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ADAPTATION STRATEGIES FOR SUNFLOWER PRODUCTION UNDER CLIMATE CHANGE FOR ARID ENVIRONMENT BY USING CROPGRO AND APSIM-SUNFLOWER MODELS

Muhammad Awais[1], Muhammad Anwar-ul-Haq[1,*], Muhammad Mubeen[2], Javaid Akhtar[1] and Syed Aftab Wajid[3]

[1]Institute of Soil & Environmental Sciences, University of Agriculture, Faisalabad 38000, Pakistan; [2]Department of Environmental Sciences, COMSATS University Islamabad, Vehari Campus, Pakistan; [3]Department of Agronomy, University of Agriculture, Faisalabad, 38000, Pakistan
[*]Corresponding author's e-mail: haqgondal@gmail.com; haq.gondal@uaf.edu.pk

Sunflower is one of the most cultivated oil seed crop in the world. Hence, the adaptation strategies for sunflower production and food security are crucial for mitigating the negative impacts of climate change. The experiments were conducted for two years to assess the climate change impacts and developing suitable adaptation strategies for sunflower in the arid environment. The CROPGRO and APSIM-Sunflower models were calibrated and evaluated with an observed experimental data among the best sowing dates at1st January with nitrogen @ 240 kg ha^{-1}. Where root mean square error (RMSE) between observed and simulated achene yield was 121.16 and 167.91 respectively. The future climate projections under the Representative Concentration Pathway (RCP)-8.5 for years 2040-2069 were obtained from the Global Climate Model (GCMs). The increase in maximum and minimum temperature by 3.5ºC and 4ºC with 30% less precipitation was observed under hotdry climate conditions. The simulations with these projected temperatures decreased achene yield 6 to 24% with the CROPGRO model and 8 to 28% with the APSIM-sunflower model with current agricultural practices in mid-century (2040-2069). The models simulate more achene yield 20% by CROPGRO and 18% by APSIM-Sunflower with the adaptations measured on current agricultural practices to mitigate the impact of climate change. For all GCMs, 11-20% achene yield would be increased with these adaptation measures in mid-century. Therefore, the improved crop genetic (phenology) and agronomic practices for sunflower as an adaptation strategy could mitigate the impacts of climate change.
Keyword: CROPGRO, APSIM-Sunflower, sowing dates, nitrogen, GCMs.

INTRODUCTION

Climate plays an important role in the agriculture production system as an abiotic factor. The vulnerability in climatic conditions increase in the duration, frequency, and intensity of temperature (Abid *et al.*, 2016; Abbas *et al.*, 2017). The projections show high risk to agriculture in warmer environmental conditions; while, the temperate region may take benefits from this climate change (Fahad and Wang, 2018). In the agriculture sector, the crop yield varies annually due to the dependence of the agriculture system to climate. The climatic projection based on previous data shows that the crop production increase in northern areas and decreases in southern region (Ongoma and Chen, 2017). The increasing CO_2 concentration in the atmosphere due to anthropogenic activities on the earth plays an important role in global warming that affects crop production and global food supply in all over the world (Nasim *et al.*, 2016). The increasing atmospheric temperature affects significantly achene filling duration and achene weight due to early maturity in sunflower (Li *et al.*, 2014). The quantity and quality of sunflower oil are affected by variability in temperature and moisture (Kaleem and Ahmad, 2011). The plant phenology and yield significantly affected by this changing climate. The different management and adaptation strategies reduce the impact of climate change on crops (Ahmad *et al.*, 2020).

Sunflower is an oilseed crop widely cultivated under varied climatic conditions in the world (Canavar *et al.*, 2010). Its higher adaption capacity provides better growth and yield as compared to other non-conventional oilseed crops. It is mainly cultivated for human food and livestock feed as oil and seed cake respectively (Agele, 2003). Its oil production ranks in 4th position at world level (Govt. of Pakistan, 2017; Amin *et al.*, 2017; Nasim *et al.*, 2018). Its growth may significantly be affected by different management factors like irrigation, plant time, fertilizer rate, plant population (Awais *et al.*, 2015). The phenological period and development might be affected due to global warming. The climate change reduces the phenological period of various species (Jing *et al.*, 2016; Nasim *et al.*, 2017). The increase in observed temperature has accelerated phenological stages in which reduced the length of growing season of crop (Abid *et al.*, 2016).

Pakistan is one of the most vulnerable countries to climate change due to the semi-arid and arid climate, so projection shows temperature increase sharply in Pakistan as compare to other countries (Ahmad *et al.,* 2017a, b). The average temperature will increase from 1.4 to 5.8°C till 2099 (IPCC, 2014). The historic studies of data from 1961 to 1990 showed that the rate of precipitation increase +3.0 to +4.5% and temperature enhanced 0.3 to 0.6° C which shows that the increasing concentration of temperature, timing, frequency and intensity of precipitation which are a key factor of climate change (Challinor *et al.,* 2009; IPCC, 2014). The climate variability significantly affects the crop yield (Fraga *et al.,* 2016). Hence, the changes in phenology and a plant's adaptive responses over time indicate the impact of climate change (Wang *et al.,* 2017).

Crop models are used to assess the effect of agronomic practices and interaction with the environment. These models are the most powerful tool for assessing the impact of spatial and climatic variability studies to reach conclusions (Jalota *et al.,* 2006). The CROPGRO and APSIM-sunflower model used the Representative Concentration Pathway (RCP) scenarios to assess the climate change impacts (Sun *et al.,* 2016; Jin *et al.,* 2017). The latest attention of crop modeling is the combined assessment of climate change risks by Global Circulation Models (GCMs) to simulate future climate data (Amin *et al.,* 2017, Amin *et al.,* 2018). The statistical downscaling of GCMs is used to assess the climatic risk for decision making at a regional scale (Bentsen *et al.,* 2013). The impacts of climate change are assessed by multiple GCMs and crop growth models used to assess because the response of climate and crop models varies widely (Corbeels *et al.,* 2018; Fronzek *et al.,* 2018). The different reports have showed that the different crop models and climatic scenarios were used to evaluate the climate change impacts on sunflower (Perez *et al.,* 2014; Wang *et al.,* 2017).

However, in this study we assessed the climate change impacts with and without adaptation on sunflower in mid-century (2040-2069). This experiment aimed to develop effective adaptation measures to mitigate the negative climatic impacts on sunflower. The novelty of this study can assist policymakers in the decision making process for sunflower production in arid environment of Punjab-Pakistan. Hence, the objectives achieved were (1) to assess the climate change impacts on sunflower achene yield under RCPs 8.5 in mid-century (2) development of adaptation measures in the future to mitigate the negative impacts of climate change on sunflower achene yield.

MATERIALS AND METHODS

***Experimental Site*:** The field experiments were conducted during 2018 and 2019 consecutively at COMSATS University Vehari Campus, Pakistan (North 30° 03" East 72° 31" 136 m alt.). Each year before the sowing of the crop, the composite soil sample to the depth of 30 cm were obtained from the experimental sites with a soil auger. The samples were analyzed for their further physio-chemical properties (Table 1). The climatic condition was arid having annual rainfall less than 125 mm. The meteorological data were gathered from the nearest Meteorological Observatory in Vehari are presented in Fig. 1.

Table 1. Soil physical, hydraulic and chemical properties of the experimental site.

Soil properties	2018	2019
Soil type	Sandy Loam	
Sand (%)	60.10	60.10
Silt (%)	26.10	26.00
Clay (%)	13.80	13.90
Saturation (%)	37.08	38.54
Field Capacity (%)	18.54	19.27
OM (%)	1.15	1.17
Soil pH	8.10	8.20
EC (d Sm^{-1})	2.91	2.99
Nitrogen (%)	0.052	0.054
Available Phosphorus (mg kg^{-1})	7.58	7.61
Available Potassium (mg kg^{-1})	163.74	167.29

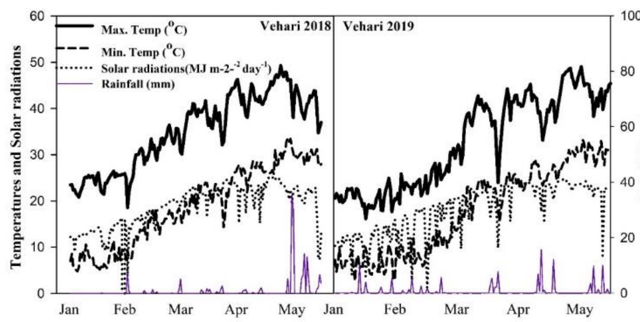

Figure 1. Monthly meteorological data of the experimental site

***Models calibration, Evaluation, and Statistics*:** The experiment comprised of four sowing dates (1st January, 16th January, 31st January, and 15th February) and three nitrogen levels (160 kg ha^{-1}, 200 kg ha^{-1}, 240 kg ha^{-1}). The crop sown on 1st January at 240 kg ha^{-1} was used to calibrate the simulation models due to the best comparative growth. After the simulation, the combination of newly developed genetic coefficients for phonology, growth, and yield were evaluated by different statistical indices as described by Hunt and Boote (1998).

After calibration, the CROPGRO model and APSIM-Sunflower model were evaluated with other treatments in 2018 and 2019 at both locations. The different statistical indices were used to assess the accuracy and reliability of these models. The root mean square error (RMSE) and mean percent difference (MPD) as described by Loague and Green (1991) were commonly used to calculate the deviation during calibration and evaluation of the model. It was used to compare the variable having the same units. The normalized root mean square error as described by Willmott (1981) used to calculate the deviation between observed and simulated data. Many researchers recommended this equation to compare the observed and simulated data (Moriasi *et al.*, 2007). The index of agreement (d) (Willmott *et al.,* 1985) was used to measure the performance of models. If the value of "d" closer to 1, it means the model's results are reliable. In all the equations, the "n" shows number of variables, Pi and Oi is the simulated and measured observation.

$$RMSE = \left[\sum_{i=1}^{n} (P_i - O_i)^2 / n\right]^{0.5} \quad (1)$$

$$NRMSE = \left[\frac{RMSE}{O_{i\,max} - O_{i\,min}}\right] \quad (2)$$

$$MPD = \left[\sum_{i=1}^{n} \left\{\frac{|Oi - Pi|}{Oi}\right\} \times 100\right]^{0.5} / n \quad (3)$$

$$\text{Error}\ (\%) = \left(\frac{(P-O)}{O}\right) \times 100 \quad (4)$$

$$d = 1 - \left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(|Pi| + |O_i|)^2}\right] \quad (5)$$

Climate change projection and adaptation: The climate change impacts on sunflower growth and yield were assessed by using CROPGRO and APSIM-Sunflower model. The baseline period consisted of 30-year weather data and 360 ppm CO_2in the atmosphere. The observed meteorological data was available for Vehari for a baseline period from (1980-2010).

The climate scenarios for the study sites generated by selecting the suitable GCMs from the CMIP5 under RCP 8.5 were calculated for future climate (2040-2069) to the current climate (1980-2010) and 936 ppm CO_2 concentration was used (Taylor *et al.*, 2012). The uncertainty in projected temperature and rainfall based climate characteristics such as hot/wet, hot/dry cool/wet, cool/dry and middle were presented by using five selected GCMs (Table 2). The change in monthly mean temperature and rainfall were calculated and compared with the 30-year future with baseline climate to generate mean and variable scenarios.

Table 2. Selected GCMs for mid-century under RCP8.5 for Vehari-Punjab-Pakistan.

Sr.	Climatic characteristic	GCMs	References
1	Hot/wet	IPSL-CM5A-MR	Wen *et al.,* 2016
2	Hot/dry	CMCC-CM	Perez *et al.,* 2014
3	Cool/wet	CESM1-BGC	Jin*et al.,* 2017
4	Cool/dry	inmcm4	Volodin *et al.,* 2010
5	Middle	NorESM1-M	Bentsen *et al.,* 2013

The monthly change and standard deviation data of baseline were also compared with future climate. The stretch distribution approach was used to applying the calculated monthly changes to baseline (Ruane *et al.,* 2015). While the solar radiations, wind speed were considered to remain the same. Finally, the climate scenarios were generated from the experimental sites for the mid-century under RCPs 8.5 by using selected GCMs. The different management measures and virtual genotype were developed by altering the genetic coefficients as adaptive measures which could possibly counterpoise the impacts of climate change (Table 3). The detail methodological framework for the calibration, evaluation, climate change impact and adaptation for sunflower are shown in Figure 2.

Table 3. The adaptation package used for climate change impact assessment on sunflower.

Adaptations	Specific Practices	Increase
Agronomic adaptation	Soil fertility	10 %
	Early Sowing	15 days
	Plant Population m^{-2}	10 %
	Organic matter	10 %
Virtual Genetics (Cultivar)	Achene Weight	10 %
	Heat/Temperature Tolerance	2ºC
	Radiation Use Efficiency	10 %
	CO_2 Response Curve	15 %

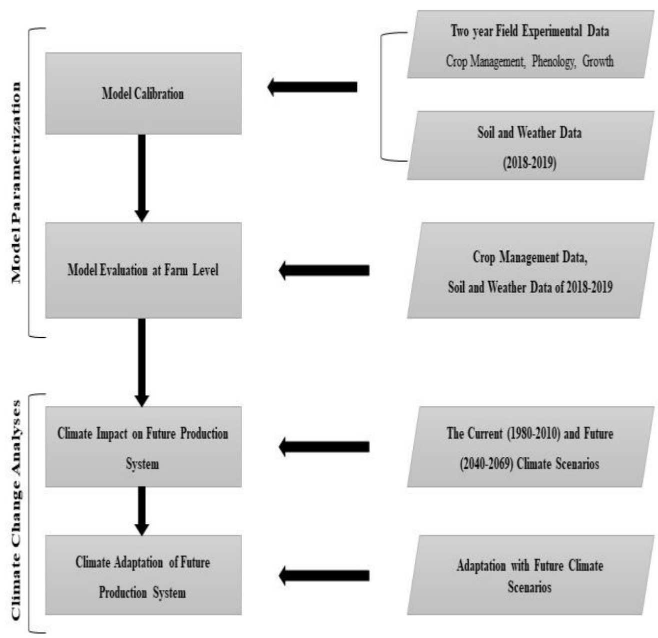

Figure 2. Methodological framework for climate change impact and development of adaptation for sunflower.

RESULTS AND DISCUSSION

***Model Calibration and Evaluation*:** The CROPGRO and APSIM-Sunflower models were calibrated and evaluated with an observed experimental data among the best sowing dates @ 1st January with N @ 240 kg ha^{-1}. The data

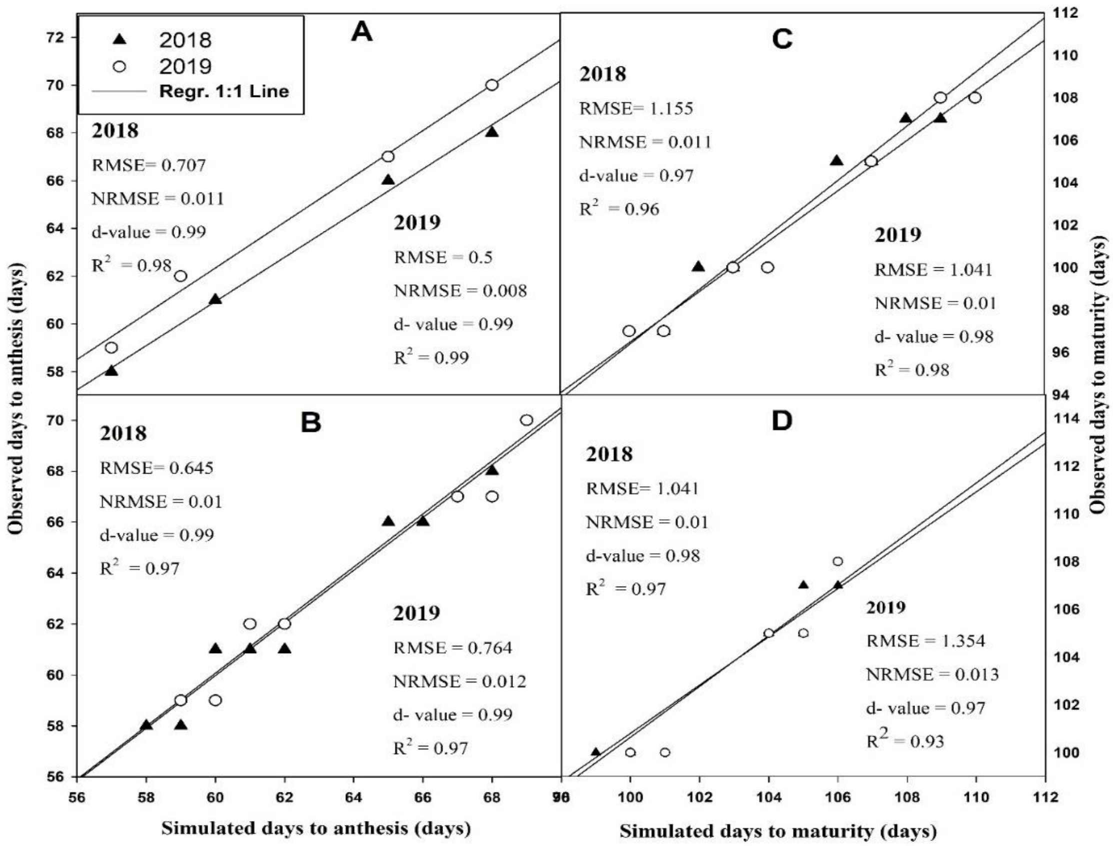

Figure 3. Performance of CROPGRO Model (A) and APSIM-Sunflower Model (B) for days to anthesis and CROPGRO Model (C) and APSIM-Sunflower Model (D) for days to maturity during both years (2018 and 2019).

presented in Figure 3 show the difference between the calibration and evaluation between the simulated and days to anthesis and maturity. In calibration, the CROPGRO model predicted the same days to anthesis (70) and maturity (108); while, the APSIM-Sunflower model predicts fewer days to anthesis (69) and maturity (106). The models evaluated results showed the accuracy of the calibration. It was noted that the CROPGRO model observed RMSE 0.705, 0.50 for days to anthesis and 1.155, 1.041 for maturity. While the RMSE observed by APSIM-Sunflower model for days to anthesis was 0.645, 0.764 and for maturity was 1.041, 1.354 during year 2018 and 2019.

Similar results were observed previously (Sun *et al.*, 2016; Tung *et al.,* 2018; Urban *et al.,* 2018) who found a good accuracy in simulations. The difference between simulated and observed value by CROPGRO model and APSIM-Sunflower model was due to change in weather parameters, growing season, planting dates, simulation function of crop model and time to time variation (atmospheric temperature and crop temperature). The performance of the model to quantify the effect of the factors affected due to these large uncertainties (Asseng *et al.,* 2015; Wang *et al.,* 2017). Two days difference was observed between simulated and observed days to anthesis and maturity (Nasim *et al.,* 2016; Nasim *et al.,* 2017). The different climatic conditions and growing seasons showed different results at different sowing dates but overall results showed similar trends (Maiorano *et al.,* 2017; Fronzek *et al.,* 2018). These models simulate under or over results compared to observe value might be due to the sensitivity to field management practices or environmental conditions (Jalota *et al.,* 2006; Amin *et al.,* 2018).

The results showed that the models over simulated the LAI (Fig. 4). The CROPGRO model simulates 1.58 % and APSIM-Sunflower simulate 2.48 % more LAI during the calibration. The evaluation of models for LAI was also good. The observed RMSE between observed and simulated LAI were (0.196 and 0.142) and d-value (0.91 and 0.95) by CROPGROW model and (0.258 and 0.1666) and d-value (0.87 and 0.94) by APSIM-Sunflower model. The minimum RMSE showed that models well-calibrated (Sun *et al.,* 2016). Nasim *et al.* (2016) also reported that the models have good RMSE in simulating LAI. The estimation of LAI by multi-model is a good approach rather than single for

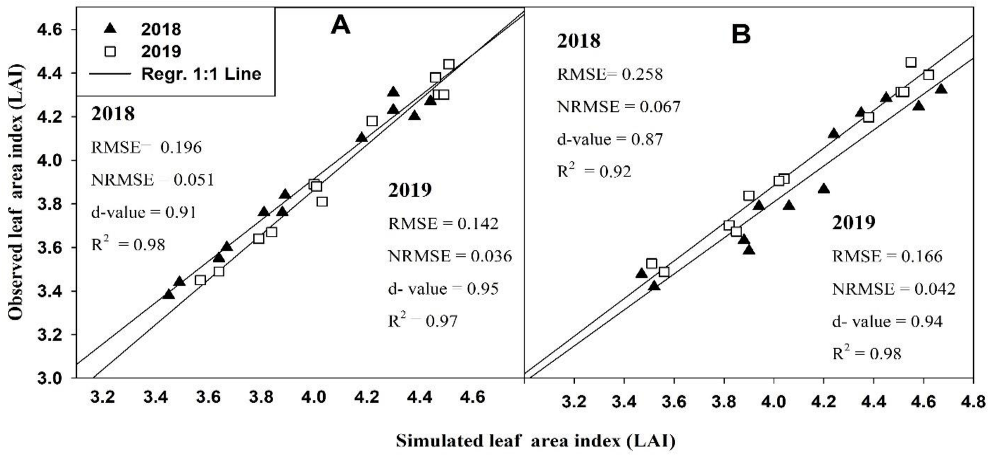

Figure 4. Performance of CROPGRO Model (A) and APSIM-Sunflower Model (B) for leaf area index (LAI) during both years (2018 and 2019).

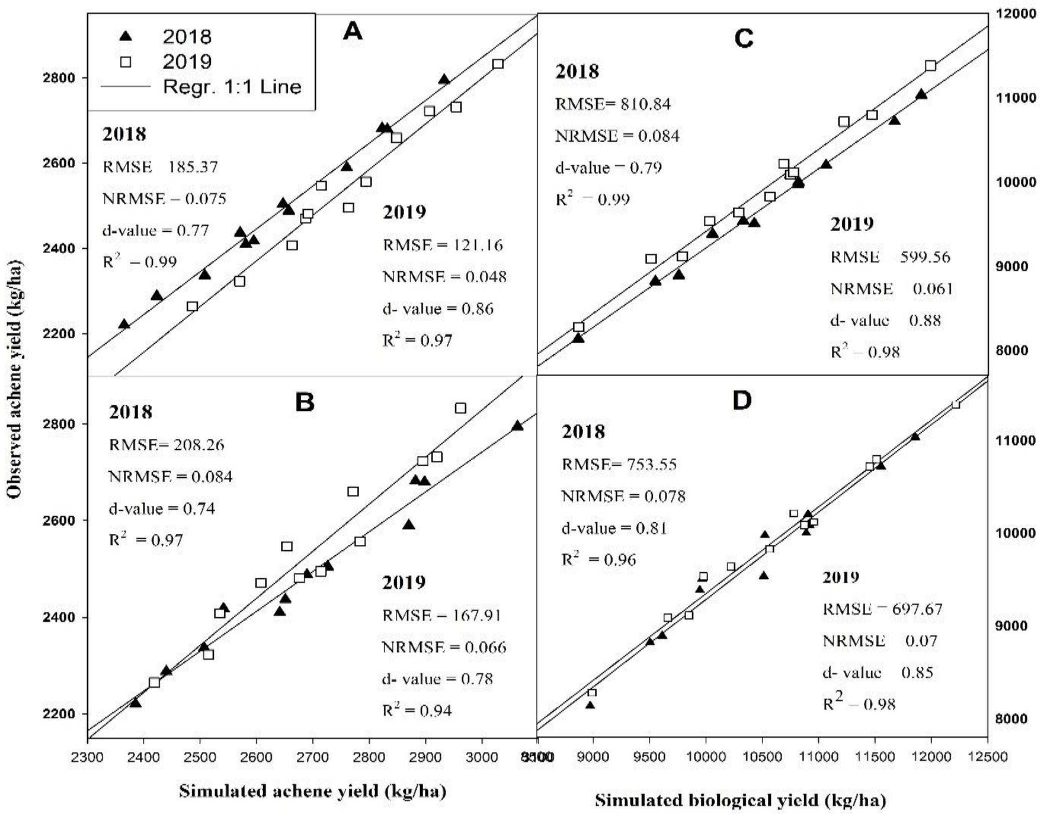

Figure 5. Performance of CROPGRO Model (A) and APSIM-Sunflower Model (B) for achene yield (kg/ha) and CROPGRO Model (C) and APSIM-Sunflower Model (D) for biological yield during both years (2018 and 2019)

better results (Tung *et al.*, 2018). The good agreement between simulated and observed value showed that the CROPGRO and APSIM-Sunflower are helpful devices to assess the impact of climate change (Singh *et al.*, 2016; Zeng *et al.*, 2016; Malik *et al.*, 2018). The Battisti *et al.* (2017) reported R2 > 0.60 and d > 0.82 for soybean by using CROPGRO and APSIM-Sunflower model.

Similarly, the models calibrate well the achene yield and biological yield (Fig. 5). The results showed that the CROPGRO model simulates 3.35% more achene yield and 5.31% biological yield. While, the APSIM-Sunflower model simulates the 4.55% more achene yield and 7.33 %

Table 4. Change in annual mean in climate projections for mid-century (2040-2069)under RCP8.5.

Scenarios	Hotwet	Hot dry	Cool wet	Cool dry	Middle
Change in Maximum Temperature	2.9	3.5	2.9	2.7	1.9
Change in Minimum Temperature	3.9	4.0	2.9	2.7	2.9
Change in Precipitation	1.6	-0.3	-0.5	-0.3	0.6

biological yield. The model evaluation results show the accuracy of the calibrated model. The high RMSE and NRMSE were observed in 2018 compared to 2019. The coefficient of determination (R2) between observed and simulated achene yield by the CROPGRO model and APSIM-Sunflower model were (0.99 and 0.97) and (0.97 and 0.94) respectively. The results showed that the CROPGRO model performed better compared to the APSIM-Sunflower model. The CROPGRO model and APSIM-Sunflower model can predict the biological yield and achene yield (Bao *et al.,* 2015; Jing *et al.,* 2016). The minimum gap between observed yield and simulated yield showed the accuracy of models (Abid *et al.,* 2016). The RMSE of estimated crop yield was 548 by the CROPGRO model and 550 by the AMSIP model and the performance of these models were assessed by the low value of RMSE (Battisti *et al.,* 2017). Bao *et al.* (2015) found a similar trend to simulate the biological yield and the highly accurate simulation for yield was also found. Amin *et al.* (2018) reported that the CROPGRO model was used at a regional scale for climate change impact assessment.

Future Climate Projections**:** The change in climate projections under RCP8.5 for sunflower is given in Table 4. The results showed that the positive increase in the maximum and minimum temperature and the strong fluctuation in precipitation were observed in the selected region as a global trend. Under hot drying conditions, the highest maximum and minimum change temperatures were recorded (3.5 and 4ºC). Although the minimum change in the maximum and minimum temperature (1.9 and 2.9ºC) was recorded under the Middle conditions of RCP8.5. The results showed that the maximum reduction in precipitation (150 mm) was observed in the cool wet and increased (160 mm) in hot wet conditions in RCP8.5. The increasing concentration of CO_2 is one of the main reason for the increasing temperature in the future. Ahmad *et al.* (2020) showed a similar trend for Faisalabad from 1951 to 2000, up to 1ºC increase in the annual mean temperature was observed (Perez *et al.,* 2014; Ongoma and Chen, 2017). A non-significant change in rainfall and the maximum projected increase in temperature was 4.8ºC reported previously (Iqbal and Zahid, 2014). More rainfall in hot wet conditions might be due to the warmer air temperature carrying more moisture (Ruane *et al.,* 2015).

Effect of Climate Change and Adaptation**:** The impact of the evolution of climatic scenarios on sunflower productivity is illustrated in Figure 6. The simulated achene yield by models with baseline (1980-2010) compared to the future climate change scenarios for mid-century (2040-2069) under RCP8.5 showed different trends. All GCMs have shown a reduction in achene yield. The results of the CROPGRO model and APSIM-Sunflower model showed that the maximum reduction was observed in achene yield were (24% and 28%) under hot drying conditions (Table 5). The cool wet climate scenarios showed the maximum reduction (16% and 17%) in cool climatic conditions. a similar trend was shown by other GCMs. While, the GCM Middle shows a minimal reduction in (6% and 8%) compared to baseline, respectively. While, virtual cultivar and agronomic adaptation increased achene yield up to 20% compared to current cultivation practices (Fig. 6). The results showed that the CROPGRO model and APSIM-Sunflower model increased (20 and 18%) achene yield with GCM Middle and the minimum increase (12 and 11%) were observed in cool dry climate.

Table 5. Yield change with adaptation compared to without adaptations in mid-century (2040-2069).

Model	Global Climate Models (GCMs)	Crop Yield without adaptations	Crop Yield with adaptations
CROPGRO	Middle	0.94	1.20
	Hot wet	0.79	1.13
	Hot dry	0.76	1.14
	Cool wet	0.84	1.13
	Cool dry	0.88	1.12
APSIM-Sunflower	Middle	0.92	1.18
	Hot wet	0.77	1.11
	Hot dry	0.72	1.12
	Cool wet	0.83	1.12
	Cool dry	0.86	1.11

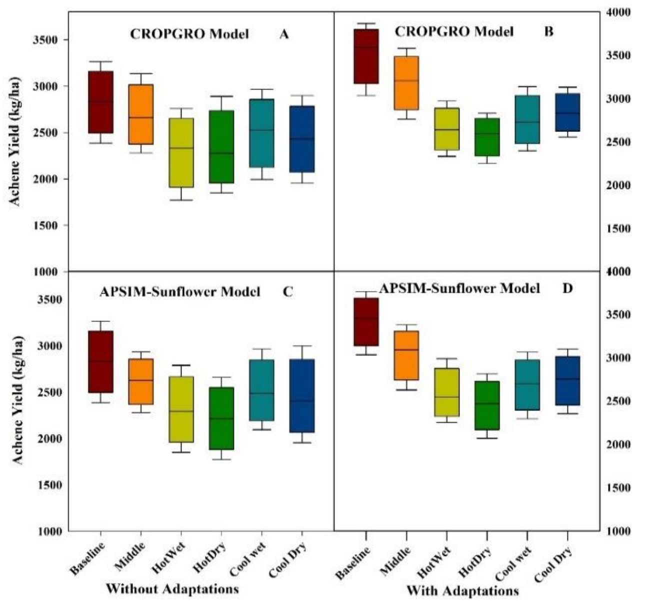

Figure 6. Climate change impact on achene yield at Vehari during Mid-Century 2040-2069.

Pakistan is one of the most vulnerable country to climate variability. Climate variability is a potential threat to crop yield (Malik *et al.,* 2012; Fahad and Wang, 2018). The Crop growth, development, and yield especially the reproductive stage are fragile to temperature (Fang *et al.,* 2015; Dreccer *et al.,* 2018). A 2ºC degree increase in temperature decrease 5 days of maturity. The phonological period decreases when the temperature exceeds 25ºC and achene yield decreases when the temperature increases from 30ºC (Schlenker and Robert, 2006). The plant phonological period decreased by increasing maximum and minimum temperature which plays an important role in crop yield (Nahar *et al.,* 2015). The crop yield significantly reduces due to increasing atmospheric temperature. The early maturity of the crop reduces biological yield and less achene filling duration due to increasing temperature reduces the yield worldwide (Awais *et al.,* 2015). The decreased water availability and increased atmospheric temperature decrease the crop phenological period (Sun *et al.,* 2016). The reduction in achene yield due to less achene fill period and weight in high atmospheric temperature is the main reason for less achene yield (Fraga *et al.,* 2016; Schauberger *et al.,* 2017).

Climate vulnerability can potentially be managed by proper adaptation measures (Wu *et al.,* 2016). The early planting dates may provide longer phonological period which may be helpful to reduce the losses in yield due to short crop phonological cycle (Shimono, 2011; Shrestha *et al.,* 2016).The soil organic matter and soil fertility help plant growth by improving water holding capacity and providing nutrients (Jalota *et al.,* 2006). The increasing plant population m^{-2} efficiently use nutrients from the soil and reduced the gap between observed and simulated yield (Awais *et al.,* 2015). The increasing CO_2 concentration increased the rate of photosynthesis in crops (Bishop *et al.,* 2018). The improved radiation use efficiency in the plant help in growth and yield (Jin *et al.,* 2017). The reports showed that the development of heat-tolerant genotypes increased 24 % yield in the future (Chebrolu *et al.,* 2016; Mondal *et al.,* 2016; Ni *et al.,* 2018).

Conclusions**:** The climatic projections showed that in hot dry GCM the increase in maximum and minimum temperature by 3.5ºC and 4ºC, respectively. While, the precipitation 30% for the hot dry GCM. The APSIM-Sunflower model simulates a more reduction in yield compared to the CROPGRO model. The maximum reduction in sunflower achene yield simulated by CROPGRO model 24% and APSIM-Sunflower model 28% in mid-century with current agricultural practices. While, the adaptive strategies were developed for mitigating the future climate change indicated that the CROPGRO model simulated 12 to 20% and APSIM-Sunflower model simulates (11 to 18%) more achene yield compared to current agricultural practices for all GCMs. Current agricultural practices negatively affect crop yield and the improved agronomic and technological development used as adaptive measures can mitigate the negative impact of climate change.

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Declaration Statement**:** No conflict of interest exists

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