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RESEARCH ARTICLE

Using crop modeling to evaluate the impacts of climate change on wheat in southeastern turkey

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Abstract

The extreme temperatures and uneven distribution of rainfall associated with climate change are expected to affect agricultural productivity and food security. A study was conducted to evaluate the impact of climate change on wheat in southeastern regions of Turkey. The CERES-wheat crop simulation model was calibrated and evaluated with data from eight surveyed farms. The four farms were used for calibration and four for evaluation. Climate change scenarios were developed for the middle (2036–2065) and late 21st century (2066–2095) under representative concentration pathways (RCPs 4.5 and 8.5) for study sites in Islahiye and Nurdagi. Model calibration results showed a good agreement between observed and simulated yield with only a 1 to 11% range of error. The model evaluation results showed good fit between observed and simulated values of all parameters with % error ranged from 0.51 to 13.3%. Future climate change projections showed that maximum temperature (*T*max) will increase between 1.6 °C (RCP4.5) and 2.3 °C (RCP8.5), while minimum temperature (*T*min) will increase between 1.0 °C (RCP4.5) and 1.5 °C (RCP8.5) for mid-century. At the end of the century, *T*max is projected to increase from 2 °C (RCP4.5) to 4 °C (RCP8.5) and *T*min from 1.3 °C (RCP4.5) to 3.1 °C (RCP8.5). Climate change impacts results showed that future rise in temperature will reduce wheat yield by 16.3% in mid-century and 16.8% at the end of the century at Islahiye and for Nurdagi, while 13.0% in mid and 14.4% end of the century. The use of climate and crop modeling technique provides useful information in evaluating the climate change impacts and may assist stakeholders to make decisions to overcome the negative impacts in the near and long term.

Keywords Crop modeling · Climate projections · Climate impacts · Wheat

Introduction

Variation in temperature and uncertainty in rainfall patterns are affecting agriculture and food security around the world (Rosenzweig et al. 2014, 2015; Ahmad et al. 2018a; Nasim et al. 2018). Climate change projections show that future global temperature will increase by 2.5 °C at 2050 (IPCC 2013a). A rise in temperatures may decrease future agricultural productivity especially in semi-arid areas like Turkey (Nasim et al. 2016b; Ben-Asher et al. 2019; Ullah et al. 2019a).

Global temperatures have increased in the past decades and are projected to increase in the future, along with the frequency of hot days (Alexander et al. 2006; Asseng et al. 2017; Ahmad et al. 2019). Future projection showed that temperature is expected to increase by 2–3 °C from 2016 to 2040 in Turkey (Nasim et al. 2016b; Demircan et al. 2017; Mahmood et al. 2017). Expected increase in temperature would cause serious risk to agriculture crops especially wheat in Turkey (Lal et al. 1998; Olesen et al. 2011; Doğan and Kendal 2012; Dogan and Karakas 2018). As wheat is a major source of world food, particularly in Turkey (Doğan and Kendal 2012), and it is cultivated mostly under rainfed conditions (Dudu and Çakmak 2018). In 2017, the annual average

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production of wheat in Turkey was 20.6 million tons (Turkish Statistical Institute 2017). Changes in temperatures and rainfall patterns cause the reduction in wheat yield under arid and semi-arid conditions (Shah et al. 2011; Valizadeh et al. 2014; Ahmad et al. 2018a; Ullah et al. 2019b). Cline (2007) reported that future average temperature would increase by 1.1 to 1.6 °C and precipitation would decrease by 30% from 2070 to 2099 in Turkey, which will decline the agricultural productivity by 11.8%. Increasing temperatures generally accelerate the phenological events and shorten the growth period (Lobell and Ortiz-Monasterio 2006; Hennessya et al. 2008). High temperatures were found to decrease the growing season length, which decreased the wheat yield by reducing the light interception, grain number, and size (Wheeler et al. 1996b; Asseng et al. 2015; Ahmed et al. 2019). Özdoğan (2011) reported that wheat yield will decline between 12 and 20% during 2040–2060 in northeastern Turkey due to 2 °C rise in temperature and 35% decreased in precipitation.

Crop growth models have been used as reliable tools to study the impact of climate change on crop yield (Jones et al. 2003; Olsson et al. 2005; Challinor et al. 2010; White et al. 2011; Rosenzweig et al. 2013; Ewert et al. 2015; Ahmad et al. 2018b; Rahman et al. 2018) by considering the interaction of soil, plant genetics, and environment in simulating crop yield (Jones et al. 2003). The CERES-wheat model is under decision support system for agro-technology transfer (DSSAT) shell (Jones et al. 2003; Xiong et al. 2007; Boote et al. 2011; Hoogenboom et al. 2015; Nasim et al. 2016a). The CERES-wheat model is a comprehensive computer model that has been widely for climate change impact studies (Travasso and Delécolle 1995; Iglesias 2006; Lobell and Ortiz-Monasterio 2006; Alganci et al. 2015). Global circulation models (GCMs) and representative concentration pathways (RCPs) provide useful information regarding uncertainly in climate change (Fenech and Comer 2013). The downscaling of GCMs is performed to estimate higher resolution climatic projections (Gaur and Simonovic 2019)

Recent studies have looked at the impact of climate change in Turkey. Özdoğan (2011) used the dynamic process–based model (AFRC2) and experimental data to evaluate the impact of climate change on wheat. Dudu and Çakmak (2018) used the computable general equilibrium (CGE) model and experimental data to assess the impact of climate change on wheat using B1 scenarios, and Dogan and Karakas (2018) used the statistical approach to study the impact of climate change. However, to date, no study has evaluated the impact of climate change at farmer field levels under RCP 4.5 and 8.5 for midcentury and end-century using CERES-wheat. Therefore, the main goal of this study was to evaluate the impacts of climate change at farm levels using the CERES-wheat model under RCPs 4.5 and 8.5. The climate change impact assessment will provide useful information to the stakeholder and a scientific basis for the development of adaptation measures

Materials and methods

Study site

The study was conducted in Nurdagi (36° 40′ N; 36° 54′ E) and Islahiye (37° 11′ N; 36° 57′ E) in the Gaziantep province of Turkey (Fig. 1). The total area under cultivation was 23 thousand ha in Nurdagi and 25 thousand ha in Islahiye during the year 2017 (Turkish Statistical Institute 2017). The recorded mean maximum temperature for 2017 was 22.23 °C, and the minimum temperature was 11.05 °C. The total rainfall for 2017 was 737 mm in Nurdagi and 791 mm in Islahiye. The major crop that grows in study regions is wheat, and other crops are red pepper, sugarbeet, maize, and cotton.

Survey data collection

Survey data of eight farms were collected from the area of interest. The survey data of six farms (TUKU, TUKO, TUMA, TUSE, TUBI, TUCE) were collected from the Islahiye region, while the survey data from another two farms (TUSA, TUGO) were collected from the Nurdagi region as shown in Fig. 1. Survey data included crop management, initial conditions, leaf area index (LAI), and wheat phenological events. Crop management data included sowing date, sowing methods, sowing depth, plants m^{-2}, fertilizer and irrigation amount, and harvest date. Crop phenological data (anthesis and maturity days) were also collected from each farms. Initial conditions such as previous crop type, root, and residues weight were also collected. Generally, wheat is planted during the second week of November by the farmers in the study area. Maximum LAI was collected at the peak stage (booting stage) of the crop during the last week of May using a LAI plant canopy analyzer (LAI-2200C, LI-COR). Survey data of each farm were used to create crop management files for the model, following the method used by Ahmad et al. (2015). The collected farm surveyed data were divided into high yielding (TUKU, TUKO, TUMA, TUSE) and medium yielding farms (TUSA, TUBI, TUCE, TUGO). Four farms (TUKU, TUKO, TUMA, TUSE) were used for model calibration while the rest (TUSA, TUBI, TUCE, TUGO) were used for model evaluation (Fig. 1).

Soil data

Physical and chemical characteristics of the soil were recorded for two locations (Islahiye and Nurdagi) at each farm. Five samples were collected randomly for each farm at 0–120 cm soil depth, with 30-cm intervals. The five samples of each

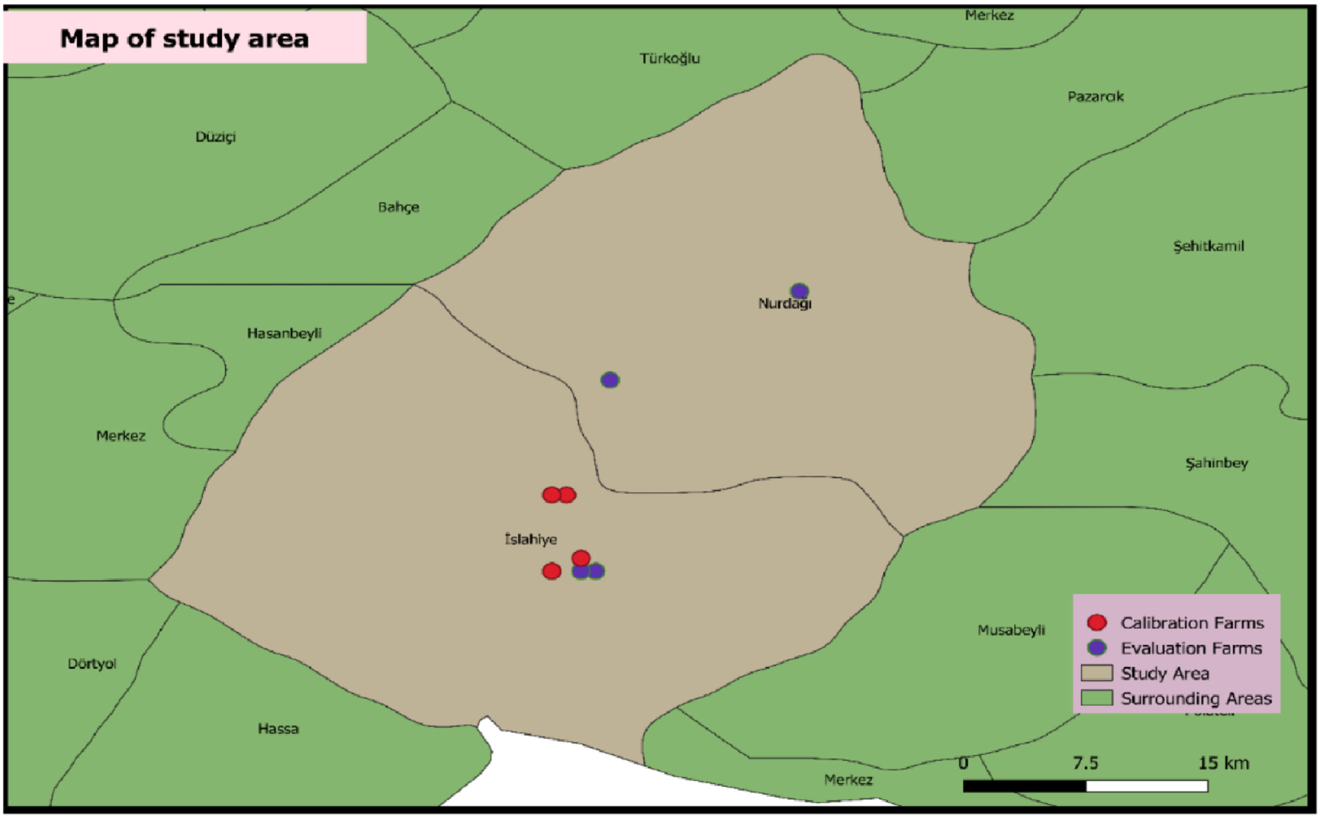


Fig. 1 Map of study area and farms used for model calibration and evaluation

depth were combined to make composite samples. Soil samples for each site were analyzed separately at the research and development analysis laboratory, Yeditepe University, Turkey. The soil physical properties such as sand, silt and clay (%), and chemical properties for potassium, phosphorus (ppm), nitrogen (%), cation exchange capacity (cmol/kg), and organic carbon (%) were analyzed for each depth at all sites. The missing data of organic carbon was calculated from the organic matter divided by 1.7 (Bowman 1997). Soil parameters are presented in Tables 1 and 2. Soil physical and chemical characteristics for each soil were then implemented to create eight soil files for the model. The missing parameters, like drainage upper and lower limit, saturation, bulk density (g cm^{-3}), saturated hydraulic conductance (cm h^{-1}), and root growth factor, were calculated using the statistical software in the model (Rawls et al. 1982; Baumer and Rice 1988). The results indicated that percentage of clay decreased, and silt increased at lower layers of the soil (Tables 1 and 2). More soil organic carbon was found in upper layers of soil and less in the lower layers. The soil pH remained the same in all profiles and sites.

Weather data

Weather data for the study sites were collected from the Turkish state meteorological service during the cropping season (November to June) for the year 2016–2017. (https://mgm.gov.tr) Weather variables include the *T*max (°C), *T*min (°C) precipitation (mm) wind speed (km/hr), relative humidity

Table 1 Soil physiochemical properties of four farms, collected from Islahiye region for model calibration

Farms	TUKU				TUKO				TUMA				TUSE			
Depth (cm)	Clay (%)	Silt (%)	OC (%)	pH	Clay (%)	Silt (%)	OC (%)	pH	Clay (%)	Silt (%)	OC (%)	pH	Clay (%)	Silt (%)	OC (%)	pH
0–30	40.3	14.3	1.0	8.5	39.5	13.3	0.9	8.1	30.6	23.1	0.9	8.3	26.8	24.7	1.0	8.3
30–60	38.6	16	0.9	8.3	37.0	14.1	0.9	8.0	28.9	19.8	0.8	8.2	25.9	25.8	1.0	8.1
60–90	37.8	16.5	0.9	8.1	35.1	14.8	0.9	8.0	26.0	19.6	0.8	8.0	24.0	26.9	1.0	8.0
90–120	36.2	18.9	0.8	7.7	33.9	16.0	0.8	7.5	25.1	18.0	0.8	7.9	22.9	27.0	0.8	7.8

Table 2 Soil physiochemical properties of four farms, collected form Islahiye and Nurdagi used for model evaluation

Farms	TUSA				TUBI				TUCE				TUGO			
Depth (cm)	Clay (%)	Silt (%)	OC (%)	pH	Clay (%)	Silt (%)	OC %	pH	Clay (%)	Silt (%)	OC (%)	pH	Clay (%)	Silt (%)	OC (%)	pH
0–30	56.0	15.4	0.9	8.4	22.0	21.5	1.5	8.0	30.9	23.6	0.9	8.3	46.0	14.1	1.0	8.0
30–60	54.0	14.9	0.8	8.3	20.0	20.7	1.3	8.3	22.0	19.8	0.7	8.3	43.4	17.9	1.0	7.9
60–90	51.0	18.0	0.7	8.1	19.5	18.7	0.8	8.2	20.0	19.8	0.8	8.0	42.9	18.0	1.0	7.4
90–120	48.7	19.8	0.6	8.0	17.0	17.3	0.7	8.0	18.0	16.7	0.6	7.8	40.1	20.6	0.9	7.3

(%), and sunshine hours. Seasonal wheat weather data showed a mean *T*max of 16.67 °C and *T*min of 5.16 °C (Fig.2). The highest rainfall was recorded during the months of January and April as shown in Fig. 2. All the collected weather data were used to create weather file for the model.

Model calibration and evaluation

CERES-wheat under DSSATV4.7.2.0 was used for this study (Hoogenboom et al. 2019). High-yielding farms (TUKU, TUKO, TUMA, TUSE) were used to calibrate the model. The genetic coefficients were adjusted using generalized likelihood uncertainty estimation (GLUE) and the sensitivity analysis tools (Hunt and Boote 1998). Crop genetic parameters related to crop phenology (P1V and P1D) were calibrated first, then growth (P5, PHINT) and yield parameters (G1, G2, G3) were adjusted. The phenological parameters (anthesis and maturity), growth (LAI. max) grain and biological yield (kg ha^{-1}) were used for calibration and evaluation, using method suggested by Ahmad et al. (2018b). The adjusted coefficients were then evaluated with the medium yield farm data (TUSA, TUBI, TUCE, TUGO). The performance of the model was assessed using root mean square error (RMSE) and percent error (% error) between observed and simulated values.

$$\mathbf{RMSE} = \sqrt{\left(\frac{1}{\mathbf{n}}\sum_{\mathbf{i=1}}^{\mathbf{n}}\left(\mathbf{Y}_{Pi}-\mathbf{Y}_{Oi}\right)^{2}\right)} \tag{1}$$

$$\mathbf{Error}\ (\%) = \left[\frac{(\mathbf{P}i-\mathbf{O}i)}{\mathbf{O}i}\right] \times \mathbf{100} \tag{2}$$

where P*i* = predicted value, O*i* = observed value, *n* = total number of observations

Evaluation of climate change impacts

Climate change scenarios generation

Climate projections were generated for the study sites using a regional climate model (RegCM4.3.4) with dynamic downscaling method based on RCP4.5 and RCP8.5 scenarios for mid-century (2036–2065) and end-century (2066–2095). The output of three global climate models (GCMs) HadGEM2-ES, MPI-ESM-MR, and GFDL-ESM 2 M were used as input data as regional climate model RegCM4. The GCMs were downscale to 20 km for study domain, using methodology describes by Demircan et al. (2017). For the quality control of GCMs,

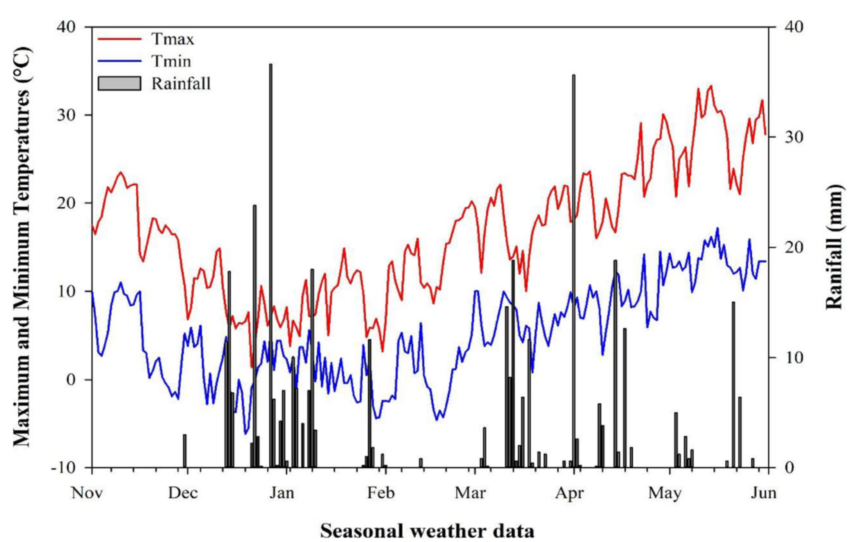


Fig. 2 Seasonal weather data of wheat for the study site during the year 2016–2017

regional model was run with baseline climate data (1980–2010), and results were compared with observed climate data. One-way nesting method was used to downscale from GCMs to study domain. The resolution of HadGEM2-ES is allowing a direct downscaling to 20 km. On the other hand, resolution of MPI-ESM-MR and GFDL-ESM 2 M is not allow directly downscaling. Firstly, MPIESM-MR and GFDL-ESM 2 M were downscaled to 50 km than they were downscaled to 20 km from 50 km outputs. A domain with 20 km horizontal resolution which has 130 × 180 grid-scale and 18 pcs sigma level was used for this study. Cumulus convection parameterization of Emanuel on the land and Grell on the sea was used as convective precipitation scheme for projection study

The CO_2 concentration was used according to the 5th assessment report of IPPC for climate change scenarios (IPCC 2013b) as given in Table 3.

Protocol for evaluation of climate change impacts

The field experimental data of phenology, growth, and yield were used for calibration of CERES-wheat model, and model was further used to assess the impact of climate change. Climate scenarios (RCPs 4.5 and 8.5) for middle and end of century were used to create the climate files for the model. The baseline period of 1981–2010 was taken as observed climate, which was used to compare the future (GCMs) results of simulated yield, following similar baseline periods used by Rosenzweig et al. (2018). The detail methodology is given in Fig. 3. The seasonal analysis in model was run with the different climate scenarios, and the impacts of climate change were calculated from the 30-year mean–simulated yield of future and observed according to the Eq. 3.

$$\mathbf{Y}\boldsymbol{c} = \frac{\mathbf{Y}\boldsymbol{f} - \mathbf{Y}\boldsymbol{b}}{\mathbf{Y}\boldsymbol{b}} \times \mathbf{100} \tag{3}$$

Where, Yc is the percent change in yield, Yf is the future simulated yield of 30 years, while Yb is the bassline yield of 30 years

Table 3 CO_2 centration used for climate change scenarios

Scenarios	CO_2 (ppm)
Baseline (1981–2010)	360
RCP 4.5 mid-century (2036–2065)	486
RCP 8.5 mid-century (2036–2065)	540
RCP 4.5 end-century (2066–2095)	531
RCP 8.5 end-century (2066–2095)	758

Results

Estimated genetic coefficients of wheat

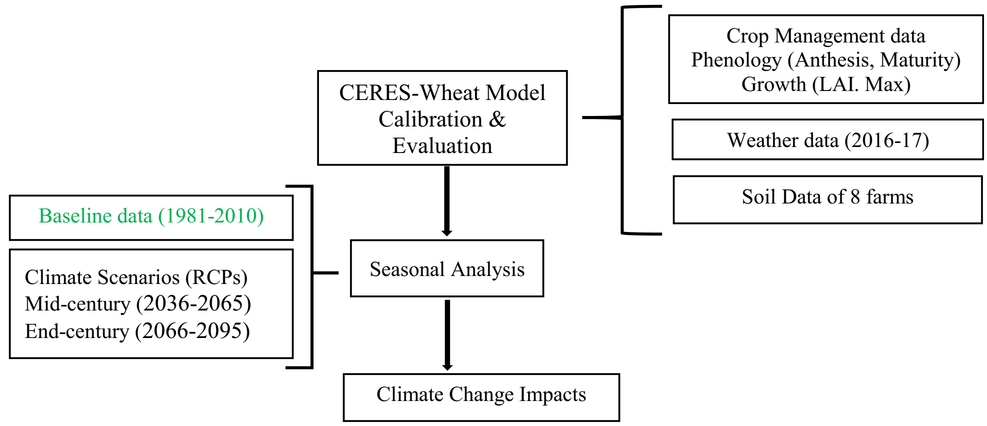
Wheat cultivar genetic coefficients related to phenology, growth and yield were estimated are shown in Table 4. The genetic coefficients PIV and P1D are directly related with the phenology, while G1 and G2 are associated with yield and yield component. The days for optimum vernalization were more because it was winter wheat, which is more sensitive to vernalization. The photoperiodic requirement (PID) and thermal time for grain fillings (P5) were found higher. The compensatory effect was found between G1 and G2. The values of G1 are decreasing with increased in G2. This could be due to fact that available assimilated for fillings are decreased when grain m^{-2} are increased, resulting decrease in individual weight due to competition. The coefficient G3 is related to biomass production and plant height. The PHINT genetic coefficient related the appearance of leaves on the main stem which is called phyllochron interval and it is highly depended on the temperature. The wheat cultivar showed a 60 °C day for this process.

Calibration and evaluation of CERES-wheat model

The calibration of CERES model was good for wheat cultivar Golia with phenological, growth and yield related traits (Table 5), showing a close fit between the observed and simulated anthesis and maturity days. A close agreement was found between observed and simulated values of LAI maximum with error of − 5.21% and RMSE of 0.21. The model tended to underestimate wheat yields with − 11.32% error and RMSE of 586 kg ha^{-1}. Simulations of tops weight were satisfactory, and the observed and simulated values showed a close fit with − 9.56 % error and RMSE of 895.9 kg ha^{-1} as shown in Table 5.

The CERES-wheat model was run with independent dataset of different farms, i.e., TUSA, TUBI, TUCE, and TUGO farms for evaluation. Results indicated that model performed well, as shown in Table 6. Simulated vs observed anthesis days were overestimated by the model by three days, while maturity days only had 1 day of difference. The simulated maximum LAI showed an error of 13.3% and RMSE of 0.56. The crop model slightly overestimated grain yield with an error of 9.45% and RMSE of 461.7 kg ha^{-1}. The model under simulated the biological yield with error of − 8.58% and RMSE of 857.90 kg ha^{-1} as shown in Table 6. Overall results indicated that the crop model was calibrated well and could be used for climate change impact assessment.

Fig. 3 Methodological diagram for evaluating the impacts of climate change on wheat yield



Climate change projections

Projected climate results of three GCMs showed an increasing trend as compared with baseline for *T*max, *T*min, as well in precipitation as shown in Figs. 4 and 5. Mean *T*max was projected to increase by 1.60 °C and 2.29 °C and mean *T*min of 1.32 °C and 1.90 °C under RCP 4.5 and 8.5, respectively, for mid-century, while *T*max of 1.99 °C and 4.16 °C and *T*min of 1.63 °C and 3.45 °C under RCP 4.5 and 8.5 for end-century. The annual rainfall is projected to increase about 115 mm and 124 mm for mid-century under RCP 4.5 and 8.5 in the Islahiye region (Figs. 4 and 5).

The future projections of the Nurdagi region showed that there will be an increase in mean *T*max of 1.72 °C and 2.35 °C and mean *T*min of 0.62 °C and 1.21 °C under RCP 4.5 and 8.5, respectively, for min-century, while *T*max of 2.08 °C and 4.19 °C and *T*min of 0.95 °C and 2.78 °C under RCP 4.5 and 8.5 for end-century. The rainfall is projected to increase about 121 mm and 38 mm for mid-century under RCP 4.5 and 8.5 in Nurdagi region (Figs. 4 and 5). It can be concluded from future projections that *T*max will increase from 1.60 to 2.30 °C, and *T*min from 1.00 to 1.50 °C for mid-century in the south-eastern part of Turkey under RCPs 4.5 and 8.5, while *T*max will increase from 2 to 4 °C and *T*min from 1.30 to 3.10 °C at the end of century (Figs. 4 and 6).

Impact of climate change on wheat

Climate change is projected to reduce yield across all locations for mid and end of century as the result of the increasing temperatures and despite the increases in rainfall. The lowest yields were projected in Islahiye with 16.55% average yield reduction, while the least affected region was Nurdagi, with 13.77% yield reduction (Table 6). Yield reductions tended to be higher under RCP 8.5 with 15.8% average yield decline, due to a higher rise in temperature by mid and end of century as shown in Figures 4 and 5. In case of GCMs, HadGEM2-ES showed a greater reduction in yield as compared with GFDL-ESM 2 M and MPI-ESM-MR for mid and end century. Reduction in mean yield of 15.89% in RCP 4.5 and 16.86% in RCP 8.5 were recorded in mid-century for Islahiye, while end century yield reduction of 16.2% in RCP 4.5 and 17.25% in RCP 8.5 were observed. HadGEM2-ES showed a greater reduction of about 27% in mid-century and 29% in end of century (Fig. 6). In the Nurdagi region, mean yield reductions of 12.94% in RCP 4.5 and 13.23% in RCP 8.5 were recorded for mid-century, with yield reductions of 13.05% in RCP4.5 and 15.87% in RCP 8.5 for end of century (Fig. 7). It was concluded that on average mean yield would be reduced by 16.3% in mid-century and 16.8% by the end of century at Islahiye and in Nurdagi average wheat yield would be reduced by 13.0% in mid and 14.4% at end of the century (Table 7). The variation in yield of both regions under RCP4.5 and 8.5 is

Table 4 Estimated genetic coefficients of wheat under CERES-wheat model

Cultivar	P1V[a]	P1D[b]	P5[c]	G1[d]	G2[e]	G3[f]	PHINT[g]
Golia	28.60	92.58	707.80	28.65	44.15	1.02	60

[a] P1V optimum days for vernalization (days); [b] P1D photoperiodic response, [c] P5 grain-filling duration (°C.d), [d] G1 kernel number/canopy weight at anthesis ($\#\cdot g^{-1}$), [e] G2 grain size under optimum conditions (mg), [f] G3 non-stressed tiller (g dwt), [g] PHINT successive leaf tip appearances interval (°C.d)

Table 5 Calibration of CERES-wheat model at phonology, growth, and yield parameters of wheat at farm levels

Parameters	Observed	Simulated	% Error	RMSE
Days to anthesis (days)	142	140	− 1.40	1.41
Days to maturity (days)	190	189	− 0.52	0.70
Leaf area index maximum	5.7	5.4	− 5.26	0.21
Grain yield (kg ha^{-1})	7321	6492	− 11.32	586.19
Tops weight (kg ha^{-1})	13245	11978	− 9.56	895.90

Table 6 Evaluation of CERES-wheat model at phonology, growth and yield parameters of wheat at farm levels

Parameters	Observed	Simulated	% Error	RMSE
Days to anthesis (days)	152	148	-2.63	2.82
Days to maturity (days)	196	195	-0.51	0.70
Leaf area index maximum	6	6.8	13.33	0.56
Grain yield (kg ha^{-1})	6907	7560	9.45	461.74
Tops weight (kg ha^{-1})	13500	12287	-8.98	857.72

shown in Figs. 6 and 7. The upper lower and quartile range was less in all GCMs at both locations; however, interquartile range was less in few GCMs such as MPI-ESM-MR at Islahiye for end of century under RCP 4.5 (Fig. 6c) and GFDL-ESM 2 M for end of century under RCP 8.5 at Islahiye and Nurdagi (Figs. 6d and 7d)

Discussion

CERES-wheat model is comprehensive computer software, which simulate the phenology, growth and yield (Chisanga et al. 2015). The genetic coefficient parameters were estimated using GLUE. The adjusted values of genetic coefficients were within the ranged of values estimated by Valizadeh et al. (2014). However, higher days to vernalizations (P1V) were due to winter wheat. The compensatory effect exists since decreasing G1 increases G2. This negative relationship could be explained by the fact that the number of available assimilates for filling decreases when the number of grains m^{-2} increases; their individual weight would be reduced because of the competition that is generated among them. Andarzian et al. (2008) and Mubeen et al. (2016) found good statistical indices for the prediction of anthesis and maturity days for wheat in Iran and Pakistan. Wheat phenology influenced the growth and yield. Therefore, accurate estimation of phenological values capture the genotypic variation, development of leaf, dry matter production, and grain yield (Robertson et al. 2002; Nasim et al. 2016a). In the current study, the model predicted growth and yields well with errors ranging from 5 to 11% during calibration at farms level (Table 5). Rezzoug et al. (2008) obtained good results in simulation of wheat yield with RMSE of 510 kg ha^{-1}. The contradiction of results could be due to calibration of the model with farm data. The farmers applied inputs such as irrigation and fertilizers without knowing the phenological stages of the crops, resulted variation in simulated and observed results.

Climate change is a serious threat to agriculture production and food security. Future climate scenarios showed increased temperatures, which are projected to decrease crop productivity (Ahmed et al. 2018). In the present study, three GCMs

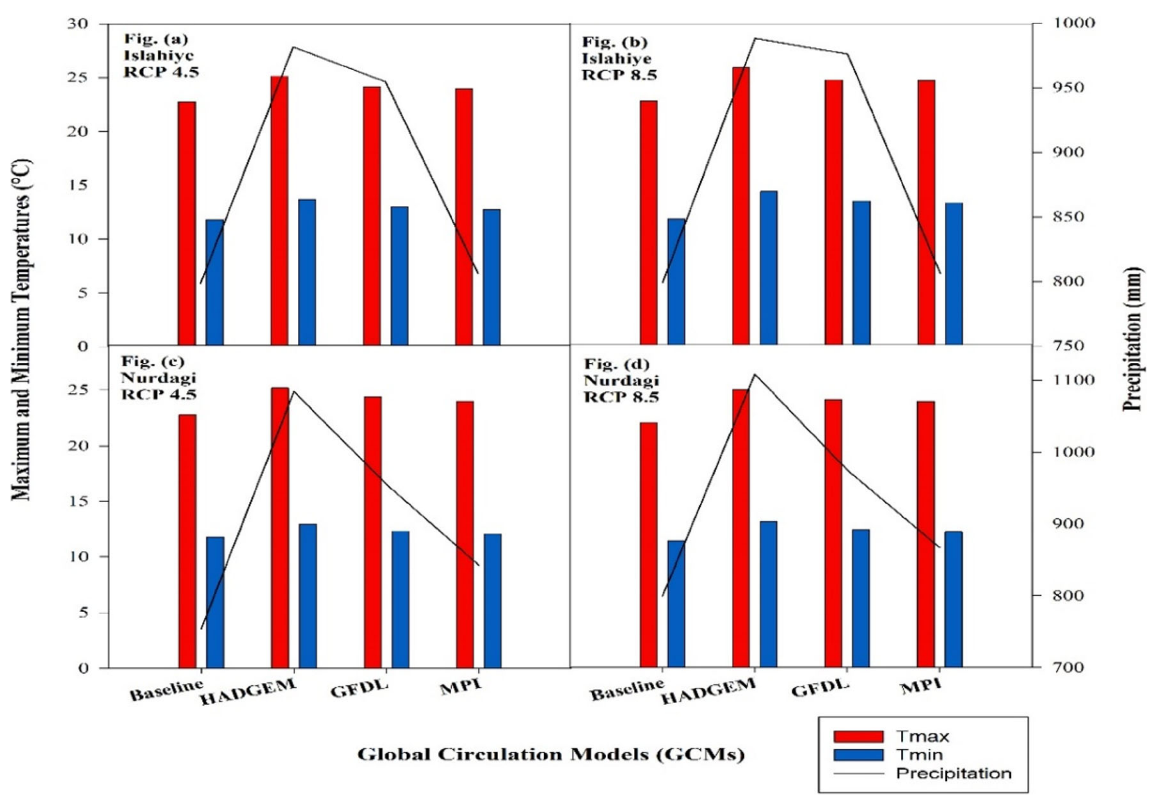


Fig. 4 Climate change projections of GCMs for mid-century under RCP 4.5 and 8.5 for study sites

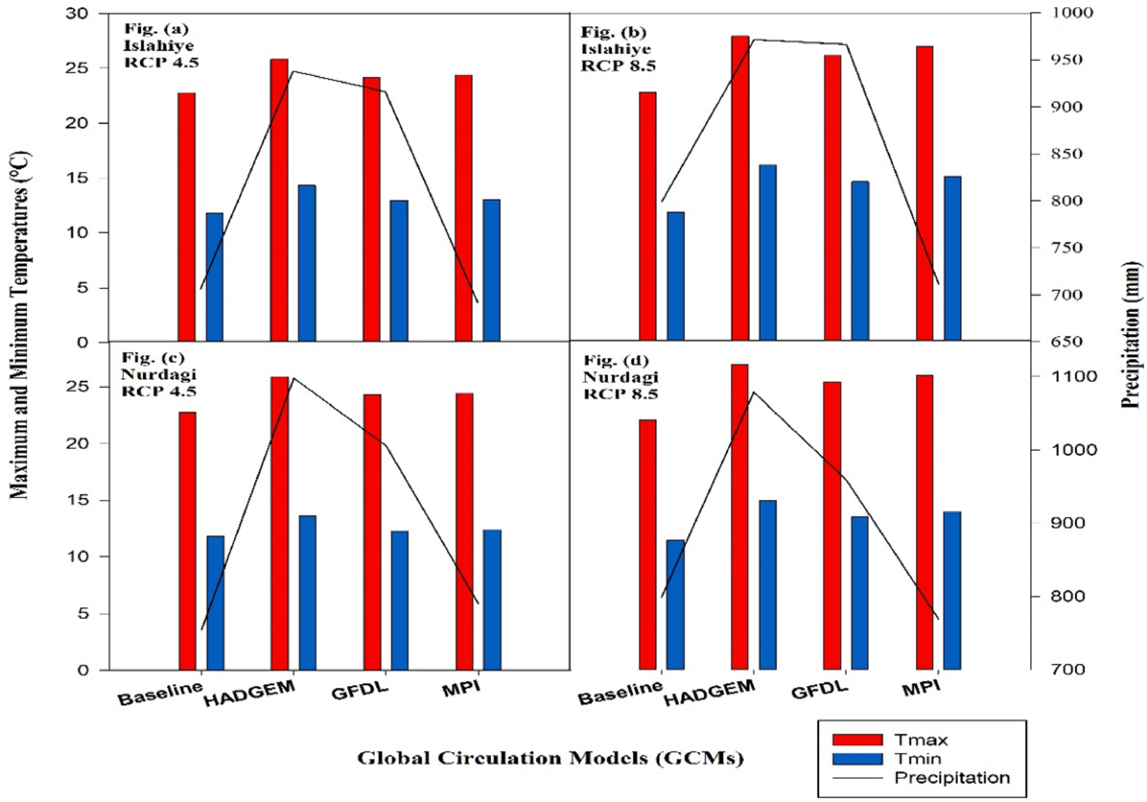


Fig. 5 Climate change projections of GCMs for end-century under RCP 4.5 and 8.5 for study sites

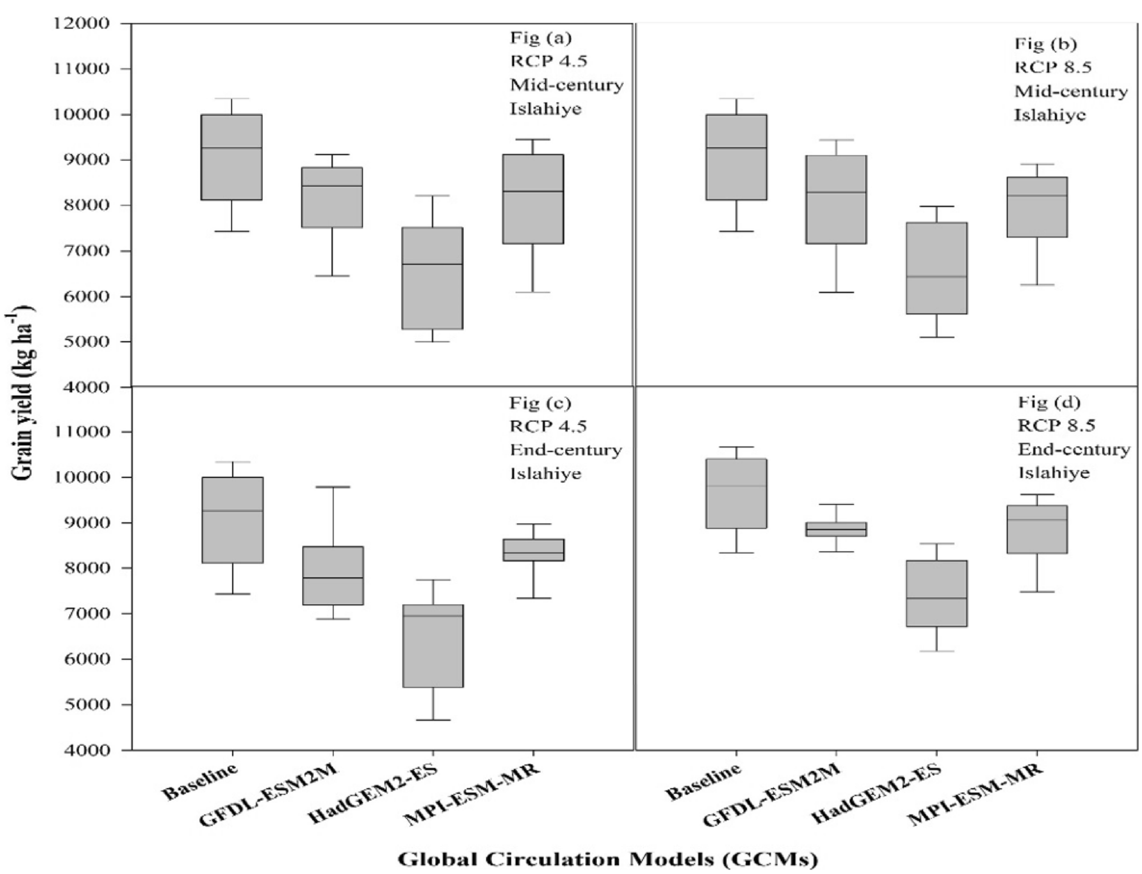


Figure 6 Climate change impacts of wheat under RCP 4.5 and 8.5 for Islahiye

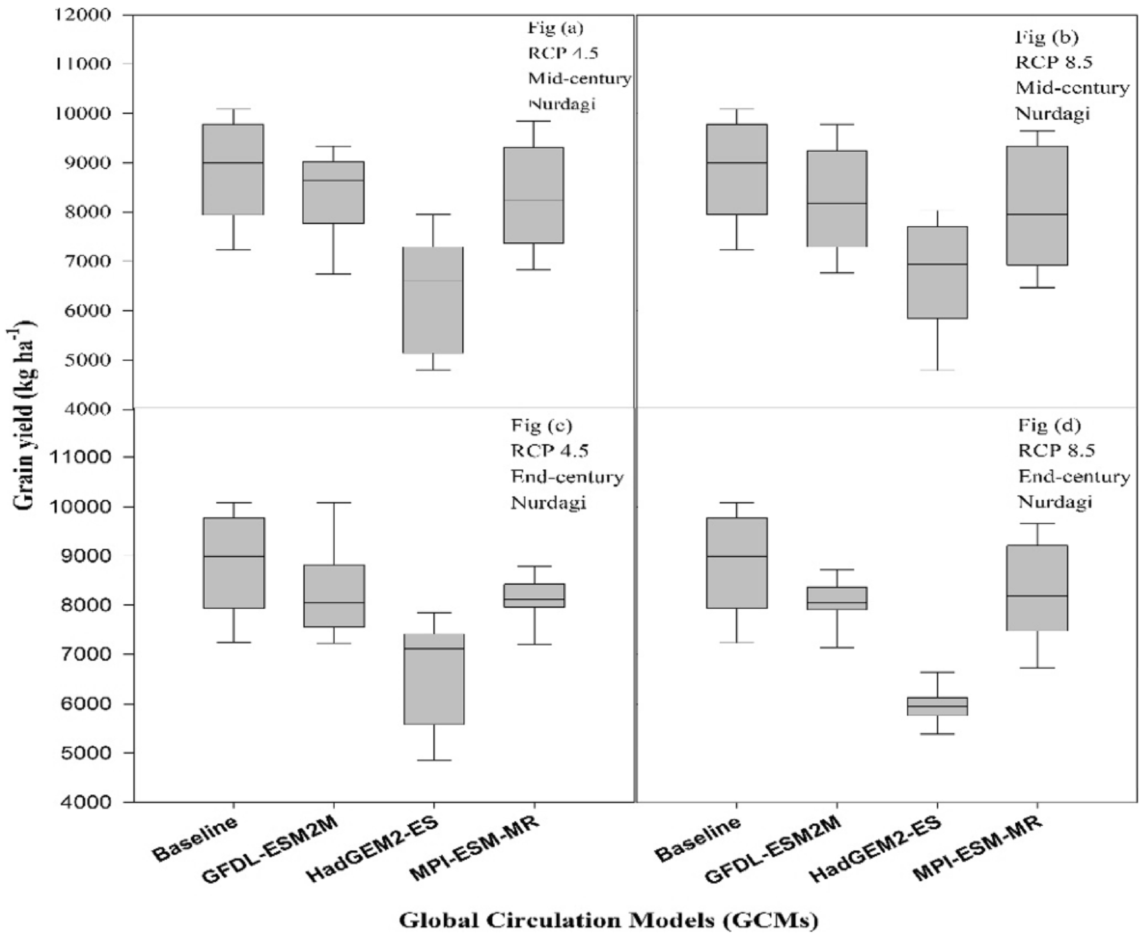


Figure 7 Climate change impacts of wheat under RCP 4.5 and 8.5 for Nurdagi

were used to reduce the uncertainty in climate change projection. The use of multiple GCMs helps to characterize the range of uncertainty in climate change analyses. In current study, dynamic downscaling of GCMs were carried out for climate change projections. The downscaling of GCMs is necessary because it increased the spatial resolution and reduce some of the biases in order to improve the usability of climate scenarios. Future projections showed that *T*max, *T*min, and precipitation are expected to increase for mid and end of century as shown in Fig. 5. Similar findings were reported by Demircan et al. (2017) for climate change projection in Turkey.

Climate change has negative impacts on wheat yield. The current study showed that future rise in temperature decreased wheat yield by about 15% in mid and 16% at end of century. The decreased yield was due to a reduction in growth cycle with an increase in temperature by accumulating degree days faster. Higher temperature reduces the grain size and weight, resulting in a decrease in yield (Wheeler et al. 1996a; Nasim et al. 2016c). High temperature above 32 °C, reduced grain filling duration in wheat that limited the time for grain development (Asseng et al. 2015). In the current study, it was found that an increase in temperature of 1 °C hastened the onset of anthesis by 10 days. Similar findings were reported by (Sayre et al. 1997; Fahad et al. 2015; Waqas et al. 2019) who reported 11 days earlier anthesis. Özdoğan (2011) found that wheat yield would decline by 5 to 35% depending upon the GCMs projections in Turkey. Reduction in yield was not only due to increase in temperature but also to acceleration of the growth process which shortened the grain filling duration. The assessment of climate change provides the information to policymakers to take the timely decision for wheat trades and provide the scientific basis for adaptations.

Conclusion

The impacts of climate change were evaluated by integrating climate and a crop modeling approach. The crop model was calibrated with data from surveyed farms, which showed a good agreement between observed and simulated yield with % error ranging from 1 to 11%. Climate change projection showed that *T*max would increase from 1.6 to 2.3 °C, and *T*min of 1.0 to 1.5 °C for mid-century in the southeastern part of Turkey under RCPs 4.5 and 8.5, while, *T*max would increase from 2 to 4 °C and *T*min from 1.3 to 3.1 °C at the end of

Table 7 Change in wheat yield under RCPs 4.5 and 8.5 for mid and end-century

Scenarios	GCMs	Islahiye		Nurdagi	
		Mid-century	End-century	Mid-century	End-century
RCP 4.5	GFDL-ESM 2 M	− 9.58	− 11.92	− 4.78	− 5.90
	HadGEM2-ES	− 27.49	− 28.26	− 27.7	− 24.66
	MPI-ESM-MR	− 10.59	− 8.43	− 6.33	− 8.58
RCP 8.5	GFDL-ESM 2 M	− 10.73	− 10.41	− 7.18	− 9.22
	HadGEM2-ES	− 27.93	− 30.62	− 23.77	− 32.25
	MPI-ESM-MR	− 11.92	− 10.71	− 8.74	− 6.15

century. Future rise in temperature would reduce the yield of wheat by 16.3% in mid-century and 16.8% at the end of century at Islahiye and 13.0% in mid and 14.4% end of century at Nurdagi under RCP4.5 and 8.5.

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