Front. Earth Sci. 2020, 14(3): 522–536
https://doi.org/10.1007/s11707-019-0806-4

RESEARCH ARTICLE

Climate change impact and adaptation on wheat yield, water use and water use efficiency at North Nile Delta

Marwa Gamal Mohamed ALI[1,2], Mahmoud Mohamed IBRAHIM[1], Ahmed El BAROUDY[1], Michael FULLEN[3], El-Said Hamad OMAR[2], Zheli DING[4], Ahmed Mohammed Saad KHEIR (✉)[2]

1 Soil and Water Department, Faculty of Agriculture, Tanta University, Tanta 33516 Egypt
2 Soils, Water and Environment Research Institute, Agricultural Research Center, Giza 12411 Egypt
3 Faculty of Science and Engineering, The University of Wolverhampton, Wolverhampton WV1 1LY, UK
4 Haikou Experimental Station, Chinese Academy of Tropical Agricultural Sciences (CATAS), Haikou 570000 China

Abstract Investigation of climate change impacts on food security has become a global hot spot. Even so, efforts to mitigate these issues in arid regions have been insufficient. Thus, in this paper, further research is discussed based on data obtained from various crop and climate models. Two DSSAT crop models (CMs) (CERES-Wheat and N-Wheat) were calibrated with two wheat cultivars (Gemiza9 and Misr1). A baseline simulation (1981-2010) was compared with different scenarios of simulations using three Global Climate Models (GCMs) for the 2030s, 2050s and 2080s. Probable impacts of climate change were assessed using the GCMs and CMs under the high emission Representative Concentration Pathway (RCP8.5). Results predicted decreased wheat grain yields by a mean of 8.7%, 11.4% and 13.2% in the 2030s, 2050s and 2080s, respectively, relative to the baseline yield. Negative impacts of climatic change are probable, despite some uncertainties within the GCMs (i. e., 2.1%, 5.0% and 8.0%) and CMs (i.e., 2.2%, 6.0% and 9.2%). Changing the planting date with a scenario of plus or minus 5 or 10 days from the common practice was assessed as a potentially effective adaptation option, which may partially offset the negative impacts of climate change. Delaying the sowing date by 10 days (from 20 November to 30 November) proved the optimum scenario and decreased further reduction in wheat yields resulting from climate change to 5.2%, 6.8% and 8.5% in the 2030s, 2050s and 2080s, respectively, compared with the 20 November scenario. The planting 5-days earlier scenario showed a decreased impact on climate change adaptation. However, the 10-days early planting scenario increased yield reduction under projected climate change. The cultivar Misr1 was more resistant to rising temperature than Gemiza9. Despite the negative impacts of projected climate change on wheat production, water use efficiency would slightly increase. The ensemble of multi-model estimated impacts and adaptation uncertainties of climate change can assist decision-makers in planning climate adaptation strategies.

Keywords DSSAT models, scenarios, adaptation, water use efficiency, climate change

Received March 2, 2019; accepted November 4, 2019

E-mail: drahmedkheir2015@gmail.com

1 Introduction

Egypt is vulnerable to climate change due to the extremely low rainfall (UNEP, 2010) and its dependence on the River Nile for irrigation water. Different studies warn of the negative impacts of climate change on crop productivity globally (Wheeler and von Braun, 2013), at multiple scales, and more specifically, in the Mediterranean region (Jeunessea et al., 2016) and in sub-Saharan Africa (Cairns et al., 2013). However, the situation in Egypt has received insufficient attention (Kheir et al., 2019). Several factors affect food security, including increased demand for wheat, expensive inputs, soil desertification, greenhouse gas emission, as well as water and land needs (Pretty et al., 2010; Hertel, 2011; Challinor et al., 2014).

Understanding the impacts of climatic parameters on food production is necessary to enable adaptation scenarios (Asseng et al., 2015; Asseng et al., 2018). Crop models (CMs) can help to quantify impacts and adaptation strategies of climate change on crop production (Rosenzweig et al., 2014), crop protein (Asseng et al., 2019), and impacts of precipitation extremes (Piras et al., 2016). Ensemble multi-models are more effective than individual models for evaluating climate change impacts, due to greater accuracy, as in experimental data, and offer the possibility to quantify levels of uncertainty (Tao et al., 2018; Wallach et al., 2018). The Decision Support System for Agro-technology Transfer (DSSAT) models (Jones et al., 2003) and the Agricultural Production Systems Simulator (APSIM) (Keating et al., 2003; Holzworth et al., 2014) are used globally and have commendable reputations. N-Wheat, formerly APSIM (Asseng et al., 1998; Holzworth et al., 2014) is derived from CERES (Ritchie et al., 1998), but with modifications. These modifications include changes in crop water uptake systems and using water demand and biomass transpiration efficiency instead of reference evapotranspiration, and Leaf Area Index (LAI) as in CERES (Kassie et al., 2016). Such modifications could cause output differences between both models. N-Wheat had recently been included in the DSSAT platform, but had not previously been studied in detail; therefore, the Model was incorporated into the current study. The role of technological diffusion processes in the environmental context, green economy, and sustainable development is also of considerable importance (Aldieri and Vinci, 2017and 2018; Hájek and Stejskal, 2018; Makkonen and Inkinen, 2018). Negative impacts of climate change on crop productivity were explored (Challinor et al., 2007; Müller et al., 2011). These impacts are expected to increase globally (Thornton et al., 2010). Africa is especially vulnerable (Wheeler and Von-Braun, 2013). Given the probable effects on global food security (Godfray et al., 2010), the impacts of climate change and variability on Africa merits further investigation (Cooper and Coe, 2011; Cairns et al., 2013). Additional studies have reported that adaptation to climate change can decrease these impacts (Challinor et al., 2014; Swart et al., 2014; Rymbai and Sheikh, 2018). However, climate change adaptation has received much less attention in arid and semi-arid environments, particularly within smallholder agricultural systems (Mostegl et al., 2019).

Wheat (*Triticum aestivum*) is one of the most strategic crops in Egypt, yet the country remains as one of the world's largest wheat importers (Asseng et al., 2018). The primary reasons for uncertainty include a limited understanding of climate models, downscaling effects, and imperfect simulations within CMs (Asseng et al., 2013). While multiple climate scenarios and Global Climate Models (GCMs) are widely used (Tebaldi and Knutti, 2007), single models with unknown uncertainties are also applied (Asseng et al., 2013). Thus, we used two CMs and three GCMs within the Representative Concentration Pathway (RCP8.5) (Moss et al., 2010) to quantify the probable impacts of these scenarios on wheat yield. The study objectives were to: 1) calibrate and validate two DSSAT models with two wheat cultivars grown on the Northern Nile Delta region of Egypt, 2) explore the impacts of climate scenarios on wheat yield and water use efficiency on the Northern Nile Delta, and 3) explore planting dates that were plus or minus the common practice as potential adaptation scenarios under projected climate change scenarios.

2 Materials and methods

2.1 The study area

We conducted an experiment using large (12.0 m^3) lysimeters (1.5 $\times$ 2.5 m^2, height 3.0 m) filled with non-saline clay soil since 1994 on the Northern Nile Delta of Egypt, Sakha (Lat. 31.3–30.0°N, Long. 31.0–31.3°E; altitude 6 m above sea-level). The lysimeters were placed in an open field and surrounded with wheat to decrease the edge-effects produced. The climate is characterized by warm winters with a mean temperature of ~21.8°C. Summer is hot with a mean air temperature of ~32.5°C and a mean relative humidity of ~65%. Annual precipitation ranges from 100 to 150 mm and partially contributes to the water requirements of winter crops. The soil type is classified as a Vertic Torrifluvent (Said, 1993). The study site could be considered representative for the whole region, including the first agroclimatic zone in Egypt (30.0–31.0°N). Initial soil analysis before cultivation is presented in Table 1.

2.2 Climatic data

Daily solar radiation, maximum and minimum temperatures, and precipitation data were gained from the Central Laboratory of Agricultural Climate (CLAC) of Egypt (Fig. 1). The Sakha region of Egypt is classified as an Agro-ecological Zone 1 with high latitudes. The regime of both soil moisture and soil temperature in this region is torric and thermic, respectively (USDA, 2010).

2.3 Climate change scenarios

Daily measured weather data were collected in Egypt by CLAC (available at CLAC website) and used for the simulation of field experiments. Daily baseline climate data (1980–2010) were abstracted from the NASA AgCFSR Climate Data set (available at NASA website) for the studied region without stress in either irrigation or fertilization. Three GCMs (GFDL-ESM2M, CSIRO-Mk3-6-0 and HadGEM2-ES) with one RCP (8.5) were prepared (Moss et al., 2010) for the 2030s (2010–2040), 2050s (2040–2069), and 2080s (2070–2099) (Wilby et al., 2004). The AgCFSR forms a coherent daily time series by combining a data set of meteorological stations, retrospective analysis, rainfall, and remotely-sensed radiation. The GCMs were selected based on their shifting projections of temperature and solar radiation. Plotting data show the range of temperature and solar radiation values under different GCMs and RCP8.5 through the 21st Century

Table 1 Initial soil physico-chemical analysis before cultivation

Soil depth/cm	Particle size distribution/%			Texture	FC/%	WP/%	AW/%
	Sand	Silt	Clay				
0–20	18.7	31.5	49.8	clay	43.0	22.0	21.0
20–40	15.7	32.6	51.7	clay	44.0	22.5	21.5
40–60	16.5	35.1	48.2	clay	41.7	21.0	20.7

Soil depth/cm	EC/($dS \cdot m^{-1}$)	pH	SOM/%	Available macronutrients/($mg \cdot kg^{-1}$)			Kc/($cm \cdot h^{-1}$)
				N	P	K	
0–20	3.2	8.1	1.5	62	10.7	249	0.45
20–40	3.4	8	1.4	48	9.9	241	0.49
40–60	3.6	7.8	1.1	35	8.5	206	0.38

Note: K_c: Saturated hydraulic conductivity; EC: soil salinity (soil paste extract); SOM: soil organic matter; FC: field capacity; WP: wilting point; AW: available water. Particle-size limits are: sand 2000–50 μm, silt 50–2 μm and clay < 2.0 μm (USDA, 2010).

(Fig. 2). The projected weather data for a baseline (1981–2010), 2030s (2010–2040), 2050s (2040–2069), and 2080s (2070–2099) under three GCMs (GFDL-ESM2M, CSIRO-Mk3-6-0, and HadGEM2ES), and RCP8.5 were derived, bias-corrected, and downscaled to a high resolution with a 0.5° × 0.5° grid. RCP8.5 was selected based on assuming high concentrations of greenhouse gas emissions. In addition, it describes a pathway that has 8.5

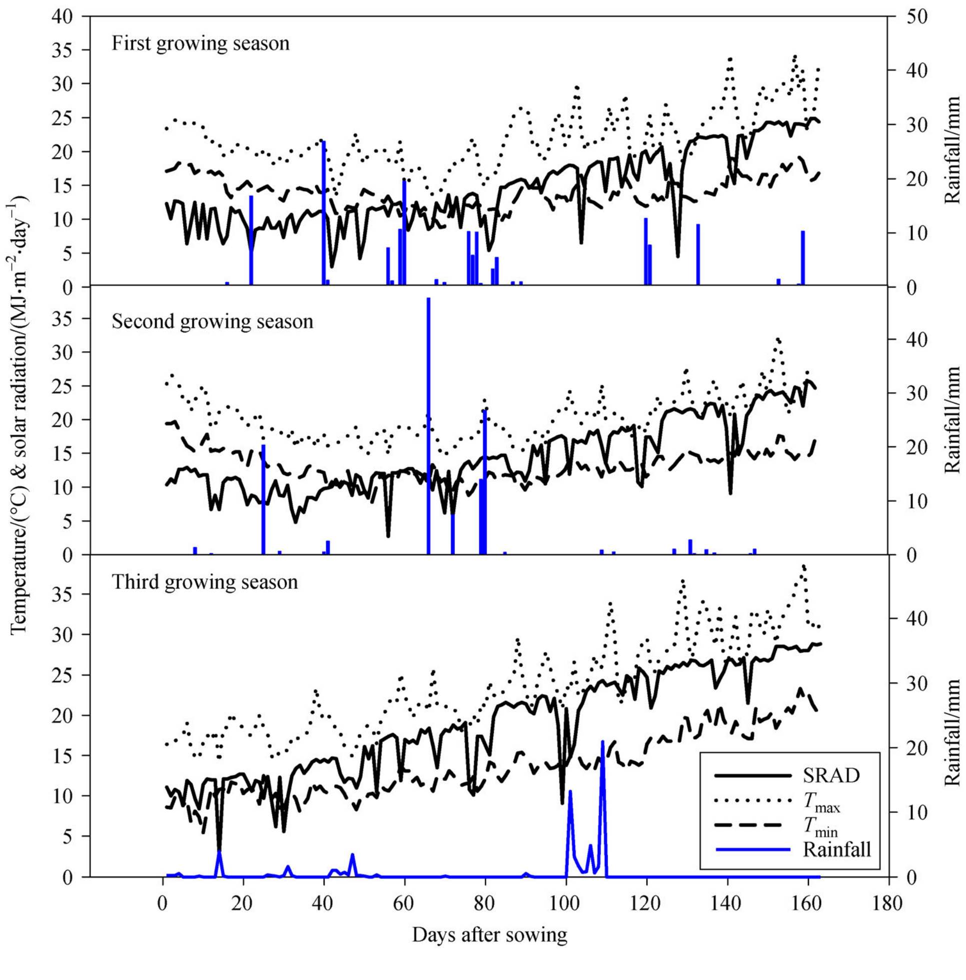

Fig. 1 Daily maximum temperature (T_{max}), minimum temperature (T_{min}), solar radiation (SRAD) and precipitation (rainfall) at Sakha during three growing seasons (2015/2016, 2016/2017 and 2017/2018).

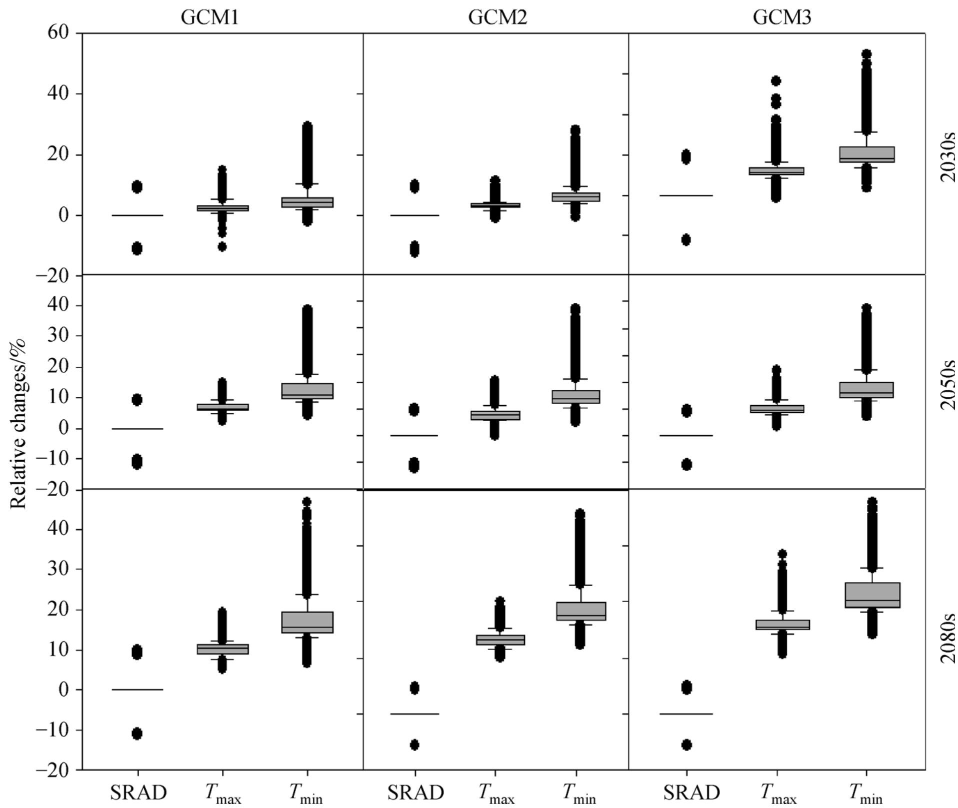

Fig. 2 Relative changes in daily solar radiation, maximum temperature and minimum temperature compared to the baseline under RCP8.5 and three global climate models (GCMs) during the 21st Century.

W m^{-2} of radiative forcing by 2100 compared with the description of other RCPs (van Vuuren et al., 2011), which corresponds to pre-industrial concentrations. The CO_2 concentrations for RCP8.5 were 432, 571, and 801 ppm for the 2030s (2010–2040), 2050s (2040–2069), and 2080s (2070–2099), respectively, whereas the CO_2 concentration for the baseline period was 360 ppm.

2.4 Model simulations

In this study, two DSSAT models (CERES-Wheat and N-Wheat) were calibrated for two wheat varieties grown in field experiments through three successive growing seasons in Egypt. Following the calibration process, models were applied to simulate wheat yield, water use, and water use efficiency under different climate change scenarios. Analysis included three GCMs and the higher emission scenario of a representative concentration pathway (RCP8.5). These were compared with the baseline climate data (1980–2010). As an adaptation option, we changed planting dates by plus or minus 5 or 10 days from the common practice. Wheat yield was predicted under the different climate scenarios using these planting dates for both models to estimate the optimum planting date under climate change scenarios in different time series (2030, 2050, and 2080). The CERES-Wheat and N-Wheat are involved in Decision Support Systems for Agrotechnology Transfer (DSSAT, v. 4.7) (Jones et al., 2003; Hoogenboom et al., 2015). The CERES-Wheat and N-Wheat models were selected from many other models due to their good reputation, particularly in climate change and food security studies (Tubiello and Ewert, 2002). DSSAT CMs are designed to predict crop development and water use in response to soil characteristics, crop features, weather, and management. The DSSAT models can simulate the development of roots and shoots, the growth and senescence of leaves and stems, biomass accumulation, as well as the growth of plant grains due to cultivar characteristics, cropping management practices, soil conditions, and weather (Lin et al., 2015). Thus, they can be used to explore the impacts of weather and soil water on crop yield, providing the significance of these models to simulate heat and drought stress actions. The models are calibrated and evaluated using the experimental data set of Misr1 (Asseng et al., 2018) and Gemiza9 wheat cultivars for yield and phenology and applied thereafter to predict yield and water use under different climate scenarios. The models ran 30 iterations for each time period and for future scenarios to cover all possible interannual changes in temperature and precipitation patterns. As such, simulations of baseline, near-term, mid-century, and end of century included runs of 1981–2010, 2010–2040, 2040–

2069, and 2070–2099, respectively, creating an average for baseline, 2030s, 2050s, and 2080s for different time periods.

2.5 The treatments and practices

The experiment was conducted in a large lysimeter during three successive wheat seasons of 2015/2016, 2016/2017, and 2017/2018 in a split-plot design, with three replicates. To ensure genetic variability under current conditions, the main plots were assigned to two wheat cultivars. Gemiza9 is sensitive to higher temperatures and drought, while Misr1 is more resistant (Asseng et al., 2018; Ahmed et al., 2012). Wheat was sown on 20 November and harvested on 15 May in all growing seasons. Irrigation treatments in sub main plots included a percentage of soil moisture deficit (SMD) at 35%, 55%, and 75%, with the 55% SMD treatment taken as the control. This value is representative of traditional farmer irrigation. Total seasonal evapotranspiration for both cultivars under different irrigation treatments is presented in supplementary Table 1.

2.6 DSSAT models calibration and evaluation

Detailed yield and phenology parameters (i.e., anthesis and maturity dates, grain yield, final biomass, grain size, maximum Leaf Area Index (LAIx), nitrogen (N) in grains and grain number per m^2) were measured.

Both models were calibrated using the 2015/2016 data set and validated using the data sets from the 2016/2017 and 2017/2018 growing seasons for Misr1 and Gemiza9 cultivars. The genetic parameters were changed manually in the calibration process to achieve the closest fit to observed data. The calibrated genetic parameters of both cultivars by two models are reported in Table 2. In calibration, the genetic parameters were incorporated in simple steps, with phenology first, then grain yield and biomass for the second step. The determination coefficient was calculated (Godwin and Singh, 1998) using a manual method. The values were justified to achieve the minimum root mean square deviation (RMSD) between predicted and observed data. The initial values of each model parameter and values after calibration for both cultivars are presented in Table 2.

The goodness of fit between the measured and predicted data were calculated using several parameters: root mean square deviation, RMSD (Jacovides and Kontoyiannis, 1995), Willmott Index of Agreement, WI (Willmott, 1984); and determination coefficient, R^2 (Moriasi et al., 2007). Uncertainty of CMs and GCMs were calculated based on standard deviations and overall grain yield values.

2.7 The relative impacts

The relative change in grain yield (GY), water use (ET), and water use efficiency (WUE) were calculated using the following equation:

$$x = \frac{y_{\text{future}} - y_{\text{baseline}}}{y_{\text{baseline}}}. \tag{1}$$

Water use efficiency (*WUE*) was calculated as follows:

$$WUE = \frac{SGY}{ET\_Crop}, \tag{2}$$

Table 2 Genetic coefficients of two cultivars (Misr1 and Gemiza9) for two crop models (CERES-Wheat and N-Wheat)

Models	Parameter	Parameter definition	Initial	*Misr1	Gemiza9
CERES-Wheat	P1D	Photoperiod sensitivity coefficient	75	30	97
	P1V	Vernalization sensitivity coefficient	5.0	30	0.0
	P5	Thermal time from the onset of grain-filling to maturity/°Cd	450	553	600
	G1	Kernel number per unit stem and spike weight at anthesis/(kernel·g^{-1})	30	32	24
	G2	Standard kernel size under optimum conditions/mg	35	35	49
	G3	Maximum stem and spike weight when elongation ceases	1.0	7.8	1.0
	PHINT	Thermal time between the appearance of leaf tips/°Cd	60	100	100
N-Wheat	VSEN	Sensitivity to vernalization	1.0	2.8	0.0
	PPSEN	Sensitivity to photoperiod	1.2	2.2	4.2
	P1	Thermal time from emergence to the end of juvenile/°Cd	400	400	400
	P5	Thermal time from beginning of grain filling to maturity/°Cd	600	510	518
	PHINT	Phyllochron interval	120	100	100
	GRNO	Coefficient of kernel number per stem weight at the beginning of grain filling/(kernels·(g stem)$^{-1}$)	24	32	32
	MXFIL	Potential kernel growth rate/(mg· kernel^{-1}·day^{-1})	1.9	3.0	3.0
	STMMX	Potential final dry weight of a single tiller, excluding grain	3.0	4.0	3.0

Note: *Misr1, calibrated previously by Asseng et al. (2018).

where SGY is the simulated grain yield (kg·ha^{-1}), and ET_Crop is the simulated cumulative evapotranspiration (mm) from sowing to maturity.

2.8 Potential adaptation options

We simulated changed planting dates as a potential adaptation option. Avoiding the current recommended planting date (20 November) and using scenarios of sowing plus or minus 5 or 10 days (i.e., 10, 15, 25, and 30 November) were selected as adaptation options. We then simulated wheat yield under different climate scenarios and calculated change of predicted yield in four new planting dates relative to the current planting date.

3 Results

3.1 Model calibrations and evaluations

The calibrations of CERES-Wheat and N-Wheat models proved successful (Fig. 3), attaining accurate predictions of wheat yield and phenology. Wheat grain yield, biomass, and phenology of both cultivars were suitably simulated by the DSSAT models, achieving lower RMSD and higher R^2 and WI values (Table 3, Fig. 3). Grain yield was simulated particularly well by the DSSAT models.

3.2 Projected changes in annual temperature

The annual mean maximum and minimum temperatures for the baseline were 27.6 and 15.4°C, respectively, with an overall mean of 21.5°C. According to the three GCMs (GFDL-ES2M, CSIRO-MK3-6-0, and HadGEM2-ES), the overall minimum temperature was expected to increase by 0.7°C, 1.0°C, and 1.6°C in 2030; 2.0°C, 2.5°C, and 3.1°C in 2050; and 3.0°C, 4.5°C, and 4.9°C in 2080, respectively (Fig. 4). Meanwhile, the increase in maximum temperature predicted by the three respective GCMs was 0.7°C, 0.9°C, and 1.7°C in the near decades (2030); 2.0°C, 2.3°C, and 3.0°C in the mid-century; and 3.1°C, 4.1°C, and 4.7°C in the late century (2080). Consequently, the annual mean temperature was expected to increase by 0.7°C, 0.9°C, and 1.6°C in 2030; 2.0°C, 2.4°C, and 3.0°C in 2050; with higher increases in 2080 of 3.0°C, 4.3°C, and 4.8°C for the three respective GCMs under RCP8.5 (Fig. 4).

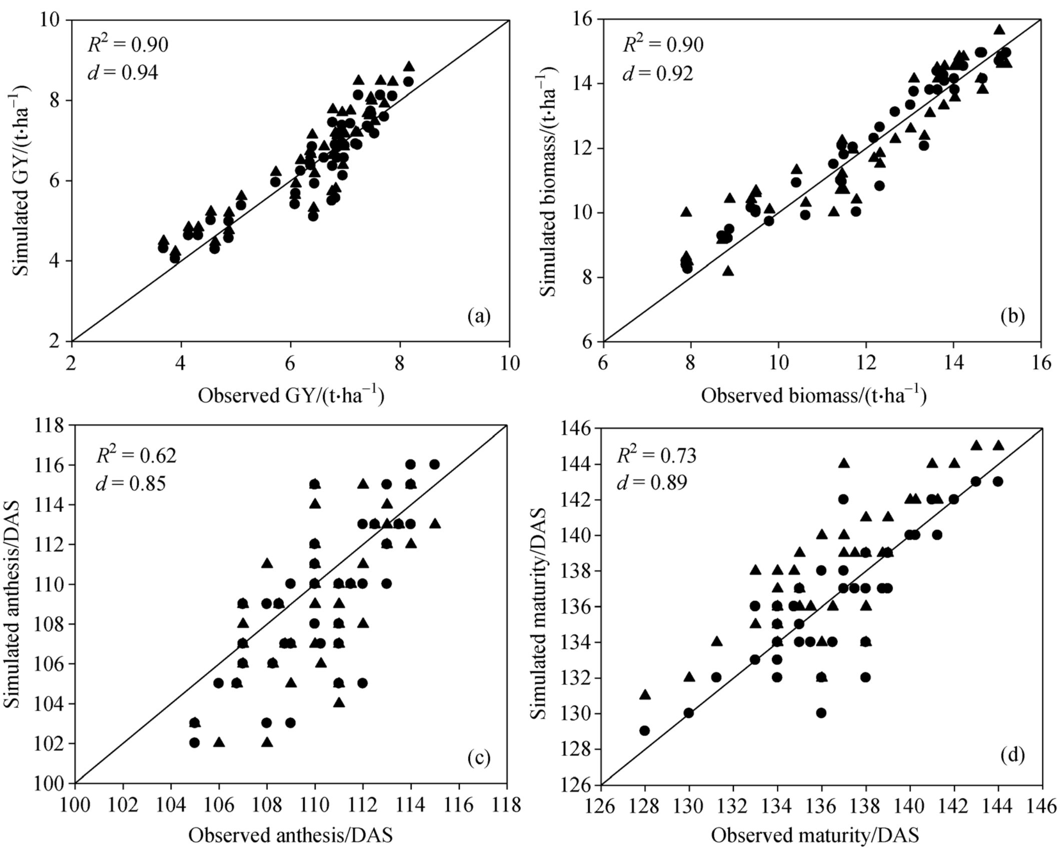

Fig. 3 Calibrations and validation of N-Wheat (triangle) and CERES-Wheat (scatter points) models under different irrigation treatments for two cultivars (Gemiza9 and Misr1) in three growing seasons.

Table 3 The performance evaluation of N-Wheat and CERES-Wheat for Misr1 and Gemiza9 spring wheat cultivars

	Model evaluation indices	N-Wheat model		CERES-Wheat model	
		Grain yield	Total biomass	Grain yield	Total biomass
Misr1	R^2	0.95	0.98	0.92	0.89
	RMSD (kg•ha^{-1})	450	591	480	995
	WI	0.98	0.98	0.96	0.97
		Anthesis	Maturity	Anthesis	Maturity
	R^2	0.67	0.73	0.62	0.73
	RMSD (days)	2	2	3	3
	WI	0.91	0.89	0.86	0.94
		Grain yield	Total biomass	Grain yield	Total biomass
	R^2	0.89	0.88	0.85	0.85
	RMSD (kg•ha^{-1})	641	1012	785	1200
Gemiza9	*WI*	0.93	0.90	0.88	0.82
		Anthesis	Maturity	Anthesis	Maturity
	R^2	0.65	0.75	0.55	0.69
	RMSD (kg•ha^{-1})	2	3	3	3
	WI	0.85	0.84	0.77	0.87

Note: R^2: determination coefficient; RMSD: root mean square deviation; *WI*: Wilmott Index of Agreement.

3.3 Climate change impacts on wheat yield, water use, and water use efficiency

The simulated mean yield of wheat in baseline (1980–2010) was 9590 kg/ha under optimum maturity growth, without stress, due to irrigation or fertilization treatments (Fig. 5(a)). Crop yield decreased under all climate scenarios relative to baseline yield (Fig. 5(b)). Crop and climate models predict decreased mean wheat yields for both cultivars relative to baseline yield (Fig. 5(c)). This reduction was calculated as 2.7%, 8.5%, and 14.9% in 2030; 8.4%, 9.5%, and 16.2% in 2050; decreasing markedly by 11.0%, 11.7%, and 17.0% in 2080 for GFDL-ES2M, CSIRO-MK3-6-0 and HADGEM2-ES, respectively (Fig. 5(c)). Due to its higher resistance resulting from delayed anthesis and maturity (long growth duration), the reduction in crop yield of the Misr1 cultivar was less under future scenarios compared with Gemiza9. The relative mean wheat yield decreases for Misr1 under the three-time series of 2030, 2050, and 2080 was 8.3%, 10.7% and 11.0%, respectively. Meanwhile, for Gemiza9, the reduction rate was greater, at 9.0%, 11.7%, and 15.7%, respectively, as a mean of the three GCMs (Fig. 5(b)). Consequently, the mean reduction of grain yield due to climate change for both cultivars was 8.7%, 11.4%, and 13.2% in 2030, 2050, and 2080, respectively, relative to the baseline yield. The future growing periods for wheat under the climate scenarios were shorter than those in the baseline scenario (Table 4). The decrease was in the descending order: GFDL-ES2M < CSIRO-MK3-6-0 < HADGEM2-ES. The shortest growth period was predicted for 2080, followed by 2050, and then 2030. Uncertainties in estimating yield impacts were relatively small at 2.3%, 5.0%, and 8.0% for GCMs for 2030s (2010–2040), 2050s (2040–2069), and 2080s (2070–2099), respectively. Uncertainty was higher for CMs at 2.5%, 5.8%, and 9.5%, compared with those predicted by GCMs (Fig. 6). Since Egyptian agriculture is highly dependent on irrigation due to low annual rainfall, crop water use and water use efficiency are vital considerations for water management systems. Water availability is predicted to decrease under future climate scenarios (Fig. 7) compared to grain yield (Fig. 5). Consequently, WUE increased under future climate scenarios (Fig. 8), despite the increase in temperatures predicted through the 21st Century.

3.4 Adaptation with changing planting dates

The highest yield occurred under the optimum planting date (20 November) for the baseline climate (1981–2010), but decreased under future climate scenarios (Fig. 5(a)). Delaying the planting date decreased the yield reduction gap under future climate scenarios. Due to the predicted decline in yield in response to increasing temperatures under future climate scenarios, the future yield in 2030s (2010–2040), 2050s (2040–2069), and 2080s (2070–2099) was predicted by postponing the planting date to 25 and 30 November, instead of the current recommended date of 20 November. Predicted grain yield reduction will be less under future climate scenarios through the 21st century due to postponed planting dates (Fig. 9). An assumed planting of 25 November partially decreased the predicted mean

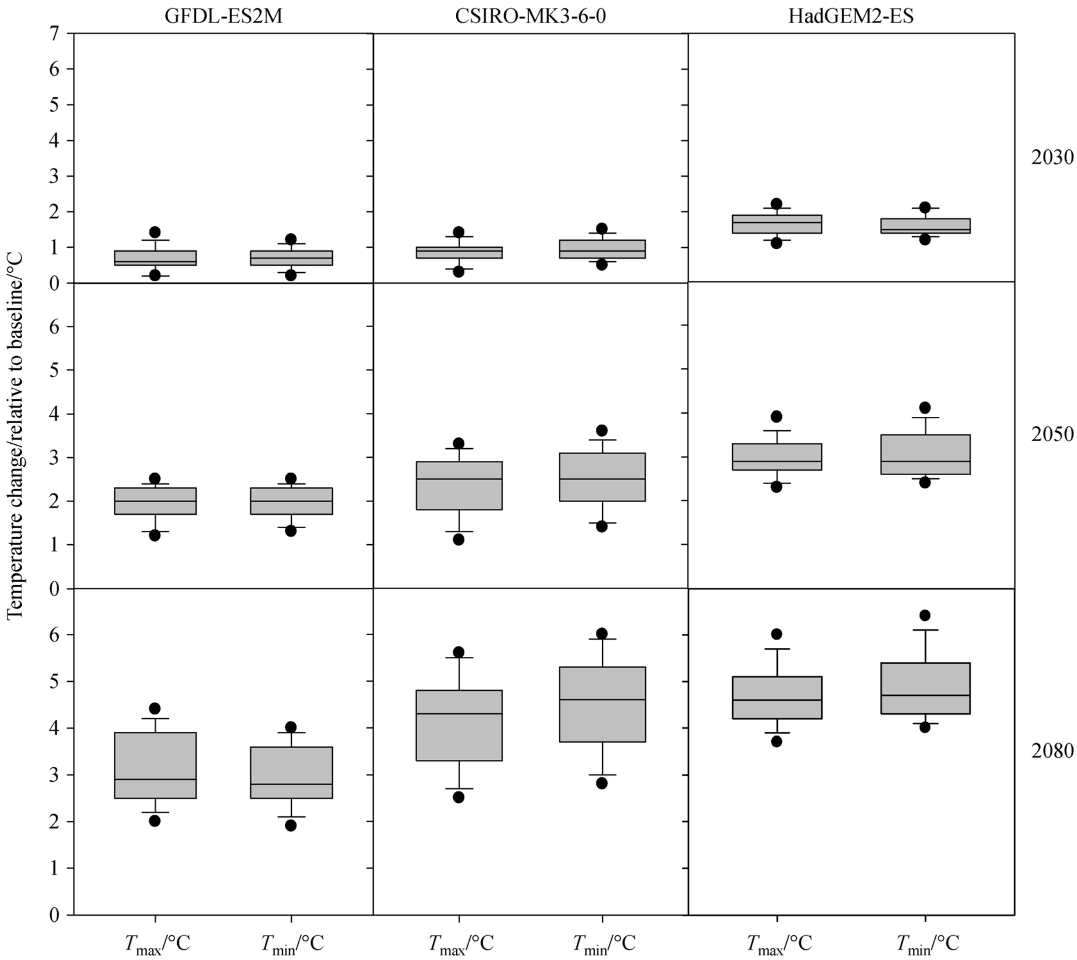

Fig. 4 Change of daily maximum and minimum temperature relative to the baseline (1981–2010) under three GCMs and RCP8.5 through the 21st century.

yield reduction of both cultivars caused by climate change to 4.8%, 7.9%, and 10.5% in 2030s (2010–2040), 2050s (2040–2069), and 2080s (2070–2099), respectively (Fig. 9 (a)). Changing the planting date to 30 November was more effective to prevent further reduction in yield, particularly in 2050 and 2080; thus, yield reduction decreased to 5.2%, 6.8%, and 8.5% in the 2030s (2010–2040), 2050s (2040–2069), and 2080s (2070–2099), respectively. The planting 5-days earlier scenario had a slight positive effect in the three time periods. Meanwhile, earlier sowing dates had negative impacts, increasing predicted yield reduction under climate change. The Misr1 cultivar achieved higher resistance to temperature than Gemiza9 with and without adaptations (Fig. 9(b)). This could be attributed to decreased heat stress from delayed planting during critical plant growth stages. Thus, delaying sowing by 5 or 10 days through the 21st century may partially offset yield reductions due to climate change.

4 Discussion

The N-Wheat and CERES-Wheat CMs could effectively be used for assessing climate change impacts on wheat production. Wheat phenology has significant impacts on growth and development and thus plays a vital role in the calibration process (Ceglar et al., 2011). The statistical model indicators confirmed accuracy in simulating anthesis and maturity in spring wheat (Fig. 3, Table 3). In N-Wheat, anthesis and maturity dates were justified by VSEN, PPSEN, and P5, respectively (Table 2), thus emphasizing the importance of these parameters in the phenology calibration process (Asseng et al..,1998, 2013, 2015). To control and modify anthesis and maturity dates in the CERES-Wheat model, different parameters, such as P1V, P1D, P5, and Phint, were used (Andarzian et al., 2015). However, changing other parameters in the genotype file (i.e., P1, P2, P3, and P4) is required to

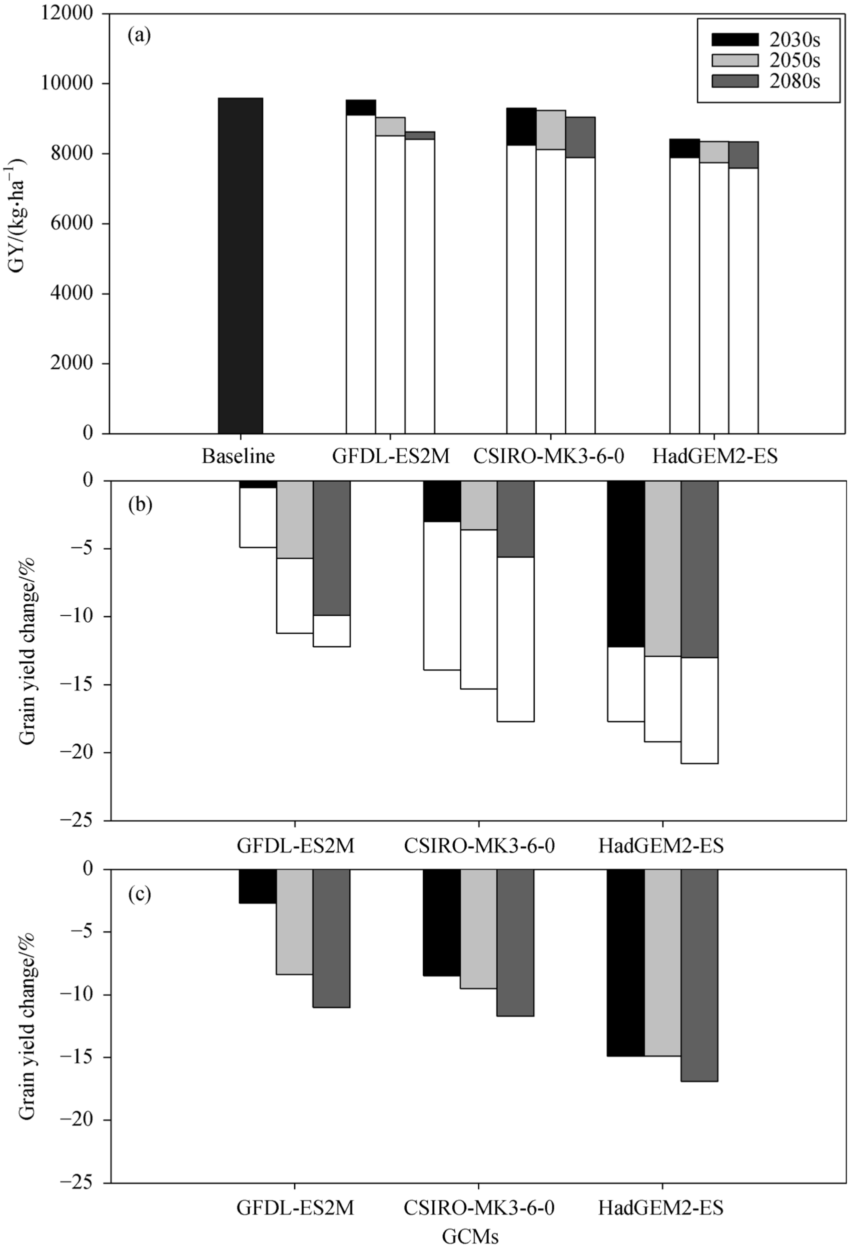

Fig. 5 Grain wheat yield (a), relative change (b) compared with the baseline (1981–2010) for both cultivars, open bars (Gemiza9) and closed bars (Misr1) and mean relative change of both cultivars (Cc) using two crop models (CMs) and three GCMs and RCP8.5 through the 21st century under current planting date (20 November) without adaptation.

Table 4 Changes in wheat growth duration (days) for the studied cultivars relative to the baseline (1981–2010) under different climate scenarios on the North Nile Delta

Cultivars	Crop model	2030			2050			2080		
		GCM1	GCM2	GCM3	GCM1	GCM2	GCM3	GCM1	GCM2	GCM3
Misr1	N-Wheat	−3	−4	−5	−5	−6	−7	−6	−7	−10
	CERES	−2	−4	−6	−3	−5	−8	−4	−8	−9
Gemiza9	N-Wheat	−4	−5	−6	−7	−8	−8	−7	−9	−13
	CERES	−3	−5	−7	−4	−6	−10	−5	−11	−14

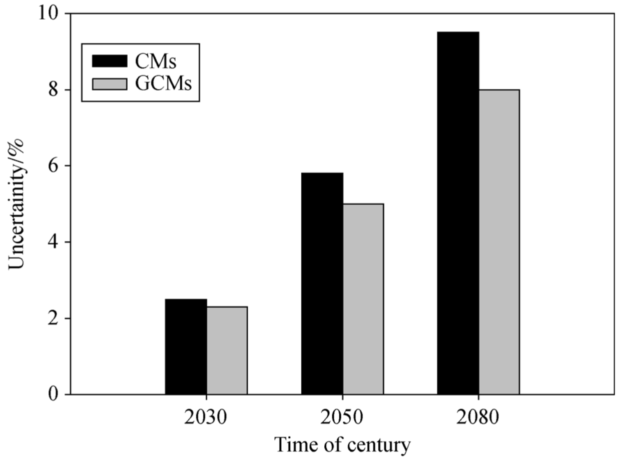

Fig. 6 Uncertainty of CMs and GCMs. Uncertainties are relative standard deviations based on two CMs (N-Wheat and CERES-Wheat) and three GCMs.

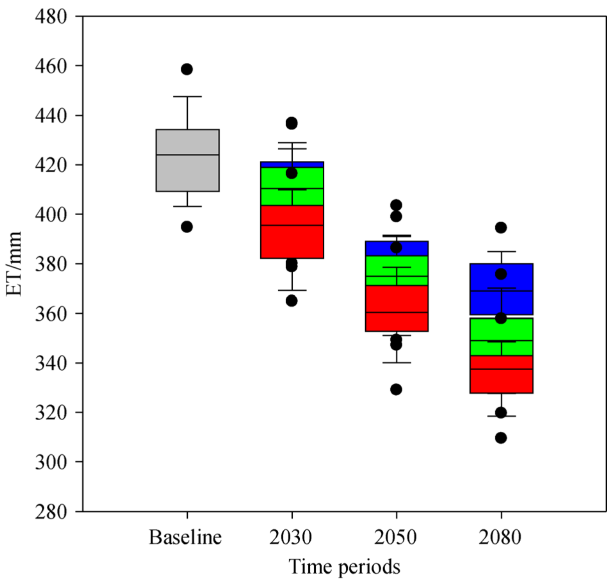

Fig. 7 Accumulated seasonal evapotranspiration in baseline, short, mid- and end of century under different GCMs blue, green, and red for GFDL-ES2M, CSIRO-MK3-6-0, and HAD-GEM2-ES, respectively.

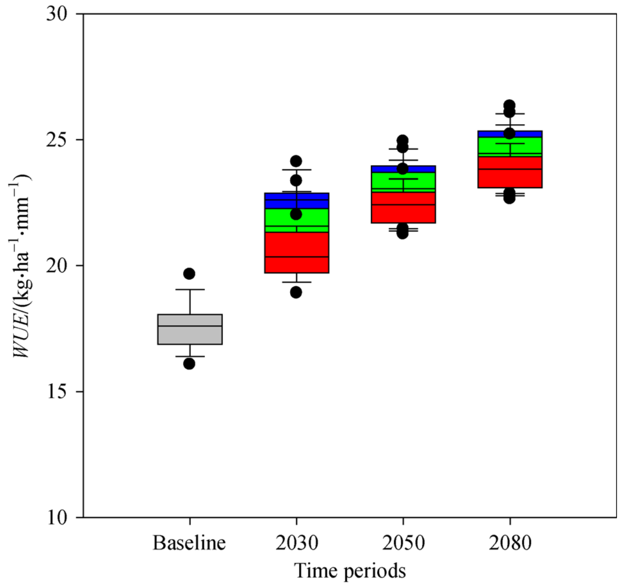

Fig. 8 Water use efficiency in baseline, short, mid-, and end of century under different GCMs blue, green, and red for GFDL-ES2M, CSIRO-MK3-6-0, and HADGEM2-ES, respectively

enhance model accuracy and reduce uncertainty (Johnen et al., 2012). Obtaining accurate phenology is considered the first priority for model calibrations (Archontoulis et al., 2014). Ensuring high quality calibration of phenological parameters could help to accurately simulate yield, growth, and biomass (Robertson et al., 2002). Radiative use efficiency and solar interception are the main factors affecting biomass production. Our biomass production predictions proved to be highly accurate (Arora et al., 2007) due to the linear relationship between grain yield and biomass (Dettori et al., 2011). The calibration of biomass for CERES-Wheat and N-Wheat used G3 and STMMX parameters, respectively (Table 2).

Different dynamic interactions between canopy cover and radiation interception are the main factors forming grain yield. The models were highly robust in simulating grain yield. GRNO and MXFIL parameters were used to calibrate grain yield for N-Wheat; while G1, G2, and G3 parameters were used for CERES-Wheat (Hunt and Boote, 1998). The calibration of grain and biomass yield should be completed after calibration of phenology (Ma et al., 2011). As a complex process, simulation modeling could be affected by soil, climate, and crop variables, creating potential uncertainty (Kassie et al., 2016). Using a single model simulation has many limitations in climate change and food security studies, and thus, couldn't be used to adequately quantify uncertainty (Rötteret al., 2011; Asseng et al. 2013; Wallach et al., 2018). Uncertainty can be quantified with reasonable accuracy using ensemble multi-models (Martre et al., 2015), by expanding existing model platforms (Feng et al., 2014). Therefore, the N-Wheat model, as a new derivative dynamic model recently added to other DSSAT models (Kassie et al., 2016), was combined with CERES in this study.

Although ensemble multiple models are valuable tools for making strategic decisions (Rosenzweig et al., 2013), some limitations have been observed due to disease and pests. Additional research and analysis during simulations could help resolve these limitations. During the past five decades, wheat yield in Egypt has steadily increased from 3.0 to 7.5 t/ha: (available at FAO website) due to

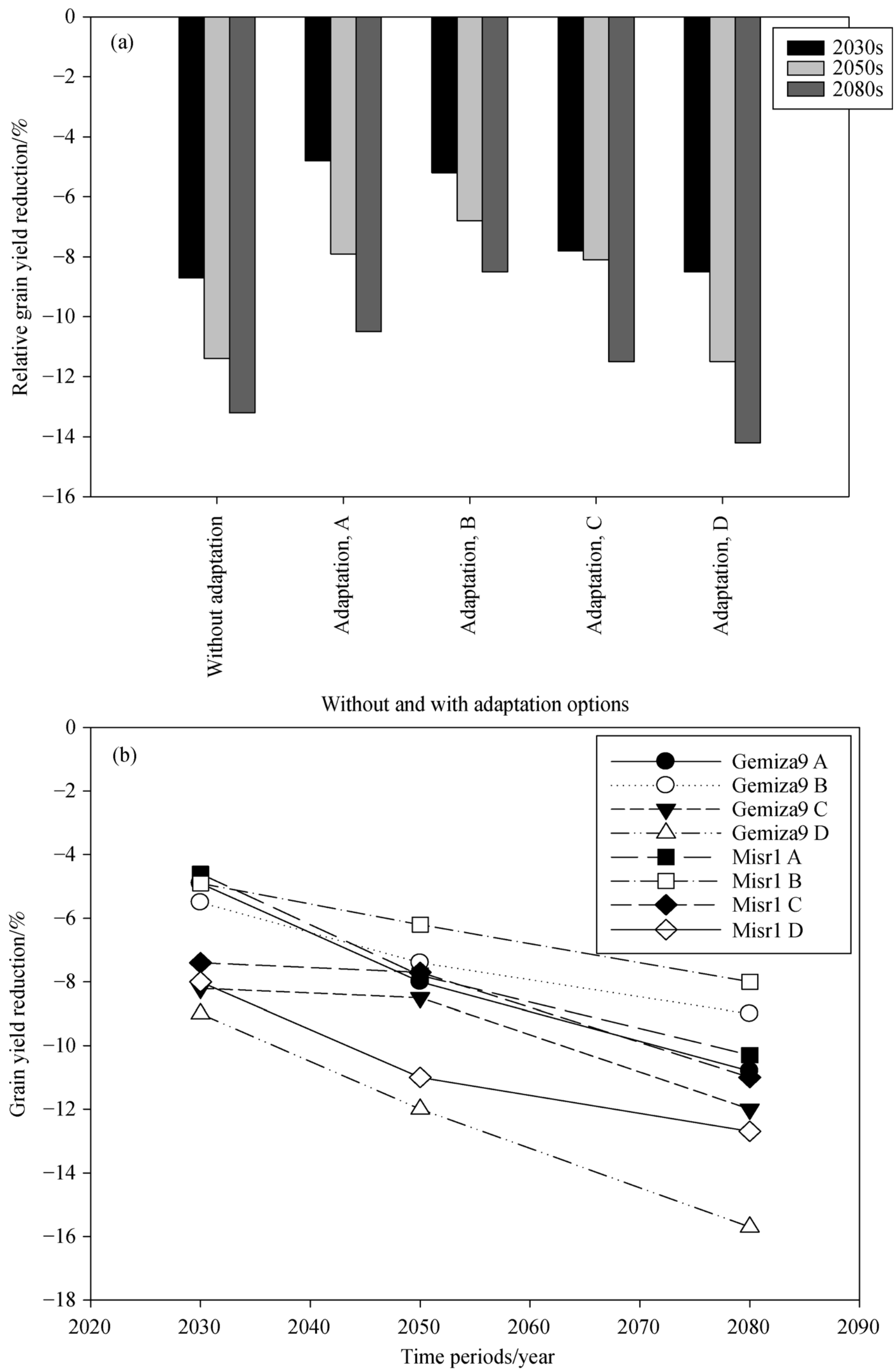

Fig. 9 Relative grain yield reduction (%) compared to the baseline in different time series as an average for both cultivars (a, above), without and with adaptations. Adaptations included A (delay sowing date by 5 days), B (delay sowing date by 10 days), C (early sowing by 5 days), and D (early sowing by 10 days), and % grain yield decrease compared to baseline data for both cultivars (Misr1 and Gemiza9) under the same adaptation options (A, B, C, and D) in 2030, 2050, and 2080 (b, below).

technological advances. Current analysis shows that climate change scenarios likely have a negative impact on future wheat yields. Thus, food security in Egypt will be negatively affected using a 'business as usual' method. Problems are compounded by increased population. Under the medium population growth scenario, the Egyptian population is expected to increase from ~100 million in 2018 to 117 million in 2030, 151 million in 2060, and 187 million in 2080 (Roser and Ortiz-Ospina, 2018).

Projections of GCMs and climate change impacts generally result in some uncertainties (Fig. 6) (Osborne et al., 2013; Whitfield, 2013; Tao et al., 2018). Similarly, CM adaptation options and agricultural strategies involve uncertainty (Rotter et al., 2011; Rosenzweig et al., 2014; Tao et al., 2018). Climate change impacts on wheat yield under GCMs will be higher (–2.7% to –14.9%, –8.4% to –16.2%, and –11.0% to –17.0%) averaged over CMs for 2030, 2050, and 2080, respectively, than between different CMs (–10.0% to –14.0%, –11.0% to –15.0%, and –14.0 to –18.0%) for the same three years (Fig. 5(b)). Therefore, we can conclude that GCMs will reign regional impact evaluations for the mid-century (2050) (Hawkins and Sutton, 2011). However, these are predicted and not absolute values (Asseng et al., 2013; Rosenzweig et al., 2014).

Decreased wheat yields in response to increasing temperature is primarily due to shortened crop growth development and decreased canopy development and thus, a shortening of the crop life cycle (Sayre et al., 1997: Asseng et al., 2015, 2018). Thus, there will be less solar radiation interception (Alexandrov and Hoogenboom, 2000; Heng et al., 2007). Water use efficiency increased, despite the projected increase in temperature with climate change scenarios (Fig. 8), due to decreasing total ET throughout the growing season (Fig. 7). Decreasing ET under projected future climate is primarily due to shorter growth duration with higher temperatures and efficient transpiration from elevated CO_2 concentrations (Deryng et al., 2016; Asseng et al., 2018). In addition to increasing temperature due to climate change scenarios, total precipitation will decrease with increasing time periods from 2030s toward 2080s and GCMs from GFDL-ES2M to HADGEM2-ES (S.Fig. 1). The projected decrease in precipitation and increased temperature are the primary causes for a decline in the future yield (Paymard et al., 2018).

Changing sowing dates is one of the most widely adopted options for adapting cropping systems to climate change (White et al., 2011). According to our findings, a later planting date will result in less of a crop loss than will earlier dates or the current recommended sowing date, in future climate scenarios. The current optimum sowing date may face a temperature increase at a critical growth stage, which could be avoided by delaying the sowing date. Rescheduling the planting date to 25 November decreased predicted wheat yield loss under future climate scenarios by 3.9%, 3.5%, and 2.7% for 2030, 2050, and 2080, respectively, relative to the current optimum sowing date in the baseline data of 20 November (Fig. 9). These rates increased slightly to 3.5%, 4.0%, and 4.2% using the second planting date (30 November). This means the gap of yield reduction in response to future climate scenarios will likely decrease using this adaptation option. Results emphasize the critical importance of changing the planting date as a potential adaptation option for climate change.

5 Conclusions and research priorities

Experimental and modeling studies were implemented in Egyptian Nile delta soils. The study investigated climate change impacts on wheat yield and water use and explored potential adaptation options. Attention focused on wheat, as it is one of the most important and strategic crops in Egypt. Various agronomic practices included irrigation and two cultivars (Gemiza9 and Misr1) in three-successive wheat growing seasons (2015/2016, 2016/2017 and 2017/2018). Different climate change scenarios through the 21st century predicted yield using two CMs (CERES-Wheat and N-Wheat). Results from the models predicted yield decreases of 8.7%, 11.4%, and 13.2% as a mean value of the two cultivars in the 2030s (2010–2040), 2050s (2040–2069), and 2080s (2070–2099), respectively, relative to the baseline data (1981–2010). These decreases are primarily attributed to increased temperatures which shorten the wheat growing season. Potential adaptation options, such as delaying the planting date, could be used to counter the negative impacts of climate change. Such adaptations will likely decrease yield reduction gaps due to climate change. However, further adaptation strategies (such as irrigation and fertilization management and modified plant density and row spacing) will require major evaluations and subsequent major modifications to adaptation systems. Moreover, the adaptation options include considerable costs and require economic evaluations. Therefore, future research should include socio-economic evaluations of all viable adaptation options.

Acknowledgements We thank the Agricultural Research Center; Soils, Water and Environment Research Institute (SWERI) for financial support. We are grateful to Dr Alex. C. Ruane (NASA Goddard Institute for Space Studies, New York, USA) for providing us with GCMs of the study area. Authors declare that there is no conflict of interest.

Electronic Supplementary Material Supplementary material is available in the online version of this article at http://dx.doi.org/10.1007/s11707-019-0806-4 and is accessible for authorized users.

References

Ahmed M A, Magda A F, Ebtesam A E (2012). Growth and yield attributes of some newly wheat cultivars in relation to missing an irrigation at different stages of growth. J Appl Sci Res, 8: 5075–5080

Aldieri L, Vinci C P (2017). The role of technology spillovers in the process of water pollution abatement for large international firms. Sustainability, 9(5): 868–875

Aldieri L, Vinci C P (2018). Innovation effects on employment in high-tech and low-tech industries: evidence from large international firms within the triad. Eurasian Business Review, 8(2): 229–243

Alexandrov V A, Hoogenboom G (2000). The impact of climate variability and change on crop yield in Bulgaria. Agric Meteorol, 104

(4): 315–327

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 Agric Sci, 14(2): 189–199

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 Model 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 G, 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, Müller 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, Stöckle C, Stratonovitch P, Streck T, Supit I, Tao F, Thorburn P J, Waha K, Wang E, Wallach D, Wolf J, Zhao Z, Zhu Y (2015). Rising temperatures reduce global wheat production. Nat Clim Chang, 5(2): 143–147

Asseng S, Ewert F, Rosenzweig C, Jones J W, Hatfield J L, Ruane A C, Boote K J, Thorburn P J, Rötter R P, Cammarano D, Brisson N, Basso B, Martre P, Aggarwal P K, Angulo C, Bertuzzi P, Biernath C, Challinor A J, Doltra J, Gayler S, Goldberg R, Grant R, Heng L, Hooker J, Hunt L A, Ingwersen J, Izaurralde R C, Kersebaum K C, Müller C, Naresh Kumar S, 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, Stratonovitch P, Streck T, Supit I, Tao F, Travasso M, Waha K, Wallach D, White J W, Williams J R, Wolf J (2013). Uncertainty in simulating wheat yields under climate change. Nat Clim Chang, 3(9): 827–832

Asseng S, Keating B A, Fillery I R P, Gregory P J, Bowden J W, Turner N C, Palta J A, Abrecht D G (1998). Performance of the APSIM-wheat model in western Australia? Field Crops Res, 57(2): 163–179

Asseng S, Kheir A M S, Kassie B T, Hoogenboom G, Abdelaal A I N, Haman D Z, Ruane A (2018). Can Egypt become self-sufficient in wheat? Environ Res Lett, 13: 094012

Asseng S, Martre P, Maiorano A, Rötter R P, O'Leary G J, Fitzgerald G J, Girousse C, Motzo R, Giunta F, Babar M A, Reynolds M P, Kheir A M S, Thorburn P J, Waha K, Ruane A C, Aggarwal P K, Ahmed M, Balkovič J, Basso B, Biernath C, Bindi M, Cammarano D, Challinor A J, De Sanctis G, Dumont B, Eyshi Rezaei E, Fereres E, Ferrise R, Garcia-Vila M, Gayler S, Gao Y, Horan H, Hoogenboom G, Izaurralde R C, Jabloun M, Jones C D, Kassie B T, Kersebaum K C, Klein C, Koehler A K, Liu B, Minoli S, Montesino San Martin M, Müller C, Naresh Kumar S, Nendel C, Olesen J E, Palosuo T, Porter J R, Priesack E, Ripoche D, Semenov M A, Stöckle C, Stratonovitch P, Streck T, Supit I, Tao F, Van der Velde M, Wallach D, Wang E, Webber H, Wolf J, Xiao L, Zhang Z, Zhao Z, Zhu Y, Ewert F (2019). Climate change impact and adaptation for wheat protein. Glob Change Biol, 25(1): 155–173

Cairns J E, Hellin J, Sonder K, Araus J L, Macrober J F, Thierfelder C, Prasanna B M (2013). Adapting maize production to climate change in sub-Saharan Africa. Food Secur, 5(3): 345–360

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 Meteorol, 151(1): 101–115

Challinor A J, Watson J, Lobell D B, Howden S M, Smith D R, Chhetri N (2014). A meta-analysis of crop yield under climate change and adaptation. Nat Clim Chang, 4(4): 287–291

Challinor A, Wheeler T, Garforth C, Craufurd P, Kassam A (2007). Assessing the vulnerability of food crop systems in Africa to climate change. Clim Change, 83(3): 381–399

Cooper P J M, Coe R (2011). Assessing and addressing climate-induced risk in sub-Saharan rainfed agriculture. Exp Agric, 47(2): 179–184

Deryng D, Elliott J, Folberth C, Müller C, Pugh T A M, Boote K J, Conway D, Ruane A C, Gerten D, Jones J W, Khabarov N, Olin S, Schaphoff S, Schmid E, Yang H, Rosenzweig C (2016). Regional disparities in the beneficial effects of rising CO_2 concentrations on crop water productivity. Nat Clim Chang, 6(8): 786–790

Dettori M, Cesaraccio C, Motroni A, Spano D, Duce P (2011). Using CERES-Wheat to simulate durum wheat production and phenology in Southern Sardinia. Field Crops Res, 120(1): 179–188

Feng Z, Yao Y, Huilong C, Feng Y (2014). Reusable component model development approach for parallel and distributed simulation. Sci World J ", 2014:1–12"

Godfray H C J, Beddington J R, Crute I R, Haddad L, Lawrence D, Muir J F, Pretty J, Robinson S, Thomas S M, Toulmin C (2010). Food security: the challenge of feeding 9 billion people. Science, 327 (5967): 812–818

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. Netherlands: Springer, 55–77.

Hawkins E, Sutton R (2011). The potential to narrow uncertainty in projections of regional precipitation change. Clim Dyn, 37(1–2): 407–418

Hájek P, Stejskal J (2018). R&D cooperation and knowledge apillover effects for sustainable business innovation in the chemical industry. Sustainability, 10(4): 1064–1083

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

Hertel T W (2011). The global supply and demand for agricultural land in 2050: a perfect storm in the making? Am J Agric Econ, 93(2): 259–275

Holzworth D P, Huth N I, Devoil P G, Zurcher E J, Herrmann N I, Mclean G, Chenu K, van Oosterom E J, Snow V, Murphy C, Moore A D, Brown H, Whish J P M, Verrall S, Fainges J, Bell L W, Peake A S, Poulton P L, Hochman Z, Thorburn P J, Gaydon D S, Dalgliesh N P, Rodriguez D, Cox H, Chapman S, Doherty A, Teixeira E, Sharp J, Cichota R, Vogeler I, Li F Y, Wang E, Hammer G L, Robertson M J, Dimes J P, Whitbread A M, Hunt J, van Rees H, McClelland T, Carberry P S, Hargreaves J N G, MacLeod N, McDonald C, Harsdorf J, Wedgwood S, Keating B A (2014). APSIM-evolution towards a new generation of agricultural systems simulation. Environ Model

Softw, 62: 327–350

Hoogenboom G, Jones J W, Wilkens P W, Porter C H, Boote K J, Hunt L A, Singh U, Lizaso J I, White J W, Uryasev O, Ogoshi R, Koo J, Shelia V, Tsuji G Y (2015). Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.6. DSSAT Foundation, Prosser, Washington

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. Netherlands: Springer, 9–39

Jacovides C P, Kontoyiannis H (1995). Statistical procedures for the evaluation of evapotranspiration computing models. Agric Water Manage, 27(3–4): 365–371

Jeunesse I, Cirelli C, Aubin D, Larrue C, Sellami H, Afifi S, Bellin A, Benabdallah S, Bird D N, Deidda R, Dettori M, Engin G, Herrmann F, Ludwig R, Mabrouk B, Majone B, Paniconi C, Soddu A (2016). Is climate change a threat for water uses in the Mediterranean region? Results from a survey at local scale. Sci Total Environ, 543(Pt B): 981–996

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 Electron 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

Kassie B T, Asseng S, Porter C H, Royce F S (2016). Performance of DSSAT N-Wheat across a wide range of current and future growing conditions. Eur J Agron, 81: 27–36

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

Kheir A M S, El Baroudy A, Aiad M A, Zoghdan M G, Abd El-Aziz M A, Ali M G M, Fullen M A (2019). Impacts of rising temperature, carbon dioxide concentration and sea level on wheat production in North Nile delta. Sci Total Environ, 651(Pt 2): 3161–3173

Lin Y, Wu W, Ge Q (2015). CERES-Maize model-based simulation of climate change impacts on maize yields and potential adaptive measures in Heilongjiang Province, China. J Sci Food Agric, 95(14): 2838–2849

Ma L,A huja 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, 1–64

Makkonen T, Inkinen T (2018). Sectoral and technological systems of environmental innovation: the case of marine scrubber systems. J Clean Prod, 200: 110–121

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

Moriasi D N, Arnold J G, Liew M W V, Bingner R L, Harmel R D, Veith T L, Moriasi D N, Arnold J G , Van Liew M W , Bingner R L , Harmel R DVeith T L (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans ASABE, 50(3): 885–900

Moss R H, Edmonds J A, Hibbard K A, Manning M R, Rose S K, van Vuuren D P, Carter T R, Emori S, Kainuma M, Kram T, Meehl G A, Mitchell J F, Nakicenovic N, Riahi K, Smith S J, Stouffer R J, Thomson A M, Weyant J P, Wilbanks T J (2010). The next generation of scenarios for climate change research and assessment. Nature, 463(7282): 747–756

Mostegl N M, Pröbstl-haider U, Jandl R, Haider V (2019). Targeting climate change adaptation strategies to small-scale private forest owners. For Policy Econ, 99: 83–99

Müller C, Cramer W, Hare W L, Lotze-Campen H (2011). Climate change risks for African agriculture. Proc Natl Acad Sci USA, 108 (11): 4313–4315

Osborne T, Rose G, Wheeler T (2013). Variation in the global-scale impacts of climate change on crop productivity due to climate model uncertainty and adaptation. Agric Meteorol, 170: 183–194

Paymard P, Bannayan M, Haghighi R S (2018). Analysis of the climate change effect on wheat production systems and investigate the potential of management strategies. Nat Hazards, 91(3): 1237–1255

Piras M, Mascaro G, Deidda R, Vivoni E R (2016). Impacts of climate change on precipitation and discharge extremes through the use of statistical downscaling approaches in a Mediterranean basin. Sci Total Environ, 543(Pt B): 952–964

Pretty J, Sutherland W J, Ashby J, Auburn J, Baulcombe D, Bell M, Bentley J, Bickersteth S, Brown K, Burke J, Campbell H, Chen K, Crowley E, Crute I, Dobbelaere D, Edwards-Jones G, Funes-Monzote F, Godfray H C J, Griffon M, Gypmantisiri P, Haddad L, Halavatau S, Herren H, Holderness M, Izac A M, Jones M, Koohafkan P, Lal R, Lang T, McNeely J, Mueller A, Nisbett N, Noble A, Pingali P, Pinto Y, Rabbinge R, Ravindranath N H, Rola A, Roling N, Sage C, Settle W, Sha J M, Shiming L, Simons T, Smith P, Strzepeck K, Swaine H, Terry E, Tomich T P, Toulmin C, Trigo E, Twomlow S, Vis J K, Wilson J, Pilgrim S (2010). The top 100 questions of importance to the future of global agriculture. Int J Agric Sustain, 8(4): 219–236

Ritchie J T, Singh U, Godwin D, Bowen W T (1998). Cereal growth, development,and yield. In: Tsuji G Y, Hoogenboom G, Thornton P K, eds., Understanding Options for Agricultural Production. Dordrecht: Kluwer Academic, 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. Proc Natl Acad Sci USA, 111(9): 3268–3273

Rosenzweig C E A, 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 Meteorol, 170: 166–182

Roser M, Ortiz-Ospina E (2018). World Population Growth vol 2017: Our World In Data.org

Rötter R P, Carter T R, Olesen J E, Porter J R (2011). Crop-climate models need an overhaul? Nat Clim Chang, 1(4): 175–177

Rymbai D, Sheikh F M (2018). The insight of agricultural adaptation to climate change: a case of rice growers in Eastern Himalaya, India. Int J Biometeorol, 62(10): 1833–1845

Said R (1993). The River Nile Geology and Hydrology and Utilization. Oxford: Pergamon

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

Swart R, Biesbroek R, LourenÃ§o T C (2014). Science of adaptation to climate change and science for adaptation. Front Environ Sci, (2)

Tao F, Rötter R P, Palosuo T, Gregorio Hernández Díaz-Ambrona C, Mínguez M I, Semenov M A, Kersebaum K C, Nendel C, Specka X, Hoffmann H, Ewert F, Dambreville A, Martre P, Rodríguez L, Ruiz-Ramos M, Gaiser T, Höhn J G, Salo T, Ferrise R, Bindi M, Cammarano D, Schulman A H (2018). Contribution of crop model structure, parameters and climate projections to uncertainty in climate change impact assessments. Glob Change Biol, 24(3): 1291–1307

Tebaldi C, Knutti R (2007). The use of the multi-model ensemble in probabilistic climate projections. Philos Trans A Math Phys Eng Sci, 365(1857): 2053–2075

Thornton P K, Jones P G, Alagarswamy G, Andresen J, Herrero M (2010). Adapting to climate change: agricultural system and household impacts in East Africa. Agric Syst, 103(2): 73–82

Tubiello F N, Ewert F (2002). Simulating the effects of elevated CO_2 on crops: approaches and applications for climate change. Eur J Agron, 18(1–2): 57–74

UNEP (2010). Africa Water Atlas. Division of Early Warning and Assessment United Nations Environment Programme, Nairobi, Kenya

USDA (2010). Keys to Soil Taxonomy. 3rd ed. United State Department of Agriculture. Natural Resources Conservation Services (NRCS)

van Vuuren D P, Edmonds J, Kainuma M, Riahi K, Thomson A, Hibbard K, Hurtt G C, Kram T, Krey V, Lamarque J F, Masui T, Meinshausen M, Nakicenovic N, Smith S J, Rose S K (2011). The representative concentration pathways: an overview. Clim Change, 109(1–2): 5–31

Wallach D, Martre P, Liu B, Asseng S, Ewert F, Thorburn P J, van Ittersum M, Aggarwal P K, Ahmed M, Basso B, Biernath C, Cammarano D, Challinor A J, De Sanctis G, Dumont B, Eyshi Rezaei E, Fereres E, Fitzgerald G J, Gao Y, Garcia-Vila M, Gayler S, Girousse C, Hoogenboom G, Horan H, Izaurralde R C, Jones C D, Kassie B T, Kersebaum K C, Klein C, Koehler A K, Maiorano A, Minoli S, Müller C, Naresh Kumar S, Nendel C, O'Leary G J, Palosuo T, Priesack E, Ripoche D, Rötter R P, Semenov M A, Stöckle C, Stratonovitch P, Streck T, Supit I, Tao F, Wolf J, Zhang Z (2018). Multimodel ensembles improve predictions of crop-environment-management interactions. Glob Chang Biol, 24(11): 5072–5083

Wheeler T, von Braun J (2013). Climate change impacts on global food security. Science, 341(6145): 508–513

White J W, Hoogenboom G, Kimball B A, Wall G W (2011). Methodologies for simulating impacts of climate change on crop production. Field Crops Res, 124(3): 357–368

Whitfield S (2013). Uncertainty, ignorance and ambiguity in crop modelling for African agricultural adaptation. Clim Chang,1–16

Wilby R, Charles S P, Zorita E, Timbal B, Whetton P, Mearns L O (2004). Guidelines for use of climate scenarios developed from statistical downscaling methods. IPCC task group on data and scenario support for impacts and climate analysis

Willmott C J (1984). On the evaluation of model performance in physical geography. In: Gaile G L, Willmott C J, eds. Spatial Statistics and Models, Boston: D. Reidel, 443–460