irrigated to rainfed, arid, semiarid, and monsoonal climate and under different management practices, climate change assessments, and adaptation measures. The models performed well under most of the conditions in simulating the growth and yield attributes. However, the performance of the models was better under non-stress environments with sufficient inputs and management. For most of the studies, the difference between the observed and simulated days to anthesis and maturity was less than 5 days. Grain yield was simulated with an RMSE of less than 1000 kg/ha, while biological yield was simulated with a RMSE of less than 1500 kg/ha for most of the studies. Although the evaluation with other growth attributes such as the number of grains, harvest index, grain weight, pod weight, and shelling percentage were limited, the studies that included these traits reported a good performance of the individual CSM crop modules.

Until now there are very limited data available with respect to soil water content, nitrogen and water uptake, N leaching, nutrient use efficiency, and water use efficiency. Therefore, more research is needed for evaluation of these traits. In addition, most of the studies only focused on model calibration and evaluation, while modeling for management of current agronomic challenges such as resource use efficiency or for adaptation measures were very limited. The use and application of the DSSAT crop models for fruit and vegetable crops is lacking and must be taken seriously given the importance of these crops for food and especially nutrition security as well as a cash crop for small-holder farmers. Modelling work on crop rotations, sequence analysis, and economic analysis are very much limited and are needed in the near future, especially for environmental and economic sustainability applications of the crop models. The state-of-the in-crop modeling was recently reviewed by Vasco Silva and Giller (2020) as part of the iCROPM 2020 International Crop Modeling Symposium (Hoogenboom *et al.,* 2020), showing that there are still many gaps as well as opportunities for systems analysis and crop modeling to have an impact.

This Meta Analysis shall serve as a review for the work that has been done with the DSSAT crop simulation models during the last decade and will serve as a roadmap for further research on crop model development, calibration, evaluation, and applications, especially with respect to south Asia and China. Although DSSAT is not the only crop modelling platform that has been used by researchers in the region, it is surely the most widely used one along with APSIM crop modeling platform. This paper shall guide researchers regarding the different adaptation practices that can be developed under future climate change. This review focuses on only one region of Asia. Therefore, more studies are required for other parts of the region and the world to obtain a better understanding on the use of crop models for the development of both economically and environmentally sustainable agricultural practices for food and nutrition security under climate change and uncertainty.

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Conflict of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Gerrit Hoogenboom acknowledges that he is responsible for the coordination and the development of the DSSAT Crop Modeling Ecosystem.

Data availability: This study is solely based on references that are publicly available. The detailed data presented in this study can be obtained from the individual references listed below.

Author contributions: **E. Dar**: Conceived, designed, article writing and review, **G. Hoogenboom:** Conceived, designed, article writing and review, **Z. A. Shah**: Conducting the literature.

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