CHAPTER TWO

A Comprehensive Review of the CERES-Wheat, -Maize and -Rice Models' Performances

Bruno Basso[*,**,1], **Lin Liu**[*], **Joe T. Ritchie**[†]

[*]Department of Geological Sciences, Michigan State University, East Lansing, Michigan, USA
[**]W.K. Kellogg Biological Station, Michigan State University, East Lansing, Michigan, USA
[†]Plant, Soil and Microbial Sciences, Michigan State University, East Lansing, Michigan, USA
[1]Corresponding author. E-mail address: basso@msu.edu

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Abstract

The Crop Environment Resource Synthesis (CERES) models have been developed and utilized for the last 30 years to simulate crop growth in response to climate, soil, genotypes and management across locations throughout the world. We reviewed 215 papers found in the literature that contained field observed data where the CERES models were tested. Over 30 simulated variables of the CERES models have been

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tested in 43 different countries under various experimental treatments. Across all testing conditions, the CERES models simulated grain yield with a root mean square error (RMSE) of less than 1400 kg/ha (~10% relative error, RE), 1200 kg/ha (~20% RE) and 800 kg/ha (~10% RE) for maize, wheat, and rice, respectively. Phenological development was simulated with less than 7 days difference from the observations in most studies. The CERES models simulated aboveground biomass, harvest index, evapotranspiration, and soil water reasonably well too. The simulations of grain number (up to 4340 root mean square error, RMSE), grain weight (up to 22% error), intercepted photosynthetically active radiation (IPAR, up to 0.41 MJ/plant), leaf area index (LAI, 31.9% error), soil temperature (over 10°C difference), and nitrogen (N) dynamics (up to 80% error) were less accurate. In fact the average error of CERES model simulations tends to be higher under marginal crop growing conditions such as extreme heat or cold, water and nutrient deficit conditions.

1. INTRODUCTION

Food security is one of the most important ecosystem services offered by agriculture (Reid et al., 2005; Zhang et al., 2007). Due to the high demand for food, there has been an expansion and intensification of agriculture (Matson et al., 1997). Considering the increasing food demand by the rising population, the agriculture sector is facing the big challenge to increase food crop productivity. Since about two-thirds of the total daily calorie-intake is from the three staple grains of wheat, rice, and maize, increasing their yields is mandatory (Cassman, 1999). Although we have witnessed extensive efforts in agricultural experiments that aimed at increasing yield and minimizing environmental impact, the results are often site specific and subject to spatial and temporal variability affected by weather, soil, and crop cultivars (Basso et al., 2011). This variability in space and time makes it difficult to transfer crop management information from one location to another for agricultural decision making (Jones et al., 1998). To understand the complex crop-soil-weather system and to facilitate farm-level decision making processes, crop models were developed to help provide the larger combinations of crop yield outcomes as influenced by variety and management for the high degree of variability in weather and soils than would be possible using trial and error experiments. The Crop Environment Resource Synthesis (CERES) models were developed in the early days of the information age. CERES-Wheat (Otter and Ritchie, 1985, Ritchie, 1985), CERES-Maize (Ritchie, 1986, Ritchie et al., 1986b, Jones et al., 1986), and CERES-Rice (Ritchie et al., 1986a) were initially developed mainly to simulate grain yield, but later served also as a decision support tool when DSSAT became available (Jones et al., 2003). The CERES models are a process-based system that simulates crop growth and development on a daily time step. The major components of phenology, growth, soil water, and nitrogen balance enable the models to simulate crop yield, using the soil water and nitrogen dynamics to provide a limitation on yield. Maize, wheat, and rice are the most tested and used, but models of barley, grain sorghum and pearl millet are included in the CERES models (Ritchie et al., 1998).

While Timsina and Humphreys (2006) reviewed the performance of the CERES-Rice and CERES-Wheat models in the rice-wheat systems, there lacked a comprehensive reviews on the CERES model performance for staple crops. Therefore, the objective of this paper is to summarize published results of worldwide tests of the CERES-Maize, CERES-wheat, and CERES-Rice providing a review of (1) the crop and soil variables that have been tested for the models, (2) the conditions under which those parameters were tested, and (3) the accuracy of the simulated variables.

Testing of models involves comparison of simulated with measured results. When the model results differ from measurements, the apparent error can be a function of the inaccuracy of one or more of the model functions and the resulting feedback, but much of the difference can often be the result of inaccurate input data or initial conditions. The CERES models are intended to be applicable in any weather, soil, and management conditions for any cultivar in which the genetic coefficient information is known and should not require calibration in space and time. Some critical input information for CERES models is often not known and has to be approximated by various procedures. The greatest uncertainty of inputs has proven to be the depth of effective rooting, one or more of the genetic coefficients, and the initial conditions of the soil, water, and nitrogen. When crops are grown under unlimited water and nitrogen, the soil properties and initial conditions are less critical for more accurate simulation. If there is no independent knowledge about the genetic coefficients, the model is often calibrated to make the phenology and yield components match the data sets. The initial conditions are frequently identified by trial and error simulations or through sophisticated parameter estimation techniques to obtain better agreement with the final measurements.

2. METHODS

The reviewed articles were obtained from the ISI Web of Science database. All peer-reviewed articles in the database that met the following criteria were selected for this metadata synthesis paper: (1) written in English, (2) published by Dec. 2014, and (3) primary studies had both field observations and simulation results obtained from the CERES models.

3. RESULTS

A total of 215 field studies tested the three CERES models. Of these, 111 studies tested the CERES-Maize model, 104 studies tested the CERES-Wheat model, and 26 studies tested the CERES-Rice model. The CERES models have been validated in 43 countries across all continents, except Antarctic (Fig. 1). The model simulations have been tested under a wide range of climate conditions: monsoonal (Liu et al., 2013), semiarid tropical (Carberry et al., 1989), subhumid, subtropical (Behera and Panda, 2009), Mediterranean (Hasegawa et al., 2000), oceanic and

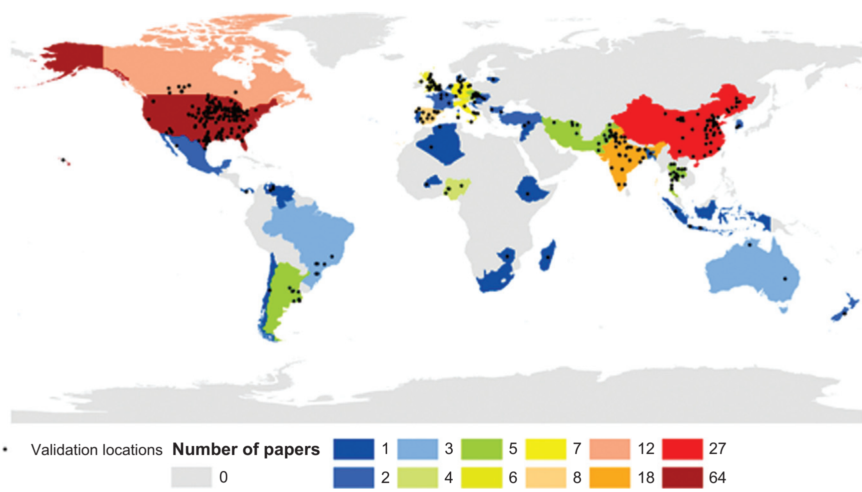

Figure 1 Locations where the CERES models have been validated and the number of studies in each model validation country.

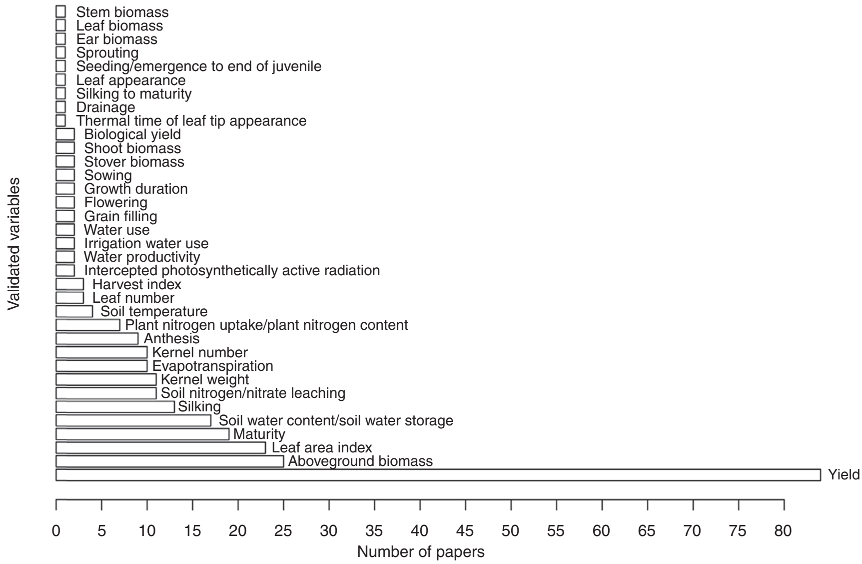

Figure 2 The number of research that validated variables in the CERES-Maize.

continental (Johnen et al., 2012), cold winter, dry summer (Thaler et al., 2012), and humid temperate (Otegui et al., 1996). The validation studies have been conducted extensively in the United States (64 studies), China (27 studies), and India (18 studies) under varied treatments, such as nonlimiting irrigation and fertilization; various irrigation water and fertilizer amounts, timings, and application methods; sowing dates; population densities; CO_2 concentrations; tillage methods; and management intensities (Fig. 1). Grain yield, aboveground biomass, leaf area index (LAI), anthesis, and maturity have been extensively tested. Variables regarding water balance (evapotranspiration and soil water content), nitrogen balance (soil nitrogen and crop nitrogen uptake and content), phonological stage (grain filling, silking, and panicle initiation), and other biomass components (leaf biomass, straw biomass, and shoot biomass; and harvest index) have been less extensively validated (Figs. 2–4).

3.1 Crop Phenology

3.1.1 CERES-Maize

The CERES-Maize model has been tested regarding sowing date (two studies), sprouting (one study), days from seedling emergence to the end of the juvenile stage (one study), leaf appearance (one study), flowering date

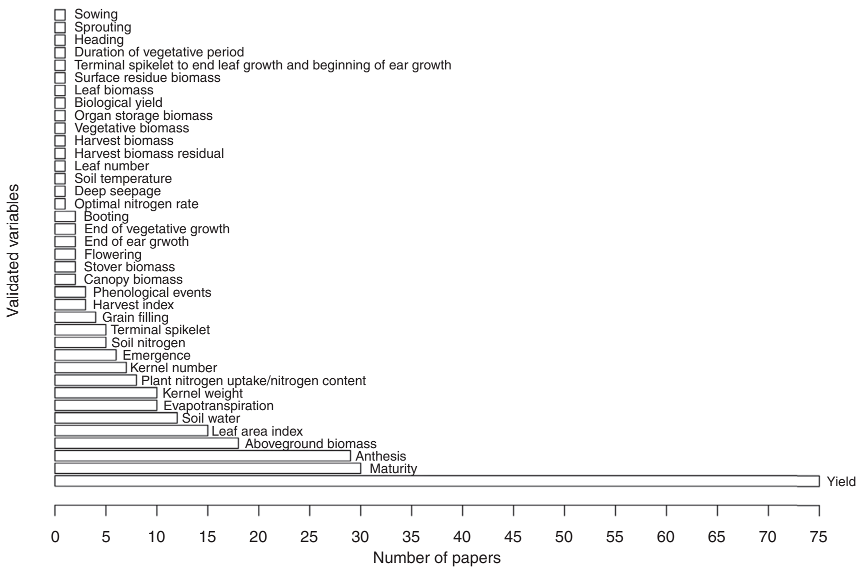

Figure 3 The number of research that validated variables in the CERES-Wheat.

(two studies), anthesis (nine studies), silking (13 studies), grain filling (two studies), silking to maturity (one study), maturity (19 studies), and growth duration (three studies) (Table 1 and Table 2). Strzepek et al. (1999) and Wang et al. (2012) showed that the simulated planting dates for maize grown in Iowa and Missouri (USA) and in one experimental maize station in China matched well with the recorded sowing dates, with at most 1 day of error. The predicted days from seedling emergence to the end of the juvenile stage in a 4-year simulation in Brazil were, on average, 3 days off from the observations (Liu, 1989). Hodges and Evans (1992) tested the leaf tip appearance variable and reported that the simulated days were delayed up to 15 days. Regarding the flowering date simulation, the RMSE was less than 4 days under the sowing date treatment in Portugal (Braga et al., 2008) and within 7 days of error in two US states (Strzepek et al., 1999). Anthesis date has been well predicted under full irrigation and moderate and severe water stress treatments in Italy, with simulation errors being within 6 days and percentage errors ranging from 0 to 2.8% (Ben Nouna et al., 2000; Mastrorilli et al., 2003). In Brazil, anthesis date simulations across irrigated and rain-fed conditions had a normalized RMSE of 1.6% (Soler et al., 2007). Under irrigated and rain-fed conditions in a county in Georgia (USA), with fertilization (141 ~ 219 kg N/ha application) and planting date (three dates across Mar.)

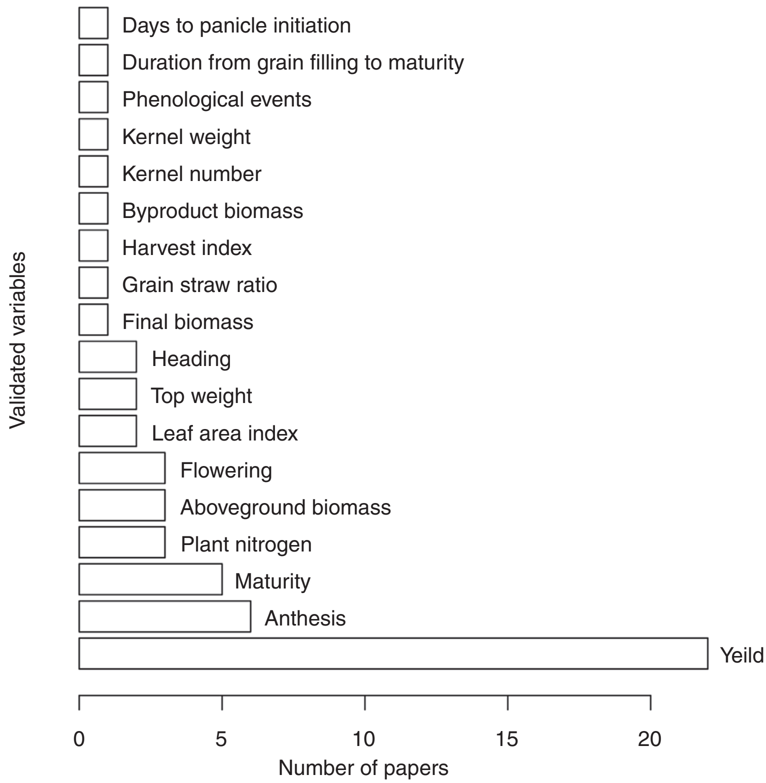

Figure 4 The number of research that validated variables in the CERES-Rice.

treatments, the anthesis date simulations were within 9 days of the measured data (Persson et al., 2009). The simulated days to anthesis for fertilizer trials in Ethiopia were within 7 days (Kassie et al., 2014). The CERES-Maize model has not only estimated anthesis date reasonably well for agriculture experimental stations for over 11 years in Georgia (RMSE = 3.5 days) and Louisiana (RMSE = 4.3 days) but also captured the inter-annual variability (Tsvetsinskaya et al., 2003). Under both irrigation and nitrogen application treatments in Iran and seven irrigation treatments in Pakistan, the days to anthesis simulations had a normalized RMSE of 2.3 ~ 2.6% and RMSEs of less than 2.2 days, respectively (Moradi et al., 2013, 2014; Mubeen et al., 2013). In terms of maize silking date simulation, the reported errors were within 4 days for simulations in Nigeria (Jagtap and Abamu, 2003; Jagtap et al., 1993), Brazil (Liu, 1989), and Venezuela (Maytin et al., 1995). The reported RMSEs were between 2 and 4 days for unfertilized maize

Table 1 Summary of the CERES-Maize model performances for phenology variable (excluding anthesis and maturity) simulations.

Treatment category	Variable name	Countries	Performance	References
Rain-fed/nonirrigated and well fertilized	Silking	Croatia	Percentage error: 1%	Vucetic (2011)
		Nigeria	Error: <3 days	Jagtap et al. (1993); Jagtap and Abamu (2003); Maytin et al. (1995)
		Venezuela		
Irrigated with a gradient of water/different scheduling time and well fertilized	Silking	United States, Italy	Differences: 0 ~ 4 days	Anothai et al., (2013); Ben Nouna et al. (2000)
		Australia	RMSE: 10.6 days	Carberry et al. (1989)
Well irrigated and fertilized with a gradient of fertilizer(s)	Silking	Nigeria	Differences: 0 ~ 14 days	Gungula et al. (2003)
	Grain filling date	Nigeria	Differences: 0 ~ 12 days	Gungula et al. (2003)
Well irrigated and well fertilized only[a]	Planting date	China	Difference: <1 day	Wang et al. (2012); Strzepek et al. (1999)
	Flowering	United States	Error: <7 days	Strzepek et al. (1999)
	Silking	United States	RMSE: 4 days	Retta et al. (1991)
		Argentina	RMSE: 6.5 days	Caviglia et al. (2013)
		China	Delay: 1 day	Wang et al. (2012)
	Grain filling	China	Error: 1 day	Wang et al. (2012)
	Growth duration	China	R: 0.99	Xiong et al. (2007)
	Silking to maturity	Brazil	Mean error: 0.5 days;	Liu (1989)
	Emergence to end of juvenile		Mean error: 3 days	
	Silking		Error: <4 days	
	Tip appearance	USA	Error: 15 days	Hodges and Evans (1992)

Irrigated with a gradient of water, not fertilized and other treatments	Flowering date	Portugal, Argentina, United States	RMSE: 6 ~ 8.26 days	Braga et al. (2008); Otegui et al. (1996); Tsvetsinskaya et al. (2003)
	Silking	Argentina	RMSE: 4.3 days	Otegui et al. (1996)
Sowing dates	Flowering	Portugal	RMSE: <4 days	Braga et al. (2008)
Planting dates, spacing	Silking	USA	RMSE: 2 ~ 3.4 days	Yang et al. (2009)
Planting dates, fertilization	Growth duration	Zimbabwe	Error: <3 days	Makadho (1996)

[a]Literature that did not include treatments were considered as "well irrigated and well fertilized"; for instance, data obtained from local reports.

Table 2 Summary of the CERES-Maize model performances for anthesis and maturity variable simulations.

Treatment category	Variables	Countries	Performance	References
Rain-fed/nonirrigated and well fertilized	Anthesis	Brazil	Normalized RMSE: 1.6%	Soler et al. (2007)
	Maturity	Nigeria, Croatia	Difference: 1 ~ 2 days Percentage error: 2%	Jagtap et al. (1993); Vucetic (2011)
		Nigeria	Differences: 7 ~ 10 days	Jagtap and Abamu (2003)
Irrigated with a gradient of water/different scheduling time and well fertilized	Anthesis	Italy	Percentage errors: 0 ~ 2.8%	Ben Nouna et al. (2003)
		Pakistan	RMSE: <2.2 days	Mubeen et al. (2013)
		Australia	RMSE: 10.6 days	Carberry et al., (1989)
	Maturity	United States, Nigeria	Differences: <5 days	Anothai et al. (2013); Gungula et al. (2003)
		Pakistan	RMSE: 3.7 days	Mubeen et al. (2013)
		Italy	Error: 0 day	Mastrorilli et al. (2003); Ben Nouna et al. (2000)
		Australia	RMSE: 10.2 days	Carberry et al. (1989)
Well irrigated and fertilized with a gradient of fertilizer(s)	Maturity	United States, China, Ethiopia	Difference: <1 day	Strzepek et al. (1999); Wang et al. (2012); Kassie et al. (2014)
	Anthesis	Ethiopia	Difference: <7 days	Kassie et al. (2014)

Well irrigated and well fertilized only[a]	Anthesis	Nigeria, Brazil, Venezuela, Argentina, United States, China, Iran	Difference: <4 days Normalized RMSE: 2.35%	Jagtap et al. (1993); Jagtap and Abamu (2003); Liu (1989); Maytin et al. (1995); Yang et al. (2009); Wang et al. (2012); Moradi et al. (2014)
	Maturity	China	Difference: 1 ~ 3 days	Wang et al. (2012)
		Argentina	RMSE: 14.3 days	Caviglia et al. (2013)
Irrigated with a gradient of water and fertilized with a gradient of fertilizer(s)	Anthesis	Iran	Normalized RMSE: 2.61%	Moradi et al. (2013)
		United States	Differences: 1 ~ 9 days	Persson et al. (2009)
	Maturity	Portugal United States	RMSE: <4 days Error: 1 ~ 9 days	Braga et al. (2008); Persson et al. (2009)
Other treatments[b]	Anthesis	United States	RMSE: 3 ~ 4 days Tsvetsinskaya et al. (2003)	
	Maturity	United States, Argentina	RMSE: <6 days	Yang et al. (2009); Otegui et al. (1996); Tsvetsinskaya et al. (2003)
			Difference: 9 ~ 11 days[c]	Strzepek et al. (1999)

[a]Literatures that did not include treatments were considered as "well irrigated and well fertilized"; for instance, data obtained from local reports.
[b]Other treatments included sowing dates, planting density, spacing.
[c]Authors pointed out that the large error might be due to the differences between simulated physiological maturity and observed grain maturity.

experiments in Argentina (Otegui et al., 1996) and sowing dates combined with spacing treatments in the USA (Yang et al., 2009). Seventy-five percent silking date simulations had RMSEs of 4 days in the United States (Retta et al., 1991) and an error of 1 day in China (Wang et al., 2012). While the good prediction of silking held for rain-fed conditions in Croatia (error: 1%) (Vucetic, 2011) and irrigation treatments in the United States (error: 0 ~ 4 days) (Anothai et al., 2013), the prediction was moderately accurate for nitrogen unavailability treatments in Nigeria (error of 0–14 days) (Gungula et al., 2003), well-irrigated and fertilized condition in Argentina (RMSE: 6.5 days) (Caviglia et al., 2013), and water stress treatments in Australia (Carberry et al., 1989). Regarding grain-filling validation, it was reported that the differences between the simulated and observed values were mostly 0 or 1 and sometimes up to 2 days under a high nitrogen application rate (90 or 120 kg/ha), but the difference was at least 4 days and sometimes up to 12 days under a low nitrogen application rate (60 kg/ha) in Nigeria (Gungula et al., 2003). Under irrigated treatments in China, the simulated grain filling date was only 1 day delayed as compared to the observed date (Wang et al., 2012). As to maize maturity, the simulated maturity date was reported to be very close to the observations across various sowing dates from May to Jun. in Venezuela (Maytin et al., 1995), across 40–100% full irrigation treatments in Colorado (USA) (Anothai et al., 2013), and under high fertilizer application rates (90 and 120 kg N/ha) in Nigeria (Gungula et al., 2003). Under water availability treatments in Italy, most simulated maturity dates were exactly the same as the observations (Ben Nouna et al., 2000; Mastrorilli et al., 2003). For fertilizer trials in Ethiopia, the difference between the simulated and the observed days to maturity was within 1 day (Kassie et al., 2014). Jagtap et al. (1993) and Vucetic (2011) also reported small errors in maturity date simulations under rain-fed treatments in Nigeria and Croatia, with 1 or 2 day differences and a 2% difference, respectively. The RMSEs for maturity simulations were within 6 days under the sowing dates between late-Apr. and mid-Jun. in treatments in Portugal (Braga et al., 2008), across irrigation treatments (irrigated at various rates and in various amount) in Pakistan (Mubeen et al., 2013), across four sowing date treatments in Argentina (Otegui et al., 1996), in agricultural stations in Georgia and Louisiana for over 11 years (Tsvetsinskaya et al., 2003), and at 11 locations in North Carolina (Yang et al., 2009). However, Carberry et al. (1989) and Caviglia et al. (2013) reported that the average RMSEs for maturity simulations across full irrigation and severe water stress treatments in Australia

(Carberry et al., 1989) and stress free conditions in Argentina (Caviglia et al., 2013) were over 10 days. Strzepek et al. (1999) and Jagtap (2003) reported that the simulation errors ranged from 7 days to 11 days in the United States and Nigeria, respectively (Jagtap and Abamu, 2003). Persson et al. (2009) simulated maize maturity dates across irrigated and rain-fed land with three levels of fertilization treatment and three planting date treatments in Georgia (USA), and the reported errors ranged from 1 to 9 days for three maize cultivars. Additionally, one study reported the days from silking to maturity in a 4-year study of a Brazilian maize cultivar and had a mean error of 0.5 days (Liu, 1989). The simulated growth durations matched the observations with high correlation coefficients of 0.99 for three production stations in China (Xiong et al., 2007) and less than 3 days of errors in Zimbabwe (Makadho, 1996).

3.1.2 CERES-Wheat

The CERES-Wheat model has been tested for sowing date (one study), sprouting (one study), emergence (six studies), booting (two studies), heading (one study), terminal spikelet (five studies), end of vegetative growth (two studies), end of year growth (two studies), duration of vegetative period (one study), flowering date (two studies), anthesis date (29 studies), grain filling date (four studies), mature date (30 studies), and other phenological events (five studies) (Tables 3–5). Sowing date and sprouting date were tested in Northwest China, with simulation errors of 0 and 2 days, respectively (Wang et al., 2012). Emergence date was tested under a well-irrigated and fertilized treatment with five sowing dates [day of year (DOY)125, 128, 129, 164, and 296] in New Zealand. Delays in the simulated emergence date of two wheat cultivars were observed, except for the DOY125 treatment simulation. The average RMSE for the emergence date of the two wheat cultivars was 12.1 days (Porter et al., 1993). With 110.5 and 241 kg N/ha application treatments in Arizona (USA), the 50% crop emergence date simulation was delayed by 1 day (Thorp et al., 2010b). Chipanshi et al. (1997) reported that the ratios between the simulated and observed emergence dates for 30 years in a long-term agricultural site in Canada were from 0.47 to 0.77 (Chipanshi et al., 1997). When the CERES-Wheat model was used to simulate spring wheat growth in 24 sites across North America, including the United States and Canada between 1930 and 1954, the days from sowing to 50% seedling emergence were underestimated for 94% of the sites, with a RMSE of 5.8 days. The model concordance correlation coefficient and bias correction factor were 0.232 and 0.396, respectively

Table 3 Summary of the CERES-Wheat model performances for phenology variable (excluding anthesis and maturity date) simulations.

Treatment category	Variables	Countries	Performance	References
Rain-fed/nonirrigated and well fertilized only	Emergence	Canada	23 ~ 53% earlier	Chipanshi et al. (1997)
	Terminal spikelet	Canada	36% earlier ~ 62% late	Chipanshi et al. (1997)
	End of vegetative growth	Canada	23% earlier ~ 44% late	Chipanshi et al. (1997)
	End of year growth	Canada	23% earlier ~ 43% late	Chipanshi et al. (1997)
	Grain filling	Canada	23% earlier ~ 41% late	Chipanshi et al. (1997)
Irrigated with a gradient of water/different scheduling time and well fertilized	Emergence	China	Difference: 0 days	He et al. (2013)
	Phenological events	India	RMSE: 4 days	Sarkar and Kar (2008)
Well irrigated and fertilized with a gradient of fertilizers	Emergence	United States	delay: 1 day	Thorp et al. (2010b)
	Phenological events	Canada	RMSE: 3.15 days	He et al. (2014)
Well irrigated and well fertilized[a]	Sowing date	China	Error: 0 day	Wang et al. (2012)
	Sprouting date		Error: 2 days	
	Emergence	United States	RMSE: 5.8 days	Wang et al. (2009)
		China	7 days earlier	Liu and Yuan (2010)
	Terminal spikelet	China	6 days earlier	Liu and Yuan (2010)
	End of vegetative growth	China	Difference: 1 day	Liu and Yuan (2010)
	End of year growth	China	Difference: 8 days	Liu and Yuan (2010)
	Flowering	China	R^2: 0.66	Zhao et al. (2011)
		China	Difference: <7 days	Wang et al. (2012)
	Grain filling	China	4 days earlier	Liu and Yuan (2010)
	Phenological events	China	RMSE: 5.6 days	
Sowing dates	Emergence	New Zealand	RMSE: 11 ~ 13.2 days	Porter et al. (1993)
	Booting	United States	RMSE: 5.3 days	Xue et al. (2004)
	Heading	United States	RMSE: 4.8 days	Xue et al. (2004)
	Terminal spikelet	New Zealand	15 days earlier ~ 19 days late	Porter et al. (1993)
		United States	RMSE: 4 ~ 7 days	Xue et al. (2004)

Sowing dates, fertilization treatments and wheat rotation systems	Duration of vegetative growth	Czech Republic	Error: 3 ~ 4 days	St'astna et al.2002
Sowing dates with varied temperatures	Duration of grain filling	United States	RMSE: <5 days	White et al. (2011)
CO_2 concentration	Booting	United States	2 days delay	Tubiello et al. (1999a)
	Terminal spikelet	United States	3 days earlier	Tubiello et al. (1999a)
	Grain filling	United States	1 day earlier	Tubiello et al. (1999a)
	Phenological events	Germany	Normalized RMSE: <15%	Biernath et al. (2011)
848 complied field dataset	Terminal spikelet to end of leaf growth	Germany	Error: <9.1 days	Johnen et al. (2012)

[a]Literatures that did not include treatments were considered as "well irrigated and well fertilized;" for instance, data obtained from local reports.

Table 4 Summary of the CERES-Wheat model performances for anthesis simulations.

Treatment category	Countries	Performance	References
Rain-fed/nonirrigated and well fertilized	Australia	Difference: <7 days	Alexandrov et al. (2002)
	United States, Australia	RMSE: 1 ~ 6 days	Xue et al. (2004); Thaler et al. (2012)
	United States	RMSE: ≥9 days	Xue et al. (2004)
Irrigated at varied rates (and timings) and well fertilized	China	Difference: 0 ~ 2 days	He et al. (2013)
	Argentina	RMSE: 2.7 days	Savin et al. (1994)
Well irrigated and fertilized at varied rates	United States	Difference: <10 days	Thorp et al. (2010b)
	India	RMSE: 5.3 days, normalized RMSE: 7%	Timsina et al. (2008)
Well irrigated and well fertilized[a]	United States, United Kingdom, Argentina, Czech Republic, China	RMSE: 4 ~ 8 days	Ottman et al. (2013); Bannayan et al. (2003); Caviglia et al. (2013); Trnka et al. (2004); Liu and Tao (2013)
	New Zealand	RMSE: 8 ~ 22 days	Porter et al. (1993)
	Italy	Normalized RMSE: 6 ~ 8%	Dettori et al. (2011)
	China	Error: ≤9 days	Xiao et al. (2013); Liu and Yuan (2010)
	China	Relative absolute error: <12%	Tian et al. (2012)

Irrigated with a gradient of water and fertilized with a gradient of fertilizer(s)	Mexico	Difference: 0 ~ 8 days	Lobell and Ortiz-Monasterio (2006)
	Spain, Bangladesh, India	RMSE: 4 ~ 7 days	Timsina et al. (1998); Abeledo et al. (2008)
Not irrigated and fertilized with a gradient of fertilizer(s)	United States	6 days earlier ~ 2 days late than the observations	Saseendran et al. (2004)
	Germany	Percentage error: <7%	Bacsi and Zemankovics (1995)
CO_2 concentration	United States	Difference: 1 day	Tubiello et al. (1999a)
		Normalized RMSE: 4%	Tubiello et al. (1999b),[b]
Sowing Date	Algeria, United States	RMSE: 4 ~ 5 days	Rezzoug et al. (2008); White et al. (2011)[c]
	India	Difference: ≤9 days	Hundal and PrabhjyotKaur (1997)
Spacing	United States	Average error: 0 days	Tsvetsinskaya et al. (2003)

[a]Literatures that did not include treatments were considered as "well irrigated and well fertilized"; for instance, data obtained from local reports.

[b]Treatments included CO_2 concentration (elevated vs. ambient) combined with two irrigation regimes (well irrigated vs. limit irrigated).

[c]Treatments included sowing dates combining with varied temperatures.

Table 5 Summary of the CERES-Wheat model performances for maturity simulations.

Treatment category	Countries	Performance	References
Rain-fed/nonirrigated and well fertilized only	Australia	RMSE: 2.1 days	Thaler et al. (2012)
Irrigated with a gradient of water/ different scheduling time and well fertilized only	Spain	15 days earlier[a]	Iglesias et al. (2000)
	Mexico	Difference: 7 days	Lobell and Ortiz-Monasterio (2006)
Well irrigated and fertilized with a gradient of fertilizer(s)	India	RMSE: 4.5 days, normalized RMSE 3.4%	Timsina et al. (2008)
Well irrigated and well fertilized[b]	Argentina, China	RMSE: <5 day	Caviglia et al. (2013); Liu and Tao (2013)
	United Kingdom, Czech Public	RMSE: 7.5 ~ 10 days	Bannayan et al. (2003); Trnka et al. (2004)
	China	Difference: <10 days	Liu and Yuan (2010); Xiao et al. (2013); Zhao et al. (2011); Tian et al. (2012); Wang et al. (2012); He et al. (2013)
	United Kingdom	R^2: 0.68	Cho et al. (2012)
Irrigated with a gradient of water and fertilized with a gradient of fertilizer(s)	Spain	RMSE: 11 days	Abeledo et al. (2008)
	Bangladesh	RSME: 2.3 days	Timsina et al. (1998)
Not irrigated and fertilized with a gradient of fertilizer(s)	United States	4 days earlier ~ 1 day delay	Saseendran et al. (2004)
	Germany	Difference: >15 days	Bacsi and Zemankovics (1995)

CO_2 concentration	United States	2 days delay	Tubiello et al. (1999a)
		Normalized RMSE: 4.3%	Tubiello et al. (1999b)
Sowing Date	India	6 days earlier ~ 3 days delay	Hundal and PrabhjyotKaur (1997)
	United States, Algeria	RMSE: <5 days	White et al. (2011)[,c], Rezzoug et al. (2008); Xue et al. (2004)
	United States	RMSE: 8 ~ 9 days	Xue et al. (2004)
	Pakistan	RMSE: 23 days	Sultana et al. (2009)
	United States	Difference: <10 days	Southworth et al. (2002)
Spacing	United States	Average error: 3 days	Tsvetsinskaya et al. (2003)

[a]The authors pointed out that the large difference was partly due to they counted harvest date as maturity date, instead of counting physiological maturity.
[b]Literatures that did not include treatments were considered as "well irrigated and well fertilized only"; for instance, data obtained from local reports.
[c]Treatments included sowing dates combining with varied temperatures.

(Wang et al., 2009). The emergence dates were perfectly simulated for wheat grown in arid Northwest China under nine irrigation treatments of various amounts and timings (He et al., 2013). However, the calibrated CERES-Wheat model simulated the emergence date as being 7 days earlier for winter wheat grown on six irrigated sites in China (Liu and Yuan, 2010). A booting date simulation was 2 days delayed under elevated CO_2 concentration (roughly 450–500 ppmv) in the Intensive Agricultural Biome of Biosphere 2 (Tubiello et al., 1999a) and had an average RMSE of 5.3 days for three wheat cultivars sown in early- and mid-Oct. (Xue et al., 2004). Xue et al. (2004) also reported that the mean RMSE between the observed and simulated heading dates was 4.8 days. The simulated terminal spikelet date was 6 days earlier in one of the irrigated wheat production regions in China (Liu and Yuan, 2010) and 3 days earlier under varied, elevated CO_2 concentrations (Tubiello et al., 1999a). Nonetheless, terminal spikelet emergence was up to 19 days late for one wheat cultivar, but up to 15 days earlier for the other under different sowing date treatments (Porter et al., 1993). A similar study with different planting dates and three wheat cultivars showed an average RMSE for terminal spikelet simulation of 6.2 days (Xue et al., 2004). The reported ratios of simulated and observed terminal spikelet in dry-land Canada ranged from 0.64 to 1.62 (Chipanshi et al., 1997). The end of vegetative growth and the end of year growth were studied using fertilized winter wheat field data in China and Canada. The test results for China indicated that the simulations were 1 and 8 days different from the observed end of vegetative growth and end of year growth, respectively (Liu and Yuan, 2010), and for Canada, the ratios between the simulations and the observations were $0.67 \sim 1.44$ and $0.67 \sim 1.43$, respectively (Chipanshi et al., 1997). The duration of the vegetative period was tested in two production regions in the Czech Republic, yielding underestimated results by 3 or 4 days (St'astna et al., 2002). The simulated flowering dates in wheat production stations in China were correlated with the observations ($R^2 > 0.6$) and were within 7 days of the observations (Wang et al., 2012; Zhao et al., 2011). The anthesis date was extensively tested under a wide variety of treatments and locations. The differences between the simulated and the observed anthesis dates were within 10 days with an elevated CO_2 concentration (about 440 ppmv) treatment (Tubiello et al., 1999a); irrigated fields in Mexico (Lobell and Ortiz-Monasterio, 2006), fertilization treatments in two states of the United States, Colorado (with $0 \sim 112$ kg N/ha application rates) (Saseendran et al., 2004) and Arizona (with 110.5 and 241.0 kg N/ha) (Thorp et al., 2010b); well-irrigated and fertilized experiments in Arizona, USA (Ottman et al., 2013); 15-year simulations in Austria (Alexandrov et al., 2002); and nine irrigation treatments in China (He et al., 2013). On average, the simulated anthesis date matched the observations for three experimental stations in South Carolina (USA) between 1991 and 1995 (Tsvetsinskaya et al., 2003). The average errors regarding the simulated anthesis date were within 7% across planting dates in late-Sep. and mid-Nov. (Nov. 10 and 16) when combined with high N rates (213 ~ 232 kg/ha) versus no N application in Germany (Bacsi and Zemankovics, 1995) and three sowing dates in Dec. in Algeria (Rezzoug et al., 2008). The average RMSEs were within 8 days under different water availability treatments combined with various nutrient availability experiments in Bangladesh (Timsina et al., 1998) and Spain (Abeledo et al., 2008), four sites in the United Kingdom (Bannayan et al., 2003), rain-fed fields in Nebraska (Xue et al., 2004), no water or nutrient stress conditions in Argentina (Caviglia et al., 2013), rotation cropping systems with different irrigation schedules and nitrogen application rates in India (Timsina et al., 2008), five wheat production stations in the Czech Republic (Trnka et al., 2004), elevated temperature combined with various sowing dates (White et al., 2011), and dry areas in Northeastern Austria (Thaler et al., 2012). The simulated anthesis dates were within the normalized RMSE of 8% for three wheat varieties in Italy (Dettori et al., 2011) and under an elevated CO_2 concentration treatment (Tubiello et al., 1999b). Nonetheless, two studies reported less accurate anthesis simulations under well-irrigated and fertilized conditions in New Zealand and India, with RMSEs of up to 22 days (Porter et al., 1993) and up to 9 days of error (Hundal and PrabhjyotKaur, 1997), respectively. When applying the CERES-Wheat model to wheat production stations in China, the simulated anthesis dates were within 4.5% error for four of the stations (Liu and Tao, 2013) and less than 5 days for eight of the stations (Xiao et al., 2013). Using 36 wheat observation stations and 42 cropping zones in China, Tian et al. (2012) reported errors of 6.5% for winter wheat and of 12% for spring wheat (Tian et al., 2012). In contrast, Liu and Yuan (2010) reported that the simulated anthesis date was 9 days earlier for winter wheat in the Southern North China Plain. In addition, the root mean square error for the wheat anthesis date simulation in adequate water availability versus early drought experiments was reported to be 2.7 days in Argentina (Savin et al., 1994). For a grain filling simulation, the beginning of the grain filling date was 1 day earlier than the observation under elevated CO_2 concentration conditions (Tubiello et al., 1999a) and, on average, 4 days earlier for four wheat production stations in China (Liu and Yuan, 2010). Chipanshi et al. (1997) reported that the simulated to observed beginning of grain filling date ratios were from 0.77 to 1.41 over 30 years for a long-term experiment site in Canada. In a heated environment with varying sowing dates, the simulated duration of grain filling showed less than 5 days RMSE (White et al., 2011). Wheat maturity date has been intensively tested under various treatments and locations as well. Under a variety of growing conditions, RMSEs for maturity simulation were less than 11 days. Those conditions and treatments included a combination of water stress (irrigated vs. rain-fed) and nutrient stress (with vs. without nitrogen application) in Spain (Abeledo et al., 2008); water- and nutrient-stress-free fields in Argentina (Caviglia et al., 2013); a heated environment (White et al., 2011); four locations over 3 years in the United Kingdom (Bannayan et al., 2003); five wheat production stations in the Czech Republic (Trnka et al., 2004); wheat rotated with rice or maize or soybean in various soils (Timsina et al., 2008); four wheat stations in China (Liu and Tao, 2013); six irrigated wheat production stations in the North China Plain (Liu and Yuan, 2010); nine wheat cultivars sown on three dates in Dec. (Rezzoug et al., 2008); eight planting dates ranging from Aug. 24 to Nov. 3 with seeding rates of 151, 301, 452, and 603 seeds/m^2 in Wisconsin (Dahlke et al., 1993; Southworth et al., 2002); eight winter wheats in the North China Plain (Xiao et al., 2013), early- and mid-Oct. sowing dates in fertilized plots in Nebraska (Xue et al., 2004); two locations Henan Plain in China (Zhao et al., 2011); winter wheat in dry regions in Austria for 9 years (Thaler et al., 2012); combinations of two water regimes (well-irrigated and rain-fed) and three nitrogen application regimes (0, 90, and 135 kg/ha) in Bangladesh (Timsina et al., 1998); and fertilized fields with various spacings in the Southeastern United States (Tsvetsinskaya et al., 2003). Studies in China showed a well-simulated maturity date. One study showed that in 36 production stations in China over 38 years, the relative absolute errors for both winter wheat and spring wheat were within 10 days (Tian et al., 2012), and two other studies showed that the errors were within 2 days in their studied regions (He et al., 2013; Wang et al., 2012). Under fluctuating and elevated CO_2 concentrations (about 440 ppmv) (Tubiello et al., 1999a), sowing dates ranging from DOY310 to DOY354 (Hundal and PrabhjyotKaur, 1997), and fertilization application treatments (0 ~ 112 kg N/ha) in rain-fed fields in the United States (Saseendran et al., 2004), the simulated maturity dates were within 7 days of error. Furthermore, the normalized RMSE was reported to be 4.3% for a maturity simulation performed with a 550 ppm CO_2 concentration treatment (Tubiello et al., 1999b). However, the differences between the simulation and the observation were over 15 days for both fertilized (with 213 ~ 232 kg N/ha rate) and unfertilized wheat maturity simulations in four sites in Germany (Bacsi and Zemankovics, 1995), experimental trials in Pakistan (Sultana et al., 2009), and wheat production sites in Spain (Iglesias et al., 2000). Lobell and Ortiz-Monasterio (2006) indicated that in a no-water-stress situation, the CERES-Wheat simulated maturity date was exactly the same as the observed one, while in a water-stress situation, the difference between the simulation and the observation was up to 7 days. In addition, Cho et al. (2012) reported a high correlation ($R^2 = 0.68$) between the observed and simulated maturity dates. Monzon et al. (2007) reported that the RMSE for simulating both anthesis and maturity in multiple fields in Argentina was 4.9 days. The overall phenological stage was tested in six irrigated wheat production sites in China and with ambient versus elevated CO_2 concentrations combined with irrigation treatments (adequate vs. limited water supply); this resulted in an RMSE of 5.6 days (Liu and Yuan, 2010) and a normalized RMSE of up to 15% (Biernath et al., 2011), respectively. The phenological event simulations had RMSEs of 3 ~ 4 days given rice residue treatment (removed vs. remained) with irrigation treatment (Sarkar and Kar, 2008) and under various soils with fertilizer applications in Canada (He et al., 2014). Nonetheless, a study using 848 field datasets in Germany showed that the average difference between the simulated and observed period from terminal spikelet development to the end of leaf growth and the beginning of year growth could be as large as 9.1 days (Johnen et al., 2012).

3.1.3 CERES-Rice

The CERES-Rice model has been tested for heading (two studies), flowering (three studies), anthesis (seven studies), maturity (six studies), days from panicle initiation and grain filling to maturity (two studies), and phenological events (one study). Yun, (2003) tested the duration from transplanting to heading in two crop experiment stations in Korea and reported that the simulation was in good agreement with the observations, with an R^2 of 0.85. Zhang et al. (2013) reported that the RMSEs were within 5 days for a heading date simulation in single- and double-season rice zones in China. Rice flowering duration was tested with 32 field experiments combining various seeding and transplanting dates, planting densities, nitrogen fertilizer rates, and levels of irrigation across India and eight rice ecological stations in China, with reported RMSEs of 4.5 days (Mall and Aggarwal, 2002) and 5.5 days (Yao et al., 2007), respectively. The simulated days to flowering were within 5% error for four rice varieties under fertilization treatments ($0 \sim 150$ kg N/ha rates and different timings) in Thailand (Cheyglinted et al., 2001). The anthesis date has been tested with five irrigation levels between 625 and 1225 mm and a seedling density between 1 and 3 seedlings per hill in Pakistan, and the simulated anthesis date was only 1 day earlier than the observed date (Ahmad et al., 2012). In contrast, the percentage error for the simulated anthesis dates given a late-Aug. seeding date treatment was 6.85% (Babel et al., 2011). The anthesis date has also been tested with water availability treatments combined with various nutrient availability experiments in Bangladesh (Timsina et al., 1998), six rice production areas in China (Tao et al., 2008), conventionally tilled soil with residual removal and direct-seeding, mulch-based cropping systems combined with manure, NPK[1], and dolomite fertilizer applications in Madagascar (Gerardeaux et al., 2011), with RMSEs ranging from 4.2 to 8.2 days. In addition, the differences between the simulated and observed days to anthesis under open field and elevated CO_2 treatments were between 2 and 4 days (Satapathy et al., 2014). The inter-annual variability of the rice anthesis date for three agricultural experiment locations in the Southern US was well-reproduced by the CERES-Rice model (Tsvetsinskaya et al., 2003). The simulated maturity dates matched perfectly with the observations under irrigation and planting density treatments in Pakistan (Ahmad et al., 2012). The reported RMSEs for maturity date simulations were within 10 days for tillage treatments in Madagascar (Gerardeaux et al., 2011), six rice production stations in China (Tao et al., 2008; Zhang and Tao, 2013), and irrigation combined with fertilization treatment in Bangladesh (Timsina et al., 1998). Over 500 experimental rice stations in China, the RMSE for maturity simulation ranged from 10 to 25 days (normalized RMSE: $6.5 \sim 19.8\%$) (Xiong et al., 2008b). The simulated days to the appearance of panicle initiation, flowering and maturity matched well with the observations given varying nitrogen application rates ($0 \sim 150$ kg/ha) in India, resulting in $3 \sim 5$ days of errors (Swain and Yadav, 2009). The simulated period from grain filling to maturity was reasonably accurate and correlated with the observations ($r^2 = 0.72$) in Korea (Yun, 2003). Phenological events were tested with transplanted and direct-seeded rice with wheat residue and various nitrogen input treatments in rain-fed fields in India. The RMSEs for the phenological event simulations were $4 \sim 5$ days and $10 \sim 11$ days for transplanted and direct-seeded rice, respectively (Sarkar and Kar, 2008). A summary of the phenological variable validations for the CERES-Rice model can be found in Table 6.

[1]NPK: 11% N, 22% P_2O_5, 16% K_2O (Gerardeaux et al., 2011).

Table 6 Summary of the CERES-Rice model performances for phenology variable simulations.

Treatment category	Variables	Countries	Performance	References
Rain-fed/nonirrigated and well fertilized	Anthesis	Thailand	Percentage error: 6.85%	Babel et al. (2011)
Well irrigated and fertilized with a gradient of nitrogen inputs	Flowering	Thailand	Percentage error: <5%	Cheyglinted et al. (2001)
	Maturity	India, China	Error: within 3 ~ 5 days RMSE: 10 ~ 25 days	Swain and Yadav (2009); Xiong et al. (2008b)
Well irrigated and well fertilized[a]	transplanting to heading	Korea	R^2: 0.85	Yun (2003)
	Grain filling to maturity		R^2: 0.72	
	Heading date	China	RMSE: 5 days	Zhang and Tao (2013)
	Flowering duration	China	RMSE: 5.5 days	Yao et al. (2007)
	Anthesis	China	RMSE: 5.6 days	Tao et al. (2008)
	Maturity	China	RMSE: 2 ~ 6.6 days	Zhang and Tao (2013); Tao et al. (2008)
Irrigated with a gradient of water and fertilized with a gradient of nitrogen	Anthesis	Bangladesh	RMSE: 4.3 days	Timsina et al. (1998)
	Maturity	Bangladesh	RMSE: 2.3 days	Timsina et al. (1998)
Over 80 treatments[b]	Flowering duration	India	RMSE: 4.5 days	Mall and Aggarwal (2002)
Fertilized, irrigated with varied amount of water and planted with varied densities	Anthesis	India	Difference: 0 ~ 1 day	Ahmad et al. (2012)
	Maturity	India	Difference: 0 day	Ahmad et al. (2012)

(*Continued*)

Table 6 Summary of the CERES-Rice model performances for phenology variable simulations.—cont'd.

Treatment category	Variables	Countries	Performance	References
Management intensities[c]	Anthesis	Madagascar	RMSE: 8.2 days	Gerardeaux et al. (2011)
	Maturity	Madagascar	RMSE: 10.2 days	Gerardeaux et al. (2011)
Varied planting dates and nitrogen inputs	Anthesis	United States	Very accurate	Tsvetsinskaya et al. (2003)
Open field and elevated CO_2	Anthesis	India	2 ~ 4 days	Satapathy et al. (2014)
	Maturity		3 ~ 11 days	Satapathy et al. (2014)
Direct seeded and transplanted rice	Phonological events	India	RMSE: 4 ~ 11 days	Sarkar and Kar (2008)

[a]Literatures that did not include treatments were considered as "well irrigated and well fertilized"; for instance, data obtained from local reports.
[b]Treatments included varied seeding and transplanting dates, planting densities, spacing, nitrogen inputs and irrigations.
[c]Management practices included conventional tillage with residual removal and direct seeding mulch-based cropping system, and fertilized with manure, NPK and dolomite combinations.

3.2 Grain Yield

There were a total of 140 studies on the yield tests for the CERES models. The models have been tested under various experimental conditions, including well-managed fields with adequate irrigation and fertilization application and management treatments such as contrasting irrigation and fertilization application, varied sowing dates and population density, various planting methods, and various tillage methods and CO_2 concentrations. In general, the simulated grain yield matched reasonably well with the observed data, with RMSEs under 1400, 1200, and 800 kg/ha for maize, wheat, and rice yield simulations, respectively.

3.2.1 CERES-Maize

Eighty-four studies have validated CERES-Maize grain yield simulations under a range of conditions. Overall, the average RMSEs for grain yield simulations were mostly ranged between 200 and 1400 kg/ha.

With adequate nitrogen input (240 and 401 kg N/ha) treatments in Florida, US, the RMSE for the maize yield simulation ranged from 305.6 to 539.5 kg/ha (Lizaso et al., 2011). Under well-irrigated and fertilized conditions in Iowa, Louisiana, North Carolina, and Colorado (US), the average RMSEs for the yield simulation were about 1000 kg/ha (Saseendran et al., 2005; Thorp et al., 2007; Tsvetsinskaya et al., 2003; Yang et al., 2009). The average normalized RMSE for eight maize cultivars under irrigated and fertilized treatments in Iran was 3.55% (Moradi et al., 2014). In contrast, the reported RMSEs were from 1315 to 2194 kg/ha in Georgia (US), Spain, and in a wheat-soybean-maize rotation system in Argentina (Caviglia et al., 2013; López-Cedrón et al., 2005; Tsvetsinskaya et al., 2003). Nonetheless, Tsvetsinskaya et al. (2003) and López-Cedrón et al. (2005) reported that the errors were less than 4% for yield simulations in the United States. Basso et al. (2007) also reported RMSEs around 2000 kg/ha for a whole field, high-yield zones, and low-yield zones. The average RMSE for simulating five maize production stations in China was 1347.6 kg/ha, but the error was within 20% (Tao and Zhang, 2010). Liu (1989) also reported that the error for a 4-year maize yield simulation in Brazil ranged from 10 to 21%, depending on the soil water initialization. Epperson et al. (1993) showed that for an irrigated field, the simulated yield was not significantly different from the observed yield at a 1% significance level. The differences between simulated and observed maize yields were within 600 kg/ha for 2-year simulations in China and 30-year simulations in Nigeria (Jagtap and Abamu, 2003; Wang et al., 2012). Studies in two locations in Zimbabwe and a sheltered intercropping system in the United States showed that the simulation errors were within 9% (Makadho, 1996; Mize et al., 2005). The simulations for six locations in Southern Québec, Canada were mostly within 7.7% for overestimation, but the error could be up to 82.2% for underestimation (Brassard and Singh, 2007). The simulated maize yield in experimental stations in Bulgaria was close to the measured yield (Alexandrov and Hoogenboom, 2000). Wang et al. (2011) and Ye et al. (2012) showed that the CERES models were able to capture spatial grain yield variation in China. Link et al. (2006) and Paz et al. (1999) also showed that the CERES model could explain 60% of spatial maize yield variability for over 5 years in Germany and 57% of temporal and spatial yield variability in a farm in the United States, respectively. On a regional scale, the simulated maize yield for over 30 years in a county in Indiana, US, was not significantly different from that in the report ($p = 0.05$) (Andresen et al., 2001). Heinemann et al. (2002) indicated that the grain yield simulation in Brazil was acceptable on a regional scale. The average root mean square deviations (RMSDs) for yield simulations at a county level for over 9 years in nine states in the United States ranged between 610 and 1520 kg/ha, with R^2 values from 0.05 to 0.8 (Kiniry et al., 1997). Weak correlations ($r \leq 0.7$) between the simulated and the recorded yield at the county level have been reported for Panama (Ruane et al., 2013) and the United States (Dhakhwa et al., 1997).

Studies have also tested grain yield under both nutrient and water stress conditions (ie, the treatment had contrasting irrigation and fertilization applications or had no nitrogen or no irrigation input). Examining four levels of nitrogen addition ranging between 20 and 280 kg/ha combined with two irrigation treatments involving fixed- versus variable-deficit trigger schedules, Pang et al. (1998) found that the simulated grain yields matched well with the observations for only the 20 and 100 kg N/ha treatments, not for the 180 and 280 kg N/ha treatments; the modeled grain yield was about 1.5 Mg/ha higher than the observed yield. Others, however, demonstrated that the CERES model was able to simulate grain yield accurately across a range of nutrient treatments (zero to high fertilizer input) combined with a range of irrigations, with an average RMSD under 360 kg/ha (Binder et al., 2008), average normalized RMSEs of 5.3% (Moradi et al., 2013), and an R^2 of 0.936 (Pang et al., 1997). Persson et al. (2009) showed that the simulation errors were 0.55 ~ 27.9% for irrigated and rain-fed maize with fertilization and planting date treatments. Sadler et al. (2000) indicated that under rain-fed conditions in South Carolina, US, with a nitrogen input of

0 ~ 220 kg/ha and a planting density of 0 ~ 15 plants/m^2, the simulated yield matched the measured yield reasonably well for some years, but not for other years.

The CERES models have also been tested given sufficient nutrients and varied available water conditions. The available soil water ranged between 30 and 75% of the maximum allowable depletion treatment. Panda et al. (2004) reported that the average RMSDs for wheat and maize grain yield simulation were under 250 kg/ha. With rain-feeding and 116 kg N/ha application treatments in Florida, the RMSE for the simulated maize yield was 290.8 kg/ha (Lizaso et al., 2011). Given irrigation treatments from optimum to moderate water stress in Pakistan, the RMSEs associated with the simulated yield for 2 years were under 560 kg/ha (Iqbal et al., 2011). Across six irrigation treatments involving 40 ~ 100% full irrigation in Colorado, US, the average normalized RMSE was under 10% (Anothai et al., 2013). Across irrigated and dry land in nine towns in Texas, US, and two irrigation treatments (with 421 and 609 mm irrigation) in Spain, the RMSEs ranged from 630 to 2140 kg/ha (Dechmi et al., 2010; Kiniry and Bockholt, 1998). Furthermore, across well-irrigated versus severe water shortage treatments in Australia and in a rain-fed treatment in Spain, the reported average RMSDs were over 3000 kg/ha (Carberry et al., 1989; López-Cedrón et al., 2008). By comparison, across three water-availability treatments (no, moderate, and severe water stress), the percentage errors were within 24%, and the simulations were more accurate for no-water-stress treatment (<12% error) than for moderate and severe water-stress treatments (>15%) (Ben Nouna et al., 2000; Mastrorilli et al., 2003). A similar pattern has been reported for experiments regarding water-stress versus sufficiently irrigated treatments in Pakistan (Mubeen et al., 2013). The reported average percentage errors for simulated maize yield on irrigated and dry land in the Corn Belt of the United States were within 10% (Hodges et al., 1987; Xie et al., 2001). The grain yield simulation was better in irrigated land than in rain-fed land for four maize hybrids in Brazil as well. The average normalized RMSDs were 3.78 and 8.29% for irrigated and rain-fed maize, respectively (Soler et al., 2007). Interestingly, another study of five rain-fed maize production stations in the North China Plain found that the model underestimated maize yield in dry years with percentage errors of 11 ~ 64% and overestimated the yield in wet years with percentage errors of 26 ~ 55.4% (Wu et al., 1989). Under rain-fed conditions, three studies reported reasonably accurate yield simulations, with errors of 5 kg/ha for 1 year and 357 kg/ha for the other year in Nigeria (Jagtap et al., 1993), an underestimation within 10% in Croatia (Vucetic, 2011), and good matching between simulated and observed yields for three sites in Venezuela (Maytin et al., 1995). For a rain-fed maize yield simulation on a regional scale in China, the reported RMSD was 1898 kg/ha, and on a farm scale, the simulated yield was highly correlated ($R^2 = 0.96$) with the observations in four rain-fed maize production stations (Xiong et al., 2007). For rain-fed fields in the Czech Republic, the simulated yield was within 17% error, and ignoring simulations with unusual weather, the simulations were within 12% error (Žalud and Dubrovský, 2002). In rotational rain-fed fields in Canada with tile drainage versus controlled tile drainage-subsurface irrigation treatments, the model efficiencies were 0.987 and 0.998, respectively, and the average normalized RMSDs were 14 and 4.3%, respectively (Liu et al., 2011). Tubiello et al. (2002) indicated that the simulated maize yield matched reasonably well with the observed yield under rain-fed conditions in five US states. Saseendran et al. (2008) tested the model using 3 years of grain yield measurements in Colorado, US, under both line-source sprinkler irrigation (with 23 ~ 106 mm, 72 ~ 188 mm, and 46 ~ 299 mm water) and rain-fed treatments. The authors reported that the simulated RMSDs were 982 and 576 kg/ha for irrigation and rain-fed treatments, respectively. DeJonge et al. (2012) also reported that the model simulated fully irrigated grain yield more accurately than limit-irrigation grain yield, with 2.47% relative error for the full-irrigation yield simulation and 12.90% for the limit-irrigation yield simulation. By contrast, DeJonge et al. (2011) simulated grain yield under adequate water and limited water treatments on the same experimental location and reported relative errors of 4.1 and 3.4% for full irrigation and limited irrigation, respectively. The grain yield simulation for an experiment with 100%-, 75%-, and 50%-full irrigation treatments in Turkey also showed that the model underestimated grain yield by 4.9, 1.7, and 9.4%, respectively, 1 year and by 4.6, 3.8and 2.3%, respectively, another year (Gercek and Okant, 2010). The reported mean errors for simulated grain yields at three sites for 3 years were 850, 933.3, and 333 kg/ha for 50%-, 75%-, and 100%-full irrigation treatments, respectively (Dogan et al., 2006). In the same research, the model was tested for overirrigated treatments as well. Given 65%-, 100%-, and 135%-full irrigated treatments for 3 years, the mean errors associated with the simulated yields were 1400, 600, and 3250 kg/ha, respectively (Dogan et al., 2006). One study in Spain considered wind speed's effect on irrigation and compared the grain yield simulations for nighttime irrigation and daytime irrigation (Salmerón et al., 2012). The reported RMSDs for the night irrigation treatment were around 1000 kg/ha for 3 years, while the RMSDs for the daytime irrigation treatment were over 1200 kg/ha for 2 years and 935 kg/ha for another year (Salmerón et al., 2012). Additionally, the simulated maize yield was highly correlated ($R^2 = 0.66$) with the reported provincial yield under primary rain-fed conditions in South Africa (Estes et al., 2013).

With fully irrigated but varying nutrient applications between 0 and 140 kg/ha, the average RMSDs in both summer and spring maize yield simulations were 350 kg/ha lower in China (Binder et al., 2008). In Florida, US, without nitrogen fertilizer application, the RMSE for the simulated grain yield was 116.7 kg/ha (Lizaso et al., 2011). When three nitrogen input rate (300 ~ 400 kg N/ha) and two sowing date (Oct. 15 and Nov. 15) treatments were applied to two maize cultivars in Chile, the average RMSE of the simulated yield was 691 kg/ha (Meza et al., 2008). Two model tests with nitrogen treatments of 0 ~ 150 kg/ha and 0 ~ 250 kg/ha in Thailand and Hungary, respectively, indicated that the simulated grain yields were close to the observations, except for those without the nitrogen addition treatment (Asadi and Clemente, 2003; Kovacs et al., 1995). Miao et al. (2006) also showed that with fertilization treatments (112 ~ 336 kg N/ha applications), the simulation errors were mostly within 10%, while in a no-fertilization treatment, the absolute errors were over 20%. In China, maize yield simulations given 0 and 165 kg N/ha application rates had normalized RMSEs of 32 and 23%, respectively (Yang et al., 2013). Similarly, in Canada, while the normalized RMSE for continuous maize with fertilization application treatment was 6%, the normalized RMSE for maize without fertilization application was 37% (Liu et al., 2014). In Ethiopia, with fertilizer addition treatments between 0 and 100 kg/ha, the model overestimated maize yield by about 300 kg/ha (Kassie et al., 2014). A study using 50 years of experimental data reported that the grain yield simulations for maize in fertilized (side-dress nitrogen of 112 kg/ha) versus nonfertilized fields showed a much higher normalized RMSD in the non-fertilized field (82%) than in the fertilized field (39%) (Liu et al., 2010). O'Neal et al. (2002) pointed out that the low correlation ($R^2 = 0.33$) between the observed and simulated grain yields given 127 ~ 227 kg N/ha application treatments was due to lower levels of fertilizer application in the treatments used. The normalized RMSDs found in the maize grain yield simulation across 0 ~ 400 kg/ha nitrogen application treatments in China were small as well (within 15%) (Liu et al., 2012). In Thailand, using a treatment with mineral fertilizer application rates and four compost fertilizer rates (0 ~ 7500 kg/ha), the grain yield was relatively well-simulated in the second and third years (normalized RMSE of 11.1 ~ 16.9% and an index of agreement over 0.55) but poorly simulated in the fourth and fifth years (normalized RMSE of 62.8 ~ 107.0% and an index of agreement below 0.45) (Pinitpaitoon et al., 2011). A study in Burkina Faso simulating grain yields given no, inorganic, and organic nitrogen inputs showed that the simulated yield was 667 kg/ha higher than the observed yield (Soler et al., 2011). In addition, with fertilization rates of 60 ~ 120 kg N/ha, the simulated yields were lower at 60 kg N/ha but higher at 120 kg N/ha compared to the observed yield (Jagtap et al., 1999).

Other test conditions included various sowing dates, planting densities, tillage methods, planting methods, soil types, CO_2 concentrations, leaf defoliation, and winter cover crops. Simulating various hybrid maize yields using four sowing dates in India (Jun. with 10-day intervals between sowing dates) and Argentina (Aug. 20 ~ Nov.), the average RMSDs were 559 and 3670 kg/ha, respectively (Otegui et al., 1996; Ramawat et al., 2012). In the historical field data for sowing date treatments in Illinois, US, the simulated yield reflected the inter-annual yield variation, and the errors were within 10% (Southworth et al., 2000). In Iran, a validation study was conducted with three maize cultivars and seven planting densities (3, 5, 7, 9, 11, 13, and 15 plants/m^2), and it showed that the average normalized RMSD was within 9% (Lashkari et al., 2011). However, a study simulating maize yield with 0 ~ 24 plants/m^2 density at two sites in North America showed that the model did not capture yield reduction in response to the increased planting density at both sites (Ritchie and Alagarswamy, 2003). The reported normalized RMSDs for simulated yield in China were 9, 16, and 23% for conventional tillage, reduced conventional tillage, and no tillage, respectively (Liu et al., 2013). Hook (1994) reported that the grain yield in four types of soil in Georgia, US, was overestimated by 260 kg/ha on average and that the error ranged between an underestimation of 1680 kg/ha and an overestimation of 1120 kg/ha. The grain yield simulation was also tested under nutrient stress combined with tillage method treatments. One research project used 4-year datasets from maize fields under conventional, rational, and dish harrow tillage with various fertilizer applications (including calcium chloride, single super-phosphate, and calcium ammonium nitrate) and calculated the mean absolute errors as 547, 645, and 1030 kg/ha, respectively, for each tillage treatment (Samuhel and Siska, 2007). With a 66% leaf defoliation rate at leaf stages 6 and 12, the CERES-Maize model yield prediction was less than desirable, with absolute percentage errors of 14 ~ 34% (Weiss and Piper, 1992). In general, the simulated maize grain yield matched well with the observed maize yield across no-cover crop treatments and winter cover crop (barley, oilseed rape, winter rape, and vetch) treatments in Spain, with RMSEs ranging from 530 to 2720 kg/ha (Salmerón et al., 2014).

3.2.2 CERES-Wheat

The model has been validated under a range of conditions, such as irrigation, fertilization, sowing date, and tillage treatments.

Under irrigated and fertilized conditions, the simulated wheat yield accurately depicted the wheat yield trends for several rice-wheat sites in India (Subash and Mohan, 2012). Several studies of wheat production showed that the simulated grain yield matched the observed yield well, with low RMSEs (RMSE: 175 ~ 588.6 kg/ha), low errors (error: <500 kg/ha), and high correlations of determination (R^2: 0.9) (Liu and Tao, 2013; Liu and Yuan, 2010; Wang et al., 2012; Zhang et al., 2013; Zhao et al., 2011). Nonetheless, a large RMSE of 897 kg/ha was reported when comparing the simulated grain yield for 141 wheat stations in China and the consensus yield (Xiong et al., 2008a). In general, the model accurately simulated wheat yields for fertilized wheat fields in Italy (RMSEs: <950 kg/ha) (Basso et al., 2007, 2009), two sites in Canada over 30 years (R^2: 0.7) (Chipanshi et al., 1999), the Pampas (RMSE: 410 kg/ha, R^2: 0.86) (Savin et al., 1995), wheat production stations in Bulgaria (the observations and simulations were scattered around a 1:1 line) (Alexandrov and Hoogenboom, 2000), four sites in the United Kingdom and five stations in the Czech Republic (RMSE: ≤ 930 kg/ha, percentage error: 8.7%) (Bannayan et al., 2003; Trnka et al., 2004), and a site in Austria over 15 years (percentage error: <17%) (Alexandrov et al., 2002). The simulated grain yield was moderately well-matched with the observed yield for three durum wheat cultivars in Italy (average normalized RMSE of 27%) (Dettori et al., 2011), eight sites in Canada over 30 years (percentage error: <28%, with one exception of 58.4%) (Brassard and Singh, 2007), and eight sites in Europe (RMSE: 1603 kg/ha, agreement index: 0.74) (Palosuo et al., 2011). In general, the simulated wheat grain yield for four counties in the United States over more than 4 years matched well with the observations, with R^2 values ranging between 0.4 and 0.72 (Rosenzweig and Tubiello, 1996). In India, the modeled irrigated wheat grain yield was significantly different from the observed yield, but the yearly yield fluctuation was well-simulated (Lal et al., 1998). Tian et al. (2012) reported that the percentage error in grain yield simulation for 36 wheat production stations in China ranged from 11.6 to 33.6%, depending on the calibration methods.

Across available soil water from 10 to 60%, combined with four ratios of $N:P_2O_5:K_2O$ fertilizer application (0, 80:40:40, 120:60:60, and 160:80:80) treatments, the average RMSDs were under 250 kg/ha, with a model efficiency of 0.95 (Behera and Panda, 2009). When simulating grain yield under both fertilizer application and irrigation treatments (five levels of nitrogen addition of 0 ~ 150 kg N/ha and irrigation 2 ~ 4 times per growing season), the CERES model performed the worst (absolute percentage deviation of 66.45%) when the crop was under the extreme conditions of low irrigation and no fertilization application, while it performed much better (absolute percentage deviation ranging between 0.38 and 12.9%) when the crop was at least fertilized with over 60 kg/ha nitrogen (Singh et al., 2008). Polilaities and Lazauskas (2010) simulated wheat grain yield in two experiments, one with 60 kg N/ha applied at various growing stages, and the other with various management intensities, and they concluded that the CERES model accurately simulated grain yield given 60 kg N/ha fertilizer addition treatment in the years without water shortage but that the accuracy declined when there was a water shortage or the plot did not receive nitrogen. In China, across treatments and with various levels of fertilization and irrigation, the normalized RMSE for gain yield was 5% (Ji et al., 2014). With fertilizer treatment and extreme conditions of both drought and nutrient deficit, the bias errors were 0.31, 0, and 0.74 for nonfertilized, fertilized at 45 kg N/ha, and extreme conditions, respectively (Touré et al., 1995). In experiments in Bangladesh with both nutrient (0 ~ 135 kg N/ha) and water treatments (rain-fed vs. irrigated), Timsina et al. (1998) reported that the overall simulated wheat yield matched well with the observations (RMSD = 467 kg/ha, $r^2 = 0.95$). Compiling 20-year yield data for a maize-wheat rotation given 0 ~ 250 kg N/ha input treatments, the maize and the wheat yields matched with the observations well (R^2: 0.82) (Kovacs et al., 1995). In contrast, another study in Spain with similar water and nutrient treatments (rain-fed vs. irrigated and fertilized at 0 vs. 250 kg N/ha) showed that the wheat grain yield simulation had an average RMSD of 1060 kg/ha and that ignoring 1 year of rain-fed data, the average RMSD would have been reduced to 790 kg/ha (Abeledo et al., 2008). Similarly, simulating grain yield in an experimental field in India, combining five irrigation treatments of various amounts and timings and four nitrogen application levels from 0 to 180 kg/ha, resulted in an average normalized RMSD of 25%, but this would decrease to 18% if grain yield under extreme irrigation and nutrient treatment were not included (Arora et al., 2007). However, Lobell and Ortiz-Monasterio (2006) indicated that the CERES model was able to simulate grain yield accurately across ranges of nutrient (low to high levels of nitrogen application) combined with a gradient of water applications (irrigation 3 ~ 5 times), with an average RMSD of 230 kg/ha. Saseendran et al. (2004) indicated that in rain-fed fields in Colorado, US, with fertilization treatment (0 ~ 112 kg/ha), the simulation was more accurate in years in which rainfall was plentiful.

Without nutrient stress but with available soil water ranging between 30 and 75% of the maximum allowable depletion treatment, Panda et al. (2003) reported that the average RMSDs for a wheat and maize grain yield simulation were under 250 kg/ha. Under rain-fed conditions in India, the CERES model simulated wheat yield reasonably well, with index of agreement of 0.87 and a model efficiency of 0.57 (Vashisht et al., 2013). For 13 US states, most of the wheat yield simulations were in good agreement with the recorded yield (Tubiello et al., 2002). Iglesias et al. (2000) found that the CERES model, in general, overestimated the grain yield across seven sites in Spain and that the simulation was more accurate for fully irrigated wheat than dry-land wheat. With a wheat yield simulation in Australia over 9 years, a study showed that the model overestimated yields with high values and underestimated yields with relatively low values, with an average error of 5.1%, and that the error was partly due to water stress (Eitzinger et al., 2003). The simulated grain yield across well-irrigated and early drought wheat fields in Argentina had a root mean square of 20 kg/ha, while the observed grain yield had a mean standard error of 40 kg/ha (Savin et al., 1994). Two studies compared the CERES model grain yield simulation's accuracy between fully available water and limited available water scenarios. Singh et al. (2008) calculated the RMSDs for grain yield simulations given irrigation 2 ~ 4 times per growing season and varied levels of nitrogen input for each irrigation treatment, and they reported that the RMSDs were over 700 and 220 kg/ha for the two least-irrigated treatments and the most frequent irrigation treatment, respectively. The errors for simulating wheat yield under irrigation 0, 1, 2, and 4 times in China ranged from a 390 kg/ha underestimation to a 150 kg/ha overestimation (Yang et al., 2006b). When simulating yield under nine treatments of various irrigation timings and amounts in China, the percentage errors ranged from 1.56 to 8.17% (He et al., 2013). Although accurate grain simulations under water stress have been reported, more studies found that grain yield simulation was not that accurate regarding fully irrigated conditions versus droughts in various growing stages treatments in New Zealand, with an RMSE of over 3000 (Jamieson et al., 1998). Interestingly, a test conducted in rain-fed experiments in Syria and Italy, involving two wheat cultivars for 2 years showed percentage errors that were mostly over 60% and not more than 21%, respectively (Pecetti and Hollington, 1997). When simulating grain yield under limited versus full water availability combined with elevated versus ambient CO_2 concentration treatments in Germany, the model efficiency was 0.5 (Biernath et al., 2011). While simulated grain yield matched well with reported yield for irrigated and rain-fed wheat in Jordan (RMSE was 586 kg/ha), the simulated yield was weakly correlated with the observed wheat yield at the county level in Canada (correlation between two standardized anomalies was 0.59), Kansas (US) (R: 0. 63), and two irrigated and fertilized fields in Mexico (R: 0.72 ~ 0.87) (Al-Bakri et al., 2011; Greene and Maxwell, 2007; Lobell et al., 2005; Mearns et al., 1992). Nonetheless, the model under-predicted yields for 303 wheat fields in England, with an average error of 2600 kg/ha (Landau et al., 1998). Nain et al. (2004) also reported a low correlation (R: 0.67) between the observed and simulated yield deviations (from the average yields) for three locations in India.

The CERES-wheat model has been tested using contrasting fertilization treatments and sufficient irrigation. The average RMSEs for the yield simulations were not larger than 471 kg/ha across various amounts and types of fertilizer application treatments in Pakistan (Bakhsh et al., 2013) and across five levels of nitrogen input with residue treatment in India (Sarkar and Kar, 2008). A study in India showed that a grain yield simulation across rotation cropping systems, with a 0 ~ 160 kg N/ha application being given to one of the systems, had an average RMSD of 617 kg/ha (Timsina et al., 2008). Wang et al. (2010) showed that for fertilization, irrigation and tillage treatments, the correlation coefficient between simulation and observation was about 0.95 for continuous wheat, while that for wheat rotation field was under 0.85. Zhang et al. (2012) suggested that with a 0 ~ 112 kg N/ha application to a wheat field, the simulated and observed grain yields were not significantly different (P = 0.05). Given 110.5 and 241.0 kg N/ha application treatments in Arizona, US, the average RMSE for the yield simulation was 7.4% (Thorp et al., 2010b). For six nitrogen input and planting density treatments in Arizona, the yield simulations were acceptable, with errors less than 1 Mg/ha (Thorp et al., 2010a). St'astna et al. (2002) found that for ten treatments, including fertilization rates (40 and 120 kg/ha), different crops preceding the wheat, and planting dates treatments, the CERES model could simulate grain yield relatively well when the crop was not infested by pest. Examining 30 years of field data regarding fertilization and non-fertilization treatments, Moulin and Beckie (1993) reported that the 1:1 line between the simulation and the observation fell out of 95% confidence band, although there was a significant relationship between the simulated and the observed yield.

Other test conditions included various sowing dates, planting densities, tillage methods, planting methods, soil types, and CO_2 concentrations. A study in India in which wheat was sown between DOY310 and DOY354 showed that the model underestimated yield for both early- and late-sown wheat, with an average percentage error of 21% (Hundal and PrabhjyotKaur, 1997). Studies in Argentina and Pakistan showed that the model simulated wheat grain yield under varied sowing dates reasonably well, with RMSEs under 851 kg/ha (Monzon et al., 2007; Sultana et al., 2009). With experiments consisting of 31 sowing dates across Nebraska, US, for 6 years, the yield simulations for two wheat cultivars had average normalized RMSEs of 39 ~ 46% and RMSEs of about 1178 ~ 1266 kg/ha (Moreno-Sotomayor and Weiss, 2004). With both humid and dry weather in Algeria and using three sowing dates in Dec., the RMSE for simulating grain yield was 790 kg/ha (Rezzoug et al., 2008). For simulating grain yield using sowing dates between late-Aug. and early-Nov. combined with seeding rates from 14 to 56 seeds/ft.^{2}, the simulation accuracy varied greatly, with about 500 kg/ha overestimation for early sown treatment (before DOY247); good estimation for DOY255, 266, and 276; and up to 1600 kg/ha overestimation for late-sown treatments (sown after DOY284) (Dahlke et al., 1993; Southworth et al., 2002). Two studies tested the CERES model under a planting density treatment. Across seeding density (350 ~ 400 seeds/m^2) combined with sowing date (Sep. 20 ~ Oct. 30) treatments, the average RMSD for the yield simulation was 240 kg/ha (Ghaffari et al., 2001, 2002). Across five planting density treatments, two irrigation levels, various levels of phosphorous input, and various seeding rates in Iran, the normalized RMSE was 5% (Bannayan et al., 2014). Under a wide range of growing conditions and various fertilizer inputs, sowing dates, and planting densities in five US states, the model tended to overestimate the grain yield (up to 36%), and the average overestimation was 8% (Tsvetsinskaya et al., 2003). Cho et al. (2012) reported that the CERES-Wheat model consistently overestimated the wheat yield in experiment fields given fertilization (48 ~ 192 kg/ha), sowing date (Sep. ~ Nov.), and seeding rate (350 ~ 450 seeds/m^2) treatments in the United Kingdom for 11 years, with an r^2 of 0.56. With various rotation systems, Staggenborg and Vanderlip (2005) reported up to 22% grain yield overestimation with RMSEs of about 1400 kg/ha for both wheat-sorghum-fallow and wheat-fallow systems in Kansas, US. Given a range of tillage treatments (eg, conventional tillage, surface tillage, minimum tillage, and no tillage), the model simulated grain yield in Spain (RMSEs: 551 kg/ha for conventional tillage and 804 kg/ha for no tillage) and Italy well (errors: 700 ~ 1200 kg/ha) (Castrignano et al., 1997; Soldevilla-Martinez et al., 2013). Langensiepen et al. (2008) noted that depending on the calibration process, the RMSE for wheat grain yield simulation in a wheat-barley-canola rotation field in Germany ranged from 700 to 2200 kg/ha. The grain yield prediction accuracy was reported for yields from various soil types as well. Eizinger et al. (2004) showed that the CERES-Wheat model overestimated the yield by 500 and 900 kg/ha with chernozem and sandy chernozem soils, respectively, and underestimated the yield by 1500 kg/ha with fluvisol soil. He et. al. (2014) reported that the RMSEs for wheat yield simulation were under 1688 kg/ha across silt and clay soil sites in Canada. The model has been tested under ambient versus elevated CO_2 concentrations (550 ppm) in combination with well-watered versus water-deficit treatments, and the normalized RMSEs ranged from 9.2 to 23.3% (Tubiello et al., 1999b).

3.2.3 CERES-Rice

Tests regarding the rice yield of the CERES model are relatively less extensive but have still been performed using a range of treatments. The reported RMSEs mostly ranged from 200 to 1672 kg/ha.

Two studies in China simulating rice yield for six to eight rice ecological stations reported that the average RMSEs for rice yield were within 800 kg/ha (Tao et al., 2008; Yao et al., 2007). The simulated rice yield was not significantly different from the observed yield over more than 10 years of field experiments in two locations in India ($P > 0.01$) (Lal et al., 1998). Subash and Mohan (2012) showed that the CERES-Rice model predicted the rice production trends in several production sites for 29 years, although the model tended to overpredict the yield. By contrast, Xiong et al. (2008) reported that the CERES models failed to reproduce the temporal rice yield variability in China. Xiong et al. (2008b) also reported that the RMSEs for rice yield simulations for more than 500 rice stations in China ranged from 1129 to 1672 kg/ha (normalized RMSE: 11.8 ~ 25.6%) and that the model, on average, overestimated rice yield by 3191 kg/ha at a regional level. Yun (2003) showed that the correlation of determination between the simulated and observed yields was 0.4, while it was over 0.9 at the regional level when growing acreages were corrected.

Studies have tested grain yield under both water and nutrient stress conditions. Experiments in Bangladesh with both nutrient (0 ~ 135 kg N/ha) and water treatments (rain-fed vs. irrigated), Timsina et al. (1998) showed that the overall simulated rice yield did not match well with the observations (RMSD = 1279 kg/ha, $r^2 = 0.52$). In contrast, Amiri et al. (2013) reported that the average RMSD was 297 kg/ha under various amounts of irrigations treatment and fertilization treatment (0 ~ 75 kg/ha) in Iran. Using 80 treatments consisting of various sowing dates, population densities, spacings, and fertilization and irrigation treatments, Mall et al. (2002) reported an overall RMSD of 698 kg/ha, but the model did not simulate grain yields accurately when the yield was under 4 Mg/ha (Mall and Aggarwal, 2002). Under rain-fed conditions in India, with six nitrogen application treatments (0 ~ 120 kg/ha) and wheat residue treatments (remains vs. removed), the simulated rice yield had a mean bias errors of 131.5 and 64.0 kg/ha for transplanted and direct-seeded rice, respectively (Sarkar and Kar, 2008).

The CERES models have also been tested under varied available water conditions. Combining irrigation water treatment (625, 775, 925, 1075, and 1225 mm) and seedling density (1 ~ 3 seedlings/hill) treatment in Pakistan, the simulated grain yield was on average 11% off of the observation, with a normalized RMSD of 1.4 ~ 2.1% for each seedling density treatment (Ahmad et al., 2012). Under rain-fed conditions with varying transplanting dates from mid-Jun. to early-Aug. in Bangladesh, the average RMSE for rice yield was 1270 kg/ha (Mahmood et al., 2003). Godwin et al. (1994) indicated that the CERES models performed less accurately when rice was under stressed conditions, with satisfactory yield prediction for continuously flooded and fertilized rice fields, heavy underestimation for continuously flooded and unfertilized rice fields, and heavy overestimation for sprinkled and fertilized rice fields.

With contrasting fertilizer input treatments, the CERES-rice model showed the ability to accurately simulate the rice yield as well. Simulating grain yield under a 0 ~ 150 kg N/ha treatment in India for a medium-duration rice variety showed the worst prediction among 150 kg/ha nitrogen addition treatments, with over 50% error, but the simulation error for the long-duration variety was 4 and 14% for the 150 kg N/ha and 10 kg N/ha treatments, respectively (Swain and Yadav, 2009). With the same fertilization treatment in three locations in Thailand, the biases were 277 ~ 407 kg/ha, while with a 75 kg N/ha addition, the biases were only 77 ~ 142 kg/ha (Cheyglinted et al., 2001). In addition, Amien et al. (1999) showed that the model slightly underestimated rice yield and that the simulated yield was highly correlated with the measured yield (r^2 of 0.87) in three regions of Indonesia using various nitrogen fertilizer sources, rates and application methods.

Others tested the CERES-Rice model using sowing date, tillage method, residue removal, elevated CO_2, and elevated temperature treatments. Babel et al. (2011) reported that the average percentage error for simulating both early- and late-sown rice in a field in Thailand was 3.13%. With 18 planting dates ranging from Jan. to Dec. and Jul. to Aug., in India, the yield simulations had indices of agreement ranging from 0 to 0.98 (the overall agreement index was 0.57) (Sudharsan et al., 2013). In Madagascar, the model was tested across two tillage treatments, conventional tillage with residue removal versus direct seeding with mulch-based tillage, and the average RMSD for the harvest weight simulation was 499 kg/ha (Gerardeaux et al., 2011). Sarkar and Kar (2006) reported that when simulating rice yield in rice-wheat rotation systems involving both residue removal and residue remaining, the average RMSDs were 267.34 and 445.21 kg/ha for transplanted rice and direct-seeded rice, respectively. Using an elevated CO_2 treatment in India, the grain yield simulation errors were within 10% (Satapathy et al., 2014). Across temperature treatments (0 ~ 2 °C elevated) combined with CO_2 concentration treatments (380 ppm and 550 ppm), the simulated yield was up to 17.6% underestimated and 9.1% overestimated (Kim et al., 2013).

3.3 Kernel Weight

3.3.1 CERES-Maize

Kernel weight has been tested on the basis of individual kernels, per square meter, and per year given irrigation, fertilization, and cover-crop treatments (Table 7). Six studies tested maize kernel weight under an irrigation treatment. Under water-stressed conditions, the kernel weight was underestimated by about 30%, while under irrigation treatments, the errors were about 3% (Mubeen et al., 2013). Across dry- and irrigated land in Kansas, US, the average RMSE for maize kernel weight was 0.061 g (Retta et al., 1991). Similarly, across well-irrigated and severe water stress treatments in Australia, the average RMSE was 0.13 g (Carberry et al., 1989). In Italy, the kernel weight tended to be underestimated, and the percentage errors were larger with severe water stress (up to 21%) than with moderate or zero water stress (within 15%) (Ben Nouna et al., 2000; Mastrorilli et al., 2003). A study in Brazil indicated that the prediction of kernel weight was worse under rain-fed conditions (normalized RMSE of 6.07%) than under irrigated conditions (normalized RMSE of 4.8%) (Soler et al., 2007). When simulating grain weight in rain-fed fields in Nigeria, the errors were less than

Table 7 Summary of the CERES-Maize model performances for kernel weight[a] and kernel number[a] variable simulations.

Treatment category	Variables	Countries	Performance	References
Rain-fed/nonirrigated and well fertilized	Kernel number	Brazil	RMSE: 102 ~ 257 Normalized RMSE: 4.56 ~ 12.87%	Soler et al. (2007)
		Nigeria	Difference: 0 ~ 174	Jagtap et al. (1993)
		Spain	RMSE: 1700	López-Cedrón et al. (2008)
	Kernel weight	Croatia	Underestimated by 3%	Vucetic (2011)
		Pakistan, Italy, China	Underestimated by 11 ~ 30%	Mubeen et al. (2013); Mastrorilli et al. (2003); Ben Nouna et al. (2000); Guo et al. (2010)
		Croatia	Overestimated by 39%	Vucetic (2011)
		Brazil	Normalized RMSE: <6.07%	Soler et al. (2007)
		Nigeria	Difference: <0.007 g Percentage error: <3%	Jagtap et al. (1993)
Irrigated with a gradient of water/different scheduling time and well fertilized	Kernel number	Italy	Underestimated by 1.7 ~ 21%	Ben Nouna et al. (2000); Mastrorilli et al. (2003)
		Australia	RMSE: 1065	Carberry et al. (1989)
	Kernel weight	United States	RMSE: 0.061 g	Retta et al. (1991)
		Australia	RMSE: 0.13 g	Carberry et al. (1989)
		Italy	Percentage error: <15%	Mastrorilli et al. (2003); Ben Nouna et al. (2000)

(Continued)

Table 7 Summary of the CERES-Maize model performances for kernel weight[a] and kernel number[a] variable simulations.—cont'd.

Treatment category	Variables	Countries	Performance	References
Well irrigated and well fertilized (Weiss and Moreno-Sotomayer, 2006)	Kernel number	Brazil	RMSE: 102 Normalized RMSE: 4.56%	Soler et al. (2007)
		Italy	Underestimated by: 8%	Ben Nouna et al. (2000); Mastrorilli et al. (2003)
	Kernel weight	Pakistan, Italy, Brazil	Percentage error: 3 ~ 15%	Mubeen et al. (2013); Mastrorilli et al. (2003); Ben Nouna et al. (2000); Soler et al. (2007)
	Kernel weight	Argentina	Overestimated it at its low weight range values, underestimated it at its high range values	Otegui et al. (1996)
Cover crops	Kernel number Kernel weight	Spain	RMSE: 188 ~ 584 RMSE: 0.012 ~ 0.03 g	Salmerón et al. (2014)

[a]Here only showed individual kernel weight and kernel number per square meter validation results; other relevant validated variables included kernel weight per square meter, kernel weight per year, kernel number per year and kernel number per plant and the results were summarized in the text.

0.007 g (within 3% error) (Jagtap et al., 1993). Under rain-fed conditions in Croatia, the model overestimated kernel weight by 39% (Vucetic, 2011). With cover-crop treatments in Spain, the kernel weight was well-simulated, with low RMSEs between 0.012 and 0.03 g (Salmerón et al., 2014). Grain weight per square meter was tested for dry- and irrigated land in Kansas, and the average RMSE was 152.2 g (Retta et al., 1991). The grain weight per year was tested for agricultural experiment stations in the Southeastern US, and the average RMSE was 59 g (Tsvetsinskaya et al., 2003). In addition, Otegui et al. (1996) indicated that when simulating kernel weight given sowing dates treatments for four maize hybrids in Argentina, the model overestimated the grain weight when it was at the low-range value but underestimated the grain weight when it was at the high-range value.

3.3.2 CERES-Wheat

Ten studies tested the weight of wheat kernels under a range of treatments (Table 8). The individual-grain-weight simulation had average RMSEs within 0.0076 g under water stress (rain-fed vs. irrigated treatments) combined with nutrient stress conditions (0 ~ 250 kg N/ha) in Spain (Abeledo et al., 2008) and fertilized cropping systems in Argentina (Monzon et al., 2007). Under well-irrigated and fertilized condition in India, the simulated grain weight for 5 years was 88 ~ 113% of the observed grain weight (Hundal and PrabhjyotKaur, 1997). In China, across nine irrigation treatments, the relative absolute errors ranged from 0 to 8.29%, with an average relative absolute error of 5% (He et al., 2013). Across rain-fed and irrigation treatments in Argentina, the grain weight simulation was in good agreement with the observation, with a root mean square of 0.0022 g (Savin et al., 1994). Two studies in Nebraska, US, reported that the normalized RMSEs for kernel weight simulations were about 0.003 g given planting population combined with sowing date treatments and about 0.0024 g given varied sowing date conditions (Moreno-Sotomayor and Weiss, 2004; Weiss and Moreno-Sotomayer, 2006). With five wheat production stations in the Czech Republic, the RMSE for a thousand-grain weight simulation was 7.5 g, which was within 20% error (Trnka et al., 2004). However, the thousand-grain weight was poorly simulated under combinations of CO_2 concentration and water availability treatments, with a model efficiency index of 0.44 (Biernath et al., 2011). Another study showed that the model underestimated the thousand-grain weight across experiments in humid and dry weather conditions in Algeria, with an average RMSE of 4.29 g for the model evaluation year (Rezzoug et al., 2008).

Table 8 Summary of the CERES-Wheat model performances for kernel weight[a] and kernel number[a] variable simulations.

Treatment category	Variables	Countries	Performance	References
Irrigated with a gradient of water/different scheduling time and well fertilized	Kernel weight	China	Percentage error: <9%	He et al. (2013)
		Argentina	Root mean square: 0.0022 g	Savin et al. (1994)
	Kernel number	Germany	Model efficiency index: 0.52	Biernath et al. (2011)[,b]
Well irrigated, fertilized with a gradient of fertilizer(s) and combined with different sowing dates	Kernel number	Germany	RMSE: 3677, R^2: 0.07	Ratjen et al. (2012)
		Netherlands	RSME: 1808, R^2: 0.77	
Well irrigated and well fertilized	Kernel weight	Argentina	RMSE: 0.0051 g R^2: 0.32	Monzon et al. (2007)
		India	Percentage error: ≤13%	Hundal and PrabhjyotKaur (1997)
	Kernel number	Czech Republic	RMSE: 2845 Percentage error: <20%	Trnka et al. (2004)
		Argentina	RMSE: 3018	Monzon et al. (2007)
Irrigated with a gradient of water and fertilized with a gradient of fertilizer(s) only	Kernel weight	Spain	RMSE: 0.0076 g Mean percentage error: 22%	Abeledo et al. (2008)
	Kernel number	Spain	RMSE: 4340 Mean percentage error: 24%	Abeledo et al. (2008)

Sowing dates	Kernel weight	United States	RMSE: 0.0023 ~ 0.0029 g Normalized RMSE: 9 ~ 12%	Weiss and Moreno-Sotomayer (2006)[,c]; Moreno-Sotomayer and Weiss (2004)
	Kernel number	United States	RMSE: 3998 ~ 4555 Normalized RMSE: 35 ~ 42%	Moreno-Sotomayer and Weiss (2004)

[a]Here only showed individual wheat kernel weight and kernel number per square meter validation results; other relevant validated variables included thousand wheat kernel weight, and thousand kernel number, and the validation results were summarized in the text.
[b]Treatment included two irrigation regimes (full irrigation vs. limit irrigation) combined with elevated CO_2 versus ambient CO_2 concentration.
[c]Treatments include Planting density combined with sowing dates.

3.3.3 CERES-Rice

One study in Indonesia showed that the CERES-Rice model underestimated the kernel weight by almost 1 mg (Amien et al., 1999).

3.4 Kernel Number

3.4.1 CERES-Maize

Maize kernel number has been tested in the form of grain number per year, grain number per square meter, and grain number per plant. It has been validated with irrigation and fertilization treatments (Table 7). Soler et al. (2007) reported that the grain number simulation for both irrigated and rain-fed fields in Brazil were reasonably good, with average RMSEs of 102 and 257, respectively, and normalized RMSEs of 4.56 and 12.87%, respectively. Jagtap et al. (1993) showed that the CERES model could underestimate the number of grains per year by 21 or overestimate it by 68, depending on the year. With severe water stress, the simulated grain number per year was up to 21% less than the observations for 1 year but only about 1.7% less for another year (Ben Nouna et al., 2000; Mastrorilli et al., 2003). Across two water availability extremes, Retta et al. (1991) reported that the grain number per year simulation across dry- and irrigated-land treatments had an average RMSE of 94, and Carberry et al. (1989) calculated the RMSE to be 127.8 across well-watered and severe water stress treatments. In Argentina, for four sowing dates between late-Aug. and late-Nov., the CERES model overestimated the low-range grain numbers and underestimated the high-range grain numbers (Otegui et al., 1996). Six studies tested the grain number per square meter. Three of them suggested that in general, grain number on a square meter basis did not match very well with the observations under limited-water conditions, with a percentage difference up to 21% (Ben Nouna et al., 2000; Mastrorilli et al., 2003) and an RMSE over 1000 (Carberry et al., 1989). Another study tested grain number per square meter under rain-fed conditions in Nigeria. The grain number per square meter seemed to be reasonably well-simulated, with errors as low as 0 and as high as 174, depending on the simulation year (Jagtap et al., 1993). In Spain, kernel number per square meter simulations with cover crop treatments had a low error (RMSE < 590) as well (Salmerón et al., 2014). By contrast, the RMSE when simulating grain number per square meter under rain-fed conditions in Spain was over 1700 (López-Cedrón et al., 2008). In terms of grain number per plant tests, Lizaso et al. (2001) used 134 treatments over 4 years in Iowa and reported that the CERES consistently overestimated kernel number when it was under 400 kernels per plant but underestimated kernel number per plant by 67 overall.

3.4.2 CERES-Wheat

Seven studies validated wheat kernel number under a range of treatments (Table 8). The reported average RMSE for grains per square meter ranged from 3998 to 4555 across irrigated and rain-fed fields in Spain (Abeledo et al., 2008) and for 31 sowing experiments in the United States (Moreno-Sotomayor and Weiss, 2004). By contrast, the RMSE ranged from 2845 to 3018 under fertilized condition in Argentina (Monzon et al., 2007) and the Czech Republic (Trnka et al., 2004). Under both water availability and CO_2 concentration treatments, the average model efficiency index for simulating grain number on a square-meter basis was 0.52 (Biernath et al., 2011). Ratjen et al. (2012) used two datasets from Germany with fertilization (0 ~ 320 kg N/ha) and sowing date treatments (Sep.–Oct.) and from the Netherlands under fertilization and sowing date treatments (varied sowing dates between Oct. 19 and 25) to test grain number per square meter and showed that the RMSEs were 3677 and 1808 grains/m^2, respectively. Savin et al. (1994) compared the standard error of the mean for the observed thousand-grain number to the root mean square of the simulated thousand-grain number across well-irrigated and early drought treatments, and the statistics were 1.34 and 0.56, respectively.

3.4.3 CERES-Rice

One simulation study used 32 experiments conducted under various locations, weather, and management conditions in India for over 13 years and showed that grain number per square meter was well-simulated when the number was over the range of 15,000–32,000 grains/m^2 (Mall and Aggarwal, 2002).

3.5 Aboveground Biomass and its Components (Excluding Grain Yield)

3.5.1 CERES-Maize

A total of 31 studies tested the biomass-related variables of the CERES-maize model, including aboveground biomass, LAI, stover biomass, biological yield, and shoot, leaf, stem, and year biomass (Tables 9 and 10). Under the maximum allowable depletion of available soil water in India, the average RMSE for aboveground biomass simulation was 202 kg/ha (Panda et al., 2004). In Turkey, with 50–100% sufficient water treatments, the model underestimated aboveground biomass by 2 ~ 8.6% (Gercek and Okant, 2010). The RMSEs

Table 9 Summary of the CERES-Maize model performances for aboveground biomass variable simulation.

Treatment category	Countries	Performance	References
Rain-fed/nonirrigated and well fertilized	Spain	RMSE: >5000 kg/ha	López-Cedrón et al. (2008)
	Nigeria	RMSE: <400 kg/ha	Jagtap et al. (1993)
	Brazil	Normalized RMSE: 10 ~ 25%	Soler et al. (2007)
	China	Percentage error: 17%	Guo et al. (2010)
	Croatia	Percentage error: 3%	Vucetic (2011)
	United States	RMSE: 1701 kg/ha	Retta et al. (1991)
Irrigated with a gradient of water/different scheduling time and well fertilized	Turkey	Underestimated by 2 ~ 8.6%	Gercek and Okant (2010)
	Spain	Overestimated by 7%	Dechmi et al. (2010)
	India, Pakistan	RMSE: 202 ~ 1116kg/ha	Panda et al. (2004); Mubeen et al. (2013)
	United States, Spain	RMSE: 1600 ~ 1708 kg/ha	Saseendran et al. (2008), Dechmi et al. (2010)
	Australia	RMSE: over 5000 kg/ha	Carberry et al. (1989)
	United States	Normalized RMSE: 22 ~ 26%	Anothai et al. (2013)
	Italy	Percentage error: 14 ~ 30%	Ben Nouna et al. (2000), Mastrorilli et al. (2003)
Varied nitrogen levels, irrigated	China	Normalized RMSE: 15 ~ 23%	Liu et al. (2012)
Well irrigated and well fertilized	Spain	RMSE: 2202 kg/ha	López-Cedrón et al. (2005)
	Portugal	RMSE: 1494.17 kg/ha	Braga et al. (2008)
	United States, Brazil, Canada	Normalized RMSE: 23 ~ 33%	Xevi et al. (1996); Soler et al. (2007); Liu et al. (2014)
	Italy	Percentage error: 5.55%	Ben Nouna et al. (2000); Mastrorilli et al. (2003)

Not fertilized	Canada	Normalized RMSE: 41%	Liu et al. (2014)
Irrigated and fertilized at varied rates	United States	Percentage error: <12%	He et al. (2011)
	Iran	Normalized RMSE: 6.6%	Moradi et al. (2013)
	United States	Percentage error: ≤16%	Persson et al. (2009)
Other treatments[a]	United States	Percentage error: ≤17%	Saseendran et al. (2005)
Cover crops	Spain	RMSE: 530 ~ 3990 kg/ha	Salmerón et al. (2014)

[a]Other treatments included sowing dates, planting density, and spacing.

Table 10 Summary of the CERES-Maize model performances for biomass-related variable (excluding aboveground biomass) simulations.

Treatment category	Variables	Countries	Performance	References
Rain-fed/nonirrigated and well fertilized	Stover biomass	Nigeria	Differences:3 ~ 701 kg/ha	Jagtap et al. (1993)
	Harvest index	Spain	Underestimated by 1.3	López-Cedrón et al. (2008)
		Croatia	Underestimated by 7%	Vucetic (2011)
Irrigated with a gradient of water/different scheduling time and well fertilized	Stover biomass	Australia	RMSD: 2421 kg/ha	Carberry et al. (1989)
	Harvest index	Spain	Underestimated by 13%	Dechmi et al. (2010)
Fertilized with different types of fertilizers	Shoot biomass	Thailand	Normalized RMSE: 16.8 ~ 79.1%	Pinitpaitoon et al. (2011)
Well irrigated and fertilized	Biological yield	Iran	Normalized RMSE: 4.22%	Moradi et al. (2014)
Irrigated with a gradient of water and fertilized with a gradient of fertilizer	Leaf biomass	United States	Agreement index: 0.65 ~ 0.85	Lizaso et al. (2011)
	Stem biomass		Agreement index: 0.85 ~ 0.9	
	Shoot biomass		Agreement index: >0.9	
	Year biomass		Agreement index: >0.93	
Planting densities	Biological yield	Iran	Normalized RMSE: 6.95%	Lashkari et al. (2011)

ranged from 1494.2 to 2202 kg/ha across 23 ~ 188 mm irrigation water treatments in Colorado, US (Saseendran et al., 2008), under well-irrigated and fertilized treatment in Spain (López-Cedrón et al., 2005) and under varied sowing dates treatments in Portugal (Braga et al., 2008). In contrast, the average RMSEs were over 5000 kg/ha across nonwater stress versus severe water stress treatments in Australia (Carberry et al., 1989) and rain-fed fields in Spain (López-Cedrón et al., 2008). When simulating biomass under seven irrigation treatments with different irrigation amounts and timings, the percentage errors were 6%, with average RMSEs over 1700 kg/ha (Mubeen et al., 2013). When simulating top biomass in seven maize production stations under rain-fed conditions in China, the percentage error was 17% (Guo et al., 2010). By comparison, for Croatia, the simulation error for rain-fed maize aboveground biomass was 3% (Vucetic, 2011). Under sowing date treatments (sown between late-Apr. and mid-Jun.), the percentage errors for biomass simulation were not larger than 17% (Saseendran et al., 2005). The simulated dry matter yield was within 12% absolute relative error given fertilization rates of 247 and 309 kg/ha and two irrigation (full irrigation and overirrigation) treatments, but the error was 29% given overirrigation with 185 kg N/ha addition treatment (He et al., 2011). Under low- and high-irrigation treatments in Spain, the total dry matter was overestimated by 7%, with an RMSE of 1650 kg/ha (Dechmi et al., 2010). Across 40 ~ 100%-full irrigation treatments in Colorado, US, the total biomass simulation had a normalized RMSE of at least 22.7% (Anothai et al., 2013). Under 141 ~ 219 kg N/ha fertilization rates with irrigation (irrigation and nonirrigation) and planting date (three dates across Mar.) treatments, the simulation errors were from 0.091 to 16.2% (Persson et al., 2009). Across three irrigation treatments (450 ~ 650 mm irrigation water) combined with four fertilization treatments (0 ~ 450 kg/ha) in Iran, the biomass yield simulation had a normalized RMSE of 6.6% and a model efficiency of 0.89 (Moradi et al., 2013). By comparison, under irrigated conditions in Nebraska, US, the normalized RMSE for simulating aboveground dry matter was 31.9% (Xevi et al., 1996). Others compared aboveground biomass simulation accuracy among treatments. The simulation research in Italy showed that with moderate and severe water stress, the CERES model consistently underestimated aboveground biomass by over 14% and over 24%, respectively, whereas it only underestimated the biomass by 5.55% without water stress (Ben Nouna et al., 2000; Mastrorilli et al., 2003). In Brazil, the aboveground biomass simulation for irrigated fields had normalized RMSEs between 23.6 and 32.9%, while that for rain-fed fields had normalized RMSEs between 10.1 and 24.7%

(Soler et al., 2007). A 2-year experiment in Kansas showed that the CERES model consistently underestimated aboveground vegetative biomass for irrigated fields but overestimated the biomass for dry-land fields. The average RMSE for the two fields was 1701 kg/ha, with a mean bias of 31 kg/ha (Retta et al., 1991). Under rain-fed conditions in Nigeria, the model overestimated the aboveground biomass by less than 400 kg/ha (Jagtap et al., 1993). Liu et al. (2012) reported that the normalized RMSEs were 23.1 and 15.4% when simulating maize aboveground biomass in the North China Plain given nitrogen application rates of 0 ~ 400 and 0 versus 180 kg N/ha, respectively. Using fertilized and unfertilized treatments in Canada, the normalized RMSEs for maize aboveground biomass were 26.8 and 41.2%, respectively (Liu et al., 2014). Given various winter cover-crop treatments, the aboveground biomass simulation under no cover crops and under winter cover crops of oilseed rape and vetch was in agreement with the observations, with an RMSE under 1600 kg/ha, but under winter rape and barley cover crop treatments, the simulations did not agree with the observations, with an RMSE over 2500 kg/ha (Salmerón et al., 2014).

Stover biomass, biological yield, shoot biomass, leaf biomass, stem biomass, shoot biomass, and year biomass have been validated as well. Under fully irrigated versus severe water stress treatments, the average RMSD when simulating maize stover biomass at maturity was 2421 kg/ha (Carberry et al., 1989). In rain-fed fields in Nigeria, the stover biomass was underestimated by 701 kg/ha for 1 year but overestimated by 3 kg/ha for another year (Jagtap et al., 1993).

In Iran, the normalized RMSE for biological yield was 6.95% under planting density treatments (Lashkari et al., 2011) and 4.22% under fertilized and irrigated treatments (Moradi et al., 2014). For shoot biomass, under mineral fertilizer and compost fertilizer treatments in Thailand, the model simulated maize shoot biomass relatively well for the second year but poorly for third ~ fifth years, with normalized RMSEs of 16.8% and 25.6 ~ 79.1%, respectively (Pinitpaitoon et al., 2011). Lizaso et al. (2011) tested leaf biomass, stem biomass, shoot biomass, and year biomass in Florida under rain-fed conditions with low nitrogen input (116 kg N/ha) and under irrigated conditions with high nitrogen input (401 kg N/ha), 0 and 240 kg N/ha, as well as with 56 and 224 kg N/ha application treatments in Iowa. The indices of agreement for the leaf biomass simulation were mostly above 0.85, with RMSEs from 584.8 to 1054.5 kg/ha, except for rain-fed fields with low nitrogen input and 0 kg N/ha application treatments in Florida (index of agreement below 0.65 and RMSEs of 1060.5 and 635.3 kg/ha, respectively).

By contrast, for stem biomass simulations, under rain-fed conditions with low nitrogen and 0 kg N/ha input treatments in Florida, the RMSEs were under 215 kg/ha, with index of agreement above 0.9, while under other treatments, the RMSEs were mostly above 1170 kg/ha, with agreement indexes around 0.85. The RMSEs for shoot biomass simulations ranged from 771.3 to 867.8 kg/ha for treatments in Florida and from 1647.7 to 2229.1 kg/ha in Iowa. The year biomass was simulated only for 0 kg N/ha and 240 kg N/ha treatments in Florida and nitrogen application treatments in Iowa. The indices of agreement were all above 0.93, with RMSEs of 396.5 ~ 1155.4 kg/ha (Lizaso et al., 2011).

3.5.2 CERES-Wheat

The aboveground biomass prediction capability of the CERES-Wheat model has been evaluated under several treatments, including water availability treatments, fertilization treatments, sowing date treatments, CO_2 concentration treatments, and management intensity treatments (Table 11). Under rain-fed conditions in India, the aboveground biomass simulation had an index of agreement of 0.98 and an r^2 of 0.95 (Vashisht et al., 2013). The average RMSEs were 333 and 900 kg/ha across irrigation treatments at 30 ~ 75% of the maximum allowable soil water depletion in India (Panda et al., 2003) and across irrigation with various amounts water and at various developmental stages in New Zealand (Jamieson et al., 1998). On average, the CERES-Wheat model underestimated the aboveground biomass by 644 kg/ha for seven production stations in China (Guo et al., 2010). Given different irrigation applications (from no irrigation to full irrigation) combined with different nitrogen fertilizer application rates (from zero to a high rate), the reported RMSEs ranged from 1200 to 2360 kg/ha (Abeledo et al., 2008; Arora et al., 2007; Singh et al., 2008). Under rain-fed and fertilization treatments (0 ~ 112 kg N/ha) in the United States, the average RMSE was 1247 kg/ha. Under well-fertilized conditions with conventional and no-till management, the RMSEs were 1999 and 2282 kg/ha, respectively (Saseendran et al., 2004; Soldevilla-Martinez et al., 2013). The average normalized RMSE was 9.5% across two nitrogen application treatments (110.5 and 241 kg N/ha) in the United States (Thorp et al., 2010b), and it was within 19% when simulating aboveground biomass under a CO_2 concentration treatment combined with irrigation treatment (Tubiello et al., 1999b) and 23.1% across three rotation experiments in India, including a wheat-rice field under nitrogen stress treatment (0 ~ 160 kg N/ha) and another wheat-rice field, a wheat-maize, and wheat-soybean fields with sufficient fertilizer input

Table 11 Summary of the CERES-Wheat model performances for aboveground biomass variable simulations.

Treatment category	Countries	Performance	References
Rain-fed/nonirrigated and well fertilized	India	R^2: 0.95	Vashisht et al. (2013)
Irrigated with a gradient of water/different scheduling time and well fertilized	India	RMSE: 333 kg/ha	Panda et al. (2003)
	New Zealand	RMSE: 900 kg/ha	Jamieson et al. (1998)
Well irrigated and fertilized with a gradient of fertilizer(s)	United States	RMSE: 1247 kg/ha	Saseendran et al. (2004)
		Normalized RMSE: 9.5%	Thorp et al. (2010b)
	India	Percentage error: 23%	Timsina et al. (2008)
Well irrigated and not fertilized	Germany	R: 0.8	Bacsi and Zemankovics (1995)
Well irrigated and well fertilized[a]	China	Underestimated by 644 kg/ha Percentage error: 11.4%	Guo et al. (2010)
Irrigated with a gradient of water and fertilized with a gradient of fertilizer(s)	India	RMSE: 1200 ~ 1940 kg/ha Normalized RMSE: 14%	Singh et al. (2008); Arora et al. (2007)
	Spain	RMSE: 2360 kg/ha Percentage error: 17%	Abeledo et al. (2008)
Conventional versus no tillage	United States	1999 ~ 2282 kg/ha	Soldevilla-Martinez et al. (2013)
CO_2 concentration with irrigation regimes	United States	Percentage error: 5 ~ 19%	Tubiello et al. (1999b)
	Germany	Normalized RMSE: 27%	Biernath et al. (2011)
CO_2 concentration	United States	Overestimated by 20 kg/ha	Tubiello et al. (1999a)

Sowing date	India	Percentage error: <20% (for over 80% of the simulations)	Hundal and PrabhjyotKaur (1997)
	Germany	Percentage error: <8%, $R^2 > 0.95$	Bacsi and Zemankovics (1995)
Planting density combined irrigation treatments; phosphorous input with seeding rates	Iran	Normalized RMSE: 4.8%	Bannayan et al. (2014)
Wheat with different fallow scheduling systems	Canada	R: 0.85	Wang et al. (2010)

[a]Literatures that did not include treatments were considered as "well irrigated and well fertilized"; for instance, data obtained from local reports.

(Timsina et al., 2008). With continuous wheat and rotation wheat cropping systems in Canada, the correlation coefficients between the simulated and the observed biomass were above 0.8 (Wang et al., 2010). Hundal and PrabhjyotKaur (1997) reported that the CERES model tended to overestimate aboveground biomass for both early- and late-sowing date treatments, but over 80% of the simulated aboveground biomass was within 20% error. Across four experiments with three sowing dates (DOY273, DOY284 and DOY289) and an unfertilized treatment with a sowing date of DOY289, the CERES model also overpredicted the total aboveground biomass at harvest, and the errors were mostly within 8%, except for the fertilized DOY289 treatment (Bacsi and Zemankovics, 1995). Across treatments with different planting densities, irrigation inputs, phosphorous levels, and seeding rates in Iran, the normalized RMSE for aboveground biomass was 4.8% (Bannayan et al., 2014). Under an elevated CO_2 concentration, the simulated aboveground biomass was overestimated by 20 kg/ha (Tubiello et al., 1999a). Across elevated and ambient CO_2 concentration treatments combined with full versus limited irrigation treatments, the average normalized RMSE was 27% for total aboveground biomass simulation (Biernath et al., 2011).

Other biomass-related variable validations, including vegetative biomass, organ biomass, straw biomass, canopy biomass, total biomass, leaf biomass, biological yield, harvest biomass residual, harvest biomass, and surface residue biomass have been reported in the literature (Table 12). Priesack et al. (2006) tested the CERES-Wheat model at an extensive managed plot to which a mixture of inorganic and organic fertilizer was applied and on which a low level of chemical plant protection was used. They reported that the simulated vegetative aboveground and organ storage biomass were close to the observations. Straw biomass has been tested with various fertilization rates. Under nutrient stress (different ratios of nitrogen, phosphorus, and potassium) combined with water stress treatments, the wheat straw biomass simulation had RMSEs of 227.9 and 318.6 kg/ha, depending on the year (Behera and Panda, 2009). Across two types of rotation cropping systems with nutrient stress, the average normalized RMSD was 39.9% (Timsina et al., 2008). Under irrigated and fertilized fields in Arizona, US, the canopy biomass simulation had a normalized RMSE of 18.6% (Thorp et al., 2012). For six experiments involving nitrogen application (about 80 and about 215 kg/ha) and planting density treatments in Arizona, the errors varied greatly, by up to 2000 kg/ha (Thorp et al., 2010a). Across two nitrogen fertilizer treatments in Arizona, the normalized RMSE for leaf mass at the end of the leaf development simulation was 12% (Thorp et al., 2010b). Bakhsh et al. (2013) reported that

Table 12 Summary of the CERES-Wheat model performances for biomass-related variable (excluding aboveground biomass) simulations.

Treatment category	Variables	Countries	Performance	References
Well irrigated and fertilized with a gradient of fertilizer (s)/different types of fertilizers	Straw biomass	India	Normalized RMSE: 40%	Timsina et al. (2008)
	Harvest index	India	RMSE: 0.135 Normalized RMSE: 35.1%	Timsina et al. (2008)
	Leaf biomass	United States	Normalized RMSE: 12%	Thorp et al. (2010)b
	Biological biomass	Pakistan	RMSE: <770 kg/ha	Bakhsh et al. (2013)
Well irrigated and well fertilized[a]	Canopy biomass	United States	Normalized RMSE: 18.6%	Thorp et al. (2012)
Irrigated with a gradient of water and fertilized with a gradient of fertilizer(s)	Total biomass	Spain	RMSE: 2360 kg/ha Mean percentage error: 17%	Abeledo et al. (2008)
	Straw biomass	India	RMSE: 227 ~ 318 kg/ha; R^2: 0.96 ~ 0.97	Behera and Panda (2009)
	Harvest index	Spain	RMSE: 0.16; percentage error: 24%	Abeledo et al. (2008)
CO_2 concentration	Harvest index	United States	Percentage error: 6%	Tubiello et al. (1999a)
Planting density combined with high versus low nitrogen	Canopy biomass	United States	Difference: <2000 kg/ha	Thorp et al. (2010a)
Rotation systems	Harvest biomass	Germany	RMSE: 2100 kg/ha	Langensiepen et al. (2008)
	Harvest biomass residuals		RMSE: 2200 ~ 2400 kg/ha	

(*Continued*)

Table 12 Summary of the CERES-Wheat model performances for biomass-related variable (excluding aboveground biomass) simulations.—cont'd.

Treatment category	Variables	Countries	Performance	References
Management insensitivity	Vegetative biomass and organ storage biomass	Germany	The simulations were close to the observations	Priesack et al. (2006)
Wheat with different fallow scheduling systems	Surface residue biomass	Canada	Error: 1800 kg/ha underestimation ~ 2400 kg/ha overestimation	Wang et al. (2010)

[a]Literatures that did not include treatments were considered as "well irrigated and well fertilized"; for instance, data obtained from local reports.

the RMSEs for biological yield simulations of 11 fertilization treatments with different amounts and types of fertilizers in Pakistan were within 770 kg/ha. Predictions for harvest biomass residual and harvest biomass were validated using 10-year data from a wheat-barley-canola rotation field in Germany. The RMSEs for harvest biomass residual ranged between 2200 kg/ha and 2400 kg/ha, depending on the genotype calibration processes, while the RMSEs for harvest biomass were about 2100 kg/ha in spite of the different calibration processes (Langensiepen et al., 2008). In continuous and rotation wheat systems in Canada, the surface residue biomass simulation had errors ranging from 1800 kg/ha underestimation to 2400 kg/ha overestimation (Wang et al., 2010).

3.5.3 CERES-Rice

Five studies validated aboveground biomass and the top weight of the CERES-Rice model (Table 13). Under both irrigation treatments (five irrigation levels ranging from 625 to 1225 mm) and seedling density treatments (3 density levels of 1 ~ 3 seedling/hill), the average RMSE was 385 kg/ha (Ahmad et al., 2012). Two studies in Thailand validated aboveground biomass/top weight under nitrogen application treatment. The authors reported that for each nitrogen application treatment (0 ~ 150 kg/ha), the absolute percentage errors were within 25% and the simulations were more accurate for 50 ~ 100 kg N/ha treatments (errors were within 10%) (Cheyglinted et al., 2001). Also, the average RMSE for top weight simulation under 0 ~ 188 kg N/ha application treatments was 1103 kg/ha, with agreement index of 0.98 (Phakamas et al., 2013). Assembling 32 experiments with 80 treatments, including planting dates, planting populations, spacings, nitrogen application rates, and irrigation rates, Mall and Aggarwal (2002) found that overall, the CERES model slightly underestimated the aboveground biomass, especially in the early crop growing stage (Mall and Aggarwal, 2002).

Additionally, by-product biomass prediction with the CERES-rice model was tested with late-seeded rice in Thailand, with a simulation error of 3.13% (Babel et al., 2011). Shoot biomass was validated in an open-field and elevated-CO_2 environment, and the normalized RMSEs were between 8 and 19% (Satapathy et al., 2014).

3.6 Harvest Index

3.6.1 CERES-Maize

For fertilized and rain-fed fields in Spain and Croatia, the harvest index was underestimated by 1.3, with an RMSE of 0.155 (López-Cedrón et al., 2008),

Table 13 Summary of the CERES-Rice model performances for biomass-related variable simulations.

Treatment category	Variables	Countries	Performance	References
Well irrigated and fertilized with a gradient of fertilizer(s) only	Aboveground biomass	Thailand	Percentage error: <25%	Cheyglinted et al. (2001)
	Top weight	Thailand	RMSE: 1103 kg/ha R^2: 0.98	Phakamas et al. (2013)
Fertilized, irrigated with varied amount of water and planted with varied densities	Aboveground biomass	India	RMSE: 137 ~ 174 kg/ha	Ahmad et al. (2012)
	Top weight	India	RMSE: 385 kg/ha	Ahmad et al. (2012)
Over 80 treatments[a]	Aboveground biomass	India	Close to the observations except for early growth stage (up to panicle initiation)	Mall and Aggarwal (2002)
Late-seeded rice	Byproduct biomass	Thailand	Error: 3.13%	Babel et al. (2011)
	Harvest index		Error: 5%	
Open filed and elevated CO_2	Shoot biomass	India	Normalized RMSE: 8 ~ 19%	Satapathy et al. (2014)

[a]Treatments included varied seeding and transplanting dates, planting densities, spacing, nitrogen inputs, and irrigations.

and by 7% (Vucetic, 2011), respectively. Across irrigation treatments of 421 ~ 609 mm in Spain, the harvest index was underestimated by 13%, with an RMSE of 0.08 (Dechmi et al., 2010) (Table 10).

3.6.2 CERES-Wheat

Three studies tested the harvest index (Table 11). Across all irrigated versus rain-fed and fertilized versus nonfertilized treatments, the overall RMSE was 0.16, and the mean percent error was 34% (Abeledo et al., 2008). Under various rotation cropping systems and different types of soils, with one of the cropping systems using an unfertilized treatment, the HI simulation had an absolute RMSE of 0.135 and a normalized RMSE of 35.1% (Timsina et al., 2008). In contrast, the error was 6% in an elevated CO_2 environment (Tubiello et al., 1999a).

3.6.3 CERES-Rice

The simulated harvest index was only about 5% off of the observation for a late-sown rice field in Thailand (Babel et al., 2011).

3.7 Leaf-Related Variables: Leaf Number, Leaf Senescence, and LAI

3.7.1 CERES-Maize

The leaf number and LAI prediction capabilities of the CERES-Maize model have been validated under irrigation, fertilization, sowing date, planting density, and spacing treatments in various countries (Tables 14 and 15). Carberry et al. (1989) tested leaf number and leaf senescence under irrigated versus severe water stress treatments in Australia. The authors found that the overall RMSE for leaf number simulation was 2.49 and that the model did not simulate leaf area senescence accurately during the growing season (Carberry et al., 1989). Gungula et al. (2003) simulated leaf number at anthesis date given 0 ~ 120 kg N/ha treatments and indicated that the simulated leaf numbers were close to the observations given 60 ~ 120 kg N/ha application treatments. Braga et al. (2008) reported that the RMSE for total leaf number simulation was 0.87.

Twenty-three papers have validated the LAI of the CERES-Maize model (Table 13). Under nonirrigated treatment, the simulated LAI was close to the observed LAI during the growing season (Sandor and Fodor, 2012). With various amounts of irrigation water and various irrigation-timing treatments, the model simulated LAI reasonably well throughout the growing season, with an agreement index over 0.8, and the simulated maximum LAIs

Table 14 Summary of the CERES-Maize model performances for LAI variable simulations.

Treatment category	Countries	Performance	References
Rain-fed/nonirrigated and well fertilized	Brazil	Percentage error:10 ~ 24%	Soler et al. (2007)
	Nigeria, India, Croatia	Percentage error: ≤6%	Jagtap et al. (1993); Panda et al. (2004); Vucetic (2011)
	Hungary	Close to the observations	Sandor and Fodor (2012)
	China	Error: 0.5 ~ 0.7	Guo et al. (2010)
Irrigated with a gradient of water/ different scheduling time and well fertilized	Italy	Percentage error: 26 ~ 46%	Ben Nouna et al. (2000); Mastrorilli et al. (2003)
	Pakistan	Percentage error: 5.9 ~ 23%	Mubeen et al. (2013)
	United States, India	Percentage error: <5%	DeJonge et al. (2011); Panda et al. (2004)
	India	RMSE: <0.2	Panda et al. (2004)
	Pakistan, United States	RMSE: 0.68 ~ 0.88	Mubeen et al. (2013); DeJonge et al. (2011)
	Australia, United States	RMSE: 0.9 ~ 1.14	Carberry et al. (1989); Retta et al. (1991)
	Spain	Closed to the observed in the early growing stages but not late growing stages	Dechmi et al. (2010)
Well irrigated and well fertilized	United States	RMSE: 0.307	DeJonge et al. (2011)
	Italy	Percentage error: 0.97%	Ben Nouna et al. (2000); Mastrorilli et al. (2003)
	Brazil, China	Percentage error: 10% ~ 24%	Soler et al. (2007); Guo et al. (2010)
	United States	Normalized RMSE: 35.7%	Xevi et al. (1996)
	Spain	RMSE: 1.2 ~ 2	López-Cedrón et al. (2005)
	Canada	Normalized RMSE:14 ~ 50%	Liu et al. (2014)

Not fertilized	Canada	Normalized RMSE: 65 ~ 98%	Liu et al. (2014)
Irrigated with a gradient of water and fertilized with a gradient of fertilizer(s)	Iran	Normalized RMSE: 5.22%	Moradi et al. (2013)
Other treatments[a]	United States	Poorly simulated	Lizaso et al. (2001); Lizaso et al. (2003b)
	United States	RMSE: 0.33 ~ 1.47	Saseendran et al. (2005); Lizaso et al. (2011); Lizaso et al. (2003a)
	Iran	RMSE: 12.79 R^2: 0.94	Lashkari et al. (2011)

[a]Other treatments included sowing dates, planting density, and spacing.

Table 15 Summary of the CERES-Maize model performances for leaf number variable simulations.

Treatment category	Variables	Validation Nations	Performance	References
Irrigated with a gradient of water/different scheduling time and well fertilized	Leaf number	Australia	RMSE: 2.49	Carberry et al. (1989)
Well irrigated and fertilized with a gradient of fertilizer(s)	Leaf number at anthesis	Nigeria	Difference: under-predicted by $0 \sim 5$ Percentage error: $0 \sim 17\%$	Gungula et al. (2003)
Sowing dates	Total leaf number	Portugal	RMSE: 0.87	Braga et al. (2008)

were within 23% error (Mubeen et al., 2013). Similarly, for both full and limited irrigation treatments, DeJonge et al. (2011) reported that the LAIs were overestimated over the growing season but were underestimated during the reproductive stage. The authors also compared the model accuracy for final LAI simulation between treatments and showed that the model simulated the LAI better for full irrigation treatments (RMSE = 0.307) than limited irrigation treatments (RMSE = 0.841) (DeJonge et al., 2011). Up to 26.96 and 46.15% underestimation of maximum LAI were found under moderate and severe water stress, respectively, but only a 0.97% overestimation was found under full irrigation condition (Ben Nouna et al., 2000; Mastrorilli et al., 2003). By comparison, when simulating LAI in rain-fed and irrigated fields in Brazil with four different maize cultivars, the normalized RMSEs were 10.4 ~ 24.2% and 10.9 ~ 24.4%, respectively (Soler et al., 2007). Others reported that the average difference between simulated and observed LAI was no greater than 0.09 under rain-fed and fertilized condition (Jagtap et al., 1993) and various levels of water availability (Panda et al., 2004). In contrast, the difference between the simulations and the observations was about 0.2 for a rain-fed, fertilized treatment in Nigeria (Jagtap et al., 1993) and an irrigated treatment in the United States (Xevi et al., 1996). Across rain-fed fields in Croatia, the model underestimated the maximum LAI by 4% (Vucetic, 2011). LAI was poorly simulated for both fertilized and unfertilized maize in Canada, with normalized RMSEs of 14 ~ 50% and 65 ~ 98%, respectively (Liu et al., 2014). Guo et al. (2010) indicated that the maximum LAI was underestimated by about 0.7 and that the mean LAI was underestimated by about 0.5 for seven stations in China. LAI during the silking developmental stages has been mostly poorly simulated under various treatments in Iowa, including planting dates, nitrogen application rates, fertilization rates, and population densities (Lizaso et al., 2001, 2003b). The LAI at silking simulation had an RMSE of 1.14 across severe water stress and full irrigation treatments in Australia (Carberry et al., 1989). The RMSEs for the LAI simulations were 0.33 and 0.84 for full irrigation and limited irrigation, respectively (DeJonge et al., 2011). The average RMSE for LAI simulation in both dry- and irrigated-land in Kansas, US, was 0.9 (Retta et al., 1991). However, with the maximum allowable depletion of available soil water, 30 ~ 75%, the average RMSE for LAI simulations was 0.194 (Panda et al., 2004). Dechmi et al. (2010) showed that early growing season LAIs were well-simulated for low- and high-irrigation treatments but that the maximum LAIs were underpredicted. The reported average RMSE for three maize hybrid LAI simulations ranged from 0.33 to 0.78 for three sowing dates between the end of Apr. and mid-Jun. in Colorado, US (Saseendran et al., 2005). The reported average normalized RMSE for the maximum LAI simulation of an irrigation treatment combined with a fertilization treatment in Iran was 5.22% (Moradi et al., 2013). However, others showed that the simulations of LAI were less accurate. For a population density treatment in Minnesota, nitrogen application in Hawaii, and in rain-fed and irrigated fields in Florida, LAI was not well-simulated, with RMSEs from 0.33 to 1.47 (Lizaso et al., 2003a, 2011). The RMSEs for LAI simulations in an experimental site in Spain were 1.21, as best result (López-Cedrón et al., 2005). Lashkari et al (2011) calculated the average RMSE for maximum LAI simulation under planting density treatments, and the value was 12.79 (Lashkari et al., 2011). Xevi et al. (1996) reported a normalized RMSE of 31.9% for LAI simulation for irrigated maize in Nebraska.

3.7.2 CERES-Wheat

One study tested leaf number with nitrogen application treatments in Arizona, US, and showed that leaf number development was reasonably well-simulated (Thorp et al., 2010b).

Fifteen studies reported LAI validation results for the CERES-Wheat model (Table 16). Bacsi et al. (1995) showed that LAI was simulated reasonably well during the course of development given a nonfertilized treatment (Bacsi and Zemankovics, 1995). However, a study in Arizona, US, with various levels of nitrogen input and planting density indicated that the predicted green LAI did not match well with the observations (Thorp et al., 2010a). The average difference between simulated and observed LAI ranged between 0.016 and 0.12 under various conditions, including various combinations of water availability and N:P:K ratios (Behera and Panda, 2009), seven wheat and maize production sites in China (Guo et al., 2010), and various levels of water availability (Panda et al., 2003). However, given 0 ~ 4 irrigation treatments in China, the differences between the simulated and the observed LAI were between 0.3 and 0.6 (Yang et al., 2006b). Given various combinations of CO_2 concentration and irrigation level, the normalized RMSE for simulated LAI was 1.27% (Biernath et al., 2011). Across different planting densities, irrigation inputs, phosphorous levels, and seeding rates in Iran, the normalized RMSE for LAI was 8% (Bannayan et al., 2014). By contrast, across various levels of irrigation combined with different fertilization application rates, the average RMSEs for LAI at 32, 54, 82, and 124 days after planting were 0.1, 0.5, 0.9, and 0.6, respectively (normalized RMSE of 25 ~ 35%) (Arora et al., 2007).

Table 16 Summary of the CERES-Wheat model performances for LAI simulations.

Treatment Category	Countries	Performance	References
Irrigated with a gradient of water/different scheduling time and well fertilized	India	RMSE: 0.108 Percentage error: 1.14% R^2: 0.92	Panda et al. (2003)
	New Zealand	The simulated LAI did not respond to drought factor	Jamieson et al. (1998)
	China	Error: 0.3 ~ 0.6	Yang et al. (2006b)
Well irrigated and fertilized with a gradient of fertilizer(s) only	United States	Normalized RMSE: 17.9%	Thorp et al. (2010b)
Well irrigated and well fertilized	China	Underestimated mean LAI by 0.5	Guo et al. (2010)
	United States	Normalized RMSE: 27.8%	Thorp et al. (2012)
Irrigated with a gradient of water and fertilized with a gradient of fertilizer(s)	India	RMSE: 0.069 ~ 0.075 R^2: > 0.9	Behera and Panda (2009)
	India	RMSE: 0.1 ~ 0.9 Normalized RMSE: 25 ~ 35%	Arora et al. (2007),[a]
	China	RMSE: 0.87 (for all LAIs), 0.67 (for LAI≥3) Normalized RMSE: 20%	Dong et al. (2013)a; Dong et al. (2013)b; Ji et al. (2014)
Planting density combined irrigation treatments; phosphorous input with seeding rates	Iran	Normalized RMSE: 8%	Bannayan et al. (2014)
Planting densities combined with high versus low nitrogen	United States	Not accurate	Thorp et al. (2010a)
CO_2 concentration combined with two irrigation treatments	Germany	Normalized RMSE: 1.27%	Biernath et al. (2011)
Sowing date combined with different nitrogen input	Germany	R^2: 0.571	Bacsi and Zemankovics (1995)

[a]Treatments included different irrigation regimes combined with fertilization regimes and four planting dates.

Ji et al. also reported that the normalized RMSE for LAI simulation was about 20% under varied nutrient and water input treatments in China (Ji et al., 2014). Similarly, the normalized RMSEs were 17.9 and 27.8% for LAI simulations under nitrogen application treatments (110.5 kg/ha vs. 241 kg N/ha) and no nutrient stress treatments, respectively, in Arizona, US (Thorp et al., 2010b; 2012). For water availability treatments, including full irrigation, early drought, late drought, and full drought, the CERES model underestimated LAI for most of the treatments, and the simulated LAI did not respond to the drought factor (Jamieson et al., 1998). Additionally, Dong et al. (2013b) found that the CERES-Wheat model overestimated LAI, particularly when the LAIs were less than 3. With four irrigation treatments (0 ~ 675 m^3/ha) and four fertilization treatments (0 ~ 225 kg N/ha), Dong et al. (2013a) also reported that the RMSEs for all LAIs and LAI ≥3.0 simulations were 0.87 and 0.67, respectively.

3.7.3 CERES-Rice

Only two studies tested the LAI variable in the CERES-Rice model (Table 17). Mall and Aggarwal (2002) used data from 32 experiments, which consisted of planting date, planting density, spacing, irrigation, and nitrogen application treatments, and showed that overall, the model simulated LAI well but slightly underestimated LAI, particularly around the flowering stage. Under irrigation and planting density treatments, the RMSEs for LAI simulation were mostly under 1.3 and were 1.12 on average (Ahmad et al., 2012).

3.8 Soil Nitrogen

Soil nitrogen content and nitrate leaching prediction have been validated for the CERES-Maize and CERES-Wheat models. No research has

Table 17 Summary of the CERES-Rice model performances for LAI simulations.

Treatment category	Countries	Performance	References
Over 80 treatments[a]	India	Overall accurate but underestimated LAI around flowering stage	Mall and Aggarwal (2002)
Fertilized, irrigated with varied amount of water and planted with varied densities	India	RMSE: 1.08 ~ 1.33, Average RMSE: 1.12	Ahmad et al. (2012)

[a]Treatments included varied seeding and transplanting dates, planting densities, spacing, nitrogen inputs, and irrigations.

reported on soil nitrogen prediction validation for the CERES-Rice model.

3.8.1 CERES-Maize

Soil nitrogen content and nitrate leaching have been tested in both continuous cropping systems and rotation systems using nitrogen availability, legume cover crop incorporation, and irrigation treatments (Table 18). Gabrielle and Kengni (1996) simulated soil mineral nitrogen content using the CERES model for five experiments at three sites over 2 years in France: a Grenoble site with two irrigated fields, one with and one without fertilization; a Laon site with one tilled field with canola straw removal and another with the straw remaining; and a Grignon site with no carbon or nitrogen input. The results showed that the simulated nitrogen for 0–90 or 0–120 cm soil did not match the measured results and mostly underestimated soil nitrogen content. The RMSE of nitrogen content in the 0–30 cm soil was up to 159 kg/ha for the nonfertilized Grenoble experiment and as low as 8.5 kg/ha for the Grignon experiment. The authors also simulated nitrate leaching for the Grenoble site. They reported that the RMSEs were 21.3 and 8.4 kg/ha for the unfertilized and fertilized experiments, respectively (Gabrielle and Kengni, 1996). Given three levels of nitrogen input for 2 years (20 ~ 280 kg/ha for 1 year and 30 ~ 270 kg/ha for the other year), the simulated nitrate leaching was significantly different from the observed leaching ($P \leq 0.05$) (Pang et al., 1998). A similar study with 0 ~ 200 kg N/ha input treatments in tropical Thailand indicated that the model tended to underestimate nitrate leaching, with a coefficient of determination of 0.86 (Asadi and Clemente, 2003). Another study in Canada showed that the model performed better for soil inorganic nitrogen simulations given afertilized maize treatments (normalized RMSE: 35.8 ~ 57.1%) than unfertilized maize treatments (normalized RMSE: 72 ~ 81%) (Liu et al., 2014). Furthermore, by simulating soil mineral nitrogen content for a year and nitrate–nitrogen loss for 3 years in both fertilized and unfertilized plots in Canada, Liu et al. (2010) calculated that the RMSEs for simulating soil nitrogen content at 0 ~ 13 cm were 2 and 1.3 kg/ha for the fertilized and the unfertilized plots, respectively, with normalized RMSEs of 58 and 64%, respectively. They also observed a consistent overestimation of soil nitrate leaching through subsurface tiles for unfertilized plots, with 160% of normalized RMSE. By comparison, in fertilized plots, the nitrogen loss was reasonably well-simulated, with a normalized RMSE of 29% and an RMSE of 12.8 kg/ha (Liu et al., 2010). Nonetheless, nitrate leaching was well-simulated for unfertilized plots and no-till plots in a study

Table 18 Summary of the CERES-Maize model performances for soil nitrogen and nitrate leaching simulations.

Treatment category	Variables	Countries	Performance	References
Well irrigated and fertilized with a gradient of fertilizer(s)	Nitrate leaching	United States	R^2: 0.5, significantly different from the observed ($P \leq 0.05$)	Pang et al. (1998)
		Canada	Matched well with the observations	Beckie et al. (1995)
		Thailand	R^2: 0.86	Asadi and Clemente (2003)
		Hungary	Close to the observed	Kovacs et al. (1995)
	Soil nitrogen content	Hungary	Close to the observed	Kovacs et al. (1995)
Well irrigated and not fertilized	Soil nitrogen content, 0–30cm	France	RMSE: 159 kg/ha	Gabrielle and Kengni (1996)
	Soil nitrogen content, 0–13cm and 0–30 cm	Canada	RMSE: 1.3 kg/ha Normalized RMSE: 64 ~ 81%	Liu et al. (2010), Liu et al. (2014)
	Nitrate leaching	France	RMSE: 21.3 kg/ha	Gabrielle and Kengni (1996)
		Canada	RMSE: 8.2 kg/ha	Liu et al. (2010)
		Canada	Normalized RMSE: 160%	Liu et al. (2010)
Well irrigated and well fertilized	Soil nitrogen content, 0–30 cm	France	RMSE: 8.5 kg/ha	Gabrielle and Kengni (1996)
	Soil nitrogen content, 0–13 cm and 0–30 cm	Canada	RMSE: 2 kg/ha Normalized RMSE: 30 ~ 34%	Liu et al. (2010), Liu et al. (2014)
		Canada	Normalized RMSE: 58%	Liu et al. (2010)
	Nitrate leaching	France, Canada	RMSE: 8.4 ~ 12.8 kg/ha	Gabrielle and Kengni (1996); Liu et al. (2010)
		Canada	Normalized RMSE: 29%	Liu et al. (2010)

Irrigated with a gradient of water and fertilized with a gradient of fertilizer(s)	Nitrate leaching	United States	Difference: 10 ~ 40 kg/ha	He et al. (2011)
Corn-alfalfa-corn rotation with and without fertilization	Nitrate leaching	United States	Unfertilized corn field nitrate leaching was well simulated; did not well simulate alfalfa effect on nitrate leaching; did not simulate tillage effect either	Gerakis et al. (2006)
Wheat-maize rotation with legume cover crop	Soil nitrogen	United States	Underestimated by 25 ~ 150 kg/ha	Hasegawa et al. (2000)
Soil types	Soil nitrate content	United States	RMSE: <8 μNO_3^-/soils	Garrison et al. (1999)

of a corn-alfalfa-corn rotation field in the Midwest of the United States. However, the model failed to simulate nitrate leaching in tilled fields and after alfalfa growth (Gerakis et al., 2006). Beckie et al. (1995) mentioned that the simulated nitrate leaching matched well with the observations for two wheat fields with and without fertilization in Canada (Beckie et al., 1995). Kovacs et al. (1995) indicated that the largest errors in nitrate leaching simulation occurred with unfertilized treatments. In their study, maize–wheat rotation fields in Hungary were fertilized with 0, 50, 150, or 250 kg/ha of nitrogen, in addition to phosphorus and potassium addition, and nitrate leaching was measured in 4 ~ 5 m soils. The test results showed that over 20 years, soil nitrogen balance and accumulative nitrate leaching simulations were in good agreement with field measurements (Kovacs et al., 1995). Garrison et al. (1999) calculated RMSEs for soil nitrate content under fertilized maize fields with two different soils and reported that the RMSEs were within 8 μg-NO_3^-/soils. For soil nitrogen simulation for a wheat–maize rotation with LCC incorporation cropping systems in the United States, the CERES-Maize model underestimated soil nitrogen by 25–150 kg N/ha in 1 year and by 25–55 kg N/ha in another year under early LCC incorporation conditions (Hasegawa et al., 2000). For six treatments combining three levels of nitrogen input (185 ~ 309 kg/ha) and two levels of irrigation water input (irrigating water use depending on soil moisture versus 1.5 times the first irrigation water use), the CERES model underestimated potential nitrate leaching for the low-nitrogen input treatment, with 10 and 31 kg/ha error for normal and overirrigated treatment, respectively, and it overestimated potential nitrate leaching for the higher nitrogen input treatment, with about 40 and about 10 kg/ha error for the normal- and over-irrigated treatments, respectively (He et al., 2011).

3.8.2 CERES-Wheat

Five studies validated the soil nitrogen variables of the CERES-Wheat model under varied treatments and rotation systems (Table 19). Popova et al. (2005) tested soil nitrate–nitrogen in two soil types with 200 kg N/ha input combined with a range of irrigation water input, from 0 to 183 mm, and reported that the coefficients of determination were 0.38 and about 0.45 for a maize field soil nitrate simulation given nonirrigated and irrigated treatments, respectively (Popova and Kercheva, 2005). When simulating soil nitrogen in a wheat–maize rotation with LCC incorporation experiment, Hasegawa et al. (2000) found that the simulated inorganic nitrogen content in the soil was within 20% error for unfertilized fallow–wheat and wheat–legume rotation systems. Beckie et al. (1995) also indicated that the total and

Table 19 Summary of the CERES-Wheat model performances for soil nitrogen and plant nitrogen simulations.

Treatment category	Variables	Countries	Performance	References
Rain-fed/nonirrigated and well fertilized	Soil nitrate-N	Bulgaria	Reasonably well simulated	Popova and Kercheva, (2005)
Well irrigated and fertilized with a gradient of fertilizer(s)	Plant nitrogen content	United States	Normalized RMSE: 10.9%	Thorp et al. (2010b)
Varied levels of irrigation and nitrogen	Canopy nitrogen	China	Normalized RMSE: 20%	Ji et al. (2014)
Well irrigated and well fertilized only[1]	Plant nitrogen content	United States	Normalized RMSE: 50.7%	Thorp et al. (2012)
Rice-wheat rotation under irrigated at different timing, fertilized with a gradient of nitrogen and two rice residue management regimes (removed vs. remained)	Grain nitrogen uptake	India	RMSE: 7.8 kg/ha	Sarkar and Kar (2008)
	Biomass nitrogen uptake	India	RMSE: 8.4 kg/ha	
Rotation systems with fertilization treatment	Soil inorganic nitrogen	United States	Percentage error: < 20%	Hasegawa et al. (2000),[a]
	Soil nitrate	Canada	Absolute error: <50 kg/ha	Beckie et al. (1995),[b]
	Plant nitrogen uptake	United States	Underestimated by 66.7%	Hasegawa et al. (2000)
		Canada	Acceptable for fertilized treatment but heavily underestimated by over 60 kg/ha	Beckie et al. (1995)
Wheat-maize rotation under different nitrogen inputs	Soil nitrogen and nitrogen balance	Hungary	Close to the field measurement with largest disagreement under highest nitrogen input treatment	Kovacs et al. (1995)

(*Continued*)

Table 19 Summary of the CERES-Wheat model performances for soil nitrogen and plant nitrogen simulations.—cont'd.

Treatment category	Variables	Countries	Performance	References
Soil types	Soil nitrate	France	RMSE: 11.6 ~ 17.8 kg/ha	Gabrielle et al. (2002)
Sowing dates combined with population density	Plant nitrogen content	United States	RMSE: 4.5 mgN/g, Normalized RMSE: 9 ~ 17%	Weiss and Moreno-Sotomayer (2006)
Sowing dates combined with different fertilizer applications	Grain and plant nitrogen uptake	United States	Percentage error: 0.2 ~ 20%	Bacsi and Zemankovics (1995)

[a]Maize-wheat rotation followed by legume cover crop, wheat was unfertilized.
[b]Treatments included five wheat-fallow rotations and continuous wheat fields under fertilized versus unfertilized treatments.

distribution of nitrate–nitrogen were well-simulated, with absolute errors mostly under 50 kg/ha for five wheat rotation and continuous cropping systems in two locations in Canada. In conventionally managed wheat fields in France, the RMSEs for soil nitrate simulations ranged from 11.6 to 17.8 kg/ha, depending on soil type (Gabrielle et al., 2002). Soil nitrogen balance and accumulative nitrate leaching were acceptably well-simulated (Kovacs et al., 1995).

3.9 Plant Nitrogen Uptake and Plant Nitrogen Content

3.9.1 CERES-Maize

Seven studies have validated the crop nitrogen uptake or crop nitrogen content of the CERES-Maize model given irrigation and fertilization treatments in both continuous cropping and rotation systems (Table 20). Two studies indicated that the simulated nitrogen uptake was highly correlated with observations for nitrogen application treatments (0 ~ 200 kg/ha) in Thailand and nitrogen application (0 ~ 360 kg/ha) combined with irrigation (20 ~ 100 mm) treatments in the United States. The regression lines between the simulations and the observations had R^2 values over 0.9, constants of 0, and respective slopes of 1.1103 and 1.013 (Asadi and Clemente, 2003; Pang et al., 1997). Another study involving a 20 ~ 280 kg/ha nitrogen input gradient with a water deficit in the United States also showed the that simulated and the observed nitrogen uptakes were not significantly different ($P \leq 0.05$), but the difference could reach 70 kg/ha for high levels of nitrogen application (about 280 kg/ha) (Pang et al., 1998). The simulations for leaf nitrogen and vegetative nitrogen content in an experiment with 0 ~ 400 kg N/ha applications in China were in agreement with the measurements, with average normalized RMSEs of 23.1 and 24.7%, respectively (Liu et al., 2012). The study of a wheat-maize rotation field with LCC incorporation systems showed that most of the simulated maize nitrogen uptakes were within 20% error in 1 year, but they were underestimated by 25 ~ 70 kg/ha in another year (Hasegawa et al., 2000). For rain-fed maize in Croatia, the grain nitrogen content and nitrogen uptake were overestimated by 30 and 14%, respectively (Vucetic, 2011). Lizaso et al. (2011) tested nitrogen content in shoots, leaves, and stems for varied treatments in Florida and Iowa, US. The RMSEs for shoot nitrogen ranged from 10.2 to 32.6 kg N/ha, with an index of agreement from 0.63 to 0.978. The leaf nitrogen concentration in the percentage simulation had small RMSEs below 0.5% for the 0 and 56 kg N/ha application treatments but large

Table 20 Summary of the CERES-Maize model performances for crop nitrogen uptake and crop nitrogen content variable simulations.

Treatment category	Variables	Countries	Performance	References
Rain-fed/nonirrigated and well fertilized only	Grain nitrogen content	Croatia	Overestimated by 30%	Vucetic (2011)
	Nitrogen uptake	Croatia	Overestimated by 14%	Vucetic (2011)
Well irrigated and fertilized with a gradient of fertilizer(s) only	Nitrogen uptake	Thailand	R^2: 0.99	Asadi and Clemente (2003)
	Leaf and vegetative nitrogen content	China	Normalized RMSE: 23 ~ 24.7%	Liu et al. (2012)
	Shoot nitrogen content	United States	Index of agreement: 0.70 ~ 0.97	Lizaso et al. (2011)
	Leaf nitrogen content		Index of agreement: 0.74 ~ 0.91	
	Stem nitrogen content		Index of agreement: 0.43 ~ 0.93	
Well irrigated and well fertilized	Shoot nitrogen content	United States	Index of agreement: 0.978	Lizaso et al. (2011)
	Leaf nitrogen content		Index of agreement: 0.614	
	Stem nitrogen content		Index of agreement: 0.817	
Irrigated with a gradient of water and fertilized with a gradient of fertilizer(s)	Nitrogen uptake	United States	R^2: 0.946	Pang et al. (1997)
		United States	Not significantly different from the observed ($P \leq 0.05$); Difference: up to 70 kg/ha	Pang et al. (1998)

Rain-fed/nonirrigated, well fertilized	Shoot nitrogen content	United States	Index of agreement: 0.632	Lizaso et al. (2011)
	Leaf nitrogen content		Index of agreement: 0.479	
	Stem nitrogen content		Index of agreement: 0.0.638	
Maize-wheat rotation with legume cover crop	Nitrogen uptake	United States	Percentage error: $<20\%$	Hasegawa et al. (2000)
Soil types combined with different irrigation treatments	Soil nitrogen	Bulgaria	R^2: 0.38 ~ 0.45	Popova and Kercheva (2005)
Wheat-maize rotation under different nitrogen inputs	Soil nitrogen and soil nitrogen balance	Hungary	Close to the field measurement with largest disagreement under highest nitrogen input treatment	Kovacs et al. (1995)

RMSEs of above 0.8% for high nitrogen inputs (above 116 kg N/ha application). Regarding stem nitrogen concentration, in the percentage simulation, the RMSEs were 0.521 ~ 1.45% (Lizaso et al., 2011).

3.9.2 CERES-Wheat

Eight studies validated the nitrogen uptake variable of the CERES-Wheat model (Table 19). Given various population density combined with sowing date treatments in the United States, normalized RMSEs for two wheat cultivars' grain nitrogen concentration ranged from 9 to 17%, and the average RMSE was 4.5 mg N/g (Weiss and Moreno-Sotomayer, 2006). Across low- and high-nitrogen-input treatments in Arizona, the average normalized RMSE for grain nitrogen content was 10.9% (Thorp et al., 2010b). The average normalized RMSE for canopy nitrogen content was 20% across various water and nutrient input rates in China (Ji et al., 2014). Across sowing dates in late-Sep. and early- and late-Nov. in Germany, combined with large fertilizer applications (about 230 kg N/ha) to wheat sown in Sep. and mid-Nov. and 0 versus 213 kg N/ha fertilizer input for wheat sown in late-Nov., the percentage errors for crop nitrogen uptake were within 20%, and the grain nitrogen uptake was overestimated by 0.2 ~ 19.6% (Bacsi and Zemankovics, 1995). The simulated nitrogen uptake for wheat in a fallow-wheat rotation was within 20% error, but it was only about one-third of the observed midwinter nitrogen uptake rate seen for the unfertilized wheat (Hasegawa et al., 2000). Beckie et al. (1995) indicated that crop nitrogen uptake simulations were acceptable for fertilized wheat but that the model heavily underestimated nitrogen uptake for unfertilized wheat by over 60 kg N/ha. In a wheat-rice rotation field in India, given a rice residue (removed vs. remained) and irrigation treatment, the nitrogen uptakes according to grain and biomass simulations had RMSEs of 7.8 and 8.4 kg/ha, respectively (Sarkar and Kar, 2008). Nonetheless, the simulation of plant nitrogen content in Arizona, US, had a normalized RMSE of 50.7% (Thorp et al., 2012).

3.9.3 CERES-Rice

Three studies in Iran and India tested nitrogen content and nitrogen uptake given a fertilization treatment (Table 21). In Iran, the nitrogen content in grains and final biomass were simulated across nitrogen inputs between 0 and 75 kg/ha combined with various levels of irrigation. The RMSEs were both 9 kg/ha, and normalized RMSEs were 12 and 20%, respectively (Amiri et al., 2013). In India, when three rice cultivars were given higher-nitrogen-input treatments (0 ~ 150 kg/ha), the simulated nitrogen uptake by the grains matched reasonably well with the measurement for those

Table 21 Summary of the CERES-Rice model performances for plant nitrogen simulations.

Treatment category	Variables	Countries	Performance	References
Irrigated with varied amount of water and fertilized with varied nitrogen levels	Nitrogen in final biomass Nitrogen in grain	Iran	RMSE: 9 kg/ha Normalized RMSE: 20% RMSE: 9 kg/ha Normalized RMSE: 12%	Amiri et al. (2013)
Well irrigated and fertilized with a gradient of nitrogen inputs	Nitrogen uptake	India	Percentage error: <25% for nitrogen input under 100 kg/ha; Percentage error: 27 ~ 68% for nitrogen input of 100 ~ 150kg/ha	Swain and Yadav (2009)
Wheat-rice rotation, rain-fed, fertilized at varied nitrogen rates, residue managements and planting methods	Nitrogen in grain	India	RMSE: 3.59 ~ 12.44 kg/ha	Sarkar and Kar (2008)

nitrogen addition treatments that were less than 100 kg/ha, with less than 25% error, whereas given high nitrogen inputs of 100 and 150 kg N/ha, the errors were 27 ~ 68% (Swain and Yadav, 2009). Another study in India tested the grain and biomass nitrogen content for transplanted and direct-seeded rice given wheat residue and nitrogen availability treatments. The results showed that the average RMSEs for transplanted and direct-seeded rice grain nitrogen were 12.44 and 3.59 kg/ha, respectively, and that those for biomass nitrogen were 20.78 and 15.38 kg/ha, respectively (Sarkar and Kar, 2008).

3.10 Soil Temperature

Soil temperature variable validation results have been reported only for the CERES-Maize and CERES-Wheat models, not for the CERES-Rice model (Table 22).

3.10.1 CERES-Maize

Four studies have validated soil temperature in the CERES-Maize model. Hasegawa et al. (2000) monitored and simulated soil temperature in a wheat-maize rotation with legume cover crop (LCC) systems. The authors showed that the simulated temperatures did not match well with the observations from Jul. to harvest for maize-LCC rotation and that over half of the simulated temperatures were 2.6 °C different from the observations; some differences were over 10.0 °C (Hasegawa et al., 2000). Under three tillage method treatments, the accuracy of the soil temperatures in a three-layer (0–5 cm, 5–15 cm, and 15–30 cm) simulation varied greatly over various years, layers, and tillage methods, with normalized RMSEs ranging between 22.5 and 49.6%. The results indicated that soil temperature was best simulated under conventional tillage treatment (Liu et al., 2013). Across eight fertilized versus unfertilized combined with irrigated versus unirrigated treatments, the CERES model did not reproduce soil temperature at depths of 5, 10, 20, 40, and 60 cm, with RMSEs of 4.28 °C, 5.5 °C, 6.17 °C, 6.02 °C, and 3.76 °C, respectively (Sandor and Fodor, 2012). Hodges and Evans (1992) tested soil temperature with 4-year field experiments involving row spacing treatments and ten hybrids and reported differences as large as 10 °C and as small as 1 ~ 2 °C.

3.10.2 CERES-Wheat

Hasegawa et al. (2000) also tested the simulated soil temperature of the CERES-Wheat model in wheat-maize rotation with legume cover crop (LCC) systems. The simulated soil temperature in the 0–15 cm and

Table 22 Summary of the CERES-Maize and CERES-Wheat model performances for soil temperature simulations.

Treatment category	Performance	Countries	Reference	Performance	Countries	Reference
	CERES-maize			CERES-wheat		
Irrigated with a gradient of water and fertilized with a gradient of fertilizer(s) only	RMSE: 4.7 ~ 6.2°C	Hungary	Sandor and Fodor (2012)			
Maize–wheat rotation with legume cover crop	Close to the observed through the mid-Aug. but overestimated by up to 10°C in the late season	United States	Hasegawa et al. (2000)	Overestimated by up to 10.7°C, 13.8 °C for 0–15 cm and 15–30 cm, respectively	United States	Hasegawa, et al. (2000)
Soybean–maize rotation with different management intensity[a]	Normalized RMSE: 22.5% ~ 49.6%	China	Liu et al. (2013)			
	RMSE: 3.8 ~ 7°C	China	Liu et al. (2013)			
Row spacing	Difference: 1 ~ 10°C	United States	Hodges and Evans (1992)			

[a]Management intensity included conventional tillage, reduced tillage, and nontillage

15–30 cm layers tended to be higher than those measured by up to 13.8 and 10.7 °C, respectively (Hasegawa et al., 2000).

3.11 Soil Water Content

3.11.1 CERES-Maize

Seventeen papers have tested the soil water validity of the CERES-Maize model, and the tests have been conducted with different soils, water, and nutrient treatments (Table 23). Gabrielle et al. (1995) reported that the mean square error for a soil water storage simulation in three locations (one location grew maize, and other two were bare soils) in France ranged between 4 and 12 cm^2. The results indicated that soil water storage was most accurately simulated for well-drained soil among these three locations in France. In Bulgaria, both soil water content and potential extractable soil water were reasonably well-simulated for both irrigated and dry plots, with normalized RMSEs within 4 and 19%, respectively (Popova and Kercheva, 2005). In Brazil, the normalized RMSEs for simulating soil moisture across rain-fed and irrigated treatments were within 15% (Soler et al., 2007). In Florida, US, the normalized RMSE for soil water content simulation during the early growing season for the whole profile, 0–5 cm, and 5–15 cm were 35.5, 51.0, and 17%, respectively (Ritchie et al., 2009). Asadi and Clemente (2003) reported that with four levels of nitrogen application from 0 to 200 kg/ha in Thailand, the simulated soil water content was reasonably well-simulated, with some notable underestimations of up to 20% error. Liu et al. (2014) reported that the normalized RMSEs for soil water content at the 0–10 cm layer under unfertilized and fertilized treatments in Canada ranged between 25 and 36%. With 119 data points for four types of irrigated soils in Georgia, US, Hook et al. (1994) calculated that the model underestimated soil water content by an average of 5.92 mm and that the accumulative absolute difference was 16.66 mm (Hook, 1994). In another US state, soil moisture was tested in four layers (0–120 cm with 30 cm intervals) on irrigated land as well. The results indicated that soil moistures were generally well-simulated for each layer, with normalized RMSEs under 14.0%, except for the top, 0–30 cm, layer (normalized RMSE of 16.6%) (Xevi et al., 1996). Anothai et al. (2013) showed that given 70%- and 100%-full irrigation treatments, the soil water content simulation using the Priestley–Taylor approach to ET estimation performed reasonably well (normalized RMSE of 13.2 ~ 29.0% for 0 ~ 15 cm) in 1 year but poorly in

Table 23 Summary of the CERES-Maize model performances for soil water and plant extractable soil water (PESW) simulations.

Treatment category	Variables	Countries	Performance	References
Rain-fed/nonirrigated and well fertilized	Soil water content	United States	Percentage error: >10%	DeJonge et al. (2011)
		United States	RMSE: 0.043 m^3/m^3	Saseendran et al. (2008)
		Spain	Not accurate	López-Cedrón et al. (2008)
Irrigated with a gradient of water and well fertilized	Soil water content	Brazil	Normalized RMSE: <15%	Soler et al. (2007)
		United States	Percentage error: <8%	DeJonge et al. (2011); Jara and Stockle (1999)
		United States	RMSE: 0.025 m^3/m^3	Saseendran et al. (2008)
	Soil water content, 0–15 cm	United States	Normalized RMSE: 13.2 ~ 58.4%	Anothai et al. (2013)
	Soil water content, 15–45 cm		Normalized RMSE: 12.7 ~ 44.7%	
	Soil water content, 45–75 cm		Normalized RMSE: 17.2 ~ 29.3%	
	Soil water content, 75–120 cm		Normalized RMSE: 9.2 ~ 25.0%	
	Soil water storage	China	Difference: <27 mm	Yang et al. (2006a)
Well irrigated and fertilized with a gradient of fertilizer(s)	Soil water content	Thailand	Underestimated by up to 20%	Asadi and Clemente (2003)

(Continued)

Table 23 Summary of the CERES-Maize model performances for soil water and plant extractable soil water (PESW) simulations.—cont'd.

Treatment category	Variables	Countries	Performance	References
Well irrigated and well fertilized	Soil water content, whole profile	Bulgaria, United States	Normalized RMSE: 4%, 35.5%	Popova and Kercheva (2005); Ritchie et al. (2009)
		United States	RMSE: 0.064 ~ 0.073 m^3/m^3	Saseendran et al. (2005)
	Soil water content, 30 cm-layers from soil depth of 30–120 cm	United States	Normalized RMSE: <14%	Xevi et al. (1996)
	Soil water content, 0–5 cm	United States	Normalized RMSE: 51%	Ritchie et al. (2009)
	Soil water content, 5–15 cm	United States	Normalized RMSE: 17%	Ritchie et al. (2009)
	Soil water content, 0–30 cm	United States	Normalized RMSE: 16.6%	Xevi et al. (1996)
	PESW	Bulgaria	Normalized RMSE:19%	Popova and Kercheva (2005)
	Soil water content, 0–10 cm	Canada	Normalized RMSE: 30 ~ 35%	Liu et al. (2014)
Not fertilized	Soil water content, 0–10 cm	Canada	Normalized RMSE: 25 ~ 36%	Liu et al. (2014)
Soil types	Soil water storage	France	Mean square error: 4 ~ 12 cm^2	Gabrielle et al. (1995)
		United States	Average underestimation: 5.92 mm	Hook (1994)
Management intensity[a]	Soil water content in each layers	United States	Average RMSE: 0.042 ~ 0.054	Garrison et al. (1999)
		China	RMSE: 0.01 ~ 0.11	Liu et al. (2013)

[a]Management intensity included conventional tillage, reduced conventional tillage, and nontillage.

another year (normalized RMSE of 49.4 ~ 58.4% for 0 ~ 15 cm). The authors also showed better simulations for deeper soils during both of the growing seasons, with normalized RMSEs of 12.7 ~ 44.7%, 17.2 ~ 29.3%, and 9.2 ~ 25% for 15–45 cm, 45 ~ 75 cm, and 75 ~ 120 cm soils, respectively (Anothai et al., 2013). Most of the study results suggested that the simulated soil water content was acceptably matched with the observations, but the model accuracies varied among the studies. Two studies in Colorado, US, with a range of irrigation water treatments showed that soil water simulations were more accurate given fully irrigated treatments. One study reported that the relative error for soil water simulations were under 8.0% for full-irrigation treatments and over 10.0% for limited irrigation treatment (DeJonge et al., 2011). The other reported that the average RMSEs were 0.025 m^3/m^3 and 0.043 m^3/m^3 for soils irrigated with a 23 ~ 188 mm treatment and a rain-fed treatment, respectively (Saseendran et al., 2008). Another study in Colorado involving well-irrigated and well-fertilized treatments reported average RMSEs of 0.064 ~ 0.073 when simulating soil water for three maize cultivars (Saseendran et al., 2005). In Iowa, US, the average RMSEs ranged from 0.042 to 0.054 cm^3/cm^3 across both tilled and no-till experiments in two types of soils in Iowa (Garrison et al., 1999). Garrison et al. (1999) also reported that the simulated soil storage was in good agreement with the measurement. A study in China also showed that given four and five irrigations per growing season, the overall errors for soil water storage were under 27.0 mm (Yang et al., 2006a). Under various management intensities, Liu et al. (2013) reported a wide range of RMSEs (from 0.01 to 0.11) for 0–20 cm and 0–30 cm soil water content simulations for various years under conventional tillage, reduced conventional tillage, and nontillage treatments. They also pointed out that the worst simulation may be due to inaccurate soil water content measurement caused by following the gravimetric water content measurement protocol (Liu et al., 2013). Jara and Stockle (1999) reported that the average RMSE for soil moisture simulation across full irrigation, partial irrigation, and no irrigation treatments in California, US, was 0.016 m^3/m^3, with relative error of 7.64%. In addition, the authors noted that the CERES model tended to underestimated soil moisture in the top 15 cm for field experiments in both Washington State and California. However, a graphical comparison between simulated and measured soil water performed by Lópz-Cedrón et al. (2008) indicated a relatively poor simulation (López-Cedrón et al., 2008).

3.11.2 CERES-Wheat

Twelve studies validated the soil water variable under various soils, water availability treatments, fertilization treatments, and management intensity treatments (Table 25). For low-permeability Vertisol soils in Bulgaria, soil water content was more accurately simulated when the soil was fertilized with a 200 kg N/ha treatment than when an unfertilized treatment was applied, with normalized RMSEs of 1.3 and 4.8%, respectively (Popova and Kercheva, 2005). The potentially extractable soil water simulation was also more accurate given a fertilized treatment (normalized RMSE = 13.3%) than an unfertilized treatment (normalized RMSE = 36.8%). With fertilized moderately permeable Chromic Luvisol soils, the average normalized RMSE for soil water content and potentially extractable soil water were 1.6 and 16.25%, respectively (Popova and Kercheva, 2005). A simulation study in Austria tested the soil water content of three soils for both the whole soil profile and at three soil depths (0–30, 0–60 and 0–90 cm). The results indicated that the soil moisture content simulations were least accurate for sandy Chernozem soil, with normalized RMSEs of 7.0, 3.8, 6.2, and 8.6% for whole soil profile moisture content and soil water content at depths of 30, 60, and 90 cm, respectively, whereas those for Chernozem and fluvisol soils were within 4.0, 1.1, 4.6, and 6.5%, respectively (Eitzinger et al., 2004). In Argentina, across full irrigation and early drought treatments, the simulated soil water content was correlated with the observations ($R^2 = 0.86$) (Savin et al., 1994). With clay and silt soils in Canada, the RMSE for soil water content at varied layers ranged between 0.025 and 0.046 (He et al., 2014). However, the simulated water content for both full-irrigation and full-drought treatments in New Zealand did not match well with the observations, with some heavy underestimation (Jamieson et al., 1998). Given 0 ~ 4 irrigations during the growing season, the differences between the simulated and observed soil water storages were within 3% for 0 ~ 2 irrigations, and the largest difference was 56 mm, which occurred given four irrigation treatments (Yang et al., 2006a). For two-fertilizer input (110.5 and 241.0 kg N/ha) treatments in Arizona, the soil water content validation showed that the model simulated deeper soil layers (normalized RMSE of 3.3 ~ 8.7% for 30–120 cm soil layers) better than the top soil layer (normalized RMSE of 18.9% for 0–30 cm soil) (Thorp et al., 2010b). The other soil water test under tillage methods, including conventional moldboard plowing 40–45 cm deep, ripper subsoiling at 60–70 cm deep, surface disc-harrowing at 15–20 cm deep, and minimum tillage with rotary hoeing treatment, was conducted in a farm in Italy. The revised CERES model, in which the evapotranspiration equation was changed and calibrated for this farm, simulated soil water fairly well, with an average standard error of regression of 0.03 cm^3/cm^3. The simulated soil water was particularly accurate for all soil layers under the ripper subsoiling treatment, except for the 20–40 cm layer, with a linear regression slope that was not statistically different from 1 ($P < 0.1$). The authors also pointed out that under minimum tillage treatment, the simulated soil water was close to the measurement except for those in a drought period (Castrignano et al., 1997). The simulated soil water storage and content in various layers were in good agreement with the measured values for long-term agricultural experiment sites in Canada for both continuous wheat and wheat rotation cropping systems (Beckie et al., 1995). In another location in Canada, the simulated soil water content was consistently smaller than the measured value for the surface layers, but it was consistently larger than the measured value for deep soils (Wang et al., 2010). Under fertilization treatments of 0 ~ 112 kg/ha nitrogen addition for 3 years, the RMSEs for soil profile moisture were within 0.074 (Saseendran et al., 2004). By comparing simulated water stress and water moisture monitored by sensors, Povilaitis et al. (2010) found that both the simulated water stress and the measured soil water content provided acceptable soil water information regarding conventional field trials with optimum fertilizer applications, integrated field trials with lower and organic fertilizer application, and no fertilizer application field trials (Povilaitis and Lazauskas, 2010).

3.12 Evapotranspiration and Deep Seepage

The evapotranspiration variable has been validated for the CERES-Maize and the CERES-Wheat models (Tables 24 and 25). The deep seepage of the CERES-Wheat model has been evaluated as well. No research has reported on the ET or deep seepage validation for the CERES-Rice model.

3.12.1 CERES-Maize

Two studies tested crop water use. Yang et al. (2006) simulated maize water use under no irrigation versus two irrigations per growing season and reported that water use was overestimated by 42.7 mm (0.418 mm/day) and 67.4 mm (0.661 mm/day), respectively (Yang et al., 2006a). The other study, in Washington, US, reported that the plant water use simulation had normalized RMSEs of 8.95 and 6.98% for limited and full irrigation, respectively (RMSEs of 0.33 and 0.27 mm/day, respectively) (Jara and Stockle, 1999).

Table 24 Summary of the CERES-Maize model performances for crop water use and evapotranspiration (ET) simulations.

Treatment category	Variables	Countries	Performance	References
Rain-fed/nonirrigated and well fertilized	ET	United States	Percentage error: >12%	DeJonge et al. (2011); DeJonge et al. (2012)
			Normalized RMSE: <10%	Anothai et al. (2013)
Irrigated with a gradient of water and well fertilized	ET	Italy, Turkey, Pakistan	Percentage error: 2.3 ~ 7.64% R^2: 0.78	Mastrorilli et al. (2003); Ben Nouna et al. (2000); Gercek and Okant (2010); Mubeen et al. (2013)
	Crop water use	United States	RMSE: 0.27 ~ 0.33 Normalized RMSE: 7 ~ 9%	Jara and Stockle (1999)
		China	Overestimated by 42.7 ~ 67.4 mm	Yang et al. (2006)a
Sowing date	ET	United States	RMSE: 3.7 ~ 5.1 cm	Saseendran et al. (2005)

Table 25 Summary of the CERES-Wheat model performances for soil water, plant extractable soil water (PESW) and evapotranspiration (ET) simulations.

Treatment category	Variables	Countries	Performance	References
Rain-fed and well fertilized	Soil water loss	China	Error: 1 cm	Yang et al. (2006b)
Irrigated with a gradient of water/different scheduling time and well fertilized	Soil water loss	China	Error: 13 ~ 43 cm	Yang et al. (2006b)
	Soil water content	Argentina	R^2: 0.86	Savin et al. (1994)
		New Zealand	Did not match well	Jamieson et al. (1998)
		China	Percentage error: <3% difference up to 56 mm	Yang et al. (2006a)
		United States	Normalized RMSE: <10% for layers below 30cm, 18.9% for 0–30 cm layer	Thorp et al. (2010b)
	ET	New Zealand	Difference: 9 ~ 60 mm	Jamieson et al. (1998)
Well irrigated and fertilized at varied rates	ET	United States	Normalized RMSE: 2.4%	Thorp et al. (2010b)
Well irrigated and fertilized[a]	ET	United States, China	Normalized RMSE: <3%	Kang et al. (2009)
Irrigated and fertilized at varied rates	ET	India, China	RMSE: 25 mm Normalized RMSE: 4 ~ 9%	Arora et al. (2007) Ji et al. (2014)
Rain-fed and varied amount of fertilizer(s)	Soil water content	United States	RMSE: <0.074	Saseendran et al. (2004)
	ET	United States	RMSE: 9.2 ~ 13.5 mm	Saseendran et al. (2004)

(Continued)

Table 25 Summary of the CERES-Wheat model performances for soil water, plant extractable soil water (PESW) and evapotranspiration (ET) simulations.—cont'd.

Treatment category	Variables	Countries	Performance	References
Soil types	Soil water content	Bulgaria, Australia, Canada	Normalized RMSE: 1.3 ~ 9% RMSE: 0.025 ~ 0.046	Popova and Kercheva (2005),[b]; Eitzinger et al. (2004); He et al. (2014)
	PESW	Bulgaria	Normalized RMSE: 13.3 ~ 36.8%	Popova and Kercheva (2005)
	ET	Australia	Overestimated by 61 ~ 87 mm	Eitzinger et al. (2004)
Tillage methods[c]	Soil water	Italy	Standard error of regression: 0.03	Castrignano et al. (1997)
Wheat-fallow and continuous wheat under different fertilization rate	Soil water levels	Canada	Accurate for 0–30 cm layers with <1 m error, significantly different for most 60–150 cm layers (P=0.05, 0.01)	Beckie et al. (1995)
	Soil water content	Canada	R^2 <0.64	Wang et al. (2010)
CO_2 concentrations with two irrigation regimes	ET	United States	Normalized RMSE: <14%	Tubiello et al. (1999b)
Planting densities combined with varied fertilization rates	ET	United States	Difference: 19 ~ 33 mm	Thorp et al. (2010a)

[a]Literatures that did not include treatments were considered as "well irrigated and well fertilized";
[b]Treatments included soil types combined with different fertilization rate treatments.
[c]Including conventional moldboard ploughing, ripper subsoiling, surface disc-harrowing, and minimum tillage with rotary hoeing.

For ET simulation validation, two studies in Colorado, US, reported ET simulations that had percentage errors under 7.5% for full-irrigation treatment and over 12.0% for limited irrigation treatment (DeJonge et al., 2011, 2012). When simulating ET given three levels of irrigation water treatments, from nonwater-stress to severe water stress, the model predicted seasonal ET well for all three levels, with zero error under nonwater-stress conditions, up to 3.5% underestimation under moderate water stress conditions, and up to 7.64% under severe water stress condition (Ben Nouna et al., 2000; Mastrorilli et al., 2003). A similar ET simulation for a 2-year experiment with three levels of irrigation, 100%-, 75%-, and 50%-full, showed that the percentage errors were about 3.0%, 2.3%-5.1%, and above 3.7%, respectively (Gercek and Okant, 2010). In Pakistan, across seven irrigation treatments of varying amounts and timings, the coefficients of determination between the simulated and observed ETs were above 0.78 (Mubeen et al., 2013). Across six irrigation treatments in Colorado, US, the average normalized RMSE for ET simulation was within 10%, with an index of agreement above 0.9 (Anothai et al., 2013). With well-irrigated and sowing date treatments, the ET simulations had RMSEs of 3.7 ~ 5.1 cm, depending on the hybrids involved (Saseendran et al., 2005).

3.12.2 CERES-Wheat

Ten studies tested the ET of the CERES-wheat model under varying water availability treatments, CO_2 concentrations, nutrient application treatments, and soils (Table 25). Arora et al. (2007) tested the seasonal ET with 5-year data collected from field experiments with varying water regimens (eg, irrigation timing at irrigation water-to-pan evaporation ratios of 1.2, 1.0, and 0.6 after sowing and 1–2 irrigations after sowing) combined with nutrient application regimens (eg, 0–180 kg N/ha, 120 kg N/ha applied at various timings, etc.). They reported that across all the field treatments, the simulated ET had an average RMSE of 25 mm, equivalent to a 9% normalized RMSE (Arora et al., 2007). Yang et al. (2006b) showed that the simulated soil water loss was close to that observed under no irrigation treatment (error: 1 cm), but the simulation did not match well with the observations given a four-irrigation treatment (error: 43 cm). A similar study in China in which wheat fields were irrigated zero to four times showed that the soil water content was mostly well-simulated (percentage error: <3%), but at the end of the growing seasons, the soil water simulation errors ranged up to 56 mm (Yang et al., 2006a). Across nine treatments with various levels of nutrient and water input in China, the normalized RMSE for the ET simulation was between 4 and 7% (Ji et al., 2014). By contrast, Jamieson et al. (1998) reported that given weekly irrigation treatment, the total ET was underestimated by 135 mm, while under no irrigation treatment, it was overestimated by 60 mm. The authors also indicated that for total ET simulations under early drought and late drought treatments, the absolute errors mostly ranged from 9 to 17 mm, with one exception of 51 mm (Jamieson et al., 1998). When simulating cumulative ET under treatments combining CO_2 concentration (ambient vs. 550 ppm) and irrigation (well-watered vs. water deficit), the normalized RMSEs were within 14% (Tubiello et al., 1999b). With nutrient applications of 0 ~ 112 kg N/ha for 3 years, the simulated seasonal ET had RMSEs from 9.2 to 13.5 cm (Saseendran et al., 2004). With 110.5 and 241.0 kg N/ha application treatments, the normalized RMSE was 2.4% (Thorp et al., 2010b). The authors also noticed that the model did not simulate deep seepage, as opposed to the approximately 30 mm of seepage that were measured (Thorp et al., 2010b). Another study in Arizona, with various nitrogen input and population density treatments, showed that the difference between the simulated and observed ET varied from 1.9 to 3.3 cm given a sparse planting and high nitrogen input treatment (Thorp et al., 2010a). One study in Austria tested ET with field experiments on three types of soils. The results indicated that the model overestimated the seasonal ET for the three types of soil by 61 ~ 87 mm (Eitzinger et al., 2004). Kang et al. (2009) used multiple seasons of wheat field data from two sites in China and the United States to validate the ET calculated by the Priestley–Taylor and Penman equations. The authors reported that the average RMSEs were 2.1 and 2.5 mm (these are either mm/day or mm/season), respectively (Kang et al., 2009).

3.13 Other Variables

3.13.1 CERES-Maize

Rezzoug et al. (2008) reported that the simulation of number of years per square meter the variable had an RMSD of 74.21 and a mean absolute percentage error of 29.66%. Popova et al. (2005) compared the simulated and the measured accumulative drainage graphically, and the results indicated that the simulated drainage was underestimated for an irrigated maize field in Bulgaria (Popova and Kercheva, 2005). Lizaso et al. (2001, 2003a,b) used two datasets from different sites in Iowa with different treatments to test the intercepted photosynthetically active radiation (IPAR) variable. Comparing the simulated IPAR to the observed IPAR under two extreme nitrogen rates (0 vs. 224 kg N/ha) combined with different maize hybrids, planting dates, and population density treatments, the authors reported that the IPAR was overestimated, especially for the nonnitrogen application treatment (Lizaso et al., 2001). Using 72 data points from experiments on irrigated maize fields with varying population densities, hybrids, and nitrogen application rates (56 vs. 168 kg N/ha) and nonirrigated maize fields with varying population densities and hybrids, the authors also found that IPAR was overestimated, with a mean error of 0.41 MJ/plant and an RMSE of 0.75 MJ/plant (Lizaso et al., 2003b). In Australia, Carberry (1991) tested the thermal time of the CERES-Maize model and showed that the observed temperature for leaf tip appearance was 48.3 °C, as opposed to the 38.9 °C simulated by the model. Two studies compared simulated irrigation water use to historical irrigation water use records. Salazar et al. (2012) reported that the simulated monthly irrigation water use was in close agreement with the historical record for the South Georgia, US, region, but there was a notable overestimation for early growing seasons when rainfall was not abundant. The study of a wheat-maize rotation field in the North China Plain showed that the simulated highest and lowest water use of the irrigated wheat matched with the records, and for the 5-year simulation, the average difference was 12 mm. When simulating the rotation irrigation water use by two crops, the average difference was 6.1 mm, and the absolute differences for each year ranged between 0 and 69 mm (Yang et al., 2006a).

Two studies in the United States and Turkey calculated and tested the water productivity variable. DeJonge et al. (2012) reported that the simulation was reasonably accurate for full irrigation (RMSD of 3.45 kg/ha per mm and underestimated by 6.53%), but much less accurate for limited irrigation (RMSD of 5.97 kg/ha per mm and underestimated by 26.7%) in a water-use efficiency simulation. By contrast, the similar study in Turkey found that water use efficiency was under-predicted by 1.5% under full irrigation conditions while it was overpredicted by 1.4 and 1.7% for 75%- and 50%-full irrigation treatments, respectively (Gercek and Okant, 2010).

3.13.2 CERES-Wheat

Zhang et al. (2012) compared the simulated and observed cumulative frequency distributions of the optimal nitrogen rate in Oklahoma, US, for 37 years and reported that the optimum nitrogen application rates were well-simulated when nitrogen application was under 67 kg/ha, underestimated for 67 and 90 kg N/ha treatments, and overestimated for 90 and 112 kg N/ha treatments. Water use efficiency and nitrogen partial factor productivity were validated with varied water and nitrogen input treatments in China, and the normalized RMSEs were 5 ~ 8 and 5 ~ 6%, respectively (Ji et al., 2014).

3.13.3 CERES-Rice

With a fertilization treatment of 0 ~ 150 kg/ha at various timings in Thailand, Cheyglinted et al. (2001) calculated the grain-straw ratio and reported that the relative absolute percentage errors for the ratio between grain and straw simulations were 21 ~ 32%.

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