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Adaptation strategies for maize production under climate change for semi-arid environments

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ABSTRACT

Maize is the third most cultivated food crop in the world. Therefore, the impact of climate change and the development of adaptation strategies for maize are crucial to agricultural production and food security. The current study was undertaken to evaluate the impact of climate change and the development of adaptations strategies for maize in semi-arid environments using the Cropping System Model (CSM)-CERES-Maize of the Decision Support System for Agrotechnology Transfer (DSSAT). The model was calibrated and evaluated with an experimental data set and compared to on-farm data. The sensitivity of the model was evaluated against Carbon, Temperature, Water and Nitrogen (CTWN) analysis for the same environments. Survey data for maize were collected from 64 farms in the Faisalabad district of Pakistan using a stratified random sampling technique. Initial crop conditions and management practices were used as input data for CSM-CERES-Maize. Current climate data from 1980 to 2010 were obtained from the nearest weather station and future climate projections for 2040–2069 were obtained from Global Climate Models (GCMs) under Representative Concentration Pathway (RCP) 8.5. Representative Agricultural Pathways (RAPs) were designed to represent the future autonomous production system. The GCM results showed an increase of 3.4 °C in maximum and 3.8 °C in minimum temperature for hot/dry conditions. The projected increase in temperatures for the hot/dry GCM would result in a 28 % reduction for the current production system and a 29 % reduction for the future maize production system by the middle of the century. The impact of climate adaption options on current production systems was evaluated and the results showed that yield increased by 21 %. Results of climate adaptation for the future production system indicated that yield would increase by 12–17 % for all GCMs. Both the current and future production systems were negatively affected by climate change. However, improved management as adaptation strategies can offset the potential decrease in yield.

1. Introduction

The global agriculture system is vulnerable to climate change (IPCC, 2014; Lal, 2019; Wiebe et al., 2019; Ye et al., 2019). Various global studies have indicated that progressive climate change is expected to negatively affect agricultural production (Ahmed et al., 2018a; Alexeeff et al., 2018; Kalra and Kumar, 2019; Ullah et al., 2019a; Vanli et al., 2019). High temperatures and uncertainty in rainfall patterns have significant impacts on overall crop growth, development, and yield (Ju et al., 2013; Deb et al., 2015b; Mann et al., 2019). Adaptation is a key factor that will reduce the severity of climate change on food production (Adger et al., 2003; Lobell et al., 2008; Klein, 2011; Deb et al., 2016; Grafakos et al., 2019).

Maize is an important crop to ensure global food security. The interest in maize production has increased due to its demand as a biofuel, food, and feed crop in many countries (Isaacson, 2005; Nuss and Tanumihardjo, 2010; Rosegrant et al., 2012). However, the impact of climate change has been shown to negatively affect maize yield (Ahmed et al., 2018b; Lobell et al., 2011; Smith and Olesen, 2010). Warmer weather conditions have accelerated crop development and reduced the length of the growing season (Ahmad et al., 2018; Liu et al., 2018; Ullah et al., 2019b; Waqas et al., 2019).

Pakistan is highly vulnerable to the potential negative impacts of climate change (Rasul and Ahmad, 2012) and according to the climate risk index, it is the seventh most vulnerable country in the world to climate change (Eckstein et al., 2018). Future projections show that the

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temperature in Pakistan is expected to increase by 2.8 °C by 2069 (Ahmad et al., 2015). In Pakistan, cereals and other crops are highly vulnerable to heat stress, a likely result of increasing temperatures (Imran et al., 2018; Ahmed et al., 2019c). An increase in temperature and uncertainty in rainfall patterns change the availability of water and nutrients, which can ultimately lead to decreases in crop yield (Javed et al., 2015; Rahman et al., 2018; Babel et al., 2019; Ullah et al., 2019a). Hussain and Mudasser (2007) found that a 3 °C increase in temperature could decrease wheat yield by 21 % in the mountain areas of Pakistan. They also found that increasing temperatures accelerate the phenological development resulting in a shorter growth period and reduced crop yield. Similar findings were reported by Hussain and Bangash (2017) for maize, in that a 1 °C increase in mean temperature could reduce yield by 7%. High temperatures were found to reduce the pollen viability, fertilization, and grain formation in maize (Hatfield and Prueger, 2015). As a C4 crop, the impact of elevated CO_2 on maize photosynthesis and transpiration is less compared to C3 crops (Ghannoum et al., 2000).

The negative effects of climate change on crops have been well documented (Schmidhuber and Tubiello, 2007; Crane et al., 2010; Schlenker and Lobell, 2010; IPCC, 2015). Adaptation is a key factor to reduce the potential negative effects of climate change (Porter et al., 2014; Ahmed et al., 2019c; Yang et al., 2019). These adaptation strategies include changes in sowing time (Lashkari et al., 2012), adjustments in irrigation management (Babel and Turyatunga, 2015; Ahmad et al., 2019a, 2019b, 2019c) or nutrient management (Bryan et al., 2013), and development of climate-resilent hybrids (Deb et al., 2015a; Xu et al., 2017). Several studies have shown that optimal adaptation strategies are region- and hybrid-specific (Bierbaum et al., 2013; Cairns et al., 2013), so it is important to select the appropriate adaptation strategies.

The global research community has identified new socio-economics pathways and scenarios concepts to assess the climate change impacts and vulnerabilities that are consistent across the local to global scale. The develoment of Representative Agricultural Pathways (RAPs) scenarios helps to characterize the range of uncertainity for climate change impact and adaptations (Antle et al., 2015). RAPs are plausible future projections of biophysical and socio-economics conditions used for climate change impact assesment (Antle et al., 2013). Biophysical and socio-economics drivers are essentail components of agriculture pathways that logically describe the adaptation and mitigation scenarios that embody associated capabilities and challenges (Valdivia et al., 2013). RAPs are needed for the assessment of vulnerabilities, such as production technologies, policies, and probability of disturbance, such as soil degradation and shortage of water. To develop pathways and corresponding scenarios at regional or local scales, teams of scientists and other experts with knowledge of the agricultural systems and regions work together (Valdivia et al., 2015). The combined use of RAPs and RCPs scenarios provides detailed insight into adapting and mitigating the effects of climate change (Chaudhury et al., 2017). Currently, climate change impacts are evaluated on current production systems with future climate scenarios, but these current production systems are likely to change over time in the future due to technological improvements (Antle et al., 2015).

Crop growth models have been used to demonstrate the effect of plant genetics and agronomic management, as well as the interaction of these two entities with environmental conditions (Tsuji et al., 1998; Jones et al., 2003). The CSM-CERES-Maize model has been used in many studies to predict the effect of climate change on growth and yield under different RCP scenarios (Abera et al., 2018; Ahmad et al., 2019a, 2019b, 2019c; Amouzou et al., 2019; Mangani et al., 2019). The intergrated assessement of climate change risk is a recent focus of crop modeling (Ewert et al., 2015). The crop-climate ensembles capture the uncertainity and provide accurate assessments. The climate scenarios are developed by General Circulation Models (GCMs) that provide an overview of current and future climate changes (Mearns et al., 2009; Yang et al., 2014). To study the climate risk at the farm level, statistical downscaling of GCMs is required for decsion making (Challinor et al., 2017). The use of a single GCM and method limits the studies because climate and crop model response tend to vary wideley (Giorgi and Francisco, 2000), and the use of multiple GCMs is a common practice when conducting climate change assessments (Semenov and Stratonovitch, 2010).

Several studies have been conducted to evalute the impact of climate change on maize using different climate change scenarios (Araya et al., 2015; Kassie et al., 2015; Lin et al., 2015; Welikhe et al., 2016; Nimusiima et al., 2018). However, in these studies climate scenarios were not used with RAPs to study the impacts of climate change on current or future production systems for maize. The combined use of RAPs with future emission scenarios (RCPs) will help to characterize the range of uncertainity in climate change impacts and adaptation strategies. There is an urgent need to evalute the potential of adaption strategies and to develop effective adaption options by considering the agricultural pathways to mitigate the risk of climate change for maize. These modeling studies can assist policy makers with the decision process. Therefore, the objectives of this study were (1) to assess the impact of climate change on maize yield under RCP 8.5 for the mid-century (2039–2069) and (2) to develop adaptations strategies and RAPs for current and future production systems of maize with a modeling framework approach that could be used for multiple semi-arid climatic risk regions.

2. Materials and methods

2.1. Study site and data collection

The study was conducted in Faisalabad, Punjab, Pakistan. This region has a semi-arid climate and mixed cropping zone, in which wheat, rice, maize, and sugarcane are dominant. Survey data for maize farms were obtained for the 2015 growing season. An extensive, random survey was conducted for 64 farms from the four different sites of the Faisalabad district. Farms were selected through a stratified random sampling technique. A total of 16 farms, 4 from each administrative region (tehsil) were selected, so that the farms would be representative of the regional farm population (Fig. 1). Surveyed information of farmers' fields included the maize hybrid that was grown, initial conditions (previous crop sown, remaining crop and root residue weight), and crop

management (sowing time, tillage, fertilizer and irrigation amounts, harvesting date, etc.). This farm management information was used to create input files for the crop model. The Lyallpur soil series data that were used for the study site were obtained from the department of Soil Survey of Pakistan. Details of the soil physical, chemical, and hydrological properties are described by Ahmed et al. (2018).

2.2. Model calibration and evaluation

The CSM-CERES-Maize model of DSSAT Version 4.6.1 was used for this study (Hoogenboom et al., 2016). This model simulates the phenology, growth, and yield of maize through the interactive effect of plant genetics, soil characteristics, crop management, and weather conditions (Jones et al., 2003; Hoogenboom et al., 2019). Temperature affects most growth and development processes, while CO_2 affects both daily photosynthesis and transpiration; a detailed description of the original CERES-Maize model can be found in Ritchie et al (1989). The genetic coefficients of CSM-CERES-Maize model were estimated with experimental data from 2015 and 2016 using the generalized likelihood uncertainty estimation (GLUE) and sensitivity analysis tools associated with DSSAT (Ahmed et al., 2018b; He et al., 2009). The experiment was comprised of four sowing dates (27 January, 16 February, 08 March, and 28 March) and three maize hybrids (Pioneer-1543, MosantoDK6103, and Syngenta-NK8711). The model was calibrated with

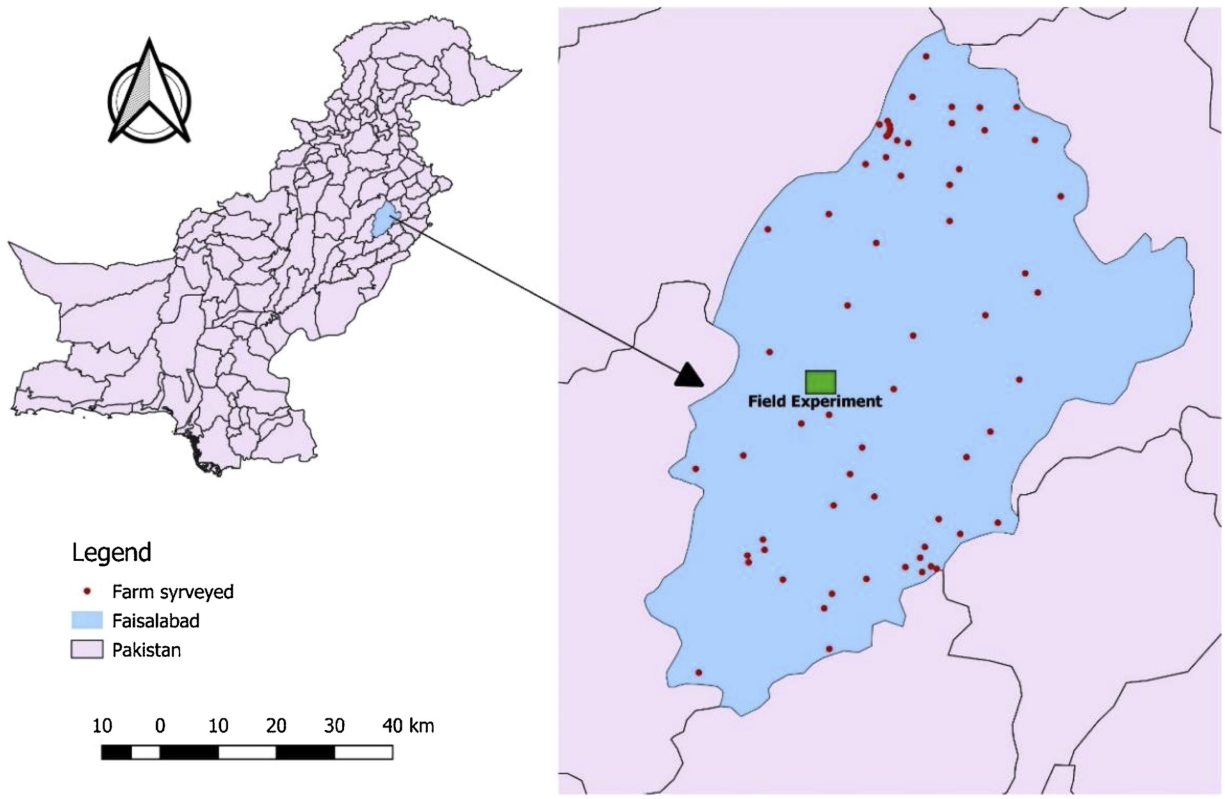

Fig. 1. Sites of the farms surveyed in the Faisalabad-Punjab, Pakistan region.

the best treatment for the 27 January 2015 planting date for three cultivars and evaluated with other sowing dates for 2015 and 2016. The physiological traits that were used for calibration and evaluation were days to anthesis, maturity, maximum Leaf area index, biomass and grain yield. The calibration, and evaluation followed procedures published previously (Ahmed et al., 2018a).

2.3. Carbon, Temperature, Water, Nitrogen (CTWN) sensitivity

A CTWN analysis was performed to evaluate the sensitivity of the CSM-CERES-Maize model to various levels of carbon, temperature, rainfall, and nitrogen fertilizer, while other parameters were fixed at their normal values. This type of analysis provides the guidance to improve the quality of assessment practices and decision support systems used in agricultural and environmental decision-making, ultimately improving model reliability, transparency, and credibility (Mwazembe et al., 2016). The analysis was conducted using the management and environmental information for the farm most representative of the demographics of the 64 farms surveyed. The baseline weather data (1980–2010) were obtained from the nearest weather station. The sensitivity of the genetic coefficients was evaluated for different conditions of carbon, temperature, water and nitrogen. The CO_2 concentrations were set to 360, 450, 540, 630 and 720 ppm at a fertilizer rate of 30 and 180 kg N ha^{-1}. The increase in CO_2 was compared to the baseline of 360 ppm. The observed daily maximum and minimum temperatures were modified by −2 °C, +2 °C, +4 °C, +6 °C and +8 °C. The precipitation was adjusted to 25, 50, 75, 100, 125, 150, 175, and 200 % of the daily values. The N fertilization was changed to 0, 30, 60, 90, 120, 150, and 180 kg N ha^{-1}. The Agview software program developed by AgMIP (tools.agmip.org/agview.php) was used for the CTWN analysis.

2.4. Development of Representative Agricultural Pathways (RAPs)

RAPs are projections of plausible future biophysical and socio-economic conditions used to carry out climate impact assessments for agriculture (Valdivia et al., 2015). These “pathways” are combinations of economic, technological, and policy drivers that represent a plausible range of possible futures. The draft of the RAPs was prepared after conducting various consultative sessions with the stakeholders such as researchers, policy makers, and farmers. The participant researchers were selected from various disciplines matching the variables, and they included economists, soil scientists, pathologists, irrigation specialists, water management experts, and plant breeders. There were four RAPs meetings and consultative sessions with researchers at different times.

During the first meeting with stakeholders the basic variables were identified, including the time horizon, magnitude of rationale. The team members were assigned to document the background information of each varaible. An Excel spreadsheet tool called DevRAP was used to develop and document the varaibles for RAPs (Valdivia et al., 2015). During the second meeting the storeline of each variable was discussed, while during the third meeting the RAPs naratives were discussed. These narratives provide a framework in which qualitative information can be translated into model parameters. The RAPs that were developed were finally refined by the crop modelers in the fourth meeting. The methodology for development of the RAPs followed the procedures set out by Antle et al. (2017). The RAPs that were quantified and finalized were increase in soil degradation, decrease in groundwater, and balanced use of fertilizers.

2.5. Climate change scenarios and selection of GCMs

Daily weather data from 1980 to 2010, including maximum (Tmax) and minimum air temperatures (Tmin), solar radiation, and rainfall were obtained from the Pakistan Meteorological Department (PMD). Current weather data were obtained from the meteorological

Table 1
Selected GCMs for mid-century under RCP8.5 for Faisalabad.

Serial No	Quadrant	GCMs	References
1	hot/wet	CSIRO-Mk3-6-0	(Gordon et al., 2010)
2	cool/wet	GFDL-ESM2G	(Su et al., 2013)
3	cool/dry	GFDL-ESM2M	(Dunne et al., 2012)
4	middle	HadGEM2-ES	(Jones et al., 2011)
5	hot/dry	CMCC-CM	(Wild et al., 2015)

observatory located at Faisalabad (31° 26′ N, 73°08 ′ E). The baseline period consisted of 30 years of daily weather records with the atmospheric CO_2 concentration set at 360 ppm. The quality of the observed weather data was checked following the protocol of the Agricultural Model Intercomparison and Improvement Project (AgMIP) protocols (Rosenzweig et al., 2013; Ahmad et al., 2015). To control the quality of the data, we identified outlying (+/- 3 standard deviations) and questionable data that may have been corrupted. We analyzed the dataset elements as time series to check for potential anomalies and then verified that the data were plausible physically, temporally (e.g., questionable value supported by preceding or following values), and spatially (e.g., questionable value supported by neighboring stations).

2.6. Statistical downscaling

Station-based downscaling was performed with data from the PMD observatory for the weather station located in Faisalabad. For the development of the mean and variability change scenarios, monthly changes in mean Tmax, Tmin, and rainfall were calculated for future climate (2040–2069) based on current climate data (1980–2010) using 29 GCMs of the CMIP5 family (Ruane et al., 2013). Monthly changes in standard deviation of Tmax and Tmin and the number of rainy days (precipitation > 0.1 mm) were also calculated for the future using current climate data from the same GCM combinations. The shape parameter of the gamma distribution for wet events was of insufficient quality in GCM simulations due to many rainy days and gamma distribution trends to distribute the data in very lengthy asymptotes (Ahmad and Rasul, 2018; Burhan and Athar, 2019). Next, we imposed monthly changes on current climate data using a stretched distribution approach that adjusts each event by comparing existing and desired values by distributional percentiles (Ruane et al., 2015). In this process it was assumed that there were no changes from the current climate in the daily variables for solar radiation, wind, and relative humidity. Consistency in vapor pressure, dew point, and relative humidity was ensured for daily maximum temperature.

In the process of generating climate change scenarios, the changes were applied to Tmax, Tmin, and precipitation only. All other atmospheric parameters were assumed to be invariant in the future. Future scenarios were created by sub-setting the five representative GCMs using the methodology developed by AgMIP (2013). Since output of GCMs in adjacent grids do not often differ significantly unless there is a major mountain in proximity, scenarios were derived only for the Faisalabad station as the sole long-term weather recording station as it was considered representative for all farms in the district. Given the homogeneity in terrain features and the relatively short distances between the farms in the district as compared to scale of the GCM's grid resolution, altitude-borne precipitation and temperature changes were assumed to be insignificant.

2.7. Climate change projections

Five of 29 GCMs of the CMIP5 family were selected to represent the uncertainty in projected temperature and rainfall changes in order to generate the climate change projection under RCP 8.5 scenarios for the study site. To classify the major categories of projected climate change in the study region for a specific growing season and RCP, coordinates-based temperature and precipitation changes with reference to their deviation from ensemble median are illustrated for each participating GCM. The selection criteria of these GCMs were based on scatter plots of mean temperature change vs. percentage precipitation change (Ruane and McDermid, 2017) in the 2040–2069 projected period (Fig. 3). A CO_2 concentration of 571 ppm was used for mid-century (2040–2069) under RCP 8.5 (Taylor et al., 2012b). Selection of a representative subset of global climate models that captures the profile of regional changes for integrated climate impacts assessment. The GCM projections are classified as cool/wet, cool/dry, hot/wet, hot/dry, and middle based on ensemble standard deviation of the growing season temperature and precipitation changes as a representation of the GCMs spread, which are shown in Table 1.

2.8. Protocol for climate change simulations and adaptations measure

The CSM-CERES-Maize model was used for climate analyses. The AgMIP translation tools including Quad UI were used to generate the input files for the crop model. Crop management, soil and weather data were used to generate 64 sets of input files, one set for each farm. The AgMIP protocol was used for climate change impact assessment and adaptation following the AgMIP protocols version 6.1 (Rosenzweig et al., 2013). For climate change impact assessment, the crop simulations were carried out by combinations of climate and management (CM), referred to as CM0 to CM6. A CM code represents a combination of climate impact and crop management. To evaluate the performance of the model, the CM0 simulations were conducted with one year of observed climate data for 2015, which is the year for which the farm survey data were collected. The CM1 analysis was carried out using the current production system with current climate (1980–2010). For CM2, current production systems were simulated with future climate scenarios under RCP 8.5. For CM3, the simulations were conducted using current climate with management systems that were designed for climate adaptations. For CM4, the simulations were conducted using current climate with the future autonomous production system (RAPs). For CM5, the simulations were conducted using future climate scenarios for a future autonomous production system (RAPs), while the CM6 simulations were conducted using future climate scenarios for a future autonomous production system (RAPs) plus adaptations. The CO_2 concentration for the current climate or baseline data was 360 ppm, while for the climate change the CO_2 was set at 571 ppm as reported by Taylor et al (2012a). The detail methodological framework for integrated climate change impacts and development of adaptations for maize is shown in Fig. 2, which is generally divided into two parts. In first part, the crop model was parametrized with experimental data while in second part, various climate analyses were carried out (Table 2).

Heat-tolerant virtual hybrids were developed by readjusting the genetic coefficient for the projected temperature. The projected increases in Tmax and Tmin of 3.4 °C and 3.8 °C in hot/dry GCMs were applied in the environmental modification section of the crop management file, resulting in a decrease in the number of days to anthesis and maturity, growth, and final yield. The genetic coefficients were readjusted to regain the phenology, growth, and yield. The new estimated coefficients were thus heat tolerant.

3. Results

3.1. Climate scenarios

A strong indicator of climate change in the target region is the trend towards increases in both Tmax and Tmin. The highest temperature increase found in this analysis was 3.4 °C for Tmax and 3.8 °C for Tmin both under hot/dry conditions for the RCP8.5 scenario. However, there were highly heterogeneous change patterns for the precipitation regime due to the high inter-annual variability in the region (Table 3). An

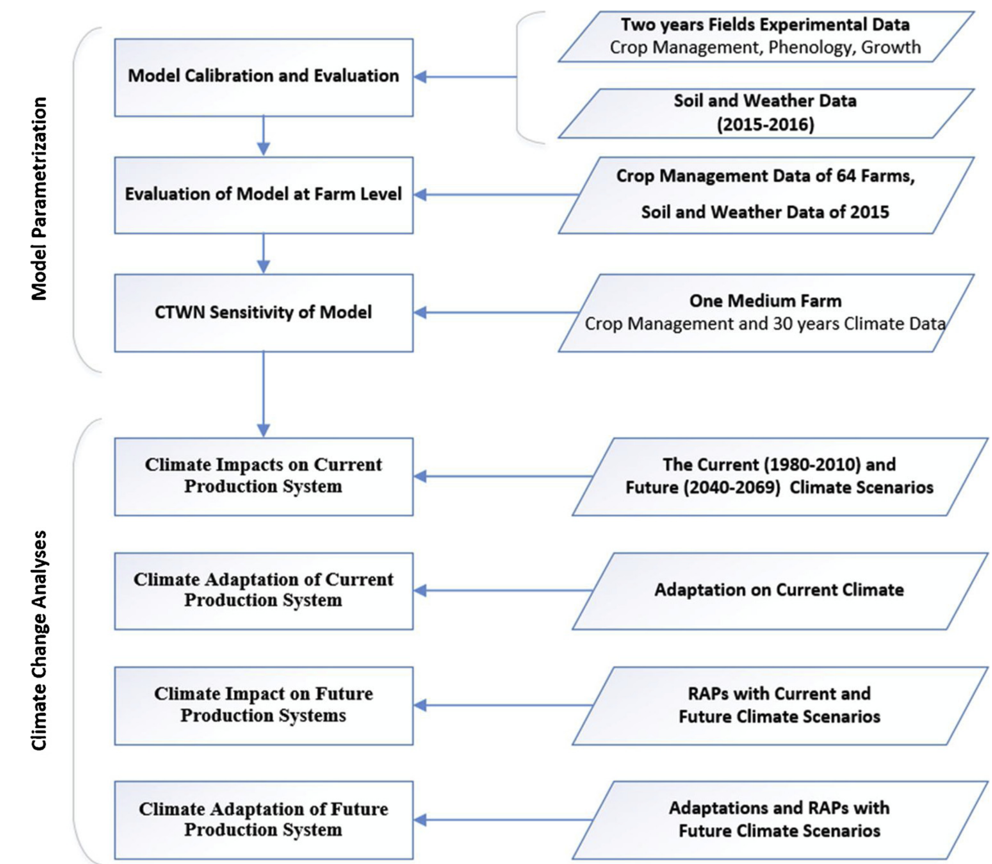

Fig. 2. Methodological framework for integrated climate change impacts and development of adaptations for maize.

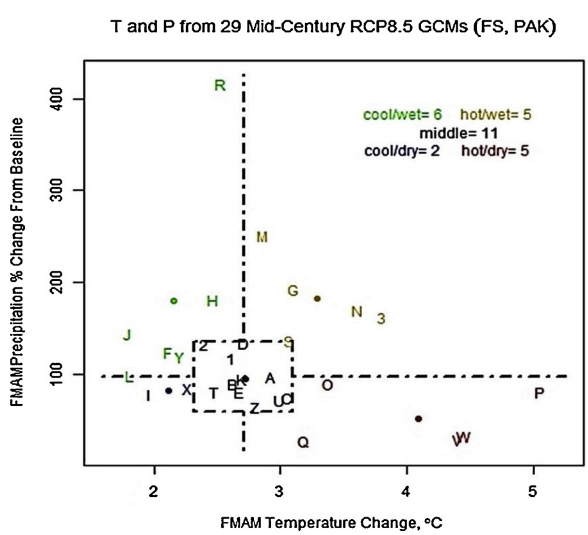

Fig. 3. Delta temperature - Delta precipitation scatter plot for the Faisalabad district for selection of the appropriate GCMs. (Note: FMAM = February to May growing season of spring maize).

annual precipitation decrease of more than 140 mm under cool/wet conditions and an increase of more than 580 mm under hot/wet conditions in RCP8.5 were projected throughout the region.

3.2. Evaluation of model at the farm level

The CSM-CERES-Maize model simulated growth, development, and yield accurately for the three maize hybrids grown for the semi-arid conditions of Punjab, Pakistan (Ahmed et al., 2018b). Performance of the model at the farm level was expressed using the probability of exceedance (Fig. 4), which represents the probability of observed and simulated yield under current production system using the weather data for 2015 (CM0) for 64 farms. The simulated yield was very close to the observed with some minor variabilities attributable to the quality of the management practices at the farm level in each tehsil. The difference between observed and simulated yields was less for those farmers who followed recommended management practices as shown in Fig. 4 (b & c). The model showed close agreement with observations as shown by the d-stat of 0.99 and a RMSE value of 127.28 kg ha^{-1} at tehsil Tandlianwala, while at tehsil Samundri d-stat of 0.99 and a RMSE value of 148.87 kg ha^{-1} were recorded. During data collection it was observed that farmers at tehsils Tandlianwala and Samundri were progressive and used the inputs according to government recommendations. High RMSE values of 231.08 at Faisalabad Sadar and 229.87 kg ha^{-1} at Chak Jhumra were found.

3.3. CTWN sensitivity analysis

3.3.1. Response of grain yield to CO_2

The responses of the model to an increase in the level of CO_2 concentration at low (30 kg N ha^{-1}) and high nitrogen (N) rates (180 kg N ha^{-1}) are presented in Fig. 5a, b. In general, the model is sensitive to CO_2 concentrations, and there was a linear increase in grain yield with an increase in the CO_2 concentration for both 30 and 180 kg N ha^{-1}. Grain yield increased by 17 % and 11 % when the CO_2 concentrations increased from 360 to 450 ppm and 450–540 ppm at 30 kg N ha^{-1}, while at higher CO_2 concentrations there was only a 4% increase in yield, despite an increase in CO_2 from 630 to 720 ppm (Fig. 5a). However, at 180 kg N ha^{-1} the grain yield increased by 12 % with an increasing CO_2 concentration from 360 to 450 ppm but increased only 9% with an increase in CO_2 concentration from 450–540 ppm. There

Table 2
Climate change analyses for the evaluation of potential changes in the agriculture system.

Production System	RAPs	Adaptation	Yield change ratio
Climate impacts on current production system	No	No	CM2/CM1
Climate adaptation on current production system	No	Yes	CM3/CM1
Climate impact for future production systems	Yes	No	CM5/CM4
Climate impact and potential adaptation for future production systems	Yes	Yes	CM6/CM5

CM1: Current climate, current management, CM2: Climate change, current management, CM3: Current climate, current management, plus adaptation, CM4: Current climate, Future RAP, CM5: Climate change, Future RAPs, CM6: Climate change, Future RAP, plus adaptation.

Table 3
Change in annual mean in climate projections for mid-century (2040-2069) under RCP8.5.

Scenarios	Change in Tmax (°C)	Change in Tmin (°C)	Change in Precipitation (mm/day)
hot/wet	2.8	3.7	1.6
cool/wet	2.9	2.9	−0.4
cool/dry	2.6	2.6	−0.2
hot/dry	3.4	3.8	−0.2
Middle	1.8	2.9	0.4

was only a 3% increase in yield with an increase in CO_2 from 630 to 720 ppm (Fig. 5b).

3.3.2. Response of grain yield to precipitation

The simulated response of grain yield to changes in rainfall is shown in Fig. 5c. There was a slight positive response by the model, with grain yield increasing up to 75 % with an increase in rainfall; an increase of 25 % in rainfall produced a 1.5 % increase in grain yield. However, when rainfall further increased from 50 % to 75 %, yield increased only by 0.85 %. The diminished response of the model to a 25 % incremental increase in rainfall could be because the maize crop was sown in an irrigated area so that water was not necessarily limiting. When rainfall was increased from 125 % to 150 %, overall yield was reduced by 0.33 %. The reduction in yield could be due to an increase in leaching of nutrients as shown in Table 4. As rainfall increases with more water, there is a potential for an increase in deep drainage and thus an increase in leaching of nitrogen, causing a potential reduction in available nitrogen for plant uptake.

3.3.3. Response of grain yield to temperature

Grain yield was negatively affected by an increase in temperature. Grain yield decreased by 16 % when there was a 2 °C increase in

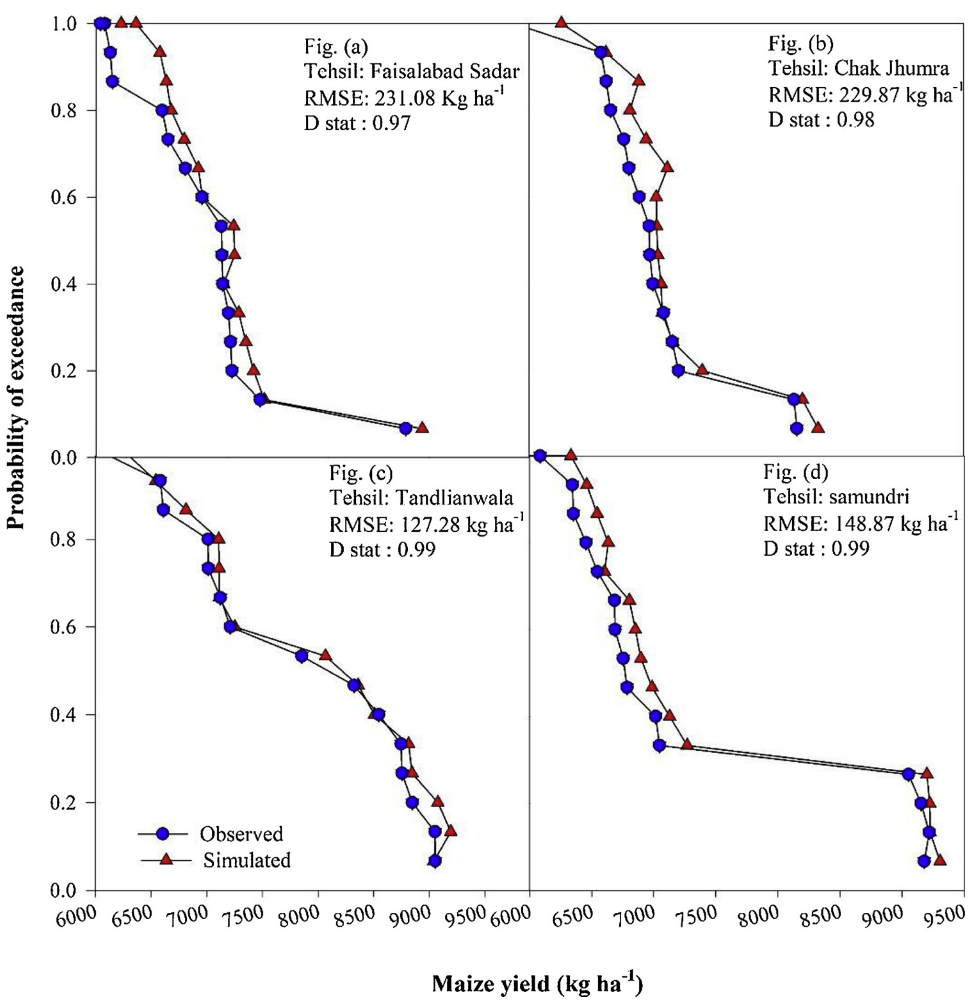

Fig. 4. Probability of exceedance for observed and simulated yield for each tehsil of Faisalabad (CM0).

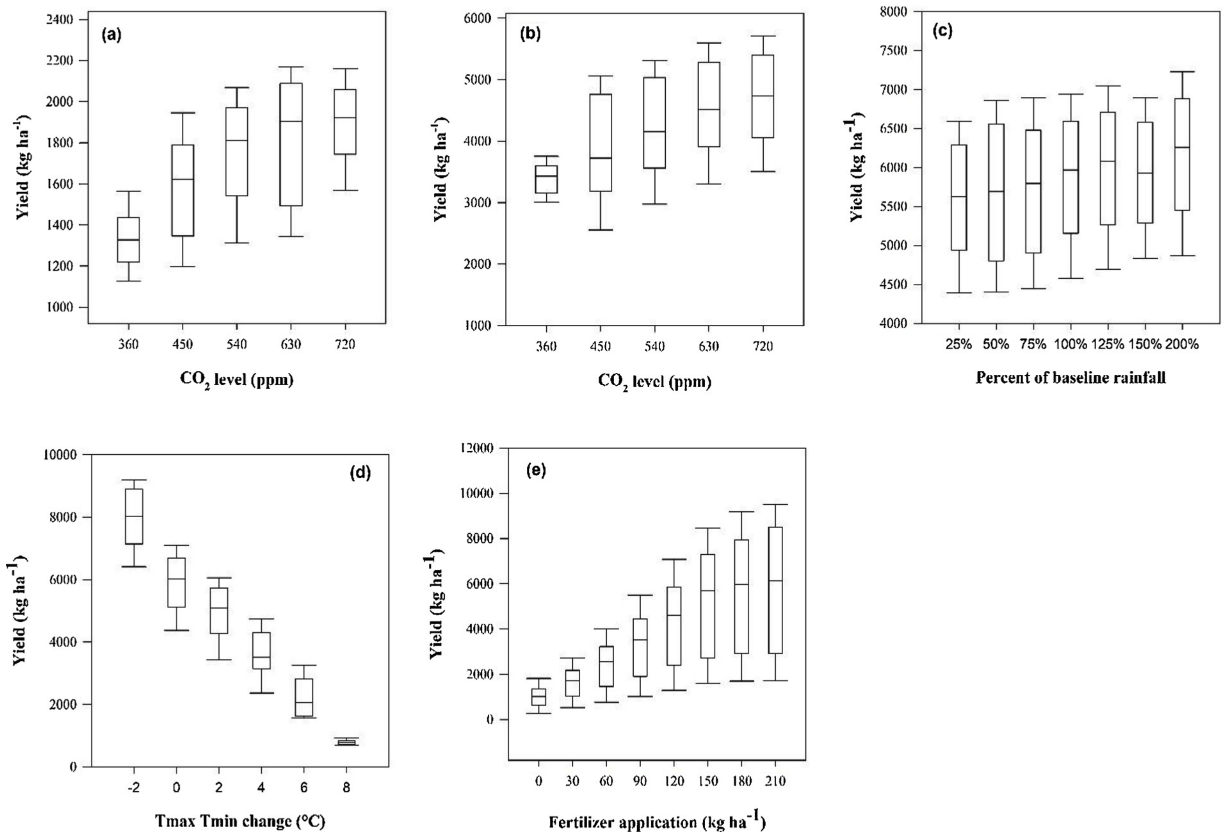

Fig. 5. Simulated yield response to (a) CO_2 at 30 kg N ha^{-1}, (b) CO_2 at 180 kg N ha^{-1}, (c) % Rainfall change, (d) Temperatures change, (e) Change in nitrogen fertilizer.

Table 4
Effect of percent change in rainfall on nitrogen leaching and nitrogen uptake from the soil.

Change in rainfall (%)	NO_3 Leaching (kg N ha^{-1})	N uptake (kg ha^{-1})
0	67.9	223.8
25	74.3	217.4
50	80.4	211.9
100	91.3	202.6
125	96.4	198.6
150	101.3	194.9
200	109.5	188.9

Table 5
Effect of changes in temperatures on maize phenology.

Change in Temperature (°C)	Days to anthesis (Days)	Days to maturity (Days)
−2	88	121
0	78	112
2	68	102
4	62	96
6	58	88
8	54	83

temperature and decreased by 25 % when the temperatures increased an additional 2 °C from 2 °C to 4 °C (Fig. 5d). The largest yield loss was found at an 8 °C temperature increase at approximately 86 %. However, grain yield increased when there was a 2 °C decrease of the current temperature. This increase can be explained by the fact that lower temperatures extended the growing period of the crop, helping to maximize the interception of light and enhance the grain yield as shown in Table 5. On the other hand, higher temperatures shortened the length of the growing period, thereby reducing the duration for grain filling and ultimately reducing grain yield (Table 5). As temperature increased from 0 °C to 8 °C, the number of days from planting to anthesis decreased by 24 days and the number of days from planting to maturity decreased by 29 days (Table 5)

3.3.4. Response of grain yield to nitrogen

Grain yield increased linearly with an increase in N fertilizer application rate from 0 to 210 kg ha^{-1}. The yield increased by 63 % with the addition of 30 kg N ha^{-1}, and a further addition of 30 kg N ha^{-1} increased the yield by 46 % (Fig. 5). The model showed that yield increased with each 30 kg increment of N up to 180 kg ha, after which there was only a 2% increase with the addition of 30 kg N ha^{-1}. As N is an essential element, increments of N fertilizer rates increased the leaf area and dry matter accumulation. A larger leaf area allows for more efficient light interception and photosynthesis, thus allocating more photosynthates to the reproductive components, ultimately leading to an increase in yield. However, excess N applications decrease N use efficiency and can potentially reduce yield, especially if vegetative growth is stimulated. High rates of nitrogen increase leaching and denitrification and can potentially reduce N uptake under irrigated conditions. (Table 6). An increase in nitrogen mineralization was found for an increase in N fertilizer from 30 to 60 kg ha^{-1}, while at higher N application rates the increase in mineralization was small.

3.4. Integrated assessment of climate change and adaptation strategies

3.4.1. Impact of climate change on the current agricultural production system

Simulations of 64 farms with the baseline for current climatic conditions (1980–2010) and future climate change scenarios for the mid-century (2040–2070) under RCP 8.5 are shown in Fig. 6a. Simulated yield based on all five GCMs showed a reduction in yield when

Table 6
Nitrogen mineralization, leaching, denitrification and uptake in response to nitrogen fertilizer.

Nitrogen fertilizer levels (N kg ha^{-1})	Mineralized N (N kg ha^{-1})	Leached NO_3 (N kg ha^{-1})	Denitrified N (N kg ha^{-1})	N uptake from Soil (N kg ha^{-1})
0	22.9	33.4	0.05	5.0
30	26.4	44.6	0.10	24.5
60	26.0	45.7	0.14	50.3
90	25.7	43.7	0.17	81.1
120	25.8	47.1	0.22	104.4
150	25.8	51.6	0.29	126.4
180	25.9	56.5	0.37	147.1
210	25.9	66.4	0.49	149.5

compared to baseline conditions. The middle climate GCMs showed a total 10 % reduction in maize yield because of an increase in Tmax of 1.8 °C and Tmin of 2.9 °C (Table 3). Cool climate scenarios such as cool/wet and cool/dry showed a 17 % and 19 % reduction in yield, respectively, as compared to the baseline, with increases in Tmax of 2.6 and 2.9 °C, respectively (Table 8). These results can be confirmed with the temperature responses of the CTWN analysis (Fig. 6d), which showed that a 2 °C increase in temperature caused a 16 % reduction in yield. However, a larger reduction in yield of 28 % was observed for the hot/dry GCM, when increases in Tmax and Tmin were 3.4 °C and 3.8 °C, respectively, and annual precipitation decreased 73 mm.

3.4.2. Current climate with current adaptations and future technology-based management

The simulations of current climate with the current adaptation package (CM3) and future technology-based management (RAPs) (CM4) are shown in Fig. 6b. The current adaptation package was developed to increase maize production for the current maize production system and included the application of nitrogenous fertilizer combined with irrigation (fertigation), early sowing of spring maize 15 days prior to the recommended sowing date (mid-February), and an increase in nitrogen fertilizer of 10 % as shown in Table 7. With this adaptation package, yield would increase by 21 % compared to current management practices for baseline climate conditions (Fig. 6b).

Future technology-based management corresponding to RAPs (CM4) were used on current climate. The RAPs were balanced application of fertilizers, increase in soil degradation by 10 %, and 10 % decrease in ground and surface water usage as shown in Table 7. By considering the future trend of management, the yield increased by 6% compared to the baseline (Fig. 6b).

3.4.3. Impact of climate change on future agricultural production system

Comparisons of future technology-based management (RAPs) on current climate (CM4) with climate change scenarios (CM5) are shown in Fig. 6c. The RAPs as shown in Table 7 were used on GCMs to see the impact of climate change on future agricultural production systems. The results indicated that future agriculture would be very sensitive to climate change with a decrease in yield from 9% for the middle and 29 % for the hot/dry GCM (Table 8). The cool climate GCMs cool/wet and cool/dry showed a 16 % and 19 % reduction in yield, respectively. The highest reduction in grain yield of 29 % was recorded in hot/dry GCM. A huge reduction of grain yield in the future production system could be due to an increase in the future Tmax and Tmin of 3.4 °C and 3.8 °C, respectively, along with soil degradation and shortage of irrigation water. A high temperature and a decrease in the availability of water shortened the duration of the growing season by 16 days. High temperatures during the reproductive phase of maize reduced the growing period and ultimate grain yield (Table 5).

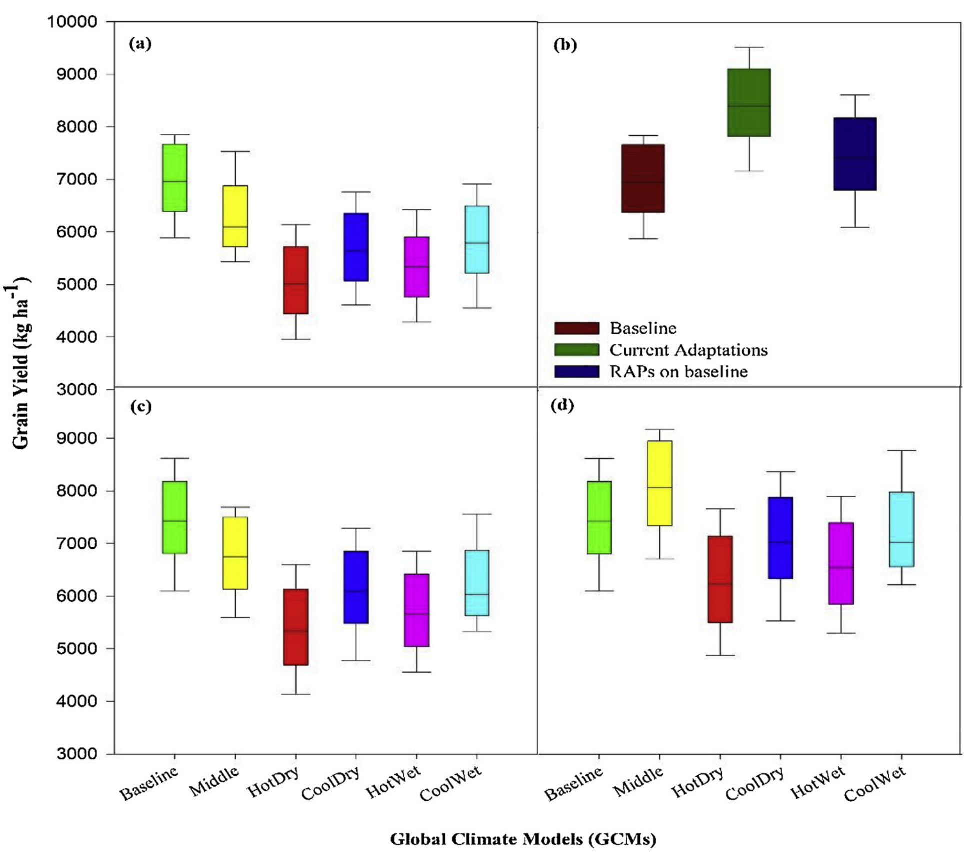

Fig. 6. Climate change impact on a) Current production system (CM1-CM2), b) Climate adaptation and RAPs on current climate (CM3-CM4), c) Future production system (CM4-CM5), and d) RAPs plus adaptation on future production system (CM5-CM6).

Table 7
RAPs and the adaptation package used for climate change impact assessment and impact on maize yield.

	Representative Agricultural Pathways (RAPs)	Variables changed in model	Increase in yield (%)
1	Balanced use of fertilizers	8% increase of the soil fertility factor (SLPF)	4.87
2	Increase in soil degradation by 10 %	10 % increase in stable soil organic matter (SOM3)	0.97
3	Decrease in ground and surface water usage by 10 %	Decrease the irrigation volume by 10 %	1.03
	Adaptations	**Variables changed in model**	
4	Application of nitrogenous fertilizer together irrigation (fertigation)	Change the method of fertilizer application to applied in irrigation water	1.11
5	Earlier sowing by 15 days from the recommended sowing date (mid-February)	Change the planting date by 15 days	1.68
6	Increase in nitrogen fertilizer of 10 %	Increase the nitrogen amount by 10 %	0.78
7	Increase in plant population by 10 %	Increase the plant population at seeding, plants m^{-2} by 10%	5.91
8	Development of heat- tolerant cultivars	The future increase in temperatures for the hot/dry GCM was implemented in the environmental modification input of the crop model. Then, the genetics coefficients were adjusted in order for the vegetative and reproductive durations to be similar to current conditions.	6.11

3.4.4. Impact of climate change adaptation on future production system

RAPs plus adaptation strategies as shown in Table 7 were used to evaluate the impact of climate change adaptation on future production systems under climate change. Accepted adaptation strategies were assessed and quantified using the model for future production systems (Valdivia et al., 2015; Rahman et al., 2018; Ahmad et al., 2019a, 2019b, 2019c). These adaptation strategies included an increase in plant population by 10 % and the introduction of heat- tolerant cultivars (Table 7). The results indicate that by introducing these adaptation practices in the future agricultural system, the yield will increase by 12%–17% for all GCMs (Fig. 6d). The middle GCM showed an increase of 17 %, while yield increased by 13 % and 14 %, respectively, for the hot/wet and hot/dry GCMs (Table 8). The number of plants per unit area was smaller for the farmer study sites, thus an increase of 10 % more seed can increase the plant population and potentially result in a yield increase. Heat-tolerant maize hybrids are currently not available, so development of these hybrids could offset the potential decrease in yield anticipated for future climate conditions. The individual effect of RAPs and management strategies on maize yield are presented in Table 7. The results show that a balanced use of fertilizers and the development of heat-tolerant cultivars are the best strategies to mitigate the negative effects of climate change.

4. Discussion

Pakistan is highly vulnerable to the effects of climate change. During the past 20 years, extreme weather events such as flood, drought, heat waves, and cyclones have affected crop productivity. To minimize the risks of extreme weather conditions, research is needed on the impact assessment and adaptation strategies. The PMD reported that the mean annual surface temperature increased between 0.6 °C and 1 °C from 1951 to 2000 (Rasul et al., 2012). Future projections (RCP 8.5) from our study showed that Tmax would increase by 3.4 °C and Tmin by 3.8 °C by mid-century for hot/dry GCMs. Similar findings by Iqbal and Zahid (2014) show that temperature in Pakistan would increase by 4.38 °C by 2080. The results of this study showed that annual precipitation would decrease by 73 mm in hot/dry GCM, while hot/wet and middle GCMs showed an increase in annual precipitation of 584 mm and 146 mm, respectively. The increase in precipitation in hot/wet GCMs could be due to the fact that high temperature rapidly evaporates the moisture from the surface. Warmer air becomes moist as the earth warms due to high temperature and causes more precipitation. A similar phenomenon was reported by Trenberth (2011).

To evaluate the impact of climate change on crop production, crop models were used to simulate the yield loss as a function of CO_2, temperature, rainfall, and nitrogen. The sensitivity analysis indicated the level of confidence of the model reliability in yield response to climate change and adaptation strategies. The model response to CO_2 concentration indicated that maize yield increased only slightly due to an increase in the CO_2 concentration from 360 ppm to 630 ppm, but there was no further change in yield with an additional increase in CO_2 from 630 ppm to 720 ppm (Fig. 4a, b). High yield with an increase in CO_2 is the result of CO_2 causing the stomatal conductance that increased the efficiency of water used due to assimilation of CO_2. Boote et al. (2011) reported a similar response in C4 species such as maize, in which grain yield showed a small response with high levels of CO_2 up to certain level due to a reduction in transpiration. Photosynthesis of C4 plants does not increase with high levels of CO_2 compared to C3 species such as soybean and wheat (Kimball et al., 2002).

The response of the model to temperatures indicated that yield decreased with increases in current temperature of +2 °C, +4 °C, +6 °C, and +8 °C, while an increase in yield was found with a -2 °C increase in current temperature (Fig. 4d). The reason for these changes could be that high temperature shortens the length of the growing season due to rapid growth that reduces the time for grain development, which ultimately limits grain yield as shown in Table 5. However, an increase in yield at -2 °C could be due to additional time for grain filling duration. Similar responses of temperatures on maize grain yield were described by Bassu et al. (2014). The model response was slightly positive with an increase in rainfall from 25 % to 125 %, but a further increase in rainfall from 125 % to 150 % reduced maize yield (Fig. 4c). The reason could be that high rainfall brings excess water that causes leaching of nutrients through drainage (Table 4). The results from the model also showed that an increase of 150 % rainfall brings excess

Table 8
Yield change of the future production system compared to the current yield level of spring maize.

Production System	Global Climate Models (GCMs)				
	Middle	cool/wet	cool/ dry	hot/ wet	hot/dry
Climate impact on current production system (CM2/CM1)	0.90	0.83	0.81	0.76	0.72
Climate impact on future production system (CM5/CM4)	0.91	0.84	0.81	0.75	0.71
Management adaptations for future agricultural production system (CM6/CM5)	1.17	1.14	1.12	1.13	1.14

water, which causes the leaching of nitrogen due to drainage from the root zone (Table 4). The model response to higher rates of nitrogen revealed that yield increased with an incremental increase of nitrogen from 0 to 180 kg ha^{-1}. However, a further increase from 180 to 210 kg ha^{-1} did not show any significant difference in grain yield (Fig. 4e). Higher rates of nitrogen increased nitrogen leaching and denitrification. However, nitrogen uptake was slightly smaller at high nitrogen rates due to higher losses in nitrogen leaching under irrigated conditions (Table 6).

Climate change impacts on current agriculture production systems showed that maize yield would be reduced by 28 % for the hot/wet GCM. However, a smaller reduction of about 17 % was found for the cool/wet GCM and about 19 % for the cool/dry GCM by the mid-century (Table 8). This large reduction in yield is be due to the high temperatures predicted by all GCMs as shown in Table 3. Higher temperatures increased the development rate and, therefore, reduced the duration of the growing season for maize (Table 4), which caused a decrease in yield. A similar response was found by Bassu et al. (2014). Climate change impacts on future production system showed that yield would be reduced by 29 % for the hot/dry GCM (Table 8). The future agriculture system could be vulnerable to a water shortage for irrigation and soil degradation due to high temperatures. Similar findings were reported by the Planning Commission of the Agriculture Policy Vision 2020 (Singh, 2002) and by (Parkes et al., 2019). An increase in temperature and shortages of available water can cause a decrease in yield due to a shorter growing period.

RAPs were used in this study to demonstrate future agricultural production systems and for the assessment of vulnerabilities, such as production technologies, policies, and the probability of disturbance, such as soil degradation and shortage of water similar to the findings reported by Valdivia et al. (2015). The participant experts in this study agreed that climate change can potentially ameliorate the changes in soil in the future. Changes in temperatures and in precipitation amount and intensity will cause wind and water erosion, depletion of organic matter, nutrient transformation, and soil microbial activity, resulting in an increase in soil degradation. It also has been reported that climate change will reduce the availability of groundwater for agriculture (Andres et al., 2019). A future increase in temperature and uncertainty in precipitation will disrupt the water cycle, and melting of the glaciers could lead to a decrease in surface water (Shannon et al., 2019). There could also be a consistent decline in groundwater storage due to groundwater withdrawal for irrigation when it exceeds natural recharge. The participant experts of soil scientists in this study focused their discussion on a balanced use of fertilizers because a future increase in temperature will decrease the efficiency of nutrients. In Pakistan, farmers apply only nitrogen fertilizer but limited of phosphate and potassium fertilizer due to insufficient knowledge about proper fertilizer management. A balanced use of nitrogen, phosphorus and potash fertilizers will enhance nutrient use efficiency and maintain soil productivity under a changing climate.

Climatic vulnerabilities can potentially be managed by proper adaptation at the farm level. The results from this study showed that by adapting the future production system, yield could increase by 12%–17% for all GCMs (Table 8). The adaptation options that were used included an increase in plant population by 10 % and the development of heat-tolerant hybrids to offset the potential negative impact of climate change on the future agricultural production system (Table 7). An optimum number of plants per unit area is very important to determine the economic yield and an optimum maize plant population helps to increase the utilization of available inputs such as water and nutrients. Sangoi (2000) found that the optimum plant density in maize resulted in mature plants that use resources such as water, nutrients and light efficiently. The development of heat-tolerant hybrids with suitable characteristics could increase the yield under changing climate scenarios. Zhang and Zhao (2017) found that by enhancing the thermal temperature of grain filling duration in maize, the yield increased by 7–10 %.

One of the limitations of the CSM-CERES-Maize model is that it does not simulate the effect of weeds, pests, and diseases, in essence assuming that there are no pests and diseases in the crop. In this study, the CSM-CERES-Maize model was calibrated and evaluated using field experimental data (Ahmed et al., 2018a). The experiment was fully controlled for weeds, insects, diseases, and other pests. After parametrization, the model was evaluated at farm level, which showed an overestimation of the yield for each site (Fig. 4), which may be partially due to assumption of no weeds, pests, or disease damages, while it is likely that these occurred under farmers' field conditions (Singh, 1986). However, the occurrence of weeds, pests, and disease damages are limited for the study sites because the study region has a mixed cropping system. The crop rotation decreases the pest population and some pathogen that cause diseases, and the farmers of the study site grow hybrid maize which is resistant to insect and pest disease (Puskaric and Carrigan, 1988). The uncertainty in pest and disease was modulated by considering the RAPs in climate analysis, thus, the model's limitation for weeds, pests, and diseases will not significantly influence the research findings.

5. Conclusion

The climate projections for Punjab, Pakistan showed that the maximum temperature would increase by 3.4 °C and the minimum temperature by 3.8 °C for the hot/dry GCM, while annual precipitation would decrease by 73 mm by the mid-century. This resulted in a 28 % reduction for the current maize production system and a 29 % reduction for the future maize production system by the middle of the century. Adaptations were developed for the future agriculture system, which indicated that yield could increase by 12–17 % for all GCMs. Current and future production systems are negatively affected by climate change but improved management as adaptations strategies can mitigate the negative impact of climate change.

Author contributions section

Ishfaq Ahmad:
Conducted whole research (Experimental and farm data collection, model calibration, Climate impact analyses and write-up of manuscript
Burhan Ahmad:
Statistical downscaling and climate scenarios generation
Kenneth Boote
Guided and help in CTWN analysis
Gerrit Hoogenboom
Review/ edits and improvement of manuscript

Declaration of Competing Interest

No conflict of interest exists.

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