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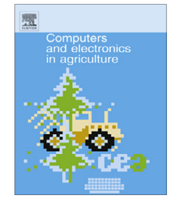

Original papers

Calibration and validation of APSIM-Wheat and CERES-Wheat for spring wheat under rainfed conditions: Models evaluation and application

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ABSTRACT

Crop growth in process based crop models is controlled by different parameters. Model calibration is necessary for application to new cultivars and environment. We applied a manual method to calibrate APSIM-Wheat and CERES-Wheat for the flowering day, maturity day, leaf area index, biomass and grain yield of five spring wheat cultivars under rainfed conditions in Pakistan. Five wheat cultivars of diverse origin namely Tatara, NARC-2009, Sehar-2006, SKD-1 and F-Sarhad were planted on 19th November, at Islamabad during the years 2007–2011. The experiments were laid out in Randomized Complete Block Design (RCBD) replicated four times with individual plot size of 5 m × 3 m. APSIM-Wheat and CERES-Wheat were calibrated for all five wheat cultivars using genetic coefficients estimated based upon measured data during 2008–09 cropping year and validated with independent data sets (experimental data of 2009–10 and 2010–11 cropping seasons) which were not used for models calibration. Both models were able to accurately simulate anthesis and maturity days, maximum leaf area index, biomass and grain yield, with normalized root mean square error (RMSE) less than 10%, D-index greater than 0.80 and model efficiency above 80% in most cases. The temporal changes in maximum LAI accumulation for all cultivars indicate that both measured and simulated values match each other. Evaluation with the measured data showed that performance of both models was realistic as indicated by the accurate simulation of crop phenology, LAI, biomass and grain yield against measured data. Climate variability results depicted that an increase in temperature from 0 °C to 5 °C resulted in a 60% average decline in the yield of wheat cultivars while increased CO_2 increased yield similar to the combined effect of increased temperature and CO_2. We concluded that to bring accuracy in the simulation outcomes of models, new cultivars should be calibrated to minimize uncertainty to allow judicious recommendations in response to climate variability.

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1. Introduction

Models are mathematical representations of real systems and they provide an efficient way to study complex biophysical systems (Holzworth et al., 2011). Quantitative application of crop based model is called crop simulation modeling. It may be explained as mathematical or statistical representations of any biological entity (Haghverdi et al., 2014; Porter and Semenov, 2005). Crop modeling facilitates development of innovative crop management strategies and agricultural sustainability under continuous changing climate as it expresses the response of crops to meteorological, edaphic and biological factors (Martín et al., 2014). Crop modeling aids in decision making, forecasting of crop growth and development, minimizing yield gaps, selection of suitable genotypes and appropriate sowing dates for sustainable crop production under changing climatic scenarios (Anwar et al., 2015; Asseng et al., 2015b; Mohanty et al., 2012). It is becoming a valuable tool for increasing the understanding of crop physiology and ecology and could be used to analyze and optimize, e.g., the planting regime (Dong et al., 2014). In an agricultural system, crop productivity varies with varying climatic and edaphic conditions. Various models have been developed primarily to understand yield gaps and to optimize yield potential. These include APES

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(Donatelli et al., 2002), APSIM (Keating et al., 2003), CERES (Ritchie et al., 1998), CROPGRO (Godwin and Singh, 1998), CropSyst (Rosenzweig and Parry, 1994; Willmott et al., 1985), DAISY (Sayre et al., 1997), DSSAT (Basso et al., 2016; Jones et al., 2003), EPIC (Wang et al., 2012), FASSET (Bassu et al., 2009), HERMES (Asseng et al., 2014), RZWQM (Ma et al., 2011), SPASS (Wang and Engel, 2000, 2002), STICS (Brisson et al., 2003), SWAP (Chen et al., 2010; Eitzinger et al., 2004; Ma et al., 2015), SOYGRO (Monsi and Saeki, 2005) and WOFOST (Eitzinger et al., 2004). An important task in experimenting with models is the testing of their performance in a wide range of circumstances to identify their scope of validity and limitations. Crop simulation models are site and crop specific in nature and should not be used in other areas until and unless validated under local conditions. A comparative study of modeling approaches was conducted by different scientists. CERES-Wheat and CropSyst were compared for water-nitrogen interaction in wheat production (Singh et al., 2008). Comparison of different modeling approaches is beneficial to select a suitable crop model for a specific locality and climate so that the model could be used to predict and simulate agricultural productivity at that location (Eitzinger et al., 2004; Martre et al., 2015; Palosuo et al., 2011; Salo et al., 2015).

The Agricultural Model Intercomparison and Improvement Project (AgMIP) is a major international effort linking the climate, crop, and economic modeling communities with cutting-edge information technology to produce improved crop and economic models and the next generation of climate impact projections for the agricultural sector (Rosenzweig et al., 2013). Rosenzweig et al. (2014) presented results from an intercomparison of multiple global gridded crop models (GGCMs) within the framework of AgMIP and the Inter-Sectoral Impacts Model Intercomparison Project (ISI–MIP) and indicated strong negative effects of climate change on crops. They suggested further research to better understand effects of climate change on agricultural production and to develop targeted adaptation strategies. Similarly, 30 different wheat crop models of the AgMIP were tested against artificial heating and field experiments where growing season mean temperatures were in the range of 15–32 °C. The results showed that many models were less accurate at higher temperatures (Asseng et al., 2015a). The performance of six crop models (APSIM-Wheat, APSIM-Nwheat, CAT-Wheat, CROPSYST, OLEARY-CONNOR and SALUS) were evaluated in response to elevated CO_2 by O'Leary et al. (2015) who concluded that model responses to elevated CO_2 were similar, and the models were able to simulate biomass, yield and water use close to experimental observations. Rötter et al. (2012) studied the performance of nine widely used and accessible crop growth simulation models (APES-ACE, CropSyst, DAISY, DSSAT-CERES, FASSET, HERMES, MONICA, STICS and WOFOST) at seven sites in Northern and Central Europe. The yield results based upon the root mean square error (RMSE) showed that HERMES, MONICA and WOFOST were the best-performing models. Soltani and Sinclair (2015) examined the transparency and robustness of four wheat models (CropSyst, SSM, APSIM and DSSAT) and concluded that simpler models (CropSyst and SSM) were more robust in yield prediction compared to more complex models (APSIM and DSSAT). Similarly, 23 different models were evaluated by Bassu et al. (2014) to study maize response under different climatic factors. They found large uncertainty in the yield response to $[CO_2]$ among models. Moreover, 13 rice models were compared against multi-year experimental yield data in response to temperature and CO_2 concentration (Li et al. (2015a). Most of the 13 models reproduced experimental data with an uncertainty of less than 10% of measured yields. Martre et al. (2015) simulated crop growth and yield using 27 wheat models and recommended that multimodel ensembles be used to create new estimators with improved accuracy and consistency in simulating crop growth dynamics. However, Schultz et al. (2000) pointed out that availability of reliable data is very important for accurate utilization of diverse agroecological models.

Crop simulation models are key tools in studying the impact of climate variability on different crops (Rezaei et al., 2015). These models have the potential to reveal different adaptation options under different climatic scenarios (Li et al., 2015b). Climate variability led to a 40% yield loss in spring wheat under water stress as simulated by a mechanistic model (Pavlova et al., 2014). Ray et al. (2015) reported that 36% of the year-to-year variability in wheat yield was due to climate variability. Similarly, high temperature/heat stress during the crop life cycle reduced crop yield (Innes et al., 2015; Prasad and Jagadish, 2015; Rezaei et al., 2015). Pirttioja et al. (2015) reported 5–7% average yield loss per 1 °C increase in temperature and 3–9% per 10% decrease in rainfall. However, a 5.3% yield reduction for each 1 °C rise in growing season average daily temperature was reported by (Innes et al., 2015).

We can use modeling approaches to design adaptation options to account for climatic stresses. The use of simulation models to evaluate the effect of different management options on crop productivity has been reported by Andarzian et al. (2015). The CERES-Wheat crop simulation model could provide recommendations about N fertilization to minimize the gap between attainable and potential yield (Abeledo et al., 2008) and to forecast wheat yield potential in response to different inputs (Andarzian et al., 2008). Similarly, CERES-Wheat could be used to study the effect of different irrigation and nitrogen management options on wheat yield (Arora et al., 2007). However, crop productivity under water limited environments needs evaluation using different management options. The potential effect of climate change on crop growth could be analyzed by using different simulation models under different climatic scenarios. The APSIM-Wheat cropping systems simulation model was evaluated under various management options – water deficit, elevated CO_2 in the dry and high N treatments and increased temperature (Asseng et al., 2004).

CERES-Wheat is a widely used, well-known crop growth model embedded in the DSSAT v4.5 software. It has been applied under different scenarios to increase understanding and management of the agricultural system in a holistic way (Bannayan et al., 2003; Timsina and Humphreys, 2006). These studies include determining optimum sowing date of wheat (Andarzian et al., 2015; Bannayan et al., 2013; Bassu et al., 2009; Chauhan et al., 2012), irrigation scheduling methods (Timsina et al., 2008), nitrogen management (Arora et al., 2007) wheat production and phenology (Dettori et al., 2011), water saving irrigation and resource saving conservation agriculture practices (Devkota et al., 2015), wheat insurance (Castañeda-Vera et al., 2015), cultivar evaluation (Fayed et al., 2015), intercropping (Knörzer et al., 2011), identifying crop technologies for future climatic conditions (Dhungana et al., 2006) and climate variability (Arora et al., 2007; Frank et al., 2015; Savin et al., 1995).

Wheat is a staple food of Pakistan and is cultivated under a wide range of climatic conditions (Fig. 1). Wheat production in the rainfed areas of Pakistan is risky because of high climatic variability. Various models are being used around the world as tools for studying crop growth, development and yield in response to climate variability. However, model application requires high quality, site-specific data on weather, soil, management and cultivar (Boote et al., 2015). Studies have been initiated in Pakistan too, but they require testing of various models to identify the models' scope and limitations. Comparative evaluation of APSIM-Wheat and CERES-Wheat models has not been undertaken for wheat growth and development in Pakistan. The present study was carried out with the objectives (i) To calibrate APSIM-Wheat and CERES-Wheat for new cultivars (ii) to validate the performance of APSIM-Wheat and CERES-Wheat for simulating spring wheat

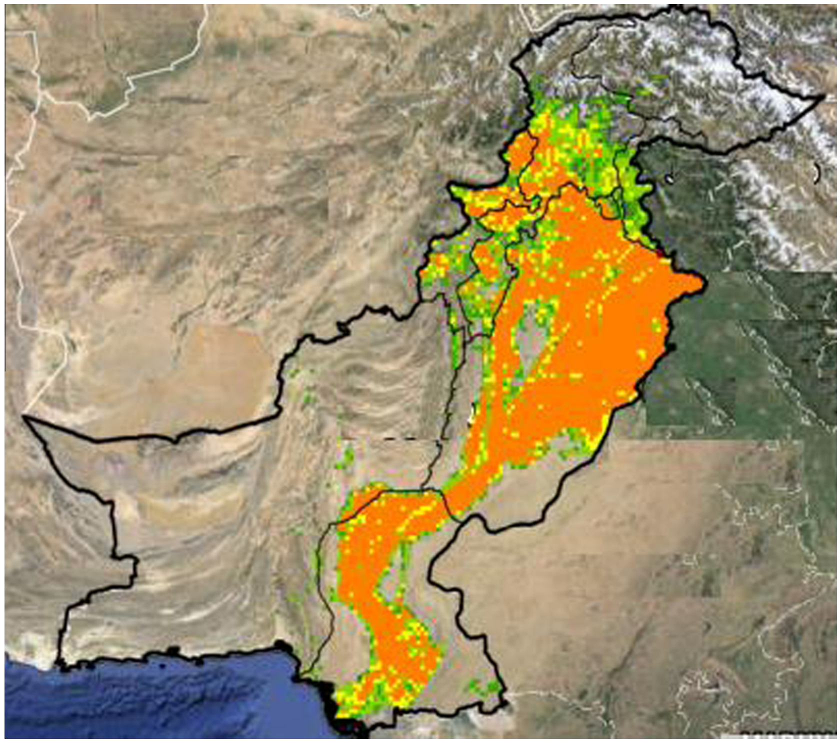

Fig. 1. Distribution pattern of wheat grown across the Pakistan represented with orange and green dots. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

growth, development and yield and (iii) to apply APSIM-Wheat and CERES-Wheat models to study impacts of climate variability on wheat yield under rainfed conditions of Pakistan.

2. Materials and methods

2.1. Field experiments

Five wheat varieties of diverse origin namely Tatara (Parentage: ATTILA, Pedigree: CM85836-50Y-0M-0Y-2M-0Y), NARC-2009 (Pedigree: INQALAB91∗2/TUKURU, Selection history: CGSS99 B00015F-099Y-099M-099Y-099M-29Y-0B-0ID), Sehar-2006 (Origin: Advance line from CIMMYT, Pedigree: CMSS95Y00645-100Y-200M-17Y-10M-0Y-0PAK), SKD-1 (Pedigree: HD-2329, Selection history: PAU-ACC-3079) and F-Sarhad (Parentage: KVZ/BUHO/KAL/BB, Pedigree: CM33027-F-15M-500Y-0M087V-0Y) were planted on 19th November, at Islamabad (33° 40′ N, 73° 10′ E, 508 m a.s.l.), during the years 2008–2011. To account for any variation in the field, the experiment was laid out in randomized complete block design (RCBD) replicated four times with individual plot size of 5 m × 3 m. . The five wheat varieties were then assigned at random to the plots within each block. The total number of treatments was 60 (5 varieties × 4 replications × 3 years = 60). Before sowing, land preparation in all plots was done by using a disk followed by a cultivator and then surface-planked for good seedbed preparation. Nitrogen and phosphorous, each at the rate of 100 kg ha^{-1}, were applied before sowing and incorporated with the cultivator. Seed rate was 100 kg ha^{-1} and row spacing was 25 cm.

2.2. Weather and soil data

The climate of the Islamabad study site is sub-humid with >1000 mm average annual rainfall (high rainfall zone) and an average annual temperature of 21.3 °C. The annual potential evapotranspiration (FAO Penman–Monteith) is about 1600 mm (van Ogtrop et al., 2014). Daily rainfall, solar radiation, maximum and minimum temperature were obtained from the Pakistan meteorology department (Fig. 2). The soil of the study site was sampled in 15 cm increments to 90 cm using a King tube with each layer analyzed separately. The soil parameters that were determined are presented in Table 1.

2.3. Models description

Agricultural Production Systems Simulator (APSIM) is a software tool that enables sub-models (or modules) to be linked to simulate agricultural systems (Keating et al., 2003;

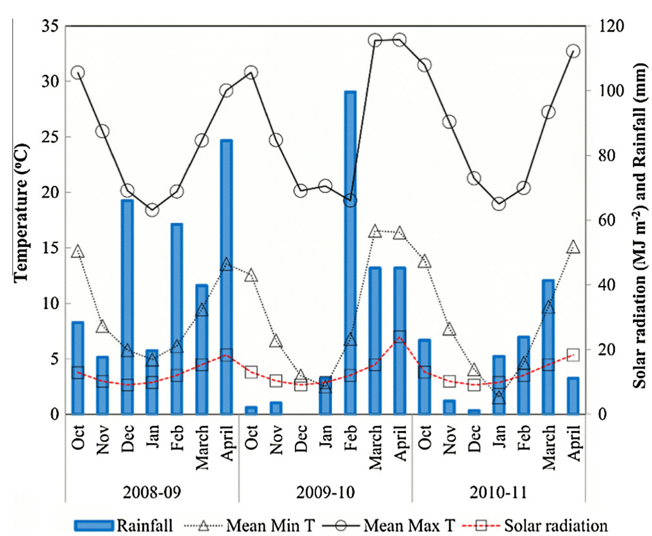

Fig. 2. Meteorological characteristics of the study site during wheat growing season.

Table 1
Soil properties for experiments conducted in Islamabad and used in simulation studies.

Soil properties	Depth (cm)					
	0–15	15–30	30–45	45–60	60–75	75–90
pH	7.4	7.5	7.9	8.2	8.4	8.4
EC (dS m^{-1})	0.23	0.2	0.2	0.21	0.22	0.21
N (%)	0.039	0.037	0.027	0.026	0.019	0.017
Nitrate-N (mg kg^{-1})	6.4	5.9	5.3	5	4.2	4.1
AV.P (mg kg^{-1})	3.1	2.9	3.3	3.2	2.3	2.2
K (mg kg^{-1})	120	135	159	165	158	180
Organic C (%)	0.72	0.69	0.5	0.47	0.35	0.32
Silt (%)	33	33	33	33	33	33
Sand (%)	35	35	35	35	35	35
Clay (%)	32	32	32	32	32	32
Soil texture	loam	loam	loam	loam	loam	loam
B.Density (g cm^{-3})	1.22	1.4	1.44	1.5	1.57	1.63
SLL (cm^3 cm^{-3})	0.07	0.09	0.09	0.09	0.09	0.09
SDUL (cm^3 cm^{-3})	0.34	0.24	0.25	0.26	0.23	0.23
Saturated SW (cm^3 cm^{-3})	0.46	0.39	0.38	0.36	0.33	0.31
Saturated hydraulic conductivity (cm h^{-1})	1.06	0.87	0.79	0.67	0.65	0.63
Soil Albedo	0.13					

Where EC; Electrical conductivity; AV.P: Available Phosphorus; SLL: Soil lower limit (Wilting point) and SDUL: Soil drain upper limit (Field Capacity).

McCown et al., 1996). The APSIM-Wheat module simulates the growth and development of a wheat crop in a daily time-step on an area basis (per square meter, not single plant) using a CERES-Wheat approach. The wheat growth and development responds to weather (radiation, temperature), soil water and soil nitrogen, and management practices (Zheng et al., 2014). APSIM-Wheat consists of eleven phasing development determined by the accumulation of thermal time and other factors like vernalisation, photoperiod and N from emergence to terminal spikelet (Chen et al., 2010). The length of each phase is linked to fixed thermal time mentioned as tt_<phase_name> in wheat.xml. The model calculates daily biomass accumulation (ΔQ) as a result of radiation interception (ΔQr) which is limited by soil water defecit. The ΔQr is the product of intercepted radiation (I), radiation use efficiency (RUE), diffuse factor (fd), stress factor (fs) and carbon dioxide factor (fc). Radiation interception (I) is calculated from the leaf area index (LAI, m^2 m^{-2}) and the extinction coefficient (k) (Monsi and Saeki, 2005).

The soil module in APSIM includes the SoilN module which describes the dynamics of both carbon and nitrogen in soil. Soil organic matter is divided into two pools (biom and hum), with the biom pool representing the more labile, soil microbial biomass and microbial products, whilst the hum pool comprises the rest of the soil organic matter. This configuration is different from CERES. SOILWAT which is a cascading layer model operating on a daily time step. The water characteristics of the soil are specified by lower limit (LL15), drained upper limit (DUL) and saturated (SAT) volumetric water contents of a sequence of soil layers. The whole soil profile could have 10 or more layers and layer thickness can be specified by the user. Typical thickness for the uppermost layer is 100 or 150 mm while for the base of profile it is 300–500 mm. The USDA-Soil curve number technique was used to calculate runoff while evaporation is based on the potential evaporation concept of Priestley and Taylor (1972). SOILWAT uses two parameters i.e. U and CONA (similar to CERES) to describe soil evaporation. U is cumulative evaporation since soil wetting but before soil supply becomes limiting, while **CONA** (from PERFECT) is the second stage of evaporation when water content of the soil has decreased below a threshold value; the rate of supply from the soil will be less than potential evaporation.

DSSAT (Decision Support System for Agrotechnology Transfer)-Cropping System Model V4.5 components CSM-CERES (Crop Environment REsource Synthesis)-Wheat (Jones et al., 2003) was used to study the genotype response. The model can simulate the effects of weather, genotypes, soil properties and management on wheat crop growth, development and yield. The model considers nine growth stages in response to thermal time from pre-sowing to harvest. The biomass accumulation was calculated as a product of radiation use efficiency (RUE) and photosynthetically active intercepted radiation (PAIR). Extension of organs depends upon potential organ growth and is limited by temperature, water and nitrogen stresses. The phasic development influences the partitioning coefficients of drymatter. Grain yield is the product of grain number (G1), plant population, and grain mass at physiological maturity (G2).

The soil water balance is modeled daily in relation to rainfall, irrigation, runoff, infiltration, drainage and transpiration. The water is allocated to different layers based upon drained upper limit (DUL) and lower limit (LL). Similarly, downward and upward flow is controlled by DUL and LL. If water content in a layer is greater than DUL it will flow down while if layer has water content between LL and DUL it will move upward. The comparison of modeling approaches used by APSIM-Wheat and DSSAT-CSM-CERES-Wheat is presented in Table 2.

2.4. Models calibration

The growth and development module of APSIM-Wheat uses sets of different coefficients (Vern_sens, photop_sens, startgf_to_mat, grains_per_gram_stem, Potential_grain_filling_rate and Phyllochron) to define the phenology, crop growth and yield in time domain (Table 3). APSIM-Wheat was calibrated for the 5 cultivars, Tatara, NARC-2009, Sehar-2006, SKD-1 and F-Sarhad with data obtained from 2008 to 09 cropping year. For calibration the cultivar coefficients were obtained step by step, first for phenological development and then for grain developmental parameters. The manual trial and error method was used to determine genetic coefficients (Godwin and Singh, 1998). The values were adjusted to have minimum root mean square error (RMSE) between simulated and observed data. The anthesis, physiological maturity date, leaf area index (LAI), biomass and yield were used to evaluate model performance. The same values of this set of parameters were used in the validation to further evaluate the performance and robustness of APSIM-Wheat.

CERES-Wheat uses different set of species, ecotype and cultivar coefficients which define the phenology and crop growth in time domain. These crop coefficients are cultivar specific and cannot be broadly applied as such under different environmental

Table 2
Comparative modeling approaches involved in APSIM-Wheat and CERES-Wheat.

	APSIM-Wheat	CERES-Wheat
Crop phenology[a]	f(TPVW)	f(TPV)
Leaf area development and light interception[b]	D	D
Light utilization/biomass production[c]	RUE/Tr	RUE
Biomass partitioning[d]	PCD	PCD
Yield formation[e]	Prt,B,LHI	B,Gn,HI
Root distribution over depth[f]	EXPO	EXPO
Stresses[g]	WAH	WN
Water stress type[h]	S	E
Heat stress type[i]	V	-
Water dynamics[j]	C	C
Water relation[k]	D	D
Plant N budget[l]	D	D
Evapotranspiration[m]	PT	PM
Soil CN model[n]	CNP(3)B	CNP(4)B
CO_2 effects[o]	RUE/TE	RUE/TE
Model relative[p]	C	C
Model type[q]	P	P

[a] Crop Phenology: f (Function) of T, Temperature; P, Photoperiod; V, Vernalisation; W, Wtaer stress.
[b] Leaf area development and Light Interception: D, Detailed approach.
[c] Light Utilization/Biomass Production : RUE, Radiation use efficiency approach; Tr, relationship between mass production and transpiration.
[d] Biomass partitioning: PCD, Detailed partitioning coefficients.
[e] Yield Formation: Prt, Partitioning during reproductive stages; B, Total above ground biomass at maturity; LHI, Linear increase in harvest index.
[f] Root distribution over depth: EXPO, Exponential.
[g] Stresses: W, Water stress; A, Oxygen stress; H, Heat stress.
[h] Water stress type: S, soil available water in root zone.
[i] Heat stress type: V, Vegetative (source).
[j] Water Dynamics: C, Tipping bucket capacity approach.
[k] Water relation: D, Detailed approach includes root growth and water absorption.
[l] Plant N budget: D, Detailed concentration curves for different organs over the growth period.
[m] Evapotranspiration: PT, Priestley –Taylor; PM, Penman–Monteith.
[n] Soil CN model: N = N model, $P(x) = x$ number of organic matter pools, B = microbial biomass pool.
[o] CO_2 effects: RUE, Radiation use efficiency; TE = Transpiration efficiency,
[p] Model relative: C, CERES.
[q] Model type: P, point model (site-specific).

Table 4
Genetic coefficients fitted for CERES-Wheat.

Crop file	Parameters	Calibrated value				
		Tatara	NARC-2009	Sehar-2006	SKD-1	F-Sarhad
Genotype	P1V	0	0	0	0	0
	P1D	103	101	101	103	103
	P_5	710	690	685	700	700
	G_1	13	12	11	13	13
	G_2	41	38	37	41	41
	G_3	1	1	1	1	1
	PHINT	101	95	93	101	101
Ecotype	P_1	235	230	210	217	222
	P_2	300	295	275	282	285
	P_3	200	190	174	182	185
	P_4	200	190	174	182	185
	SLAS	180	180	180	180	180
	PARUE	4.6	4.4	4.5	4.5	4.5
	PARU2	4.6	4.4	4.5	4.5	4.5
Species	TRGFW					
	T_{base}	4.5	4.5	4.5	4.5	4.5
	T_{opt1}	13	13	13	13	13
	T_{opt2}	23	23	23	23	23
	T_{max}	34	34	34	34	34

Where TRGFW: temperature response, grain filling, dry weight (°C); T_{base}: base temperature, below which increase in grain weight is zero; T_{opt1}: 1st optimum temperature, at which increase in grain weight is most rapid; T_{opt2}: 2nd optimum temperature, highest temperature at which increase in grain weight is still at its maximum; T_{max}: maximum temperature, at which increase in grain weight is zero; P_1: duration of phase end juvenile to terminal spikelet (GDD Growing Degree Days); P_2: duration of phase terminal spikelet to end leaf growth (GDD); P_3: duration of phase end leaf growth to end spike growth (GDD).
P_4: duration of phase end spike growth to end grain fill lag (GDD); SLAS: specific leaf area (cm^2 g^{-1}); PARUE: PAR conversion to dry matter ratio before the last leaf stage (g MJ^{-1}).
PARU2: PAR conversion to dry matter ratio after the last leaf stage (g MJ^{-1}); P1V: Days at optimum vernalization temperature required to complete vernalization; P1D: Percentage reduction in development rate in a photoperiod 10 h shorter than the optimum relative that optimum; P_5: Grain filling (excluding lag) period duration (GDD); G_1: Kernel number per unit canopy weight at anthesis (g^{-1}); G_2: Standard kernel size under optimum condition (mg); G_3: Standard non-stressed dry weight (total, including grain) of a single tiller at maturity (g) and PHINT: Phyllochron interval (GDD).

conditions. They are usually specified by users (Table 4) and in present study these parameters were estimated using measured data obtained during 2008–09 cropping season. The cultivar coefficients were obtained sequentially, first for phenological development parameters related to flowering and maturity dates (P1V, P1D, P5 and PHINT), followed by crop growth parameters like kernel filling rate and kernel numbers per plant (G1, G2 and G3). Meanwhile, ecotype and species parameter files were also adjusted to have perfect model calibration (Godwin and Singh, 1998). Furthermore, calibrated cultivar coefficients were used in the validation to confirm the robustness of CERES-Wheat model. The parameters were adjusted to minimize RMSE between simulated and observed data. The calibration and evaluation were performed by comparing simulated data of anthesis and maturity dates as well as yield data with observed field data.

2.5. Models validation

Validation is an important step to verify model performance (Andarzian et al., 2011) and it involves comparison between field measurements and output generated by the model. Recorded anthesis and maturity days after sowing, maximum leaf area index, biomass accumulation at maturity and grain yield from field

Table 3
Genetic coefficients fitted for APSIM-Wheat.

Name	Unit	Tatara	NARC-2009	Sehar-2006	SKD-1	F-Sarhad
Cultivars parameters						
photop_sens (Photoperiod sensitivity)	–	3.5	3.5	3.5	3.5	3.5
vern_sens(Vernailsation sensitivity)	–	0	0	0	0	0
tt_end_of_juvenile (Thermal time needed from sowing to end of juvenile)	°C days	350	650	600	450	370
tt_flowering (Thermal time needed in anthesis phase)	°C days	80	180	170	130	100
tt_floral_initiation (Thermal time from floral initiation to flowering)	°C days	400	900	800	500	450
tt_start_grain_fill (Thermal time from start of grain filling to maturity)	°C days	550	1000	900	700	550
max_grain_size (Maximum grain size)	g	0.039	0.065	0.055	0.053	0.045
potential_grain_growth_rate (Grain growth rate from flowering to grain filling)	g grain^{-1} day^{-1}	0.001	0.002	0.002	0.001	0.001
potential_grain_filling rate (Potential daily grain filling rate)	g grain^{-1} day^{-1}	0.003	0.006	0.006	0.005	0.005
grains_per_gram_stem (Grain number per stem weight at the start of grain filling)	g	45	60	60	50	50

experimental data during the 2009–10 and 2010–11 growing seasons were used to validate the performance of both models. Different statistical indices like the coefficients of determination (R^2), D-index (Willmott, 1981; Willmott et al., 1985), RMSE, %RMSE (Loague and Green, 1991) and model efficiency (ME) were used to check the agreement between observed and simulated values. The coefficient of residual mass (CRM) was used to check whether model predictions provided over or underestimation (Xevi et al., 1996).

$$d-index = 1 - \frac{\sum_{i=1}^{n}[(Pi-\overline{O})-(Pi-\overline{O})^2]}{\sum_{i=1}^{n}[(|Pi-\overline{O}|)-(|Pi-\overline{O}|)^2]}$$

$$RMSE = \left[\sum_{i=1}^{n}\frac{(Pi-Oi)^2}{n}\right]^{0.5}$$

$$\%RMSE = \left[\sum_{i=1}^{n}\frac{(Pi-Oi)^2}{n}\right]^{0.5} \times \frac{100}{O}$$

$$ME = 1 - \frac{\sum_{i=1}^{n}(Pi-Oi)^2}{\sum_{i=1}^{n}(Oi-O)^2}$$

$$CRM = 1 - \frac{\left(\sum_{i=1}^{n}Oi - \sum_{i=1}^{n}Pi\right)}{\sum_{i=1}^{n}Oi}$$

where Oi and Pi refer to observed and predicted values for all studied variables and O is the mean of the observed variable.

2.6. Model application

Long term historical weather data were used to develop the genetic coefficients for the studied wheat cultivars and to validate APSIM-Wheat and CERES-Wheat under rainfed field conditions. These models can further be used for seasonal analysis to investigate good management strategies. A widely accepted approach to analyze the possible effects of different climate change parameters on crop yield is to incrementally change temperature, moisture and CO_2 etc., and to apply these changes uniformly to a baseline climate (Rosenzweig and Parry, 1994). Main scenarios that were used in the present study to assess the impact of climate change on wheat yield are given in Table 5. These were: (i) increased temperature (average of 50 years as the baseline temperature and increase in temperature by +1, +2, +3, +4 and +5 °C respectively) (ii) increased CO_2 concentration in the atmosphere (370 ppm as the baseline concentration and 470, 570, 670, 770, 870 and 970 ppm as determined HadGEM2-ES : Hadley Global Environment Model 2-Earth System under Representative Concentration Pathways (RCP) 8.5 W/m^2 scenario) and (iii) combined effect of increased temperature and elevated CO_2 on spring wheat grain yield. Since future climate changes are expected to pose serious threats to our agriculture, both models were evaluated using the above described hypothetical scenarios.

Table 5
Hypothetical climate change scenarios for impact assessment on wheat yield using Representative Concentration Pathways (RCP) 8.5 W/m^2 scenario.

Scenario	Parameters
Baseline (1960–2010)	Daily observed temperature and Rainfall/ CO_2 level = 360 ppm during wheat growing season
If only temperature changes	Temperature Change = 0, +1, +2, +3, +4 and +5 °C
If only CO_2 level changes	CO_2 level = 370, 470, 570, 670, 770, 870 and 970
If both CO_2 and temperature changes	CO_2 level = 370, 470, 570, 670, 770, 870 and 970 ppm Temperature Change = 0, +1, +2, +3, +4 and +5 °C

3. Results

3.1. Model calibration

The experimental data of 2008–09 at Islamabad were used to calibrate CERES-Wheat and APSIM-Wheat for all cultivars. Table 6 shows that the methodology used to calibrate CERES-Wheat and APSIM-Wheat is robust and works well. The calibration of both models provided an accurate prediction of anthesis and maturity for all cultivars. APSIM-Wheat was initialized with specified sowing date, plant density, and observed initial soil water and soil nitrogen conditions with default genotypic coefficients to simulate flowering and maturity dates. Afterward, parameters for phenology (Table 3) were derived using trial and error to match the simulated flowering and maturity dates with observed dates (Table 6). Thereafter, leaf development, biomass at harvest and grain yield were calibrated using the resulting coefficients. Similarly, in case of CERES-Wheat the calibrated simulated values of crop traits (days to anthesis and maturity, mLAI, biomass at harvest and grain yield) remained close to the experimental ones (Table 6). Cultivar genotypic coefficients were adjusted first to bring into line observed and simulated values of crop traits in CERES-Wheat. Furthermore, some ecotype (P1, P2, P3, P4, SLAS and PARUE) and species (TRGFW) parameters were also adjusted (Table 4). Adjustments in SLAS and PARUE parameters is very important to get accurate leaf area expansion and biomass production under different climatic conditions. These parameters are also specific to cultivar characteristics. Similarly, modification in the TRGFW is necessary under conditions like ours where heat stress prevails during grain filling. The vernalization coefficient (P1V) was set zero for all cultivars as spring wheat has no vernalization sensitivity. The PID values for cultivars Tatara, NARC-2009, Sehar-2006, SKD-1 and F-Sarhard were 103,101,101,103 and 103 respectively. The values used for P5, G1, G2, G3 and phyllochron interval coefficient (PHINT) in genotype file for all cultivars calibration have been shown in Table 3. The observed and simulated crop traits after calibration are presented in Table 6 which shows good agreement between observed and simulated values.

3.2. Models validation

The performance of both models APSIM-Wheat and CERES-Wheat were validated with experimental data sets obtained during the 2009–10 and 2010–11 growing seasons, which data were not used for models calibration. The crop variables which were validated included crop phenology (anthesis and maturity), biomass, maximum leaf area index (mLAI) and grain yield.

3.2.1. Cultivar validation for phenology (anthesis and maturity days after sowing)

Wheat cultivar anthesis ranged from 99 to 126 das during the two years used for validation (Table 7). The observed physiological maturity for all cultivars were in the range of 139–167 das (Table 8). Both models simulated the anthesis date with good accuracy (ME $\geqslant$ 0.85) as shown in Table 7. The value for RMSE, normalized RMSE, D-Index, CRM, ME and R^2 confirm the robustness of the models. RMSE for APSIM-Wheat model for cultivar SKD-1 (1.76 day) was lowest followed by NARC-2009 (1.96 day) and Sehar-2006 (1.93 day). RMSE was highest for Tatara (4.27 day) and F-Sarhad (3.60 day). RMSE for CERES-Wheat to simulate anthesis revealed that it was lowest for cultivar Sehar-2006 (1.96 day) and highest for F-Sarhad (7.22 day). The model performance trend was evaluated by normalized RMSE and Index of agreement (D-index). CRM was used to check the models' tendency to under or overestimate the results. CRM values for all cultivars remained

Table 6
Calibration results for CERES-Wheat and APSIM-Wheat models for five spring wheat cultivars using experimental data of 2008–09 wheat cropping season.

Crop Traits	CERES-Wheat									
	Tatara		NARC-2009		Sehar-2006		SKD-1		F-Sarhad	
	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim
Anthesis (DAP)	123	126	116	117	124	125	121	123	120	127
Maturity (DAP)	171	174	161	162	160	162	162	161	166	169
mLAI ($m^2\ m^{-2}$)	5.1	5.2	4.4	4.5	3.6	3.7	3.7	3.8	3.9	4.1
Biomass at harvest ($t\ ha^{-1}$)	13.48	13.53	11.32	11.27	7.94	7.96	9.12	9.18	10.65	10.47
Dry Grain yield ($t\ ha^{-1}$)	4.87	4.89	3.97	3.95	2.7	2.77	3.02	3.01	3.43	3.47
Crop Traits	APSIM-Wheat									
	Tatara		NARC-2009		Sehar-2006		SKD-1		F-Sarhad	
	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim
Anthesis (DAP)	123	127	116	116	124	125	121	120	120	123
Maturity (DAP)	171	172	161	163	160	161	162	160	166	170
mLAI ($m^2\ m^{-2}$)	5.1	5.4	4.4	4.6	3.6	3.8	3.7	3.9	3.9	4.2
Biomass at harvest ($t\ ha^{-1}$)	13.48	13.51	11.32	11.41	7.94	8.12	9.12	9.22	10.65	10.69
Dry Grain yield ($t\ ha^{-1}$)	4.87	4.79	3.97	4.01	2.7	2.95	3.02	3.12	3.43	3.5

DAP: Days after planting.
mLAI: maximum leaf area index.

Table 7
Models evaluation indices of evaluating comparative performance of APSIM-Wheat and CERES-Wheat models in predicting anthesis days after planting for spring wheat cultivars.

Cropping year	Crop models	Tatara		NARC-2009		Sehar-2006		SKD-1		F-Sarhad	
		Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim
2009–10	APSIM-Wheat	110	107	104	105	100	101	100	101	99	101
	CERES-Wheat		106		106		102		102		105
2010–11	APSIM-Wheat	126	127	118	119	121	122	122	123	121	125
	CERES-Wheat		129		119		122		125		127
Models evaluation indices											
RMSE (day)[a]	APSIM-Wheat	4.27		1.93		1.96		1.76		3.60	
	CERES-Wheat	3.27		2.20		1.96		3.12		7.22	
Normal-RMSE (%)[b]	APSIM-Wheat	3.35		1.66		1.58		1.46		3.00	
	CERES-Wheat	2.59		1.89		1.58		2.59		6.02	
D-Index[c]	APSIM-Wheat	0.87		0.91		0.95		0.93		0.87	
	CERES-Wheat	0.88		0.89		0.95		0.91		0.83	
CRM[d]	APSIM-Wheat	−0.030		−0.010		−0.007		−0.005		−0.020	
	CERES-Wheat	−0.020		−0.007		−0.007		−0.020		−0.050	
ME[e]	APSIM-Wheat	0.88		0.98		0.95		0.97		0.84	
	CERES-Wheat	0.93		0.98		0.95		0.90		0.89	
R^2 (1:1)[f]	APSIM-Wheat	0.80		0.83		0.90		0.88		0.82	
	CERES-Wheat	0.81		0.81		0.90		0.87		0.79	

[a] Root mean square error.
[b] Normalized root mean square error.
[c] Wilmot's index of agreement.
[d] Coefficient of residual mass.
[e] Model efficiency.
[f] Coefficient of determination for the 1 to 1 line ($p < 0.05$; $n = 8$).

negative, which showed that both models had a tendency to overestimate time to anthesis. ME provided further evidence that APSIM-Wheat and CERES-Wheat could accurately simulate anthesis timing (ME $\geqslant$ 0.84) for all cultivars. The values of R^2 further confirms the good prediction of anthesis by both models (Table 7). There was also close agreement between observed and simulated physiological maturity dates. Days to maturity for Tatara was different during three study years (Table 8). The simulated days to maturity by both crop models were in close agreement with the observed values during both years. The indices revealed that performance of APSIM-Wheat was comparatively better in the simulation of Tatara maturity. However, results for NARC-2009 depicted better performance of CERES-Wheat in simulating maturity. The model evaluation indices like RMSE, Normal-RMSE (%), D-Index, CRM, ME and R^2 remained 2.20, 1.37, 0.90, −0.007, 0.97 and 0.91 respectively comparatively better than APSIM-Wheat indices (Table 8). The days to maturity were different during the years used for validation. The values for RMSE, Normal-RMSE (%), D-Index, CRM, ME and R^2 for physiological maturity showed that observed and simulated data were in good agreement with each other. The results showed that both models were very robust in simulating the critical phenological growth stages (anthesis and maturity) of the wheat crop.

3.2.2. Trend of maximum leaf area index (mLAI) among all cultivars

The observed mLAI was highest (4.9 $m^2\ m^{-2}$ and 5.0 $m^2\ m^{-2}$) during 2009–10 and 2010–11, respectively, for Tatara followed by NARC-2009 (4.2 $m^2\ m^{-2}$ and 4.3 $m^2\ m^{-2}$) during 2009–10 and 2010–11, respectively. The observed mLAI for all cultivars was in the range of 3.4–5.0 $m^2\ m^{-2}$ during the years used for validation (Table 9). Validation confirmed that the crop coefficients used to simulate mLAI by APSIM-Wheat and CERES-Wheat were accurate.

Table 8
Models evaluation indices of evaluating comparative performance of APSIM-Wheat and CERES-Wheat models in predicting maturity days after planting for spring wheat cultivars.

Cropping year	Crop models	Tatara		NARC-2009		Sehar-2006		SKD-1		F-Sarhad	
		Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim
2009–10	APSIM-Wheat	152	153	145	146	140	141	142	141	139	144
	CERES-Wheat		151		144		139		143		143
2010–11	APSIM-Wheat	167	168	162	163	161	163	159	162	160	167
	CERES-Wheat		166		161		162		157		165
Models Evaluation Indices											
RMSE (day)[a]	APSIM-Wheat	2.03		3.26		3.51		2.12		5.09	
	CERES-Wheat	3.26		2.20		1.06		1.76		3.31	
Normal-RMSE (%)[b]	APSIM-Wheat	1.19		2.01		2.29		1.36		3.28	
	CERES-Wheat	1.90		1.37		0.69		1.13		2.13	
D-Index[c]	APSIM-Wheat	0.88		0.83		0.81		0.91		0.79	
	CERES-Wheat	0.85		0.90		0.95		0.95		0.87	
CRM[d]	APSIM-Wheat	−0.006		−0.010		−0.010		0.009		−0.030	
	CERES−Wheat	−0.010		−0.007		−0.004		0.008		−0.010	
ME[e]	APSIM-Wheat	0.98		0.95		0.85		0.97		0.85	
	CERES-Wheat	0.95		0.97		0.98		0.98		0.93	
R^2 (1:1)[f]	APSIM-Wheat	0.90		0.87		0.82		0.91		0.81	
	CERES-Wheat	0.87		0.91		0.93		0.92		0.89	

[a] Root mean square error.
[b] Normalized root mean square error.
[c] Wilmot's index of agreement.
[d] Coefficient of residual mass.
[e] Model efficiency.
[f] Coefficient of determination for the 1 to 1 line ($p < 0.05$; $n = 8$).

Table 9
Models evaluation indices of evaluating comparative performance of APSIM-Wheat and CERES-Wheat models in predicting leaf area index ($m^2\ m^{-2}$) for spring wheat cultivars.

Cropping year	Crop models	Tatara		NARC-2009		Sehar-2006		SKD-1		F-Sarhad	
		Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim
2009–10	APSIM-Wheat	4.9	5.2	4.2	4.4	3.4	3.5	3.5	3.7	3.8	4.3
	CERES-Wheat		5.1		4.3		3.4		3.6		4.2
2010–11	APSIM-Wheat	5.0	5.2	4.3	4.5	3.5	3.6	3.6	3.8	3.7	3.9
	CERES-Wheat		5.1		4.4		3.4		3.7		3.8
Models Evaluation Indices											
RMSE ($m^2\ m^{-2}$)[a]	APSIM-Wheat	0.23		0.31		0.14		0.22		0.32	
	CERES-Wheat	0.16		0.32		0.09		0.11		0.20	
Normal-RMSE (%)[b]	APSIM-Wheat	4.65		7.11		4.00		6.03		8.39	
	CERES-Wheat	3.20		7.25		2.62		3.14		5.28	
D-Index[c]	APSIM-Wheat	0.89		0.96		0.97		0.88		0.91	
	CERES-Wheat	0.91		0.96		0.99		0.90		0.93	
CRM[d]	APSIM-Wheat	−0.040		−0.030		−0.020		−0.050		−0.080	
	CERES-Wheat	−0.020		−0.020		0.003		−0.020		−0.050	
ME[e]	APSIM-Wheat	0.82		0.99		0.97		0.87		0.65	
	CERES-Wheat	0.92		0.99		0.99		0.85		0.74	
R^2 (1:1)[f]	APSIM-Wheat	0.91		0.97		0.96		0.90		0.83	
	CERES-Wheat	0.93		0.97		0.98		0.91		0.86	

[a] Root mean square error.
[b] Normalized root mean square error.
[c] Wilmot's index of agreement.
[d] Coefficient of residual mass.
[e] Model efficiency.
[f] Coefficient of determination for the 1 to 1 line ($p < 0.05$; $n = 8$).

Therefore, these coefficients can be used to calibrate and validate APSIM-Wheat and CERES-Wheat for the prediction of spring wheat mLAI. Model evaluation indices for Tatara showed that the accuracy of CERES-Wheat was good compared to APSIM-Wheat. The negative value of CRM for both models confirms the slight overestimation of leaf area index. Similar results for CRM analysis were observed for all other cultivars but with better performance by APSIM-Wheat. The robustness of both models to simulate mLAI can also be confirmed by the ME model evaluation index (Table 9). Temporal changes in leaf area index (LAI) accumulation for all cultivars indicate that both measured and simulated values match during the study years (Fig. 3). The statistical indices also confirm these observations for both wheat models.

3.2.3. Biomass accumulation (t ha^{-1})

Wheat cultivar biomass at maturity remained in the range of 7.63–13.21 t ha^{-1} during 2009–10 and 2010–11 (Table 10). The highest (13.21 t ha^{-1}) value of biomass was observed for Tatara

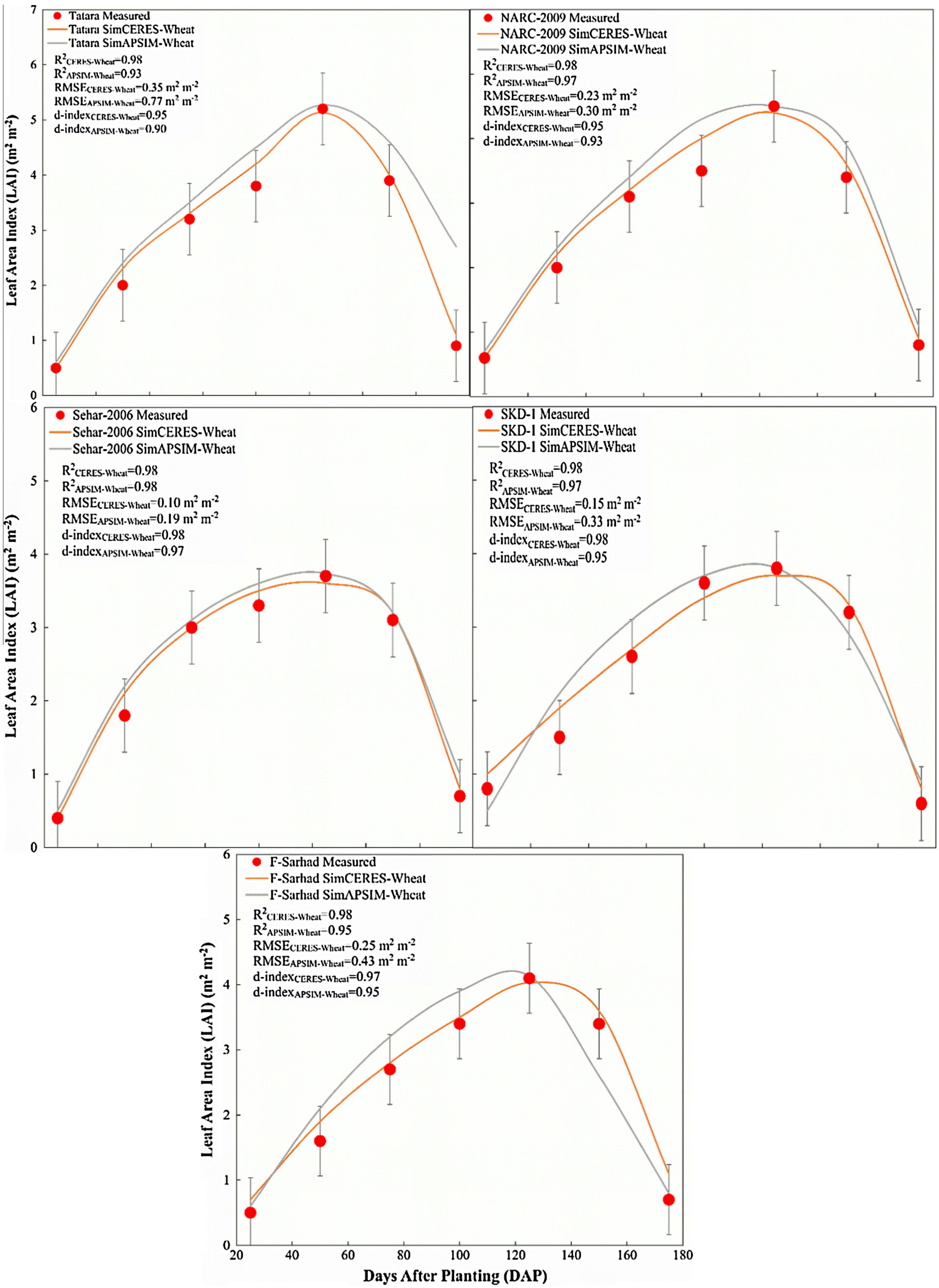

Fig. 3. Measured and Simulated (Sim) leaf area index (LAI) of five cultivars Tatara, NARC-2009, Sehar-2006, SKD-1 and F-Sarhad sown on 19th November 2009–2011 at Islamabad.

Table 10
Models evaluation indices of evaluating comparative performance of APSIM-Wheat and CERES-Wheat models in predicting biomass accumulation (t ha^{-1}) for spring wheat cultivars.

Cropping year	Crop models	Tatara		NARC-2009		Sehar-2006		SKD-1		F-Sarhad	
		Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim
2009–10	APSIM-Wheat	12.97	13.01	11.12	11.23	7.63	7.72	8.81	8.85	10.35	10.55
	CERES-Wheat		12.92		11.19		7.69		8.79		10.30
2010–11	APSIM-Wheat	13.21	13.28	11.21	11.21	7.91	7.93	9.03	9.14	10.55	10.67
	CERES-Wheat		13.26		11.20		7.89		9.07		10.52
Models Evaluation Indices											
RMSE (t ha^{-1})[a]	APSIM-Wheat		0.40		0.15		0.18		0.18		0.16
	CERES-Wheat		0.12		0.17		0.08		0.18		0.13
Normal-RMSE (%)[b]	APSIM-Wheat		2.98		1.30		2.31		2.06		1.56
	CERES-Wheat		0.94		1.53		1.09		2.01		1.21
D-Index[c]	APSIM-Wheat		0.89		0.91		0.93		0.93		0.97
	CERES-Wheat		0.90		0.92		0.95		0.93		0.98
CRM[d]	APSIM-Wheat		−0.010		−0.010		−0.020		−0.010		−0.010
	CERES-Wheat		−0.007		0.014		0.009		−0.010		0.010
ME[e]	APSIM-Wheat		0.86		0.86		0.85		0.85		0.88
	CERES-Wheat		0.95		0.88		0.97		0.86		0.93
R^2 (1:1)[f]	APSIM-Wheat		0.92		0.95		0.96		0.97		0.97
	CERES-Wheat		0.93		0.96		0.98		0.97		0.98

[a] Root mean square error.
[b] Normalized root mean square error.
[c] Wilmot's index of agreement.
[d] Coefficient of residual mass.
[e] Model efficiency.
[f] Coefficient of determination for the 1 to 1 line ($p < 0.05$; $n = 8$).

during 2010–11 while lowest (7.63 t ha^{-1}) was for Sehar-2006 during 2009–10. All other cultivars' biomass remained between these two extremes. The comparison between observed and simulated values for Tatara revealed that both models accurately simulated biomass (ME ⩾ 0.85). Model evaluation indices confirmed these outcomes. The values of statistic indices for APSIM-Wheat to simulate biomass of cultivar Tatara were RMSE = 0.40 t ha^{-1}, Normal-RMSE = 2.98%, D-index = 0.89, CRM = −0.010, ME = 0.56 and R^2 = 0.92. Similarly, model evaluation indices for CERES-Wheat for same cultivar were RMSE = 0.12 t ha^{-1}, Normal-RMSE = 0.94%, D-index = 0.89, CRM = −0.007, ME = 0.95 and R^2 = 0.93. Overall both models were accurate in simulating biomass at maturity but CERES-Wheat simulation was closer to the observed values as confirmed by model evaluation indices (Table 10). Fig. 4 shows the time course of observed and simulated above ground dry biomass for all cultivars. The highest biomass was observed for Tatara which was accurately simulated by both models. The sequential observed and simulated biomass distribution followed a sigmoid pattern. Similar trends were observed for all other cultivars, however, it remained lower than for Tatara. The simulated above ground dry biomass agrees well with observed values. However, there was slight overestimation by the models. Fig. 4 also shows the reasonably good agreement between observed and simulated spring wheat biomass at maturity during the 2009–10 and 2010–11 wheat crop growing season. Both models simulated wheat biomass at maturity very well (RMSE (t ha^{-1}) for APSIM-Wheat = 0.15–0.4, RMSE (t ha^{-1}) for CERES-Wheat = 0.08–0.17, ME for APSIM-Wheat = 0.86–0.97 and ME for CERES-Wheat = 0.86–0.97; Table 10)

3.2.4. Grain yield (t ha^{-1})

APSIM-Wheat and CERES-Wheat models simulated grain yield very well (Table 11). The simulated grain yields by both wheat models were in the range of 2.41–4.68 t ha^{-1} which was close to the observed yield (2.39–4.60 t ha^{-1}). The highest grain yield was observed for Tatara during the years used for model evaluation followed by NARC-2009, while the lowest was recorded for Sehar-2006 (Table 11). The grain yield was higher among all cultivars during the 2010–11 cropping year compared to 2009–10. There was a good correlation between observed and simulated grain yield for all cultivars. Model evaluation indices RMSE (0.12–0.31 t ha^{-1} for APSIM-Wheat; 0.04–0.18 t ha^{-1} for CERES-Wheat), Normal-RMSE (4.05–11.85% for APSIM-Wheat; 1.12–6.94% for CERES-Wheat), D-index (0.76–0.96 for APSIM-Wheat; 0.84–0.98 for CERES-Wheat), CRM (−0.110–0.047 for APSIM-Wheat; −0.003–0.008 for CERES-Wheat), ME (0.82–0.95 for APSIM-Wheat; 0.97–0.98 for CERES-Wheat) and R^2 (0.82–0.97 for APSIM-Wheat; 0.93–0.98 for CERES-Wheat) confirm the robustness of both models to simulate grain yield with great accuracy.

3.3. Model application: determining the impact of climate variability on wheat grain yield

The impact of increased temperature on grain yield of all wheat cultivars was evaluated using five temperature levels (Fig. 5). All cultivars depicted decreased grain yield with the rise in temperature. The yield of Tatara remained highest in response to increased temperature. The performance of both models to simulate grain yield were similar. However, the effect of increased CO_2 on grain yield of spring wheat simulated by both models showed a trend of increasing yield (Fig. 6). The yield ratio response to elevated CO_2 was calculated by considering yield at 370 ppm CO_2 concentration as baseline. The result shows that yield ratio increases from 1.0 to 1.53 for Tatara in case of CERES-Wheat while it was in the range of 1.0–1.60 simulated by APSIM-Wheat in response to elevated CO_2. Similarly, for NARC-2009 the simulated increase in the yield ratio in response to increased CO_2 from 370 ppm to 970 ppm by CERES-Wheat model was 1.0–1.62 while range was 1.0–1.60 for APSIM-Wheat. The increased ratio for Sehar-2006 in response to elevated CO_2 was 1.0–1.62 and 1.0–1.67 for CERES-Wheat and APSIM-Wheat models respectively. Similar trends were simulated by both models for all other cultivars (Fig. 6).

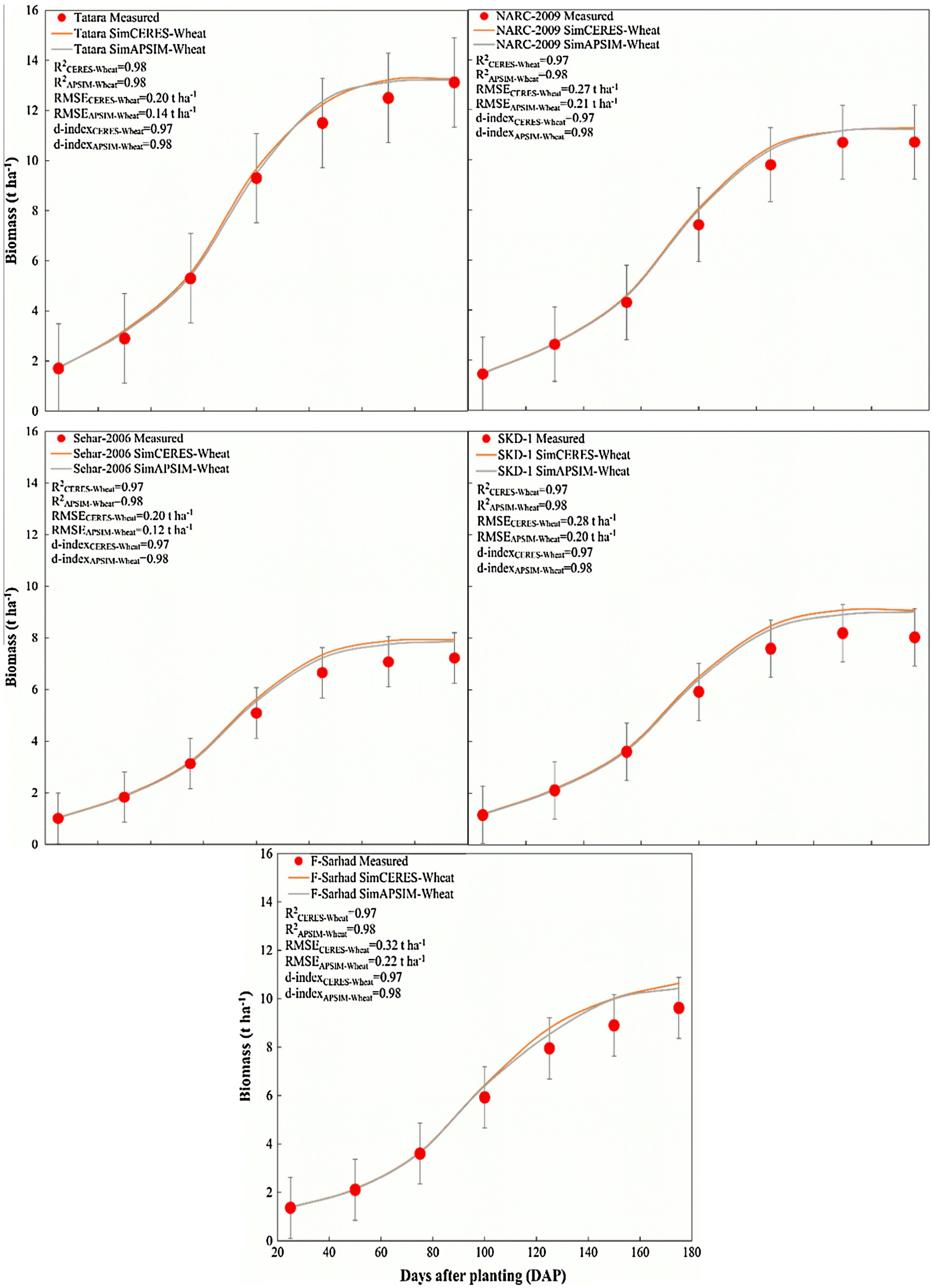

Fig. 4. Measured and Simulated (Sim) biomass of five cultivars Tatara, NARC-2009, Sehar-2006, SKD-1 and F-Sarhad sown on 19th November 2009–2011 at Islamabad.

The combined effect of increased temperature and CO_2 on wheat grain yield revealed that with a 1 or 2 degree rise in temperature, increased CO_2 had a positive effect on the grain yield of wheat for all cultivars. The grain yield was 35% higher on

Table 11
Models evaluation indices of evaluating comparative performance of APSIM-Wheat and CERES-Wheat models in predicting grain yield (t ha^{-1}) for spring wheat cultivars.

Cropping year	Crop models	Tatara		NARC-2009		Sehar-2006		SKD-1		F-Sarhad	
		Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim
2009–10	APSIM-Wheat	4.36	4.40	3.65	3.71	2.39	2.49	2.71	2.75	3.13	3.33
	CERES-Wheat		4.45		3.72		2.41		2.72		3.23
2010–11	APSIM-Wheat	4.60	4.47	3.73	3.80	2.66	2.79	2.93	2.97	3.33	3.41
	CERES-Wheat		4.68		3.75		2.70		2.94		3.39
Models Evaluation Indices											
RMSE (t ha^{-1})[a]	APSIM-Wheat		0.21		0.27		0.31		0.12		0.16
	CERES-Wheat		0.05		0.04		0.18		0.06		0.09
Normal-RMSE (%)[b]	APSIM-Wheat		4.35		6.74		11.85		4.05		4.71
	CERES-Wheat		1.13		1.12		6.94		1.99		2.89
D-Index[c]	APSIM-Wheat		0.81		0.76		0.89		0.96		0.93
	CERES-Wheat		0.91		0.84		0.97		0.98		0.95
CRM[d]	APSIM-Wheat		0.019		0.047		−0.110		−0.030		−0.030
	CERES-Wheat		−0.003		0.004		−0.030		0.008		−0.010
ME[e]	APSIM-Wheat		0.82		0.90		0.95		0.94		0.92
	CERES-Wheat		0.97		0.97		0.98		0.98		0.97
R^2 (1:1)[f]	APSIM-Wheat		0.82		0.84		0.97		0.93		0.94
	CERES-Wheat		0.98		0.93		0.99		0.95		0.97

[a] Root mean square error.
[b] Normalized root mean square error.
[c] Wilmot's index of agreement.
[d] Coefficient of residual mass.
[e] Model efficiency.
[f] Coefficient of determination for the 1 to 1 line ($p < 0.05$; $n = 8$).

average among all cultivars from baseline to a 2 °C rise in temperature simulated by APSIM-Wheat and CERES-Wheat crop model (Fig. 7). However, Tatara showed a more stable increase in grain yield with increased temperature and CO_2 compared to other cultivars. Further increases in temperature from 3 to 4 and 4 to 5 °C with increased CO_2 concentration resulted in a drop in the grain yield among all cultivars (Fig. 7).

4. Discussion

Simulation outcomes from APSIM-Wheat and CERES-Wheat in our findings showed that both models can be used as suitable tool in the selection of appropriate cultivars and to investigate the effect of climate variability on wheat growth and yield. Phenology of wheat has a strong influence on development and grain yield of the crop (Ceglar et al., 2011). In our studies APSIM-Wheat predicted phenological stages like anthesis and maturity close to the observed values (Makowski et al., 2006). Model evaluation indices confirmed the robustness of APSIM-Wheat to simulate the flowering and maturity times of spring wheat (Table 7 and 8). In APSIM-Wheat, flowering time was controlled by tt_floral_initiation and vern_sens while maturity time was determined by tt_start_grain_fill. Therefore, to calibrate the phenology of wheat in APSIM these three parameters should be considered (Zhao et al., 2014). However, in CERES-Wheat flowering and maturity dates were controlled by parameters like P1V, P1D, P5 and PHINT (Andarzian et al., 2015) in the genotype file. Yet, to enhance the accuracy and remove discrepancies between predicted and observed phenological stages, adjustment of the parameters P1, P2, P3 and P4 in the Ecotype file was also made in this study as suggested earlier (Johnen et al., 2012). Accurate phenology is the first priority to calibrate crop models (Archontoulis et al., 2014). By estimating crop phenology accurately, models will be able to capture all genotypic variations which affect the leaf area development, biomass production and grain yield (Robertson et al., 2002). Crop phenology could be modified by crop management like cultivar selection (early, medium and late maturing), and it would help to maximize crop yield. Calibrated and validated APSIM-Wheat and CERES-Wheat (Mohanty et al., 2012; Timsina et al., 2008; Timsina and Humphreys, 2006) simulation indicated good to fair predictions of flowering and maturity time of wheat cultivars as indicated by different validation scores (Table 7 and 8).

The ability of APSIM-Wheat and CERES-Wheat to simulate leaf area index was close to the observed values which confirmed the robustness of both models to simulate LAI of spring wheat cultivars (Fig. 3). The maximum LAI was in Tatara and was predicted well by both wheat models (ME $\geqslant$ 0.82). Leaf area index in APSIM-Wheat increased quickly in present study after emergence untill the flowering stage and it was controlled by vern_sens (vernalization sensitivity) (Zhang et al., 2013). Changing the parameter of vern_sens resulted in the increased or decreased LAI (Zhao et al., 2014). Meanwhile, in the case of CERES-Wheat, adjustment of the SLAS and PARUE parameters resulted in a better simulation of leaf area (Andarzian et al., 2015).

Biomass production is directly related to the amount of solar radiation intercepted by the crop and efficiency of radiation use to produce biomass, which is a cultivar specific trait. The ability of the APSIM-Wheat and CERES-Wheat models to predict biomass at harvest in the rainfed environment confirms the models, accuracy to simulate biomass at maturity. Our results showed that process based models have good potential to simulate crop biomass production (Arora et al., 2007). Since biomass production has a strong relationship with grain yield (Dettori et al., 2011) models which accurately simulate biomass could be considered robust. In our findings biomass production in APSIM-Wheat was controlled by vern_sens and tt_floral initiation parameters (Zhao et al., 2014) while in CERES-Wheat PARUE and PARU2 are the main parameters which control biomass production.

Grain yield is the product of radiation interception by crop canopy, radiation use efficiency (RUE) and harvest index. Yield prediction in precision farming is very important for the improvement of crop management (Pantazi et al., 2016). The results of simulations from both models showed that the yield remained close to the observed values among all cultivars as confirmed by the validation skill scores (Table 11). In APSIM-Wheat parameters which

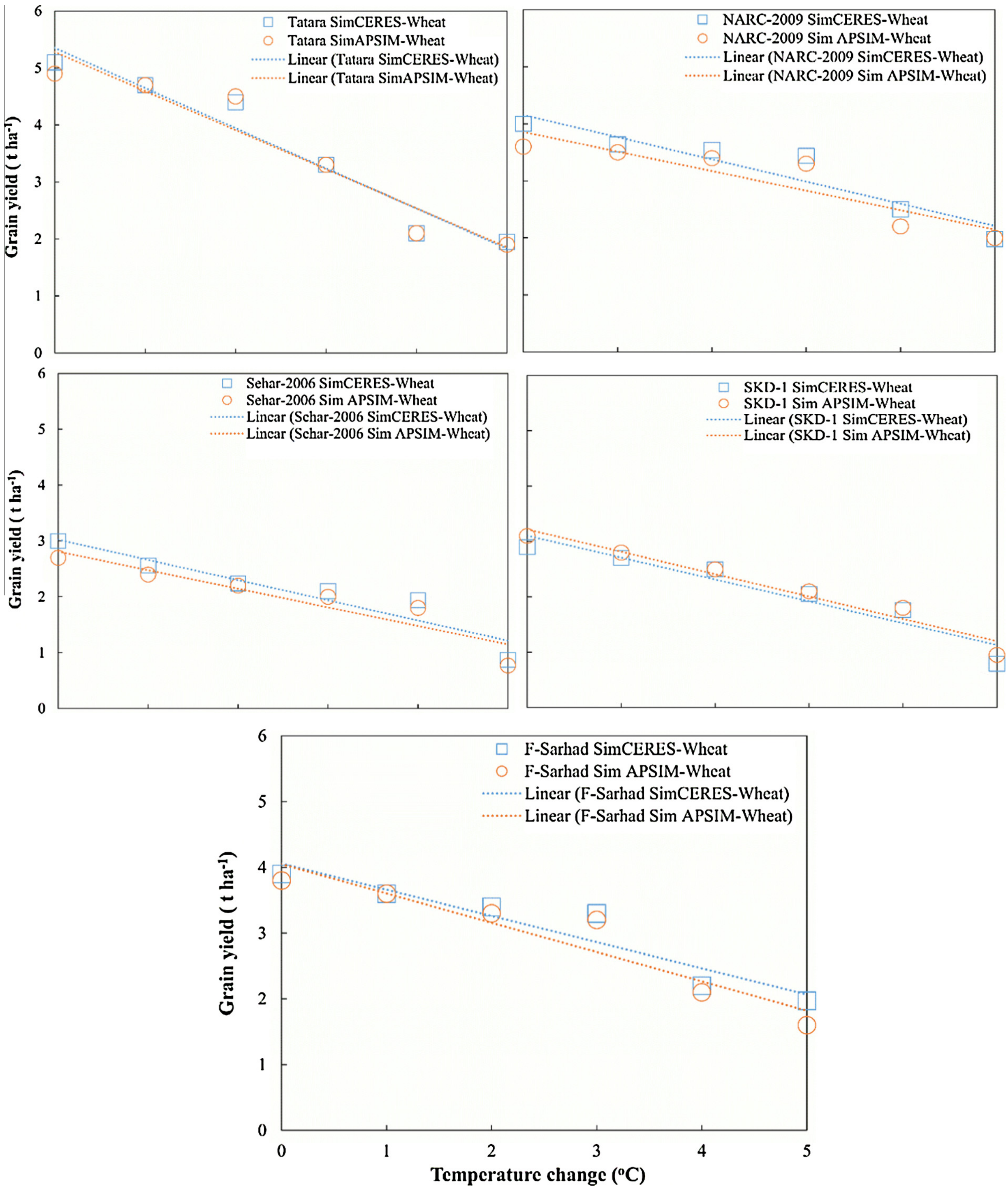

Fig. 5. Impact of increased temperature on yield of five wheat genotypes simulated by APSIM-Wheat and DSSAT-CERES-Wheat.

have a strong influence on grain yield are tt_floral initiation and tt_start grain fill, grains per unit stem mass, max grain size and potential grain filling rate. However, in the case of CERES-Wheat TRGF (species file), G1, G2 and G3 were the parameters in the genotype file controlling grain yield (Hunt and Boote, 1998). Therefore, by adjusting these parameters grain yield of a specific cultivar could be increased or decreased but it should be adjusted after first calibrating the phenology of the crop (Ma et al., 2011). The impact of increased temperature on yield of five wheat genotypes simulated by APSIM-Wheat and CERES-Wheat showed a negative trend (Fig. 5) which might be due to accelerated crop development stages and decreased biomass production. The increased temperature also resulted in the shortening of crop life cycle (Sayre et al., 1997) and ultimately less interception of solar radiation and decreased biomass production (Heng et al., 2007). Climate variability in the form of higher temperature resulted in shortening of crop life cycle and yield loss (Alexandrov and Hoogenboom, 2000). In the present study Tatara, showed significant sustainability in yield compared to other cultivars with increased temperature. Since temperature variability is identified as a major future yield-determining factor, crop models could provide an opportunity to minimize risk by providing options related to the cultivar

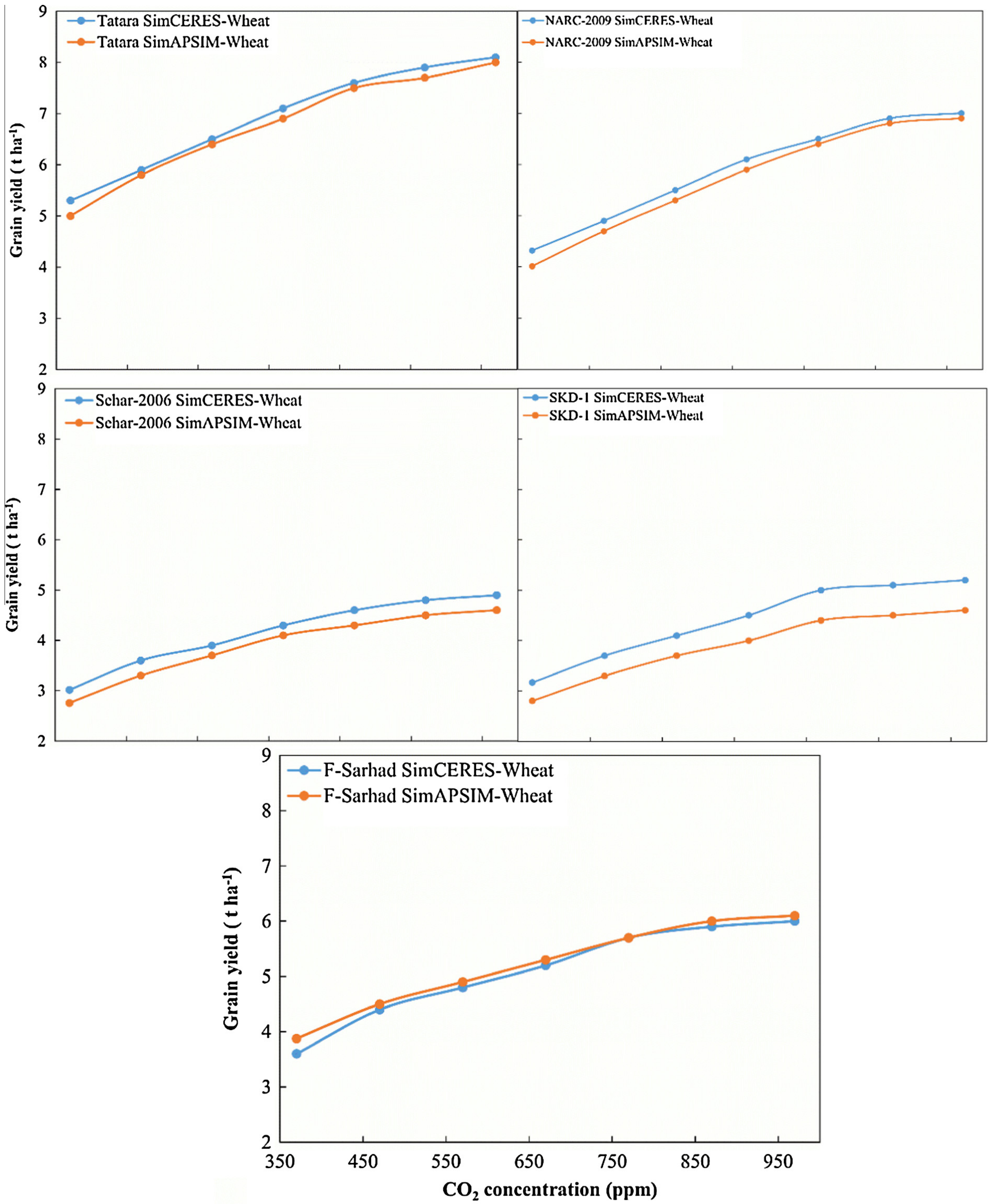

Fig. 6. Impact of increased CO_2 concentration on yield of five wheat genotypes simulated by DSSAT-CERES-Wheat and APSIM-Wheat.

selections. Similarly, Pantazi et al. (2016) developed and evaluated a yield prediction model for wheat. Our results are consistent with a number of simulation studies under different climatic scenarios (Dettori et al., 2011; Özdoğan, 2011; Palosuo et al., 2011) where they highlighted the yield reduction due to increased temperature. Reduction in wheat yield due to 2–4 °C seasonal increase in temperature was also reported by earlier researchers (Wheeler et al., 2000).

Simulated results of elevated CO_2 on grain yield of wheat depicted increasing trends among all cultivars (Fig. 6). Generally elevated CO_2 increased crop yield by increasing intercellular CO_2 concentration (increased net photosynthesis rates) and reducing stomatal conductance (reduced transpiration) (Asseng et al., 2004). Furthermore, the combined effect of increased temperature and CO_2 led to higher wheat yield but after a 3 °C increase in temperature, yield started decreasing with elevated CO_2 in temperature-susceptible cultivars (Fig. 7). Our findings confirm that the negative effect of warmer temperatures could be countered by the increased rate of crop growth by resistant cultivars at elevated atmospheric CO_2 (Wheeler et al., 2000). Similarly,

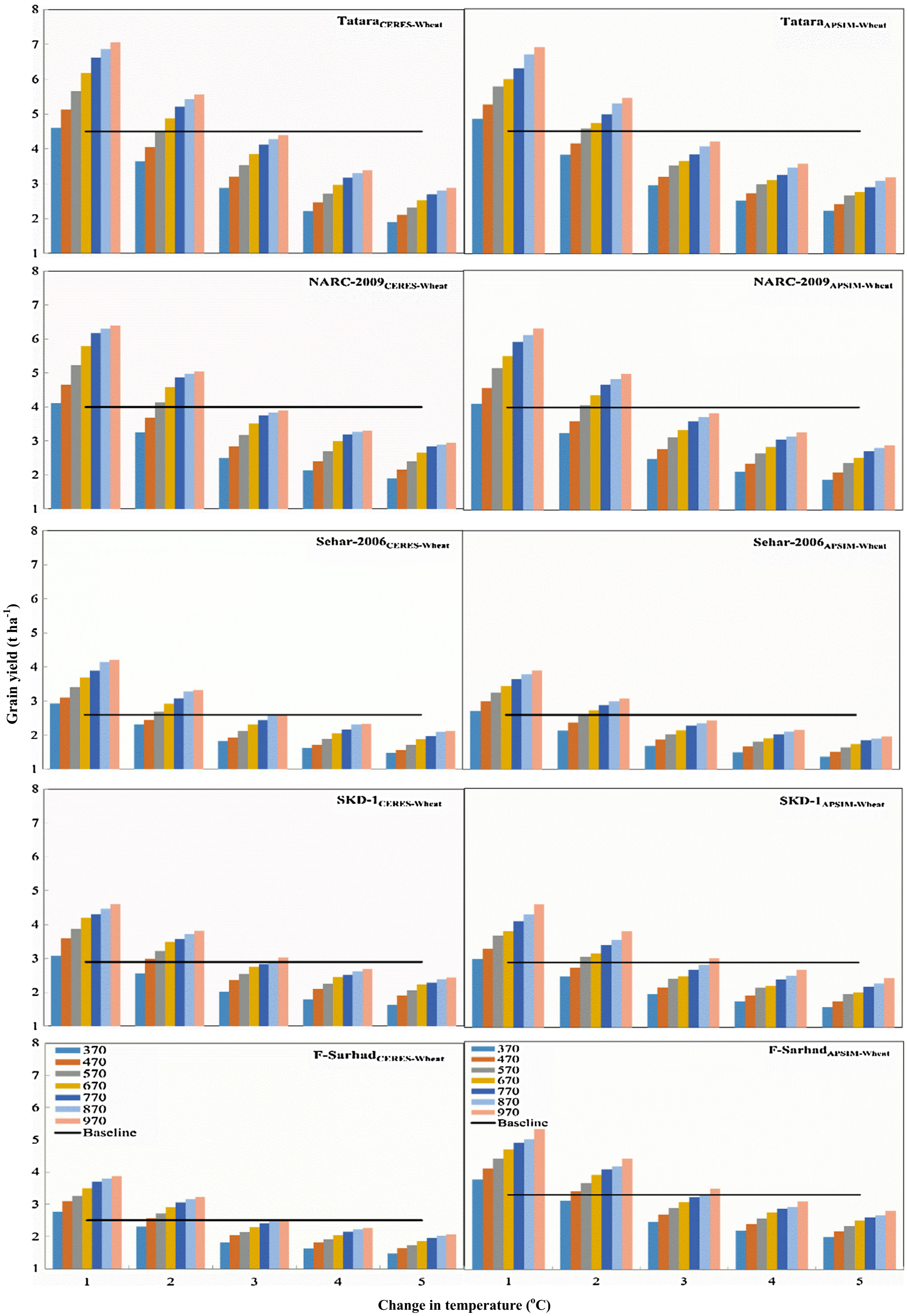

Fig. 7. Simulated combined impact of increased temperature and CO_2 concentration on five spring wheat cultivars.

Dias de Oliveira et al. (2015) reported that elevated CO_2 increases grain yield in wheat by enhancing grain number per ear. Their work further elaborated that elevated CO_2 resulted in increased net leaf photosynthetic rate and availability of carbon assimilates to floret. This reduced the rates of floret death and increased the potential number of grains up to 42%. They suggested breeding of cultivars with a greater potential number of florets to have higher CO_2 fertilization effect under heat and terminal drought stress.

5. Conclusions

APSIM-Wheat and CERES-wheat model depicted great potential to simulate phenological stages (flowering and maturity day), LAI, biomass and grain yield close to the observed field data of the crop. The model evaluation indices RMSE, Normal-RMSE, D-index, CRM, ME and R^2 confirmed the robustness of the both wheat models. The validated models could be used as research tools to provide different management options under rainfed conditions. APSIM-Wheat and CERES-Wheat five outputs viz. flowering day, maturity day, leaf area index, biomass and grain yield to five cultivar parameters were analyzed using trial and error adjustments. In the case of APSIM-Wheat, flowering and maturity time of the wheat crop was controlled by vern_sens, tt_floral initiation and tt_start_grain_fill parameters while in CERES-Wheat it was controlled by parameters P1V, P1D, P5 and PHINT. Similarly, LAI in APSIM-Wheat was sensitive to vern_sens and in case of CERES-Wheat SLAS and PARUE were the parameters controlling leaf area. Biomass production in APSIM-Wheat was controlled by vern_sens and tt_floral initiation parameters while in CERES-Wheat, PARUE and PARU2 were the main parameters which controled biomass production. The yield in APSIM-Wheat was controlled by parameters like tt_floral initiation, tt_start grain fill, grains per gram stem, maximum grain size and potential grain filling rate while in CERES-Wheat yield controlling parameters were TRGF, G1, G2 and G3. Both models were run with climate change scenarios of increased temperature, elevated CO_2 and increased temperature + elevated CO_2 for all five cultivars under rainfed conditions in Pakistan. The trend showed that increased temperatures had a negative effect on crop yield while elevated CO_2 had a positive effect. However, the combined effect of increased temperature + elevated CO_2 concentration increased grain yield untill a 3 °C increase in temperature. As such these models can be used to select cultivars which can bring sustainability in yield by mitigating the impact of increased temperature on crop growth and development.

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References

Abeledo, L.G., Savin, R., Slafer, G.A., 2008. Wheat productivity in the Mediterranean Ebro Valley: analyzing the gap between attainable and potential yield with a simulation model. Eur. J. Agron. 28 (4), 541–550.
Alexandrov, V.A., Hoogenboom, G., 2000. The impact of climate variability and change on crop yield in Bulgaria. Agric. For. Meteorol. 104 (4), 315–327.
Andarzian, B., Bakhshandeh, A.M., Bannayan, M., Emam, Y., Fathi, G., Alami Saeed, K., 2008. WheatPot: a simple model for spring wheat yield potential using monthly weather data. Biosyst. Eng. 99 (4), 487–495.
Andarzian, B., Bannayan, M., Steduto, P., Mazraeh, H., Barati, M.E., Barati, M.A., Rahnama, A., 2011. Validation and testing of the AquaCrop model under full and deficit irrigated wheat production in Iran. Agric. Water Manage. 100 (1), 1–8.
Andarzian, B., Hoogenboom, G., Bannayan, M., Shirali, M., Andarzian, B., 2015. Determining optimum sowing date of wheat using CSM-CERES-Wheat model. J. Saudi. Soc. Agri. Sci. 14 (2), 189–199.
Anwar, M.R., Liu, D.L., Farquharson, R., Macadam, I., Abadi, A., Finlayson, J., Wang, B., Ramilan, T., 2015. Climate change impacts on phenology and yields of five broadacre crops at four climatologically distinct locations in Australia. Agric. Syst. 132, 133–144.
Archontoulis, S.V., Miguez, F.E., Moore, K.J., 2014. A methodology and an optimization tool to calibrate phenology of short-day species included in the APSIM PLANT model: application to soybean. Environ. Modell. Softw. 62, 465–477.
Arora, V.K., Singh, H., Singh, B., 2007. Analyzing wheat productivity responses to climatic, irrigation and fertilizer-nitrogen regimes in a semi-arid sub-tropical environment using the CERES-Wheat model. Agric. Water Manage. 94 (1–3), 22–30.
Asseng, S., Ewert, F., Martre, P., Rotter, R.P., Lobell, D.B., Cammarano, D., Kimball, B. A., Ottman, M.J., Wall, G.W., White, J.W., Reynolds, M.P., Alderman, P.D., Prasad, P.V.V., Aggarwal, P.K., Anothai, J., Basso, B., Biernath, C., Challinor, A.J., De Sanctis, G., Doltra, J., Fereres, E., Garcia-Vila, M., Gayler, S., Hoogenboom, G., Hunt, L.A., Izaurralde, R.C., Jabloun, M., Jones, C.D., Kersebaum, K.C., Koehler, A. K., Muller, C., Naresh Kumar, S., Nendel, C., O'Leary, G., Olesen, J.E., Palosuo, T., Priesack, E., Eyshi Rezaei, E., Ruane, A.C., Semenov, M.A., Shcherbak, I., Stockle, C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Thorburn, P.J., Waha, K., Wang, E., Wallach, D., Wolf, J., Zhao, Z., Zhu, Y., 2015a. Rising temperatures reduce global wheat production. Nat. Clim. Change 5 (2), 143–147.
Asseng, S., Jamieson, P.D., Kimball, B., Pinter, P., Sayre, K., Bowden, J.W., Howden, S. M., 2004. Simulated wheat growth affected by rising temperature, increased water deficit and elevated atmospheric CO_2. Field Crop Res. 85 (2–3), 85–102.
Asseng, S., Zhu, Y., Basso, B., Wilson, T., Cammarano, D., 2014. Simulation modeling: applications in cropping systems. Enc. Agri. Food Syst., 102–112
Asseng, S., Zhu, Y., Wang, E., Zhang, W., 2015b. Chapter 20 – crop modeling for climate change impact and adaptation. In: Calderini, V.O.S.F. (Ed.), Crop Physiology, second ed. Academic Press, San Diego, pp. 505–546.
Bannayan, M., Crout, N.M.J., Hoogenboom, G., 2003. Application of the CERES-Wheat model for within-season prediction of winter wheat yield in the United Kingdom. Agron. J. 95 (1), 114–125.
Bannayan, M., Eyshi Rezaei, E., Hoogenboom, G., 2013. Determining optimum planting dates for rainfed wheat using the precipitation uncertainty model and adjusted crop evapotranspiration. Agric. Water Manage. 126, 56–63.
Basso, B., Liu, L., Ritchie, J.T., 2016. A comprehensive review of the CERES-Wheat, -Maize and -Rice models' performances. In: Donald, L.S. (Ed.), Advances in Agronomy. Academic Press, pp. 27–132.
Bassu, S., Asseng, S., Motzo, R., Giunta, F., 2009. Optimising sowing date of durum wheat in a variable Mediterranean environment. Field Crop Res. 111 (1–2), 109–118.
Bassu, S., Brisson, N., Durand, J.-L., Boote, K., Lizaso, J., Jones, J.W., Rosenzweig, C., Ruane, A.C., Adam, M., Baron, C., Basso, B., Biernath, C., Boogaard, H., Conijn, S., Corbeels, M., Deryng, D., De Sanctis, G., Gayler, S., Grassini, P., Hatfield, J., Hoek, S., Izaurralde, C., Jongschaap, R., Kemanian, A.R., Kersebaum, K.C., Kim, S.-H., Kumar, N.S., Makowski, D., Müller, C., Nendel, C., Priesack, E., Pravia, M.V., Sau, F., Shcherbak, I., Tao, F., Teixeira, E., Timlin, D., Waha, K., 2014. How do various maize crop models vary in their responses to climate change factors? Glob. Change Biol. 20 (7), 2301–2320.
Boote, K.J., Porter, C., Jones, J.W., Thorburn, P.J., Kersebaum, K.C., Hoogenboom, G., White, J.W., Hatfield, J.L., 2015. Sentinel site data for crop model improvement-definition and characterization, improving modeling tools to assess climate change effects on crop response. American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America, Inc., Madison, WI.
Brisson, N., Gary, C., Justes, E., Roche, R., Mary, B., Ripoche, D., Zimmer, D., Sierra, J., Bertuzzi, P., Burger, P., Bussière, F., Cabidoche, Y.M., Cellier, P., Debaeke, P., Gaudillère, J.P., Hénault, C., Maraux, F., Seguin, B., Sinoquet, H., 2003. An overview of the crop model STICS. Eur. J. Agron. 18 (3–4), 309–332.
Castañeda-Vera, A., Leffelaar, P.A., Álvaro-Fuentes, J., Cantero-Martínez, C., Mínguez, M.I., 2015. Selecting crop models for decision making in wheat insurance. Agric. For. Meteorol. 68, 97–116.
Ceglar, A., Črepinšek, Z., Kajfež-Bogataj, L., Pogačar, T., 2011. The simulation of phenological development in dynamic crop model: the Bayesian comparison of different methods. Agric. For. Meteorol. 151 (1), 101–115.
Chauhan, B.S., Mahajan, G., Sardana, V., Timsina, J., Jat, M.L., 2012. Chapter six – productivity and sustainability of the rice-wheat cropping system in the indo-gangetic plains of the indian subcontinent: problems, opportunities, and strategies. In: Donald, L.S. (Ed.), Adv Agron. Academic Press, pp. 315–369.
Chen, C., Wang, E., Yu, Q., 2010. Modelling the effects of climate variability and water management on crop water productivity and water balance in the North China Plain. Agric. Water Manage. 97 (8), 1175–1184.
Dettori, M., Cesaraccio, C., Motroni, A., Spano, D., Duce, P., 2011. Using CERES-Wheat to simulate durum wheat production and phenology in Southern Sardinia, Italy. Field Crop Res. 120 (1), 179–188.
Devkota, K.P., Hoogenboom, G., Boote, K.J., Singh, U., Lamers, J.P.A., Devkota, M., Vlek, P.L.G., 2015. Simulating the impact of water saving irrigation and conservation agriculture practices for rice–wheat systems in the irrigated semi-arid drylands of Central Asia. Agric. For. Meteorol. 214–215, 266–280.
Dhungana, P., Eskridge, K.M., Weiss, A., Baenziger, P.S., 2006. Designing crop technology for a future climate: an example using response surface methodology and the CERES-Wheat model. Agric. Syst. 87 (1), 63–79.
Dias de Oliveira, E., Palta, J.A., Bramley, H., Stefanova, K., Siddique, K.H.M., 2015. Elevated CO_2 reduced floret death in wheat under warmer average temperatures and terminal drought. Front. Plant Sci. 6, 1010.

Donatelli, M., Van Ittersum, M.K., Bindi, M., Porter, J.R., 2002. Modelling cropping systems-highlights of the symposium and preface to the special issues. Eur. J. Agron. 18 (1–2), 1–11.

Dong, C., Hu, D., Fu, Y., Wang, M., Liu, H., 2014. Analysis and optimization of the effect of light and nutrient solution on wheat growth and development using an inverse system model strategy. Comput. Electr. Agric. 109, 221–231.

Eitzinger, J., Trnka, M., Hösch, J., Žalud, Z., Dubrovský, M., 2004. Comparison of CERES, WOFOST and SWAP models in simulating soil water content during growing season under different soil conditions. Ecol. Model. 171 (3), 223–246.

Fayed, T.B., El-Sarag, E.I., Hassanein, M.K., Magdy, A., 2015. Evaluation and prediction of some wheat cultivars productivity in relation to different sowing dates under North Sinai region conditions. Ann. Agric. Sci. 60 (1), 11–20.

Frank, S., Schmid, E., Havlík, P., Schneider, U.A., Böttcher, H., Balkovič, J., Obersteiner, M., 2015. The dynamic soil organic carbon mitigation potential of European cropland. Glob. Environ. Change 35, 269–278.

Godwin, D.C., Singh, U., 1998. Nitrogen balance and crop response to nitrogen in upland and lowland cropping systems. In: Tsuji, G., Hoogenboom, G., Thornton, P. (Eds.), Understanding Options for Agricultural Production. Springer, Netherlands, pp. 55–77.

Haghverdi, A., Ghahraman, B., Leib, B.G., Pulido-Calvo, I., Kafi, M., Davary, K., Ashorun, B., 2014. Deriving data mining and regression based water-salinity production functions for spring wheat (*Triticum aestivum*). Comput. Electr. Agric. 101, 68–75.

Heng, L.K., Asseng, S., Mejahed, K., Rusan, M., 2007. Optimizing wheat productivity in two rain-fed environments of the West Asia-North Africa region using a simulation model. Eur. J. Agron. 26 (2), 121–129.

Holzworth, D.P., Huth, N.I., deVoil, P.G., 2011. Simple software processes and tests improve the reliability and usefulness of a model. Environ. Modell. Softw. 26 (4), 510–516.

Hunt, L.A., Boote, K.J., 1998. Data for model operation, calibration, and evaluation. In: Tsuji, G., Hoogenboom, G., Thornton, P. (Eds.), Understanding Options for Agricultural Production. Springer, Netherlands, pp. 9–39.

Innes, P.J., Tan, D.K.Y., Van Ogtrop, F., Amthor, J.S., 2015. Effects of high-temperature episodes on wheat yields in New South Wales, Australia. Agric. For. Meteorol. 208, 95–107.

Johnen, T., Boettcher, U., Kage, H., 2012. A variable thermal time of the double ridge to flag leaf emergence phase improves the predictive quality of a CERES-Wheat type phenology model. Comput. Electr. Agric. 89, 62–69.

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T., 2003. The DSSAT cropping system model. Eur. J. Agron. 18 (3–4), 235–265.

Keating, B.A., Carberry, P.S., Hammer, G.L., Probert, M.E., Robertson, M.J., Holzworth, D., Huth, N.I., Hargreaves, J.N.G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J.P., Silburn, M., Wang, E., Brown, S., Bristow, K.L., Asseng, S., Chapman, S., McCown, R.L., Freebairn, D.M., Smith, C.J., 2003. An overview of APSIM, a model designed for farming systems simulation. Eur. J. Agron. 18 (3–4), 267–288.

Knörzer, H., Grözinger, H., Graeff-Hönninger, S., Hartung, K., Piepho, H.P., Claupein, W., 2011. Integrating a simple shading algorithm into CERES-wheat and CERES-maize with particular regard to a changing microclimate within a relay-intercropping system. Field Crop Res. 121 (2), 274–285.

Li, T., Hasegawa, T., Yin, X., Zhu, Y., Boote, K., Adam, M., Bregaglio, S., Buis, S., Confalonieri, R., Fumoto, T., Gaydon, D., Marcaida, M., Nakagawa, H., Oriol, P., Ruane, A.C., Ruget, F., Singh, B., Singh, U., Tang, L., Tao, F., Wilkens, P., Yoshida, H., Zhang, Z., Bouman, B., 2015a. Uncertainties in predicting rice yield by current crop models under a wide range of climatic conditions. Glob. Change Biol. 21 (3), 1328–1341.

Li, Z.T., Yang, J.Y., Drury, C.F., Hoogenboom, G., 2015b. Evaluation of the DSSAT-CSM for simulating yield and soil organic C and N of a long-term maize and wheat rotation experiment in the Loess Plateau of Northwestern China. Agri. Syst. 135, 90–104.

Loague, K., Green, R.E., 1991. Statistical and graphical methods for evaluating solute transport models: overview and application. J. Contam. Hydrol. 7 (1–2), 51–73.

Ma, L., Ahuja, L.R., Saseendran, S.A., Malone, R.W., Green, T.R., Nolan, B.T., Bartling, P. N.S., Flerchinger, G.N., Boote, K.J., Hoogenboom, G., 2011. A Protocol for Parameterization and Calibration of RZWQM2 in Field Research. In: Ahuja, L. R., Ma, L. (Eds.). Methods of Introducing System Models into Agricultural Research, Am Society Agron, Crop Science Society of America, Soil Science Society of America, pp. 1–64.

Ma, Y., Feng, S., Song, X., 2015. Evaluation of optimal irrigation scheduling and groundwater recharge at representative sites in the North China Plain with SWAP model and field experiments. Comput. Electr. Agric. 116, 125–136.

Makowski, D., Naud, C., Jeuffroy, M.-H., Barbottin, A., Monod, H., 2006. Global sensitivity analysis for calculating the contribution of genetic parameters to the variance of crop model prediction. Reliab. Eng. Syst. Safe. 91 (10–11), 1142–1147.

Martín, M.M.-S., Olesen, J.E., Porter, J.R., 2014. A genotype, environment and management (GxExM) analysis of adaptation in winter wheat to climate change in Denmark. Agric. For. Meteorol. 187, 1–13.

Martre, P., Wallach, D., Asseng, S., Ewert, F., Jones, J.W., Rötter, R.P., Boote, K.J., Ruane, A.C., Thorburn, P.J., Cammarano, D., Hatfield, J.L., Rosenzweig, C., Aggarwal, P.K., Angulo, C., Basso, B., Bertuzzi, P., Biernath, C., Brisson, N., Challinor, A.J., Doltra, J., Gayler, S., Goldberg, R., Grant, R.F., Heng, L., Hooker, J., Hunt, L.A., Ingwersen, J., Izaurralde, R.C., Kersebaum, K.C., Müller, C., Kumar, S. N., Nendel, C., O'Leary, G., Olesen, J.E., Osborne, T.M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M.A., Shcherbak, I., Steduto, P., Stöckle, C.O., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., White, J. W., Wolf, J., 2015. Multimodel ensembles of wheat growth: many models are better than one. Glob. Change Biol. 21 (2), 911–925.

McCown, R.L., Hammer, G.L., Hargreaves, J.N.G., Holzworth, D.P., Freebairn, D.M., 1996. APSIM: a novel software system for model development, model testing and simulation in agricultural systems research. Agric. Syst. 50 (3), 255–271.

Mohanty, M., Probert, M.E., Reddy, K.S., Dalal, R.C., Mishra, A.K., Subba Rao, A., Singh, M., Menzies, N.W., 2012. Simulating soybean–wheat cropping system: APSIM model parameterization and validation. Agric. Ecosyst. Environ. 152, 68–78.

Monsi, M., Saeki, T., 2005. On the factor light in plant communities and its importance for matter production. Ann. Bot-London 95 (3), 549–567.

O'Leary, G.J., Christy, B., Nuttall, J., Huth, N., Cammarano, D., Stöckle, C., Basso, B., Shcherbak, I., Fitzgerald, G., Luo, Q., Farre-Codina, I., Palta, J., Asseng, S., 2015. Response of wheat growth, grain yield and water use to elevated CO_2 under a Free-Air CO_2 Enrichment (FACE) experiment and modelling in a semi-arid environment. Glob. Change Biol. 21 (7), 2670–2686.

Özdoğan, M., 2011. Modeling the impacts of climate change on wheat yields in Northwestern Turkey. Agric. Ecosyst. Environ. 141 (1–2), 1–12.

Palosuo, T., Kersebaum, K.C., Angulo, C., Hlavinka, P., Moriondo, M., Olesen, J.E., Patil, R.H., Ruget, F., Rumbaur, C., Takáč, J., Trnka, M., Bindi, M., Çaldağ, B., Ewert, F., Ferrise, R., Mirschel, W., Şaylan, L., Šiška, B., Rötter, R., 2011. Simulation of winter wheat yield and its variability in different climates of Europe: a comparison of eight crop growth models. Eur. J. Agron. 35 (3), 103–114.

Pantazi, X.E., Moshou, D., Alexandridis, T., Whetton, R.L., Mouazen, A.M., 2016. Wheat yield prediction using machine learning and advanced sensing techniques. Comput. Electr. Agric. 121, 57–65.

Pavlova, V.N., Varcheva, S.E., Bokusheva, R., Calanca, P., 2014. Modelling the effects of climate variability on spring wheat productivity in the steppe zone of Russia and Kazakhstan. Ecol. Model. 277, 57–67.

Pirttioja, N., Carter, T.R., Fronzek, S., Bindi, M., Hoffmann, H., Palosuo, T., Ruiz-Ramos, M., Tao, F., Trnka, M., Acutis, M., Asseng, S., Baranowski, P., Basso, B., Bodin, P., Buis, S., Cammarano, D., Deligios, P., Destain, M.F., Dumont, B., Ewert, F., Ferrise, R., François, L., Gaiser, T., Hlavinka, P., Jacquemin, I., Kersebaum, K.C., Kollas, C., Krzyszczak, J., Lorite, I.J., Minet, J., Minguez, M.I., Montesino, M., Moriondo, M., Müller, C., Nendel, C., Öztürk, I., Perego, A., Rodríguez, A., Ruane, A.C., Ruget, F., Sanna, M., Semenov, M.A., Slawinski, C., Stratonovitch, P., Supit, I., Waha, K., Wang, E., Wu, L., Zhao, Z., Rötter, R.P., 2015. Temperature and precipitation effects on wheat yield across a European transect: a crop model ensemble analysis using impact response surfaces. Clim. Res. 65, 87–105.

Porter, J.R., Semenov, M.A., 2005. Crop responses to climatic variation. Philos. T. Roy. Soc. B 360 (1463), 2021–2035.

Prasad, P.V.V., Jagadish, S.V.K., 2015. Field crops and the fear of heat stress – opportunities, challenges and future directions. Proc. Environ. Sci. 29, 36–37.

Priestley, C.H.B., Taylor, R.J., 1972. On the assessment of surface heat flux and evaporation using large-scale parameters. Mon. Weather Rev. 100 (2), 81–92.

Ray, D.K., Gerber, J.S., MacDonald, G.K., West, P.C., 2015. Climate variation explains a third of global crop yield variability. Nat. Commun. 6.

Rezaei, E.E., Siebert, S., Ewert, F., 2015. Intensity of heat stress in winter wheat—phenology compensates for the adverse effect of global warming. Environ. Res. Lett. 10 (2), 024012.

Ritchie, J.T., Singh, U., Godwin, D.C., Bowen, W.T., 1998. Cereal growth, development and yield. In: Tsuji, G., Hoogenboom, G., Thornton, P. (Eds.), Understanding Options for Agricultural Production. Springer, Netherlands, pp. 79–98.

Robertson, M.J., Carberry, P.S., Huth, N.I., Turpin, J.E., Probert, M.E., Poulton, P.L., Bell, M., Wright, G.C., Yeates, S.J., Brinsmead, R.B., 2002. Simulation of growth and development of diverse legume species in APSIM. Aust. J. Agric. Res. 53 (4), 429–446.

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A.C., Müller, C., Arneth, A., Boote, K.J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T.A.M., Schmid, E., Stehfest, E., Yang, H., Jones, J.W., 2014. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. P. Natl. Acad. Sci. USA 111 (9), 3268–3273.

Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P., Antle, J. M., Nelson, G.C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., Winter, J.M., 2013. The Agricultural Model Intercomparison and Improvement Project (AgMIP): protocols and pilot studies. Agric. For. Meteorol. 170, 166–182.

Rosenzweig, C., Parry, M.L., 1994. Potential impact of climate change on world food supply. Nature 367 (6459), 133–138.

Rötter, R.P., Palosuo, T., Kersebaum, K.C., Angulo, C., Bindi, M., Ewert, F., Ferrise, R., Hlavinka, P., Moriondo, M., Nendel, C., Olesen, J.E., Patil, R.H., Ruget, F., Takáč, J., Trnka, M., 2012. Simulation of spring barley yield in different climatic zones of Northern and Central Europe: a comparison of nine crop models. Field Crop Res. 133, 23–36.

Salo, T.J., Palosuo, T., Kersebaum, K.C., Nendel, C., Angulo, C., Ewert, F., Bindi, M., Calanca, P., Klein, T., Moriondo, M., Ferrise, R., Olesen, J.E., Patil, R.H., Ruget, F., Takáč, J., Hlavinka, P., Trnka, M., Rötter, R.P., 2015. Comparing the performance of 11 crop simulation models in predicting yield response to nitrogen fertilization. J. Agric. Sci. FirstView, 1–23.

Savin, R., Satorre, E.H., Hall, A.J., Slafer, G.A., 1995. Assessing strategies for wheat cropping in the monsoonal climate of the Pampas using the CERES-Wheat simulation model. Field Crop Res. 42 (2–3), 81–91.

Sayre, K.D., Rajaram, S., Fischer, R.A., 1997. Yield potential progress in short bread wheats in Northwest Mexico. Crop Sci. 37 (1), 36–42.

Schultz, A., Wieland, R., Lutze, G., 2000. Neural networks in agroecological modelling — stylish application or helpful tool? Comput. Electr. Agric. 29 (1–2), 73–97.

Singh, A.K., Tripathy, R., Chopra, U.K., 2008. Evaluation of CERES-Wheat and CropSyst models for water–nitrogen interactions in wheat crop. Agric. Water Manage. 95 (7), 776–786.
Soltani, A., Sinclair, T.R., 2015. A comparison of four wheat models with respect to robustness and transparency: simulation in a temperate, sub-humid environment. Field Crop Res. 175, 37–46.
Timsina, J., Godwin, D., Humphreys, E., Yadvinder, S., Bijay, S., Kukal, S.S., Smith, D., 2008. Evaluation of options for increasing yield and water productivity of wheat in Punjab, India using the DSSAT-CSM-CERES-Wheat model. Agric. Water Manage. 95 (9), 1099–1110.
Timsina, J., Humphreys, E., 2006. Performance of CERES-Rice and CERES-Wheat models in rice–wheat systems: a review. Agric. Syst. 90 (1–3), 5–31.
van Ogtrop, F., Ahmad, M., Moeller, C., 2014. Principal components of sea surface temperatures as predictors of seasonal rainfall in rainfed wheat growing areas of Pakistan. Meteorol. Appl. 21 (2), 431–443.
Wang, E., Engel, T., 2000. SPASS: a generic process-oriented crop model with versatile windows interfaces. Environ. Modell. Softw. 15 (2), 179–188.
Wang, E., Engel, T., 2002. Simulation of growth, water and nitrogen uptake of a wheat crop using the SPASS model. Environ. Modell. Softw. 17 (4), 387–402.
Wang, X.-C., Li, J., Tahir, M.N., Fang, X.-Y., 2012. Validation of the EPIC model and its utilization to research the sustainable recovery of soil desiccation after alfalfa (*Medicago sativa* L.) by grain crop rotation system in the semi-humid region of the Loess Plateau. Agric. Ecosyst. Environ. 161, 152–160.
Wheeler, T.R., Craufurd, P.Q., Ellis, R.H., Porter, J.R., Vara Prasad, P.V., 2000. Temperature variability and the yield of annual crops. Agric. Ecosyst. Environ. 82 (1–3), 159–167.
Willmott, C.J., 1981. On the validation of models. Phys. Geogr. 2 (2), 184–194.
Willmott, C.J., Ackleson, S.G., Davis, R.E., Feddema, J.J., Klink, K.M., Legates, D.R., O'Donnell, J., Rowe, C.M., 1985. Statistics for the evaluation and comparison of models. J. Geophys. Res.: Oceans 90 (C5), 8995–9005.
Xevi, E., Gilley, J., Feyen, J., 1996. Comparative study of two crop yield simulation models. Agric. Water Manage. 30 (2), 155–173.
Zhang, Y., Feng, L.P., Wang, J., Wang, E.L., Xu, Y.L., 2013. Using APSIM to explore wheat yield response to climate change in the North China Plain: the predicted adaptation of wheat cultivar types to vernalization. J. Agric. Sci. 151 (06), 836–848.
Zhao, G., Bryan, B.A., Song, X., 2014. Sensitivity and uncertainty analysis of the APSIM-wheat model: interactions between cultivar, environmental, and management parameters. Ecol. Model. 279, 1–11.
Zheng, B., Chenu, K., Doherty, A., Doherty, T., Chapman, L., 2014. The APSIM-Wheat Module. APSRU Toowoomba, Australia, pp. 1–44.