Journal of Arid Environments 182 (2020) 104256

Contents lists available at ScienceDirect

Journal of Arid Environments

journal homepage: www.elsevier.com/locate/jaridenv

Determining optimum nitrogen management as a function of planting date for spring wheat (Triticum aestivum L.) under semi-arid conditions using a modeling approach

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ARTICLE INFO

Keywords:
Genetic coefficients
Sustainable production
Crop model
Systems analysis
DSSAT

ABSTRACT

A crop modeling approach can be used to assess various crop management options and water productivity to improve crop production for different environments. The goal of this study was to determine optimum planting dates and nitrogen management options using a systems analysis approach based on the Cropping System Model (CSM) CERES-Wheat of DSSAT v 4.6. Wheat experiments were conducted from 2007 to 2013 under semi-arid conditions at the experimental fields of the Nuclear Institute for Agriculture and Biology (NIAB), Faisalabad, Pakistan. The CSM-CERES-Wheat model was calibrated for wheat (Triticum aestivum L.) cultivar Sehar-2006 from a 3-year field experiment data on flowering day, maturity day, canopy cover, grain yield, biomass, grain nitrogen content, and nitrogen harvest index. After calibration, the CSM-CERES-Wheat model produced satisfactory simulations for wheat phenology and crop growth parameters. The model was then evaluated using six years of independent datasets for both irrigated and rainfed conditions. The evaluation showed that the model performed well as indicated by the accurate simulation of wheat phenology [the normalized root mean square error *(NRMSE)* = 3%] and crop growth parameters such as crop cover (*NRMSE* = 7%–13%), biomass *(NRMSE* = 17%), and grain yield (*NRMSE* = 9%) against measured data. The model's performance was less satisfactory for biomass production under high soil moisture or rainfed conditions. Focusing on differences in temperature and rainfall patterns during the potential growing season, the model was used to estimate the optimum planting dates and in-season nitrogen management options using 39 years (1974–2013) of historical weather data for short-term adaptation against climate variability. The scenario simulations for planting dates showed that growing wheat under rainfed conditions at the study region is not a viable option. However, based on the simulation results, we concluded that early planting from November 1st to 10th for irrigated conditions with applications of 150 kg N ha^{-1} in three equal splits with the first at sowing and the rest two splits during vegetative growth phase could result in higher crop yield and water use efficiency. This study showed that the model can be a promising tool for providing crop management recommendations under high-temperature conditions found in the semi-arid conditions.

1. Introduction

Wheat (Triticum aestivum L.) is a major crop in arid and semi-arid regions of the South Asia where it is grown on millions of hectares on a wide range of soils, with topographic and climatic diversity from the mountainous areas of the Himalayan, Karakorum and Hindukush in the north to the sea level in the south (as spring wheat). The difference between potential yield of a newly developed wheat cultivar (7.9 t ha^{-1})

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https://doi.org/10.1016/j.jaridenv.2020.104256
Received 11 March 2020; Received in revised form 1 July 2020; Accepted 3 July 2020

at a research station and the best yield for a farmer is about 33%–51% in favor of the research station. At the same time, the potential wheat yield at the research station is also less than the biological yield potential (10 t ha^{-1}) compared to global and regional wheat yield averages (Hussain et al., 2014). Depending on the soil type and summer season rainfall patterns, wheat is generally grown in rice-wheat and cotton-wheat rotations in the South Asia. In the irrigated areas, a major constraint to achieving higher wheat yield is late planting due to late maturity of rice and cotton. Such delays result in shorter growing seasons (Zahedi and Jenner, 2003) and expose the wheat crop to higher temperatures during anthesis and grain formation stages resulting in flower abortion, pollen sterility, and increased photorespiration (Wahid et al., 2007). Estimated anthropogenic global warming is currently increasing at 0.2 °C per decade due to past and ongoing emissions (IPCC, 2018). Recent studies focusing on changes in prevailing weather conditions of the major crop-producing province of Punjab (Abbas, 2013; Abbas et al., 2014) showed an increase a lengthening of summer by 3 days, and a decrease in extreme cold days by 3.94 and nights by 0.61 days per decade since 1981. The impact of these changes is an overall warming of the region with higher temperatures during the winter months when wheat is grown. An imbalanced use of fertilizer is another important factor affecting overall wheat crop productivity. Effective management of nitrogen (N) fertilizer is central to increasing crop productivity and mitigating climate change. Although many studies have examined the relationship between wheat grain yield and N application rate at specific locations or different scales (Liu et al., 2016; Valkama et al., 2013; Gaudin et al., 2015) using regression models nevertheless the current wheat crop management practices require adjustments to account for changing climatic conditions in order to sustain and improve current yield levels. In addition to N rate, other factors such as the type and timing of N supply and seasonal variation also influence wheat yield (Wang et al., 2015; Woolfolk et al., 2002). However, there are very few studies that have made an extensive use of combined experimental and systems analysis approaches to study N effect with planting dates on wheat crop yield in semi-arid environments (Jahan et al., 2018; Smith et al., 2019). To fill this gap we carried out the study that combines experimental and modelling research at a field level for wheat cropping system in semi-arid conditions and covering a wide range of weather conditions and management options including both irrigated and rainfed, N-fertilizer, and planting dates that reflect both in-season growth and development, and the end-of-season results.

A comprehensive cropping system approach is needed to examine the effects of climate variability and change on nitrogen fertilizer availability for crop growth. To evaluate various crop management options to improve crop production for different environments crop genetics, local soil properties, weather conditions, and irrigation and fertilizer management must be integrated. Mathematical models, particularly crop models, are an efficient way to study the complex nature of crop production and to develop appropriate crop management strategies. These models can simulate the effect of different management practices and plant characteristics, soil properties, climatic variables on crop growth, yield formation, soil moisture balance, and nutrient dynamics (Jones et al., 2016). Crop modeling supports decision-making by facilitating development of the optimal crop management strategies and agricultural sustainability under various environmental conditions (Kadiyala et al., 2015; Tsuji et al., 1998).

Various crop models have been developed during the past 30 years and the Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 2003; Hoogenboom et al., 2015, 2019) is one of the most widely used crop modeling platforms. DSSAT is a process-based and crop management-oriented crop modeling system that comprises more than thirty crop models. It includes the Crop Environment Resource Synthesis (CERES) - Wheat model (Ritchie et al., 1998) that can simulate wheat growth and development on a daily time-step from planting to harvest based on biophysical processes that describe the response of a crop to soil, weather conditions, and management options. The CERES-Wheat model has the capability to synthesize results accumulated through experiments to provide a reliable alternative for extrapolation of results to areas with different soil characteristics and climatic conditions (Hoogenboom et al., 2015, 2019). The application domain of the CERES-Wheat has evolved significantly in the past decade to include the evaluation of appropriate planting date and yield forecasting (Andarzian et al., 2015; Jahan et al., 2018), simulation of wheat production and phenology (Dettori et al., 2011). CERES-Wheat was used for exploration of water-nitrogen interaction and management (Arora et al., 2007; Singh et al., 2008), for water-saving irrigation scheduling and for economic analysis (Devkota et al., 2015; Timsina et al., 2008). Other uses of the model are simulation of agricultural practices for different environments (Araya et al., 2017), climate variability (Ahmed et al., 2016; Arora et al., 2007) and climate change impact studies for different cereals (Abbas et al., 2017; Valizadeh et al., 2014).

The present study was part of six years (2007–2013) of experiments conducted to simulate and assess the impact of changing climate on wheat yield and productivity, and to devise crop management strategies for sustainable crop production. The study was carried out with the main objective to determine optimum planting dates and nitrogen management options using a systems analysis approach based on the Cropping System Model (CSM) CERES-Wheat of DSSAT v 4.6. To ensure that the model accurately predicts wheat growth and development in the region prior its application, corresponding sub-objectives were first to calibrate the CSM-CERES-Wheat crop simulation model for spring wheat cultivar Sehar-2006 in the semi-arid conditions, and second to evaluate the performance of the calibrated CSM-CERES-Wheat model for growth, development and grain yield under optimal and suboptimal soil moisture/rainfed conditions.

2. Materials and methods

2.1. Field experiments

Wheat experiments were conducted from 2007 to 2013 under optimal and sub-optimal water supply conditions at the experimental fields of the Nuclear Institute for Agriculture and Biology (NIAB), Faisalabad, Pakistan (31°23′ N; 73°2′ E; 184 m elevation). The commercial spring wheat cultivar Sehar-2006 was planted during the 2nd and 3rd weeks of November each year of the study period. Prior to planting, seeds (125 kg ha^{-1}) were treated with fungicide and then planted at a soil depth of 4–5 cm with a row spacing of 15 cm using a tractor-mounted seed drill. Fertilizer was applied once prior to planting because a split application of fertilizer was not possible due to the irrigation system. Therefore, a sufficient amount of nitrogen (urea at a rate of 150 kg ha^{-1}) and phosphorus [di-ammonium phosphate (18%N & 46% P_2O_5) at a rate of 300 kg ha^{-1}], was applied uniformly to the field and was incorporated to a soil depth of 20 cm at seed bed preparation.

The crop development stages were defined when 50% of the plants showed visual signs of the stage being considered. The development stages recorded included: emergence, start and end of flowering, senescence, and physiological maturity. Twenty plants in each of three replications were tagged after emergence. For the crop growth analysis, a randomly selected area of 1 m^2 from each replicate plot was harvested weekly or fortnightly after seedling establishment and dried to a constant weight at 70 °C for 48 h. In-season canopy growth was determined with duplicate photographs taken at 1–1.5 m above the canopy in order to include a fair number of plants with the viewing plane of the camera parallel to the ground surface. The photographs were taken between 12:00–13:30 and digitized using a JAVA Program (Image-J; https://imagej.nih.gov/ij) for the canopy cover (CC, %) calculation. The daily leaf area index (LAI) for wheat predicted by the model was converted to CC using empirical data and similar regression relationship as by Hsiao et al. (2009):

$$CC = 94.00[1 - exp((-0.43\,LAI)]^{0.52} \quad (1)$$

The crop was harvested at physiological maturity and then final total biomass and grain yield were obtained.

2.2. Weather conditions and soil characteristics

The study area features a semi-arid climate (BWh) in the Köppen–Geiger classification with average annual rainfall of 250 mm. Rainfall is highly seasonal, and approximately 80% falls during the monsoon season that extends from late June to mid-September (Abbas et al., 2014). The daily minimum and maximum air temperature in the area ranges from 15 to 31 °C and from 32 to 50 °C, respectively (Abbas, 2013). The long-term climate data for maximum and minimum air temperature, solar radiation, and rainfall from 1974 to 2013 were obtained from the Pakistan Meteorological Department (PMD) observatory, operated at an aerial distance of 600 m from the experimental field. Weather data during the field experiments, including daily maximum and minimum air temperature, solar radiation, rainfall, relative humidity, and wind speed were obtained from an automated weather station (DAVIS instrument Model Vantage Pro-2) which was located at the experimental site. During the study period from 2007 to 2013, the average air temperature for the months of November and March ranged from 19 to 20 °C. December and February had similar maximum air temperatures (≈21.5 °C), but the minimum air temperature was 1.5 °C higher in February (13.5 °C) compared to December (Fig. 1a). During the study period the average maximum, the mean, and the minimum air temperatures were 18.7, 11.6 and 4.5 °C, respectively. January was the coldest and driest month with no rainfall.

The long-term average rainfall (1974–2013) during the wheat growing season was 3.0 mm in November, 8.0 mm in December, 10.0 mm in January, 20.0 mm in February, and 23.0 mm in March (Fig. 1b).

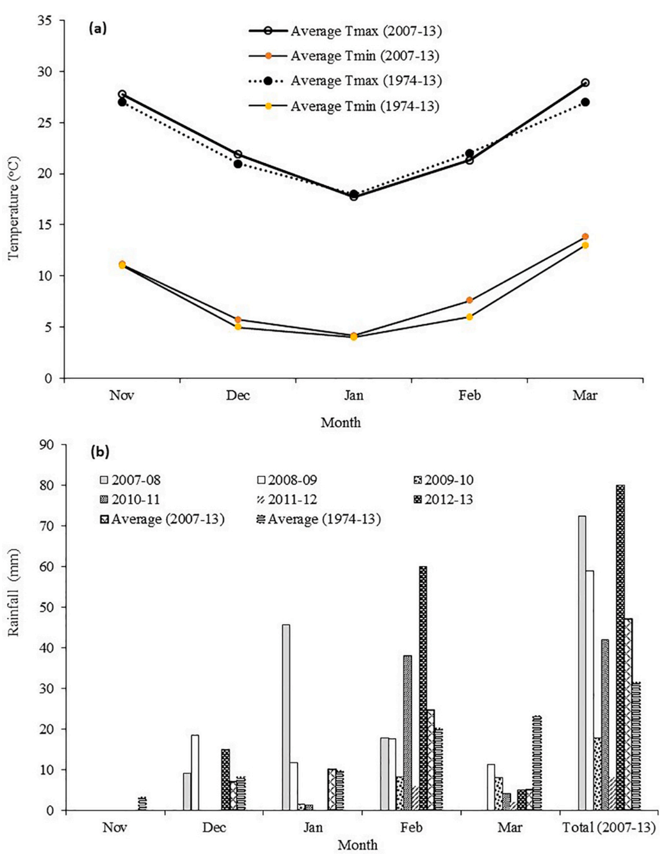

Fig. 1. (a) Average monthly maximum and minimum air temperatures, °C and (b) rainfall, mm during wheat growing months of the study (2007–2013) along with long-term averages (1974–2013) for Faisalabad, Pakistan.

During this study, the highest rainfall of 72 mm was recorded during the 2007–2008 growing season, followed by 59 mm during the 2008–2009 growing season. The 2011–2012 growing season was the driest year with 7.0 mm rainfall which occurred during late February (5.5 mm) and early March (1.5 mm). This amount was too low to be considered effective rainfall. Although the total rainfall appeared to be higher in 2010–2011 (42 mm) compared to 2011–2012, almost all rainfall events occurred in March when the crop was near maturity. The growing season of 2008–2009 was comparatively better with respect to the rainfall amount distribution.

The soil of the study area is Himalayan alluvial, deposited by the Ravi and Chenab rivers, loamy textured developed in a mixed calcareous with medium texture, and very poor in organic carbon and total soil nitrogen. The soil is classified as Haplic Yermosol according to the Food and Agricultural Organization (FAO) classification system (IUSS Working Group WRB, 2015). The soil physical, chemical, and hydraulic properties (bulk density, field capacity, permanent wilting point, saturated hydraulic conductivity, soil texture, electrical conductivity (EC), pH, ammonium and nitrate concentration, and the soil organic carbon) were calculated based on soil samples taken before seed bed preparation from each individual soil layer up to a depth of 105 cm. The minimum data required as input parameters for the model are presented in Table 1.

Free lime ($CaCO_3$) was present in the soil with lesser availability of soil phosphorus and micronutrients. Therefore, the soil fertility factor (SLPF) for this experiment was adjusted to 0.93 during the model calibration to minimize the differences between simulated and observed biomass. The experimental area was relatively flat with low runoff potential, therefore the runoff curve number (SLRO) was adjusted considering soil texture, drainage rate and the soil slope (SLRO = 73). Drainage rate (SLDR; fraction day^{-1}) values were estimated based on soil texture and bulk density of the soil. The soil of the experimental area was well-drained, accordingly SLDR = 0.6. The soil color was recorded in according to the Munsell color system, which is the international standard for soil colors. The soil of the study site had a brown to dull yellowish-brown color (10 YR 4/3; soil albedo = 0.13) up to 105 cm depth. The experimental field did not have a root restrictive layer.

Irrigation water was collected in a tank (4m x 4m x 2 m) and was pumped through a pipe system. This practice ensured full and uniform water coverage/distribution in the sub-plots. The amount of water that was applied was measured using a flow meter connected between the pump and delivery pipeline. Irrigations were terminated by the second week of March, allowing the soil to dry and to facilitate crop maturity.

2.3. The model description

The CSM-CERES-Wheat model uses the concept of the biomass production as a function of intercepted solar radiation and radiation use efficiency (*RUE*), which remains constant under non-stressed conditions during growing season. The model simulates phenological development of the crop along with root, stem, leaf, and grain formation as well as growth in a daily time step; and biomass and yield are simulated as a function of soil-plant-atmospheric dynamics under prescribed or simulated management options (Jones et al., 2003; Ritchie et al., 1998). The variation in phenological development and growth stage duration of a crop in response to temperature and photoperiod are managed by genetic specific coefficients. Genetic coefficients related to photoperiod sensitivity, vernalization requirement, duration of grain filling, conversion of mass to grain number, and grain-filling rate are required inputs to define a unique cultivar (Hunt et al., 1993).

Potential crop growth rate (*PCARB*, g plant^{-1}) is calculated using *RUE* (g dry matter MJ^{-1}), photosynthetically active radiation (*PAR*), plant population (*PLTPOP*; plants m^{-2}), *LAI*, atmospheric CO_2 concentration (CO_2, ppmv), and light extinction fraction (k):

$$PCARB = \frac{RUE \times PAR}{PLTPOP}\left(1 - e^{(-k \times LAI)}\right) \times CO_2 \quad (2)$$

Table 1
Soil physical, chemical and hydrological characteristics for the study site.

Soil depth cm	Clay %	Silt %	Organic C %	Total N %	Saturation %	ρ_b g cm^{-3}	EC $_{(1:1)}$ dS m^{-1}	pH	θ_{FC} m^3 m^{-3}	θ_{PWP} m^3 m^{-3}
0–15	27	32	0.48	0.09	48	1.48	0.48	8.25	0.27	0.15
15–35	24	37	0.30	0.08	47	1.40	0.35	7.96	0.26	0.14
35–55	23	34	0.21	0.05	46	1.39	0.41	8.08	0.23	0.13
55–75	21	34	0.15	0.01	46	1.47	0.46	8.19	0.27	0.15
75–105	21	34	0.01	0	45	1.47	0.50	8.13	0.27	0.13

Organic C – Organic Carbon, Total N – Total Nitrogen, Saturation – Saturated Water Content, ρ_b - bulk density, EC – Electrical Conductivity, pH – measure of soil acidity, θ_{FC} – Field Capacity, θ_{PWP} - Permanent Wilting Point.

The soil water balance is modeled on a daily basis and includes the following components: rainfall, irrigation, runoff, infiltration, drainage, soil evaporation, and transpiration. During soil water dynamics simulation, the water is allocated by the soil layers and downward and upward water flow is controlled by the drained upper limit or field capacity of soil (*DUL*) and by soil water content at the lower limit or permanent wilting point (*LL*). If water content in a layer is greater than *DUL,* saturated flow occurs, and if a layer has water content between *LL* and *DUL,* water can move either downward or upward depending on the soil water content of the two neighboring layers. A detailed description of the model can be found in Ritchie et al. (1998).

2.4. Model calibration and evaluation

For the spring wheat cultivar Sehar-2006, the cultivar coefficients of the model were calibrated using in-season data samplings from the well-watered treatments conducted during three growing seasons, including 2007–2008, 2008–2009 and 2009–2010. The approach and order for calibration followed the procedures described by Boote (1999). The calibration process was started using the basic information for the cultivar coefficients provided with the CSM-CERES-Wheat model supporting cultivar file distributed with DSSAT v4.6 (Hoogenboom et al., 2015). Adjustments were made sequentially, starting with phenology data including dates for flowering and maturity and then crop growth parameters, i.e., accumulated biomass during growing season, canopy cover, final biomass, and grain yield at harvest along with biomass and grain nitrogen contents and nitrogen harvest index. The parameters were adjusted by minimizing *RMSE* (the Root Mean Square Error) between model simulated and observed data. The calibrated model was then evaluated using independent datasets for the growing seasons 2010–2011, 2011–2012, and 2012–2013 for irrigated conditions and for all rainfed treatments for the growing seasons from 2007 to 2013. Observations included phenological dates, in-season data on biomass and canopy growth, and grain yield and biomass at harvest.

2.5. Seasonal analysis for determining optimal planting dates and nitrogen application levels

After the calibration and evaluation procedures, the model was used to simulate biomass and grain yield of wheat for a range of planting dates and nitrogen (N) application levels using the seasonal analysis program (Thornton and Hoogenboom, 1994) of DSSAT v4.6. The program allows users to compare the simulation results obtained from the model runs with different crop management options for a particular environment such as cultivars, planting dates, nitrogen application rates, etc. Following the simulations, the outputs are processed with biophysical and economic analysis options of the program. These analyses and comparisons can isolate and quantify the variability related to crop performance associated with the interactions between weather and other factors of the physical environment (Tsuji et al., 1998). The information obtained can be used to pre-screen a variety of different possibilities, the most favorable of which can then be further evaluated under field conditions.

In the present study, a simulation experiment made up of different planting dates was set up for irrigated and rainfed conditions using 39 years (1974–2013) of historical weather data for six planting dates at 10-day intervals starting on October 22 until December 12. The best planting date was then used to determine the optimum amount and number of split applications of N fertilizer to maximize yield under irrigated conditions. Eleven nitrogen application levels were simulated in this study, in increasing increments of 30 kg N ha^{-1} from 0 to 300 kg N ha^{-1}, either split into two or three equal applications at varied times or a single application at planting (Table 2).

2.6. Statistical measures of model performance

The statistical measures used for model performance estimation were difference measures, which try to quantify errors (percent deviation - *D*, the root mean square error - *RMSE*, the normalized root mean square error - *NRMSE*) and summary measure, which describes the quality of simulation (*d*-index). Values for *D* (%) were calculated using the following formula (Hsiao et al., 2009):

$$D = \frac{Simulated - Measured}{Measured} \times 100 \tag{3}$$

A negative value of *D* indicates an under prediction while a positive value of *D* indicates an over prediction.

In general, correlation coefficient (*r*) and coefficient of determination (R^2) are used to determine the association between simulated and measured values. However, the magnitudes of *r* and R^2 are not consistently related to the accuracy of prediction, i.e., where accuracy is defined as the degree to which model predictions approach the magnitude of their measured counterparts and they alone are insufficient to deduce any meaningful distinctions between the models. Therefore, average error estimates in measured and simulated in-season biomass growth, biomass at harvest, and grain yield were calculated using *RMSE* and the normalized root mean square error (*NRMSE*) using the following relationships:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}} \tag{4}$$

$$NRMSE = \frac{RMSE}{M} \times 100 \tag{5}$$

Table 2
Description of the treatments for split nitrogen (N) applications used in simulation.

Treatment	Number of splits and total N applied	Time of application
1	1/3N + 1/3N + 1/3N	At planting +20 DAP (1st irrigation) +50 DAP (2nd Irrigation)
2	0.5N + 0.5N	At planting + 20 DAP (1st irrigation)
3	0.5N + 0.5N	At planting + 50 DAP (2nd Irrigation)
4	0.5N + 0.5N	20 DAP (1st irrigation) + 50 DAP (2nd Irrigation)
5	N	All applied at planting

Note: DAP - Days after planting.

where S_i and O_i are the simulated and measured values for the variables studied, M is the mean of measured values, n is the number of observations, and i is the index variable. *NRMSE* gives a percent measure of the relative difference between simulated and measured values. The simulation was considered excellent when *NRMSE* values were less than 10%, good with values greater than 10% but less than 20%, satisfactory with values greater than 20% but less than 30%, and poor with *NRMSE* greater than 30%.

To estimate the relative size of average difference and nature of the difference in time course simulation of crop biomass and yield, a widely used descriptive measure for cross comparison, i.e., Willmott index of agreement (d) (Willmott et al., 1985) was calculated using the following equation:

$$d = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(|S_i - M| + |O_i - M|)^2} \quad (6)$$

Model performance is improved as d approaches one.

The results for both planting dates and nitrogen management were then analyzed for the best management option that would give a higher and sustainable crop yield. The grain yields simulated under the alternative crop planting dates and nitrogen management options were compared using exceedance probability (P_r, %) distributions according to the following relationship (Weibull, 1939):

$$P_r = 100 \times m/(n + 1) \quad (7)$$

where m is the rank order of each yield estimate arranged in descending order and n is the number of observations.

3. Results

3.1. Model calibration

3.1.1. Crop phenology, biomass and grain yield

After the model was calibrated the simulated and observed number of days from planting to flowering and to physiological maturity were in good agreement as shown by D ranging from −3 to 3% and from −1 to 3%, respectively. The mean D across the calibration years was approximately 1% for both parameters. Statistical indicators of model performance showed *RMSE* (*NRMSE*) of 3 days (≤3%) for both number of days to flowering, and for number of days to maturity (Fig. 2a).

The simulated and measured values of biomass production for the growing season 2007–2008 were 13.25 and 14.20 ± 1.23 t ha^{-1}, for 2008–2009 were 14.73 and 14.74 ± 1.32 t ha^{-1}, and for 2009–2010 were 13.08 and 12.90 ± 0.88 t ha^{-1}. Values for D were −7, 0, and 2% for the growing seasons 2007–2008, 2008–2009, and 2009–2010, respectively. Similarly, model-simulated and measured values of grain yield for 2007–2008 season were 5.41 and 5.20 ± 0.38 t ha^{-1}, for 2008–2009 were 5.00 and 4.83 ± 0.45 t ha^{-1}, for 2009–2010 were 4.83 and 4.78 ± 0.29 t ha^{-1}.

The D values were 4, 3, and 1%. Statistical indicators of the model's ability to predict biomass and grain yield at harvest showed good performance with d -index values of 0.87 and 0.88 for biomass and grain yield along with *RMSE* of 0.57 and 0.16 t ha^{-1}, and *NRMSE* of 4 and 3%, respectively (Fig. 2b).

3.1.2. Nitrogen uptake and harvest index

Total above-ground biomass N content (N_b) simulated by the model and measured value in the growing seasons of 2007–2008 were 154 and

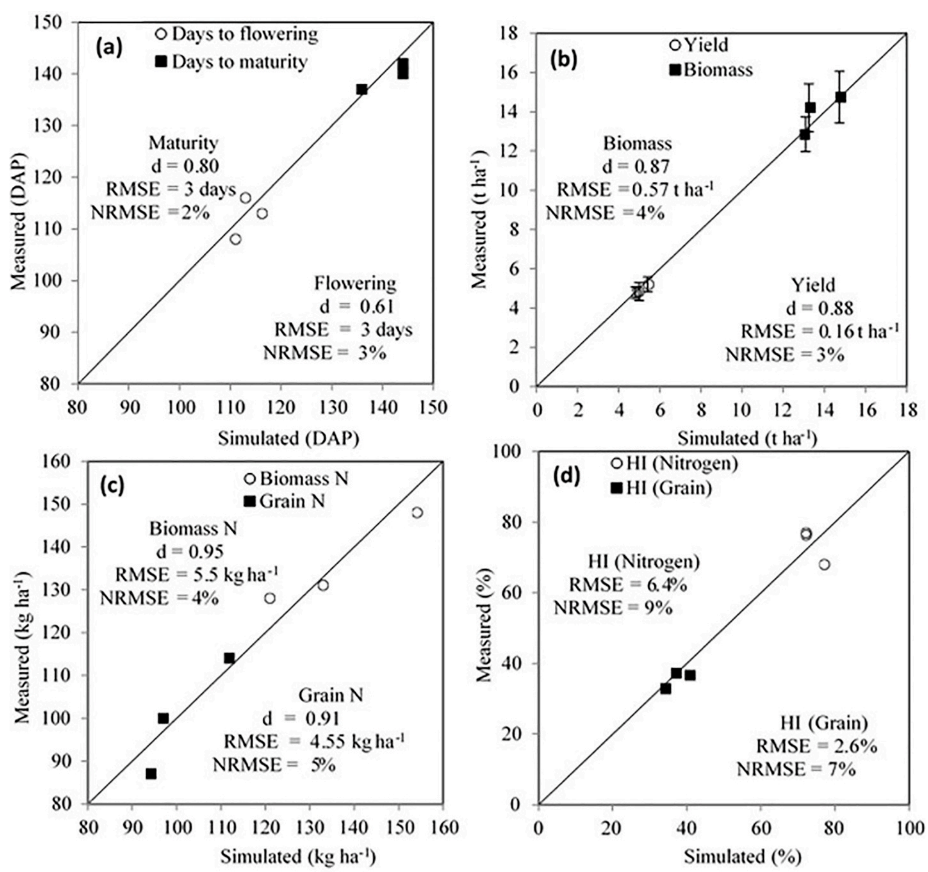

Fig. 2. Comparison between simulated and measured days from planting to flowering and to physiological maturity (a), biomass and grain yield at harvest (b), total above-ground biomass nitrogen and grain nitrogen concentration (c), and harvest index of nitrogen and grain (d) for model calibration based on the growing seasons 2007–2008, 2008–2009, and 2009–2010. Whiskers denote the standard error of the mean.

148 kg N ha^{-1}, in 2008–2009 were 121 and 128 kg N ha^{-1}, and in 2009–2010 were 133 and 131 kg N ha^{-1}. The statistical indicators *d*, *RMSE* (*NRMSE)* for N_b were 0.95 and 5.5 kg N ha^{-1} (4%), respectively (Fig. 2c). The measured nitrogen concentration in the wheat grain at maturity (N_g, %) was 2.2 and 2.1% in the growing seasons of 2007–2008 and 2009–2010. The model predicted 5% less N concentration in the both growing seasons. The measured N_g was 1.8% in the 2008–2009 growing season and the model over predicted by 5%. Simulated and measured values averaged across growing seasons had *d* -index of 0.85, *RMSE (NRMSE)* of 0.1% (5%). The difference in simulated total grain N (Ng) at maturity and measured grain N content resulted in 112 kg N ha^{-1} in the crop growing season 2007–2008 and 94 kg N ha^{-1} in 2009–2010. Both were 2–3% less than measured. In 2008–2009, the difference was 97 kg N ha^{-1}, which was 8% higher than measured. The statistical indicators of *d* (0.91), *RMSE* (4.55 kg N ha^{-1}) and *NRMSE* (5%) showed excellent performance of the model in predicting N_b and N_g at harvest (Fig. 2c).

The CSM-CERES-Wheat model predicted 12% higher values for grain harvest index (HI_g) than measured in the growing season of 2007–2008, and 3% higher values in 2009–2010. However, the model predicted 1% lower values for 2008–2009. Overall *NRMSE* of 7% indicated excellent model simulation for grain HI_g (Fig. 2d). Similar results were obtained for nitrogen harvest index (HI_N), which is a ratio of N accumulated in grain to N accumulated in grain plus straw, with *RMSE* (*NRMSE*) of 6.4% (9%) (Fig. 2d).

3.1.3. Biomass and canopy cover dynamics

The CSM-CERES-Wheat model was calibrated with the data set of in-season biomass (t ha^{-1}) and *CC* (%) measured in 2007–2008, 2008–2009 and 2009–2010. In-season biomass was accurately simulated by the model after calibration. This accuracy is confirmed by the high values of the *d* -index ($0.97 \leq d \leq 0.99$) and good to satisfactory *NRMSE* values (11%≤ *NRMSE* ≤ 23%) (Fig. 3 a,c,e). The model predictions of biomass were good for crop growing seasons 2007–2008 with *NRMSE* of 11%, 2009–2010 with *NRMSE* of 19%, and satisfactory for 2008–2009 with *NRMSE* of 23% with respective *RMSE* of 0.70, 0.88, and 1.50 t ha^{-1} (Fig. 3 a,c,e).

The *RMSE* values ranged from 10 to 13% (Fig. 3 b,d,f) for model-simulated values of *CC* compared to the measured values after the calibration process. The respective *d*-index and *NRMSE* values for crop growing season 2007–2008 were 0.94 and 20%, for 2008–2009 were 0.96 and 15%, and for 2009–2010 were 0.93 and 17% (Fig. 3 b,d,f).

The comparison between the simulated and observed data show a reasonably good calibration of the CSM-CERES-Wheat model for crop phenology, in-season biomass and canopy cover, biomass and grain yield at harvest, and nitrogen uptake along with grain and nitrogen harvest index. Final values for the cultivar coefficients for the wheat cultivar Sehar-2006 following calibration are presented in Table 3.

3.2. Model evaluation

Model evaluation assesses the adequacy of the calibration process prior to model application and it involves comparison between field measurements and outputs generated by the model. The evaluation of the CSM-CERES-Wheat model for the calibrated cultivar was performed with an independent data set that was not used for model calibration. These datasets were collected during three consecutive well-watered growing seasons, i.e., 2010–2011, 2011–2012, and 2012–2013, and for six growing seasons from 2007 until 2013 under rainfed conditions.

3.2.1. Phenology, and biomass and grain yield at harvest

The simulated and observed number of days from planting to flowering averaged across the growing seasons under irrigated conditions were 100 ± 5 and 98 ± 6 days, respectively. The statistical indicators of *D*, *d*-index, and *RMSE* were 1.36%, 0.82 and 3 days, respectively. Similarly, simulated and observed number of days from planting to

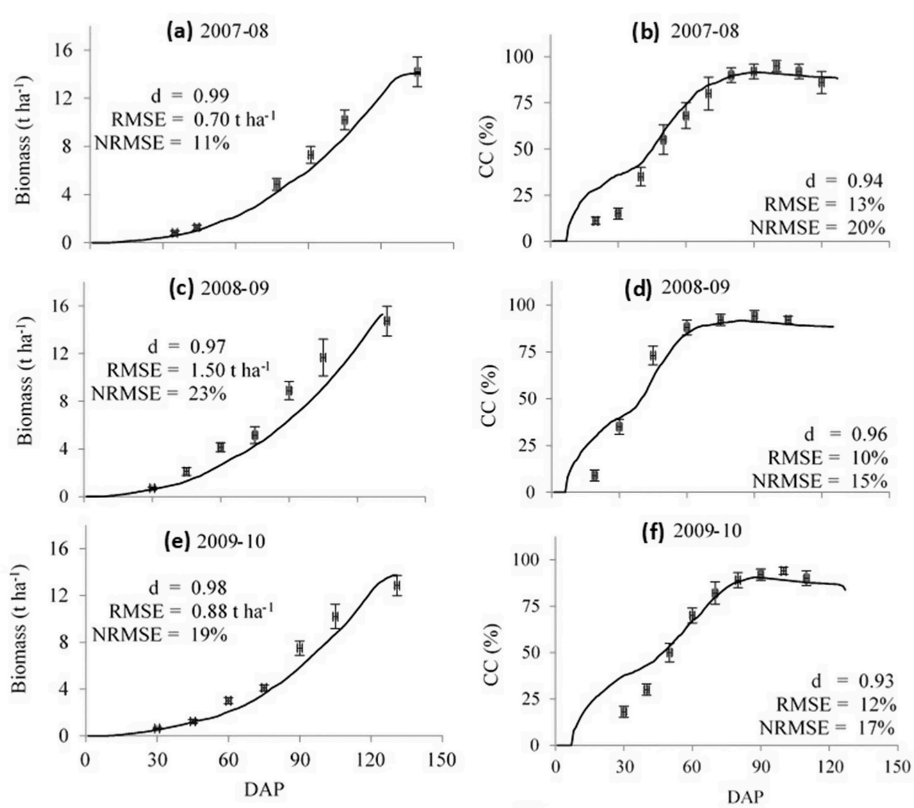

Fig. 3. Simulated (line) and measured (dots with *SD* – Standard Deviation): in-season biomass (a,c,e), percent canopy cover (*CC*) (b,d,f) of wheat under unstressed conditions during model calibration.

Table 3
Original and calibrated genetic coefficients of the wheat cultivar Sehar-2006 for the CERES-Wheat model.

abrAbbreviation	Definition	Original values	Modified values
Eco Type: UKWH01			
PARUE	PAR conversion to dm ratio, before last leaf stage (g MJ^{-1})	2.7	2.8
PARU2	PAR conversion to dm ratio, after last leaf (g MJ^{-1})	2.7	2.8
LAFV	Increase in potential area of leaves, vegetative phase (fr $leaf^{-1}$)	0.10	0.18
LAFR	Increase in potential area of leaves, reproductive phase (fr $leaf^{-1}$)	0.30	0.45
Cultivar coefficients			
P1V	Optimum vernalizing temperature required for vernalization	30	13
P1D	Photoperiod response (% reduction in rate 10 hr^{-1}. drop in photo period)	83	28
P5	Grain filling (excluding lag) duration (°C d)	515	530
G1	Kernel number including spike dry weight at anthesis (1 g^{-1})	15	32
G2	Standard kernel size under optimum conditions (mg)	44	18
G3	Standard, non-stressed mature tiller weight (total, including grain) of a single tiller at maturity (g)	3.2	3.0
PHINT	Thermal time between successive leaf tip appearances (°C d)	100	90

maturity averaged across three growing seasons were 132 ± 6 and 130 ± 5 days, respectively, with a *D* of 1.2%, *d* index of 0.81, and *RMSE* of 4 days. The *NRMSE* of 3% for both the days to flowering and to physiological maturity indicated excellent performance of the model for simulating crop phenology.

The performance of the CSM-CERES-Wheat model to simulate biomass at harvest under irrigated conditions was excellent, with *D* of −4% for 2010-11 and 1% for both 2011-12 and 2012-13. The simulated and measured biomass averaged across growing seasons were 14.90 ± 1.01 and 14.97 ± 0.65 t ha^{-1}, respectively, characterized by lower *D* (1%), higher *d*-index (0.94), lower *RMSE* (0.32 t ha^{-1}) and *NRMSE* (2%) (Fig. 4). The model's ability to predict biomass at harvest under rainfed conditions was comparatively less satisfactory because of salinity of the soil profile which together with moisture stress resulted in higher differences.

The model-simulated and the measured biomass at harvest averaged across six growing seasons (2007–2013) were 4.09 ± 1.28 and 6.85 ± 1.30 t ha^{-1}, respectively, characterized by higher D (−40%), lower *d*-index (0.42), higher *RMSE* (2.97 t ha^{-1}) and *NRMSE* (43%) (Fig. 4). Overall the ability of the model to predict biomass at harvest averaged across irrigation levels (well watered and rainfed) was good with *d* -index and *RMSE* (*NRMSE)* of 0.97 and 2.44 t ha^{-1} (17%), respectively.

The simulated yield matched well with the measured yield for well-watered conditions; the CSM-CERES-Wheat model slightly under-predicted the grain yield for 2010-11 and 2012-13 by −3 and −9%, respectively, but it over-predicted yield by 6% for 2011-12. The model-simulated yield (5.08 ± 0.60 t ha^{-1}) compared to the measured yield (5.18 ± 0.42 t ha^{-1}) averaged across growing seasons had a *D* of −2%. The statistical indicators confirmed that model predicted wheat yield reasonably well, with respective *d*-index and *RMSE* (*NRMSE)* of 0.82 and 0.34 t ha^{-1} (7%). Overall, model performance for rainfed conditions was good with a comparable measured yield in the different crop growing seasons (−12% ≤ *D* ≤ 20%). The six-year mean of simulated (1.56 ± 0.35 t ha^{-1}) and measured (1.47 ± 0.34 t ha^{-1}) yield had a *D* of 6%, *d*-index 0.92, and *RMSE* (*NRMSE*) 0.17 t ha^{-1} (11%). The simulated grain yield (2.73 ± 1.81 t ha^{-1}) averaged across growing seasons and irrigation levels was 1% higher than the mean measured yield (2.71 ± 1.89 t ha^{-1}) with a *d*-index and *RMSE* (*NRMSE)* of 0.99 and 0.24 t ha^{-1} (9%), respectively (Fig. 4).

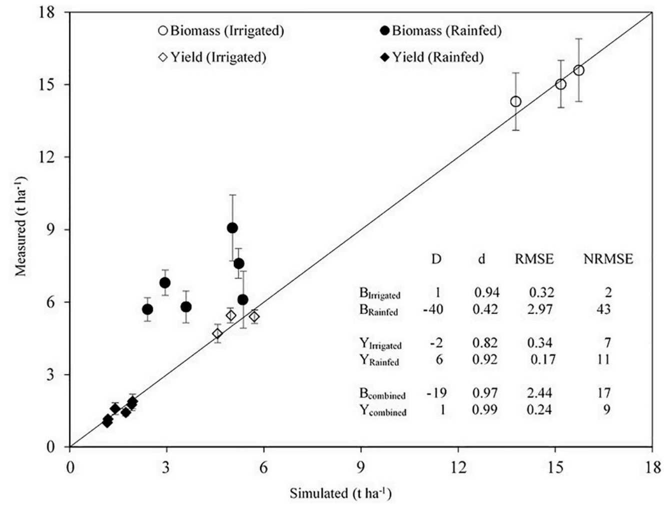

Fig. 4. Model simulated vs measured values and their statistical indicators for biomass ($B_{irrigated}$, $B_{rainfed}$) and grain yield ($Y_{irrigated}$, $Y_{rainfed}$) under irrigated (2010–2013) and rainfed (2007–2013) conditions, as well as combined values ($B_{combined}$, $Y_{combined}$) during the CERES-Wheat model evaluation. Note: Error bars indicate SD of the measured values.

3.2.2. *Biomass and canopy cover dynamics*

In-season biomass growth and *CC* for irrigated conditions are presented in Fig. 5. Under well-watered conditions, the *d*-index for biomass growth was 0.98 for 2010-11 and 0.99 for both 2011-12 and 2012-13 with respective *RMSE* of 1.13, 0.93 and 1.03 t ha^{-1}. The range of *NRMSE* (13% ≤ *NRMSE*≤ 20%) indicated a good fit between simulated and measured in-season biomass growth (Fig. 5 a,c,e).

The model simulated in-season biomass growth reasonably well under irrigated conditions compared to rainfed ones. The shape of the simulated biomass growth appeared to be sigmoid compared to somewhat linear for measured values (Fig. 5 a,c,e). The model uses the concept of RUE which is the slope of relationship between intercepted photosynthetically active radiation (IPAR) and above-ground biomass (Tsuji et al., 1998). Under non-limiting conditions of water and nutrients, the cumulative light interception is linearly related to biomass production (Monteith and Moss, 1977). The model over predicted certain water and nitrogen stresses from germination to the end of the vegetative growth period, which caused a loss of linearity between above-ground biomass and IPAR. The ability of the model to predict biomass at harvest was better under irrigated conditions than rainfed ones, for which the model underestimated final biomass. However, the model simulated grain yield with reasonably good accuracy.

For *CC* the *d*-index was greater than 0.95 (0.95 ≤ *d* ≤ 0.99), *RMSE* was less than 7% (6% ≤ *RMSE*≤ 7%), and *NRMSE* was 12, 13, and 7%. This showed that the model was able to simulate canopy development well under well-watered conditions (Fig. 5 b, d, f). However, for rainfed condition the performance was not as well with a lower *d* value (0.66 ≤ *d* ≤ 0.94), higher *RMSE* (1.1 t ha^{-1} ≤ *RMSE* ≤ 2.50 t ha^{-1}) and *NRMSE* (29% ≤ *NRMSE* ≤ 67%). Generally, *NRMSE* was higher in the years receiving lower rainfall, causing a decline in simulated biomass growth rate and thus a lower biomass at final harvest. The statistical measures of the model-simulated canopy growth values were satisfactory to good for rainfed conditions. The *NRMSE* was highest for 2009-10 at 27% and lowest for 2012-13 at 13%, followed by 22% for 2011-12, 20% 2010-11, 18% for 2008-09 and 13% for 2012-13 (Fig. 6). Based on the model results, the stress was higher under rainfed conditions compared to full

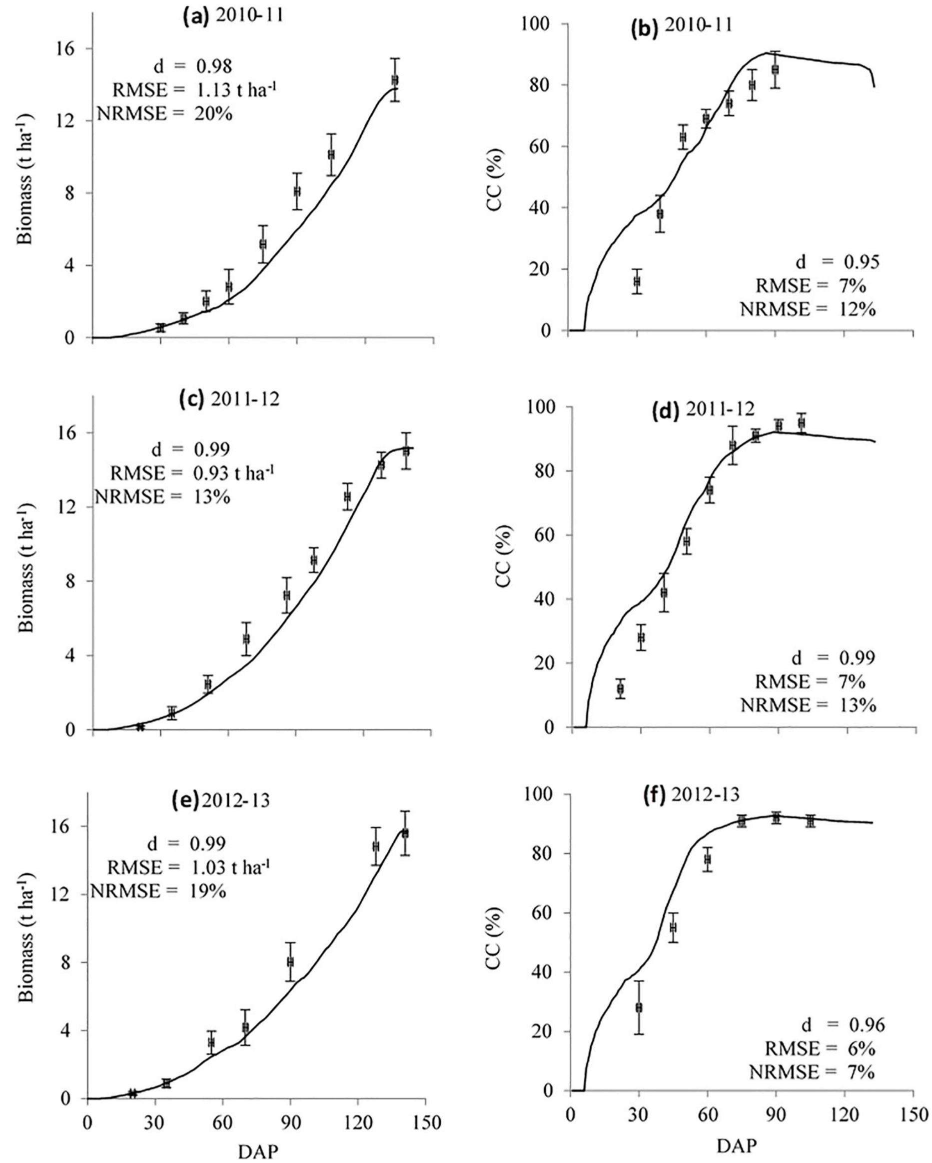

Fig. 5. Simulated (line) and measured (dots with *SD*): in-season biomass (a, c, e) and percent canopy cover (*CC, %*) (b, d, f) under irrigation conditions for model evaluation from 2010 to 2013.

irrigation or unstressed conditions.

The model over predicted canopy cover in the first half of the crop growing cycle, i.e., up to about 60–90 DAP in different years, and it predicted a higher increase in canopy cover from germination to 30 DAP. Over prediction of canopy cover in the early vegetative growth phase may be due to over estimation of LAI at emergence, which in turn affected subsequent daily predicted LAI values. As the relationship between LAI and CC (Eq. (1)) suggested by Hsiao et al. (2009) and used in our study was dealing with winter wheat, it may require some modifications before its application to spring wheat. Further studies on the relationship between LAI and CC for spring wheat grown under high temperature conditions are recommended.

3.3. Model application

3.3.1. Defining optimum planting dates under irrigated conditions

Thirty-nine years of simulations from 1974 to 2013 were conducted for the wheat for planting dates October 20, November 1, 10, 20, 30, and December 10 using the same cultivar, crop management options, initial soil moisture contents, and soil characteristics. Averaged across the simulation period, the mean biomass at harvest for November 1 (12.0 ± 1.33 t ha^{-1}) and November 10 (12.0 ± 1.31 t ha^{-1}) planting date simulations were close to each other and higher than for other planting dates (Fig. 7a). The lowest value of the mean biomass of 10.7 ± 1.40 t ha^{-1} was simulated for the planting date December 10. The biomass accumulation response to planting dates followed a polynomial trend with the lower simulated biomass for the early planting date on October 20 and the late planting date in December. After November 1, decrease in biomass was of 1, 3, 7, and 11% for every successive 10-day delay in planting.

The simulated yield also showed a year-to-year variability due to weather conditions and planting dates. Average yields were higher for the 1st and 10th of November planting dates with the values of 5.62 ± 0.61 and 5.68 ± 0.72 t ha^{-1}, respectively (Fig. 7b). The model simulated lower yields before and after these planting date windows with the lowest values 4.82 ± 0.60 and 4.91 ± 0.67 t ha^{-1} for early (October 20) and late (December 10) planting dates, respectively. Each successive a 10-day delayed planting from 10th of November to 10th of December progressively reduced the grain yield. For November 10 planting the grain yield reduced by 1%, for November 10 by 6%, and for November

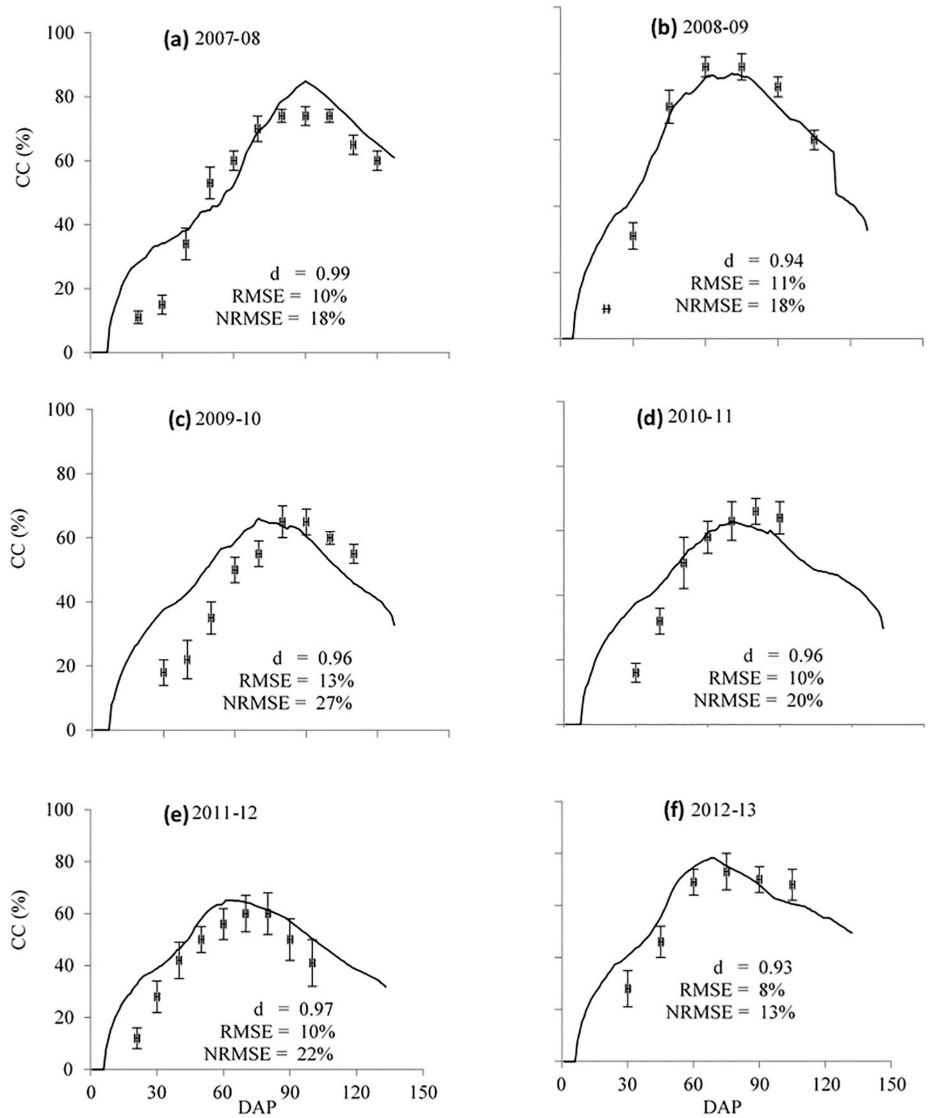

Fig. 6. Simulated (line) and measured (dots with *SD*) canopy cover (*CC*) for the rainfed treatments for the 2007 to 2013 growing seasons.

30 by 13% over the same 39-year period.

The 50% of Pr of a biomass under irrigated conditions simulated by model was 11.4 t ha^{-1} for October 20, 12.3 t ha^{-1} for November 1 plantings, 12.2 t ha^{-1} for November 10 planting, 11.8 t ha^{-1} for November 20 planting, 11.4 t ha^{-1} for November 30 planting and 11.0 t ha^{-1} for December 10 planting (Fig. 7c). For grain yield, the simulated 50% of Pr was 5.8 t ha^{-1} for crop planting on November 1, followed by 5.6 t ha^{-1} for crop planting on November 10 (Fig. 7d).

3.3.2. Defining optimum planting dates under the rainfed conditions

The average simulated biomass under rainfed conditions increased close to linearly from 2.35 ± 1.25 to 3.05 ± 1.70 t ha^{-1} when the planting was delayed from October 20 to December 10 (Fig. 8a). The percent increase in the average biomass for the crop planting on November 1 was 6%, on November 10 planting was 9%, on November 20 planting was 16%, on November 30 planting was 19%, and on December 10 planting was 22% compared to early plantings on October 20. Similarly, for the grain yield, the simulated yield increased from 1.13 ± 0.62 to 1.78 ± 1.03 t ha^{-1} when the planting was delayed from October 20 to December 10 (Fig. 8b). The percent of increase in the average yield for the crop planting on November 1 was 15%, for planting on November 10 was 30%, for planting on November 20 was 45%, for planting on November 30 was 53% and for planting on December 10 was 57% compared to early planting on October 20.

The 50% of Pr of a biomass under rainfed conditions simulated by the CERES-Wheat model was 2.03 t ha^{-1} for both October 20 and November 1 plantings, 2.16 t ha^{-1} for November 10 planting, 2.46 t ha^{-1} for November 20 planting, 2.56 t ha^{-1} for November 30 planting and 2.82 t ha^{-1} for December 10 planting (Fig. 8c). For grain yield, the simulated 50% of Pr was 0.9 t ha^{-1} for crop planting on October 20, 1.1 t ha^{-1} for crop planting on November 1, and 1.3 t ha^{-1} for crop planting November 10. Successive plantings from November 20 to December 10 had a similar median yield of 1.5 t ha^{-1} with 25% probability of getting more than 2.5 t ha^{-1} (Fig. 8d).

3.3.3. Simulation of yield and water use efficiency with different N fertilizer levels

Nitrogen (N) applications generally increase crop yield. However, maximum utilization of applied N is another important consideration to reduce the quantity of N that remains in the soil and that may be lost through leaching, ammonia volatilization or immobilization by micro-organisms depending upon quantity and timing of N application. Once the appropriate crop planting time was simulated, i.e. November 1 to 10, seasonal analyses of different N application rates and management strategies (Table 2) were made with crop planting on November 10. The simulated values of grain production increased with N application rate,

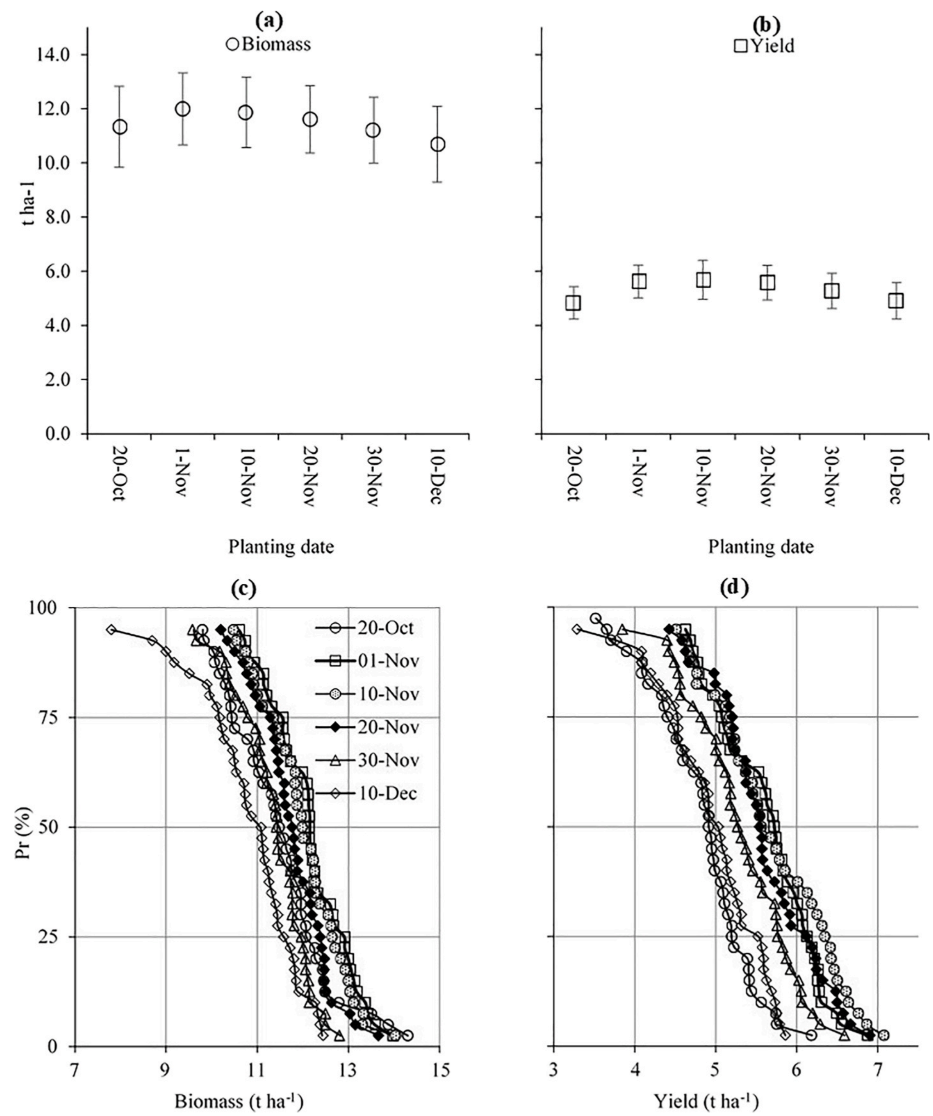

Fig. 7. The CERES-wheat model-simulated (a) biomass, (b) grain yield (mean ± *SD*), and (c, d) their probability of exceedance (*Pr*, %), as affected by planting dates under irrigated conditions.

showing a low coefficient of variation (CV) of 6–7% for 0, 30, 60 and 90 kg N ha^{-1}. The *CV* of the grain yield was higher (10–11%) by 210 kg ha^{-1} for higher N application levels. The mean grain yield simulated by the CERES-Wheat model was between 2.6 ± 0.15 (control without N) and 5.6 ± 0.62 t ha^{-1} (300 kg N ha^{-1}). The second-degree polynomial equation describing the wheat yield response to the applied N within the range of 0–300 kg N ha^{-1}, was defined as:

$$y = -0.04\text{N}^2 + 0.76\text{N} + 1.95 \ \text{R}^2 = 0.99 \text{ for } 0 \leq \text{N} \leq 300 \quad (8)$$

The relationship showed that the grain yield response of wheat cultivar Sehar-2006 to N application level was adequately described by the polynomial equation (Fig. 9 a). The simulated.

R^2 of 0.99 indicates that 99% of the total variation in the mean simulated wheat yield could be explained by the equation. The model-predicted yield increased with a decreasing trend having percent yield increase of 28, 52, 71, 86, 96, 104, 110, 113, 115 and 116% for each successive application of 30 kg N ha^{-1} from unfertilized to 300 kg N ha^{-1}, respectively. However, the percent of yield increase in higher N application levels from 180 kg N ha^{-1} was only 3–6% (Fig. 9 b).

The probability of exceedance curve between N application rates and wheat yield showed 50% probability of reaching 4.80, 5.10, and 5.30 t ha^{-1} grain yield at 120, 150, and 180 kg N ha^{-1}, respectively (Fig. 9c). The model-simulated 50% probability at 210 kg N ha^{-1} and higher N application rates (5.50 t ha^{-1}) was similar. The probability of exceedance of 75% was 4.80 t ha^{-1} for 150 and 4.94 t ha^{-1} for 180 kg N ha^{-1}. The simulated yield never exceeded 5.5 t ha^{-1} at N application rate of 120 kg ha^{-1} whereas maximum simulated yield of approximately 6.2 t ha^{-1} was achieved at 180 kg N ha^{-1}.

Along with the quantity of N application, maximum utilization of applied N is also critical to maximize crop yield. The simulations for different split applications were made for all N-applications rates. The results of the treatments with conventional/standard (120 kg N ha^{-1}) practice and higher (150 and180 kg N ha^{-1}) are presented here. The efficiency of the applied N for the grain production differed by the rate and time of N application. The nitrogen application in two splits with half N applied with the first irrigation (20 *DAP*), half at the second irrigation (50 *DAP*), and no N applied at planting was the least productive and resulted in reduced grain yield in all N-application levels. Average yield losses of 5, 10, and 18% were predicted in the treatment with no application at crop planting compared to a single application of N at crop planting in 120, 150 and 180 kg N ha^{-1}, respectively. A single application of N at seed bed preparation/crop planting was also less productive, while applying the N in two or three splits increased the grain yield. The simulated yield did not show much difference between

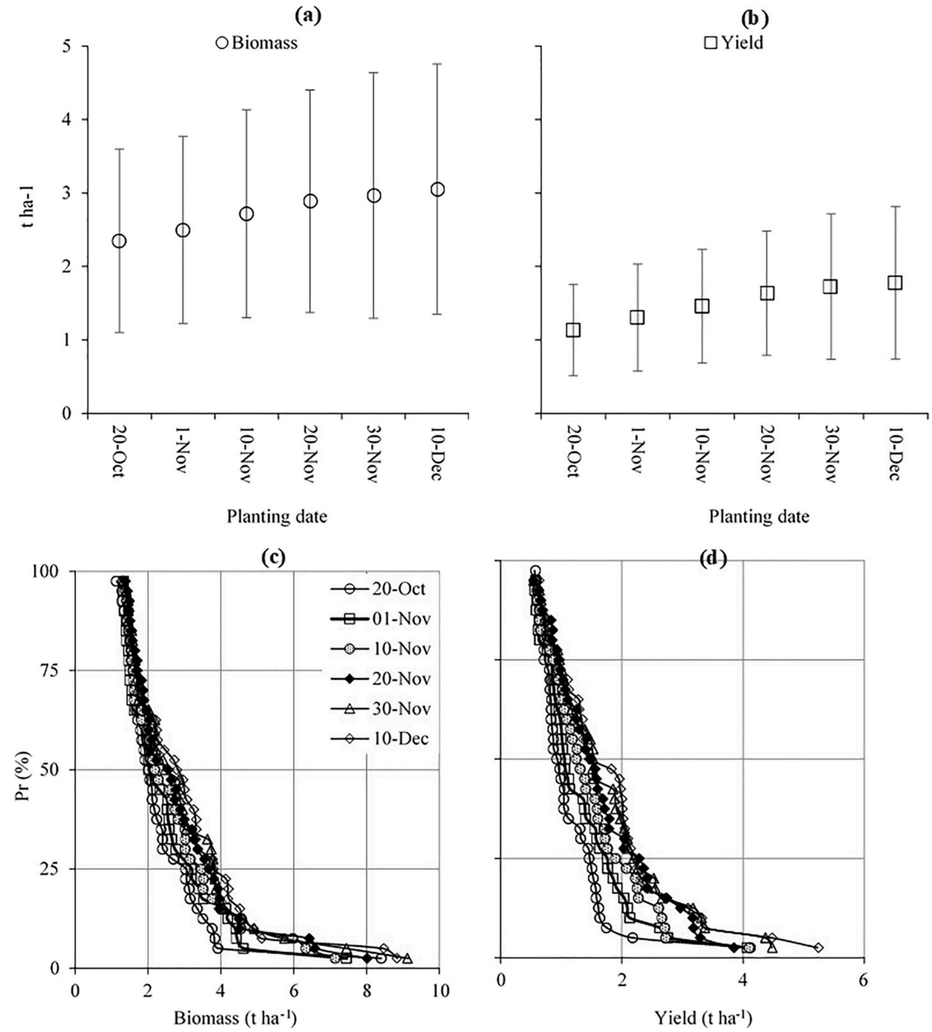

Fig. 8. The CERES-Wheat model simulated (a) biomass and (b) grain yield (mean±*SD*) and (c,d) their probability of exceedance (*Pr*, %), as affected by planting dates under rainfed conditions.

two or three splits or quantity of N applied in different split applications. The seasonal analysis of N-application rates indicated that 180 kg N application at seed bed preparation had a 50% probability of getting more than 5.3 t ha^{-1} wheat yield (Fig. 9c).

The overall yield increase from no N application to 180 kg N ha^{-1} under un-stressed soil moisture conditions resulted in higher grain-based water use efficiency (WUE_g). The mean WUE_g simulated by the CERES-Wheat model was between 12 ± 1.01 (control without N) and 29.2 ± 3.09 kg ha^{-1} mm^{-1} (300 kg N ha^{-1}). The second-degree polynomial equation describing the response of wheat WUE_g to the applied N within the range of 0–300 kg N ha^{-1}, was defined as:

$$WUE_g = -0.27N^2 + 4.69N + 9.36 \; R^2 = 0.96 \text{ for } 0 \leq N \leq 300 \qquad (9)$$

The relationship showed that the grain yield response of the wheat cultivar Sehar-2006 to N application level was adequately described by the polynomial equation (Fig. 10a). The simulated R^2 of 0.96 shows that 96% of the total variation in the mean simulated WUE_g could be explained by the equation. The model-predicted WUE_g increased with a decreasing trend having percent increase of 34, 18, 10, 6, 3 and 2% for each successive application of 30 kg N ha^{-1} from unfertilized to 150 kg N ha^{-1}, respectively. The percent yield increase in higher N application levels from 180 kg N ha^{-1} was only 0–2%.

The probability of exceedance curve between N application rates and WUE_g showed 50% probability of getting 25, 27, and 28 kg ha^{-1} mm^{-1} WUE_g at 90, 120 and 150 kg N ha^{-1}, respectively (Fig. 10c). The model-simulated 50% probability at 150 kg N $ha^{-1}$and higher N-application rates (28 kg ha^{-1} mm^{-1}) was similar. There was a 75% probability of exceedance for 25 kg ha^{-1} mm^{-1} for 150 and 26 kg ha^{-1} mm^{-1} for 180 kg N ha^{-1}.

The simulation results for the different split application showed a similar trend as that simulated for grain yield. The N application in two splits with the half the N applied with the first irrigation (20 DAP), the half at the second irrigation (50 DAP), and no N applied at planting was the least productive and resulted in the lowest WUE_g. The results of seasonal analysis indicated that 150 kg N ha^{-1} application in three splits applied at crop planting (50 kg N ha^{-1}) and at the 1st (50 kg N ha^{-1}) and 2nd irrigations (50 kg N ha^{-1}) with applications at 20 and 50 *DAP* would produce highest grain yield and WUE_g.

4. Discussion

Climate variability and future climate change in semi-arid subtropics of the South Asia require appropriate management practices (planting dates, N application) to ensure that wheat, an important staple crop in this area, responds in efficient and sustainable way to changes in environmental conditions. The CSM-CERES-Wheat model was calibrated and then evaluated for predicting flowering and maturity dates, modeling above-ground biomass growth, grain yield, canopy cover, nitrogen uptake, harvest index, and water use efficiency by wheat grown under irrigated and rainfed production systems and current weather conditions

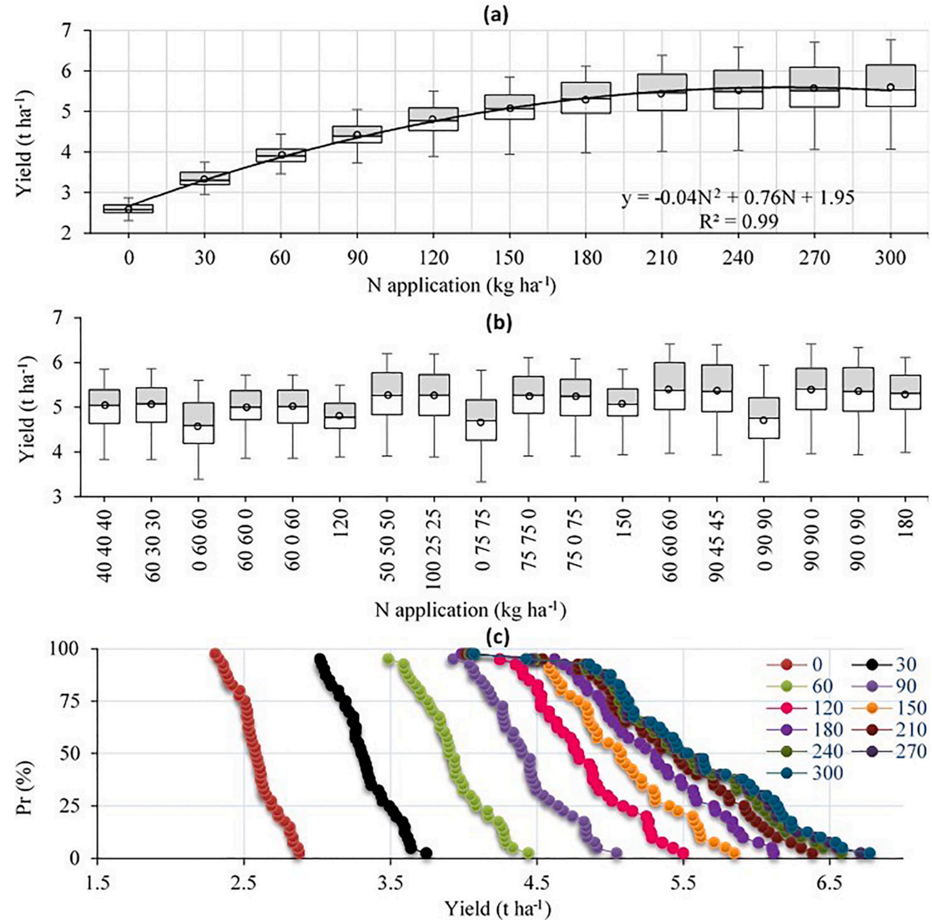

Fig. 9. Simulated wheat yield as affected by different nitrogen application levels (a), split application (b), and probability of grain yield distribution (c) under irrigated conditions. Box-whisker plots visualize the minimum, mean (open circle), median (solid line), standard errors (mean±*SD*) and maximum values.

of the semi-arid region in Pakistan. The evaluated model was applied to determine optimum planting dates and to assess responses of wheat to different nitrogen and irrigation management strategies under historical climate conditions in the region.

Simulations carried out for 39 years showed that early planting resulted in higher yields. Germination of spring wheat may occur between 4 and 37 °C with an optimal temperature range of 12–25 °C (Acevedo et al., 2002). The average thermal and photo thermal time (°C days) from sowing to maturity required by the crop at the study site was about 1280 °C days and 225 °C days, respectively. Although it is a generally accepted fact that earlier planting dates is associated with longer crop duration to achieve higher yield, studies in different agro-ecological regions in south Asia have found that beyond late October, wheat successively planted the first and second fortnights in November and into December resulted in losses of varying degrees (Coventry et al., 2011; Tripathi et al., 2005). The unfavorable maximum air temperature above 30 °C during planting in early October can adversely affect the tillering capacity, early flowering, flower abortion (Wardlaw and Moncur, 1995), floret sterility, lower CO_2 assimilation, and overall grain yield due to terminal heat stress (Lobell et al., 2012), while crops planted in December usually encounter comparatively lower air temperature below 12 °C, which may result in poor germination/seedling emergence, more chances of winter injury, fewer tillers, and lower grain weight and number of grains per plant. Reduction in thermal time in all phenological stages crops planted the 10th of December decreases the crop growing period and the crop is subjected to heat stress at anthesis and the grain filling stage (Coventry et al., 2011). The model also simulated shortening of the growing season length in delayed planting after November 10, slower growth rate due to reduced temperature and solar radiation, as well as exposure of the crop to heat stress during the grain filling period. Based on known experimental data (Akhtar et al., 2012; Ali et al., 2004; Aslam et al., 2013; Khokhar et al., 2010), the optimum planting dates were November 1 to 10 and crop planting after November 10 resulted in a yield loss of 60 kg ha^{-1} day^{-1} (Ortiz-Monasterio et al., 1994). The yield losses of 2, 6 and 13% for successive plantings after November 10 on November 20 and 30, and December 10, coincide with the simulated losses of 2, 7, and 14%, respectively, in our study. Higher yields for plantings in late November and early December were likely attributable to rainfall events and lower daily air temperature during this time period (Fig. 1). The crop is in the tillering and vegetative growth period at this time and moisture availability through rain may result in higher production compared to earlier plantings.

The results of seasonal analysis indicated that 150 kg N application in three splits combined with irrigation could produce higher yields. Earlier research (Ortiz-Monasterio et al., 1994) also found lower N application to be a major yield-limiting factor in south Asia. Assuming a recovery of 0.8, which is seldom achieved at a farmer's field, the recommended N-level of 120 kg ha^{-1} over most of the sub-continent is insufficient to obtain more than 5.0 t ha^{-1} grain yield (Hobbs et al., 1998). Sultana et al. (2009) also reported a higher wheat yield with applications of nitrogen ranging from 150 to 220 kg N ha^{-1} under irrigated conditions of Punjab, Pakistan. The simulated results by our study indicated that growing wheat under rainfed conditions is not a suitable strategy, which makes irrigation application along with appropriate nutrient management crucial for higher yield.

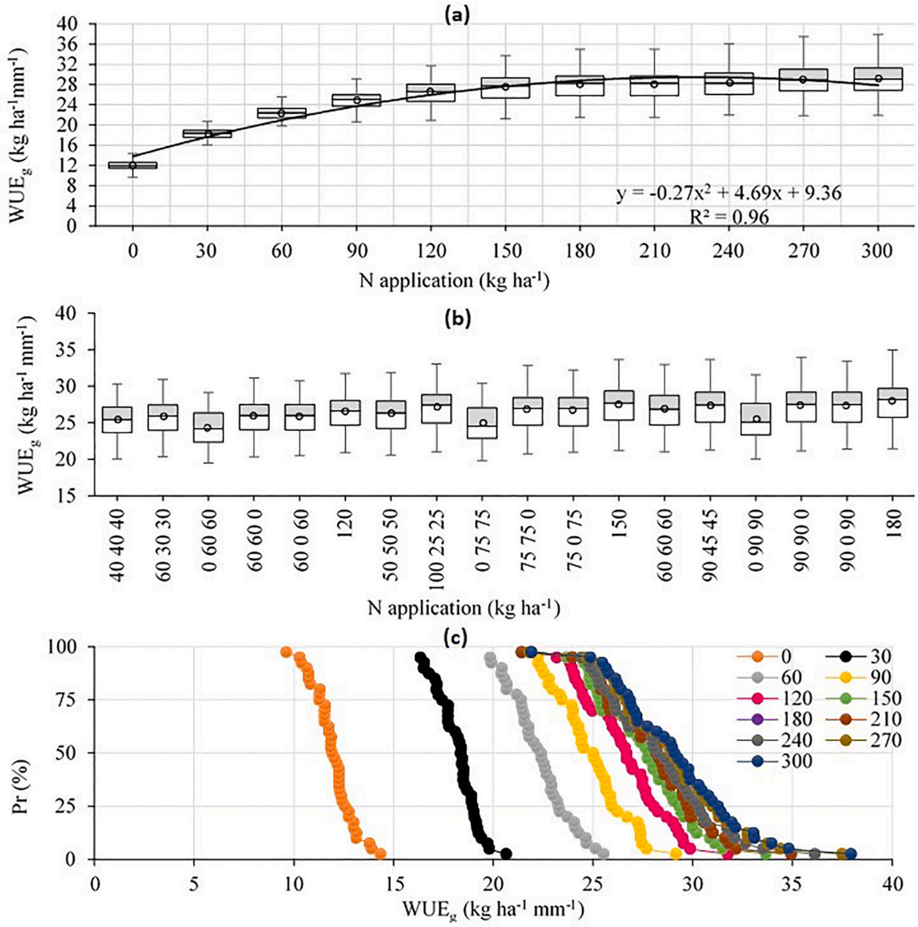

Fig. 10. Simulated wheat water use efficiency for grain production as affected by different nitrogen application levels (a), split application (b) and probability of grain yield distribution (c) under irrigated conditions. Box-whisker plots visualize the minimum, mean (open circle), median (solid line), standard errors (mean±*SD*) and maximum values.

5. Conclusions

The performance of the calibrated DSSAT CSM-CERES-Wheat model was evaluated as a decision support tool in the semi-arid conditions of Pakistan. The analysis indicated satisfactory performance of the model for phenology, biomass, grain at harvest, and canopy cover across a range of data sets covering varying levels of water- and N-management during 6 years for both irrigated and rainfed conditions. However, the model simulated in-season biomass growth better under irrigated conditions compared to rainfed ones. Based on the seasonal analysis of a 39-year simulation, the optimal combination of planting date and in-season nitrogen management was sowing during the first ten days of November with 150 kg N ha^{-1} in three equal splits. The outcomes of this study can have general application for wheat management for the semi-arid region of South Asia where it is one of the main food crops. Yield and other experimental data demonstrate how the field experiments can contribute to a better understanding of the bio-physical processes related to wheat crop growth and its consequences for final yield using simulations.

CRediT authorship contribution statement

Wajid Ishaque: Investigation, Data curation, Formal analysis, Writing - original draft. **Vakhtang Shelia:** Formal analysis, Writing - review & editing. **Jakarat Anothai:** Formal analysis, Writing - review & editing. **Mohammad Zaman:** Formal analysis, Funding acquisition. **Gerrit Hoogenboom:** Conceptualization, Methodology, Formal analysis, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the Pakistan Atomic Energy Commission (PAEC), Islamabad, Pakistan, and by the International Atomic Energy Agency (IAEA), Vienna, Austria, through the research project IAEA-CRP-14504. The authors would like to thank the Higher Education Commission of Pakistan (HEC) for providing financial support for the senior author to visit the AgWeatherNet Program at Washington State University, USA, under the International Research Support Initiative Program (IRSIP).

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