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Full Text

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Quantifying Major Sources of Uncertainty in Projecting the Impact of Climate Change on Wheat Grain Yield in Dryland Environments

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Abstract: Modelling the impact of climate change on cropping systems is crucial to support policy-making for farmers and stakeholders. Nevertheless, inherent uncertainty exists in such projections. General Circulation Models (GCMs) and future climate change scenarios (different Representative Concentration Pathways (RCPs) across various future time periods) represent major sources of uncertainty in projecting climate change impacts on crop grain yield. This study quantified the different sources of uncertainty associated with future climate change impacts on wheat grain yield in dryland environments (Shiraz, Hamedan, Sanandaj, Kermanshah, and Khorramabad) in eastern and southern Iran. These five representative locations can be categorized into three climate classes: arid cold (Shiraz), semi-arid cold (Hamedan and Sanandaj), and semi-arid cool (Kermanshah and Khorramabad).

Accordingly, the downscaled daily outputs of 29 GCMs under two RCPs (RCP4.5 and RCP8.5) in the near future (2030s), middle future (2050s), and far future (2080s) were used as inputs for the Agricultural Production Systems sIMulator (APSIM)-wheat model. Analysis of variance (ANOVA) was employed to quantify the sources of uncertainty in projecting climate change impacts on wheat grain yield. Years from 1980 to 2009 were regarded as the baseline period. The projection results indicated that wheat grain yield was expected to increase by 12.30%, 17.10%, and 17.70% in the near future (2030s), middle future (2050s), and far future (2080s), respectively. The increases differed under different RCPs and time periods, ranging from 11.70% (under RCP4.5 in the 2030s) to 20.20% (under RCP8.5 in the 2080s) when averaging across all GCMs and locations, implying that future wheat grain yield depends largely upon rising CO_2 concentrations. ANOVA results revealed that more than 97.22% of the variance in future wheat grain yield was explained by locations, followed by scenarios, GCMs, and their interactions. Specifically, at the semi-arid climate locations (Hamedan, Sanandaj, Kermanshah, and Khorramabad), most of the variation arose from the scenarios (77.25%), while at the arid climate location (Shiraz), GCMs (54.00%) accounted for the greatest variation. Overall, the ensemble use of a wide range of GCMs should be prioritized to narrow uncertainty when projecting wheat grain yield under changing climate conditions, particularly in dryland environments characterized by large fluctuations in rainfall and temperature. Moreover, this research identified specific GCMs (e.g., IPSL-CM5B-LR, CCSM4, and BNU-ESM) that produced moderate effects in projecting climate change impacts on wheat grain yield, which can be used to project future climate conditions in similar environments worldwide.

Keywords: wheat grain yield; climate change; Agricultural Production Systems sIMulator (APSIM)-wheat model; General Circulation Models (GCMs);

arid climate; semi-arid climate; Iran

1 Introduction

Wheat is counted among the "big three" cereal crops in the world, with over 0.219$\times10^{9}$ hm^2 of land harvested annually (FAO, 2020). Crops will be substantially affected by climate change in the future (Liu et al., 2021; Obembe et al., 2021). Hence, it is essential to accurately project future climate change to assess its impacts on crop grain yield, especially wheat grain yield, since even a small bias in climate variable projections can result in significant variations in predicting crop phenological development and final grain yield (Ruiz-Ramos et al., 2016; Wang et al., 2018).

General Circulation Models (GCMs) accompanied by crop simulation models have been broadly applied to investigate future climate change impacts on different crop grain yields worldwide (Asseng et al., 2013; Tao et al., 2018; Rahimi-Moghaddam et al., 2019). These are useful tools for assessing climate change impacts in a low-cost and time-saving manner. However, a major problem is that using GCMs under various greenhouse gas emission scenarios (i.e., Representative Concentration Pathways (RCPs)) and future time periods (i.e., 2030s, 2050s, and 2080s) across different climate types is associated with uncertainty (Wang et al., 2018). Uncertainty is defined as a state of incomplete knowledge resulting from a lack of information or disagreement about what is known, with many types of sources including imprecise data, ambiguously defined concepts or terminology, uncertain projections of human activities, etc. (Edenhofer, 2014). Substantial uncertainty can result from model resolution at different spatiotemporal scales, model parameterization, model structure, and downscaling methods (Asseng et al., 2013; Eghdamirad et al., 2017; Hosseinzadehtalaei et al., 2017; Chapagain et al., 2022).

Previous studies have indicated that uncertainty in climate change impact assessments was related to climate models (Kassie et al., 2015), greenhouse gas emission scenarios (Shi et al., 2020), crop models (Asseng et al., 2013), downscaling methods (Khan et al., 2006), future time periods (Hawkins et al., 2016), and soil types (Wang et al., 2018). For example, a simulation study in Ethiopia (Kassie et al., 2015) found that uncertainty arising from GCMs was about –28.00% to –8.00% higher than those between GCMs and crop models (–20.00% to –19.00%) and between GCMs and RCPs (–22.00% to –17.00%). A similar study in southeastern Australia concluded that the major factors affecting uncertainty in projecting drought were the GCMs, with variability values of 19.20%–53.00%, followed by their interaction with RCPs, with variability values of 17.20%–44.30% (Shi et al., 2020). Rettie et al. (2022) assessed climate change impacts on wheat growth in Ethiopia based on a multi-model uncertainty analysis and reported that uncertainty in wheat grain yield changes was largely dominated by variations in crop models (with coefficient of variation

(CV) values of 71.00%–80.00%), followed by climate models (with CV values of 11.00%–25.00%).

It is also important to assess sources of uncertainty across different climate types in agricultural research, particularly for management practices such as developing suitable adaptation strategies to mitigate climate change impacts on crop grain yield. The uncertainty associated with projecting climate change impacts on crop yield stems not only from the above-mentioned sources but also from the climate conditions studied (Olesen et al., 2007). A global-scale study reported that 17 GCMs collectively underestimated (–4.00% to –2.00%) the mean annual maximum temperature in arid and semi-arid regions of the Sahara and the southwestern United States, which are most subject to severe heat waves and droughts (Cheng et al., 2015). The results also showed that most GCMs tended to underestimate historical annual maximum temperature in the United States and Greenland, while there is widespread disagreement in their simulations over cold regions. In another global-scale study (Freychet et al., 2021), researchers predicted that climatological bias in the difference between hot days (the number of days above the daily climatological 98th percentile during the warm season) and normal days in GCMs caused an underestimation of the frequency of unusually hot days in many low-latitude areas such as tropical regions (1.00%–48.00%) and Southeast Asia (1.00%–22.00%) in the future. These biases could lead to uncertainty in future crop yield projections. For example, Rahman et al. (2018) assessed uncertainty in projecting climate change impacts on cotton production in Pakistan and found large variations in projected climatic variables (increases of 3.80% to 12.40% for mean temperature and changes of –8.00% to 22.00% for rainfall in the future period compared to the baseline period) under different GCM projections, RCPs, and future time periods. These uncertainties resulted in large variability of cotton seed yield prediction (–70.00% to 4.00%).

The current research was conducted to quantify the major sources of uncertainty when projecting climate change impacts on wheat grain yield in dryland environments with arid and semi-arid climates, where the ratio of mean annual rainfall to mean annual potential evapotranspiration (i.e., Aridity Index) varies from 0.05 to 0.20 for arid climate and 0.20 to 0.50 for semi-arid climate (UNEP, 1992; Amiri et al., 2016). Specifically, the downscaled daily outputs of 29 GCMs under RCP4.5 and RCP8.5 scenarios in the near future (2030s), middle future (2050s), and far future (2080s) were used as inputs for the Agricultural Production Systems sIMulator (APSIM)-wheat model. Additionally, this research focused on identifying specific GCMs that produce moderate effects in projecting climate change impacts on wheat grain yield, which can be used to project future climate conditions in similar environments worldwide.

2.1 Study Area and Data Sources

The current research focused on five provinces (Fars, Hamedan, Kurdistan, Kermanshah, and Lorestan) in eastern and southern Iran, which account for approximately 42.00% (i.e., 1.40$×10^{6}$ hm^2) of the total global dryland wheat planting area. We selected one representative location from each province based on climate diversity and cultivated area. We then categorized the five representative locations (Shiraz, Hamedan, Sanandaj, Kermanshah, and Khorramabad) into three climate classes (arid cold, semi-arid cold, and semi-arid cool; Table 1) according to the agroclimatic classification defined by the United Nations Educational, Scientific and Cultural Organization (UNESCO) (UNESCO, 1979; De Pauw et al., 2018). Long-term (1980–2009) monthly climate characteristics of the five representative locations are shown in Table 2 .

Long-term (1980–2009) meteorological records for the five representative locations were obtained from the Agricultural Meteorological Organization of Iran (www.irimo.ir). Climate data included daily solar radiation (MJ/($m^2 \cdot$ d)), maximum temperature (°C), minimum temperature (°C), and rainfall (mm). Soil property data including depth (mm), bulk density (BD; g/m^3), particle size distribution (silt, sand, and clay; %), and organic carbon (OC; %) were also obtained from the Agricultural Meteorological Organization of Iran (www.irimo.ir), which were used to estimate soil parameters required by the crop model. Soil parameters included drained upper limit (DUL; mm/mm), crop lower limit of water availability (CLL; mm/mm), and saturated water content (SAT; mm/mm). The study adopted the soil-plant-air-water (SPAW) model to estimate soil parameters based on pedotransfer functions (Saxton and Willey, 2005) and soil property data (depth, BD, particle size distribution, and OC), since direct measurements of DUL, CLL, and SAT could be time-consuming and tedious.

Local management practices (e.g., sowing window and depth, tillage method, initial soil water, and nitrogen application) at each location were obtained from local experts at the Ministry of Agriculture and the Agricultural and Natural Resources Research and Education Center, Iran, as well as from the previous study of Rahimi-Moghaddam et al. (2021). Sowing depth (5.00 cm), tillage method (conventional cultivation), and nitrogen application (180.00 kg N/hm^2) were held constant throughout all simulations. According to local practices, farmers apply half of the nitrogen fertilizer at sowing time and the other half at stem elongation. The sowing window was from 23 September to 23 November, and the average initial soil water was 30.00 mm across the five representative locations. All simulations were carried out under water-limited conditions with no other abiotic or biotic constraints.

2.2 Crop Model

The Agricultural Production Systems sIMulator (APSIM)-wheat model version 7.7 (Holzworth et al., 2014) was used in this study. The model can capture the effects of environmental changes and management practices on crop growth and development on a daily time scale. The inputs required to run the model consist of daily climate variables, soil parameters, genetic coefficients for each cultivar, and management data to simulate crop growth and development, leaf area index, water-nitrogen balance, and grain yield (Holzworth et al., 2014).

Biomass accumulation is a function of photosynthetically active radiation intercepted by the canopy and radiation use efficiency (RUE). RUE is affected by temperature, phenological stage, CO_2 concentration, and nitrogen level. Temperature is a function of the daily mean temperature linearly interpolated by the APSIM-wheat model, which affects RUE from sowing to harvest. Increasing CO_2 concentration can enhance transpiration efficiency (TE) and RUE through the factors fC,TE and fC,RUE, respectively. fC,TE is the CO_2 factor for TE, which is a function of CO_2 concentration and linearly increases from 1.00 to 1.37 when CO_2 concentration rises from 350.00 to 700.00 mg/L. fC,RUE is the CO_2 factor affecting the RUE of C_3 plants (e.g., wheat), which can be calculated by a function of CO_2 concentration (C; mg/L), temperature-dependent CO_2 compensation point (Ci; mg/L), and daily mean temperature (Tmean; °C) as follows (Reyenga et al., 1999):

$$f_{C,RUE} = \frac{C - C_i}{C + 2 \cdot C_i} \cdot \frac{1}{1 + e^{0.3 \cdot (T_{mean} - 25)}}$$

The phenological stages in the APSIM-wheat model are mainly driven by the accumulation of thermal time. Each stage has a fixed thermal time limit, which can be adjusted based on the phase under consideration using cultivar-specific parameters (e.g., vernalization and photoperiod sensitivity). Both photoperiod and vernalization affect the development rate between emergence and floral initiation. Partitioning of assimilates into different plant organs is based on partitioning coefficients that vary across phenological stages.

The APSIM-wheat model can also capture the impact of extreme temperature on wheat growth and grain yield using the heat-shock module embedded in the model. The impact of extreme temperature on grain number and grain size can be estimated using sensitivity factors ranging from 0.00 to 1.00. The effect of daily maximum temperature on grain number (when daily maximum temperature exceeds 26.00°C) and the number of days required to consider the effect (7 d) before and after anthesis can also be captured in the heat-shock module. Further details regarding the heat-shock module in the APSIM-wheat model can be found in Lobell et al. (2015).

Soil-water balance in the APSIM-wheat model was projected on a daily scale, taking into account soil evaporation, plant transpiration, drainage, and runoff, based on water inputs from rainfall and irrigation. We calculated each process individually according to the relationships implemented in the APSIM-wheat model. Crop transpiration, for instance, was projected by potential crop growth rate, potential biomass accumulation, and TE. Runoff was determined through the United States Department of Agriculture (USDA) curve number method (Boughton, 1989; Ponce and Hawkins, 1996; Hawkins et al., 2008). Additional details about the APSIM-wheat model can be found in Holzworth et al. (2014) and the APSIM website (http://www.apsim.info/).

Thus far, the APSIM-wheat model has been successfully applied as a powerful tool to assess the impact of future climate change on wheat grain yield under different climate types in Iran (Rahimi-Moghaddam et al., 2019) and other countries (Araya et al., 2015; Wang et al., 2018; Saddique et al., 2020). Moreover, the model has also been used in many scientific reports for sensitivity and uncertainty analysis to predict crop grain yield (Zhao et al., 2014; Hao et al., 2021; Collins et al., 2022; Vogeler et al., 2022). In this study, we adopted 'Azar-2', the most commercial and dominant dryland wheat cultivar in the Iranian dryland agro-ecosystem, as a case study. The APSIM-wheat model was calibrated for this cultivar to obtain the genetic cultivar-specific parameters (Table 3) required for the model and validated across six locations for 13 seasons in dryland environments (Rahimi-Moghaddam et al., 2021) (Supplementary Table S1).

Table 3 Description of the parameters in the APSIM-wheat model used to predict the grain yield of 'Azar-2' cultivar

Parameter	Value	Unit
Thermal time at the end of juvenile stage	300	°C • d
Number of grains per gram of stem	25	Kernel/(g • stem)
Thermal time at floral initiation stage	500	°C • d
Maximum grain size	45	mg
Thermal time from the start of grain filling to maturity	600	°C • d
Photoperiod sensitivity	3.5	-
Vernalization sensitivity	3.0	-

Note: APSIM, Agricultural Production Systems sIMulator; -, dimensionless.

2.3 Projections of Future Climate Change

In this study, we projected future climate change for the five representative locations based on the monthly outputs of 29 GCMs from the Coupled Model Intercomparison Project Phase 5 (CMIP5) under two emission scenarios (RCP4.5 and RCP8.5) for three future time periods (2030s, 2050s, and 2080s).

The Agricultural Model Intercomparison and Improvement Project (AgMIP) methodology (AgMIP, 2013) was used to downscale daily station-scale meteorological observations from the large-scale monthly outputs of GCMs. Using the AgMIP downscaling approach, we projected daily future climate data based on the absolute change in minimum and maximum temperatures and relative change in rainfall in the climate model using the delta change method (Ruane et al., 2013; Kidanemariam et al., 2021). The detailed description of the AgMIP methodology for downscaling and projecting was previously reported by AgMIP (2013). The projected climate conditions were input into the APSIM-wheat model to simulate wheat grain yield under future climate change scenarios. CO_2 concentrations under RCP4.5 and RCP8.5 scenarios in different future time periods can be found in Araya et al. (2015). Two future climate change scenarios were projected to evaluate the positive effect of CO_2 concentration on wheat grain yield. In one scenario, both CO_2 concentration and temperature were elevated, while in the other scenario, temperature was elevated without CO_2 concentration increase.

2.4 Statistical Analyses and Uncertainty Decomposition

Three sources of uncertainty were considered in projecting future climate change impacts on wheat grain yield: climate models (29 GCMs), future climate change scenarios (RCPs_{future} time periods, including RCP4.5_{2030}s, RCP8.5_{2030}s, RCP4.5_{2050}s, RCP8.5_{2050}s, RCP4.5_{2080}s, and RCP8.5_{2080}s), and five representative locations (Shiraz, Hamedan, Sanandaj, Kermanshah, and Khorramabad). Variations arising from these three sources of uncertainty were assessed using analysis of variance (ANOVA), which has been widely applied in previous studies (Tao et al., 2018; Wang et al., 2018; Zhang et al., 2019). In the current study, three-way ANOVA (with three factors as sources of uncertainty) was used to estimate the main effects:

$$SST = SS_L + SS_G + SS_S + E$$

where SST is the total sum of squares; SS_L is the sum of squares due to location; SS_G is the sum of squares due to GCM; SS_S is the sum of squares due to scenario; and E is the interaction effect among the factors.

All data analyses were performed using R statistical software, version 3.4.1 (R Core Team, 2017). The package "agricolae" was applied for data pre-processing and three-way ANOVA analysis.

3.1 Projected Future Climate Change

There was considerable variability in the baseline period (1980–2009) for seasonal mean temperature (October to June of the next year) and seasonal cumulative rainfall (October to June of the next year) among different climate types (Table 2). In the arid cold climate region, wheat crops experienced the highest seasonal mean temperature (15.11°C), while in the semi-arid cold regions, wheat crops completed growth with cooler weather (8.92°C). The five representative locations received 397.84 mm of seasonal cumulative rainfall on average during 1980–2009, ranging from 319.40 mm in the arid cold regions to 488.05 mm in the semi-arid cool regions.

At the five representative locations, compared to the baseline period, the seasonal mean temperature of multi-GCM ensembles was projected to increase by 0.50°C under RCP4.5 and 0.60°C under RCP8.5 in the near future (2030s) (Fig. 1a [Figure 1: see original paper]1–a5). In the middle future (2050s), the projected increase in seasonal mean temperature was 0.90°C under RCP4.5 and 1.30°C under RCP8.5. In the far future (2080s), the likely increase in seasonal mean temperature would be 1.50°C under RCP4.5 and 2.60°C under RCP8.5, compared to the baseline period. Raising greenhouse gas emissions and lengthening the time periods (from the 2030s to the 2080s) enlarged the magnitude of rainfall change in the future compared to the baseline period. The change was defined from quantile 10 (Q10) to quantile 90 (Q90). When averaged across all five representative locations, Q10–Q90 of multi-GCM ensembles for seasonal cumulative rainfall varied considerably under RCP4.5 (Fig. 1b1–b5). It ranged from –12.00% to 36.00% in the 2030s, from –17.00% to 29.00% in the 2050s, and from –22.00% to 25.00% in the 2080s. Under RCP8.5, the corresponding values ranged from –17.00% to 32.00% in the 2030s, from –24.00% to 31.00% in the 2050s, and from –41.00% to 19.00% in the 2080s. When averaged across all GCMs, RCPs, and future time periods, the maximum and minimum increases in future seasonal mean temperature were recorded in Shiraz (1.26°C) and Kermanshah (0.71°C), respectively (Fig. 1a1–a5), where the climate is characterized as arid cold and semi-arid cool, respectively. The maximum change in seasonal cumulative rainfall was projected in Shiraz (–28.60% to 18.40%; arid cold climate), and the minimal change was projected in Hamedan (–13.90% to 10.20%; semi-arid cold climate) (Fig. 1b1–b5).

3.2 Projected Future Wheat Grain Yield

In the baseline period (1980–2009), the averaged wheat grain yield across all representative locations was 3.00 t/hm^2, with the maximum yield in Khorramabad (3.94 t/hm^2; semi-arid cool climate) and the minimum yield in Shiraz (2.60 t/hm^2; arid cold climate).

In future projections, the change trends of wheat grain yield for the different sets of GCMs, RCPs, and future time periods were positive at all representative locations. When taken as a multi-GCM ensemble, the median of projected future wheat grain yield increased by 15.70% on average across all representative locations, RCPs, and future time periods (Fig. 2a [Figure 2: see original paper]–e). Nevertheless, the magnitude of the increase was still dependent on locations, RCPs, and future time periods. For example, across the five representative locations, 29 GCMs, and two RCPs, projected future wheat grain yield was expected to increase by 12.30%, 17.10%, and 17.70% in the near future (2030s), middle future (2050s), and far future (2080s), respectively. Additionally, across the five representative locations, the median of projected future wheat grain yield from multi-GCM ensembles under RCP4.5 and RCP8.5 respectively increased by 17.80% and 20.20% in the 2080s, 17.70% and 20.00% in the 2050s, and 11.70% and 12.70% in the 2030s (Fig. 2a–e). As shown in Figures 2a–e and 3, the projected future wheat grain yield varied significantly across locations. When averaged across all GCMs, RCPs, and future time periods, the changes in projected future wheat grain yield ranged from –14.20% to 53.62% in Hamedan (semi-arid cold climate) and from –2.50% to 5.50% in Khorramabad (semi-arid cool climate) (Fig. 2a–e).

The variability in projected future wheat grain yield was also affected by GCMs (length of boxplots in Fig. 2a–e). The greatest change in projected future wheat grain yield due to GCMs was observed under RCP8.5 in the 2080s in Hamedan, Kermanshah, and Shiraz, while the minimal change was found under RCP4.5 in Khorramabad and Sanandaj (Fig. 2a–e). Figure 3 [Figure 3: see original paper] shows the projected future wheat grain yield using 29 GCMs under two RCPs for all representative locations in the middle future. Only the 2050s timeline was included for simplicity. According to the results from 29 GCMs under two RCPs at all representative locations (Fig. 3), compared to the baseline period, the maximum change in future wheat grain yield was projected by the IPSL-CM5A-LR GCM (from –56.40% to 45.70%), whereas the minimum change was projected by the IPSL-CM5B-LR GCM (from –33.00% to 43.10%).

3.3 Relative Contribution of Major Sources of Uncertainty in Projected Future Wheat Grain Yield

Figure 4 [Figure 4: see original paper] indicates the total variance of the major sources of uncertainty in projected future wheat grain yield, partitioned into three major sources (locations, GCMs, and scenarios (i.e., RCPs_{future} time periods)) and their interactions. As more than 97.22% of the variance was captured by locations, the share of each source of uncertainty associated with GCMs, scenarios, and scenario×GCM was presented for each location separately (Fig. 4). As indicated in Figure 4, a large share of the variance (77.25%) was explained by scenarios at the semi-arid locations (e.g., 82.34% in Sanandaj, 78.61% in Hamedan, 75.51% in Kermanshah, and 69.97% in Khorramabad). In contrast, at the arid location (Shiraz), the overall uncertainty from GCMs was substantial, such that 53.60% of the variance was explained by GCMs, followed by scenarios and scenario×GCM, explaining 32.39% and 14.01% of the variance, respectively. Interaction between scenarios and GCMs was the least important source of uncertainty at all locations. The uncertainty related to GCM×scenario was just 4.03% in Khorramabad, followed by 4.94% in Sanandaj, 5.49% in Hamedan, 6.47% in Kermanshah, and 14.01% in Shiraz.

4.1 Changes in Projected Future Wheat Grain Yield and Its Associated Uncertainty

In the baseline period (1980–2009), the maximum and minimum wheat grain yields were recorded in Khorramabad (3.94 t/hm^2) with a semi-arid cool climate and Shiraz (2.60 t/hm^2) with an arid cold climate, respectively (Fig. 2f). This can be related to cumulative rainfall during the wheat growing season, as wheat crops received more seasonal rainfall in Khorramabad (409.60 mm) than in Shiraz (319.40 mm) (Table 2). Figure 2a–e indicated that projected future wheat grain yield increased under different RCPs and future time periods at all representative locations. This increase was largely associated with the rise in CO_2 concentrations projected for the future (Fig. 5a [Figure 5: see original paper]1–a5). In fact, as previously discussed in similar areas (e.g., Lv et al., 2013; Amiri et al., 2021), the positive effect of CO_2 fertilization can offset the negative impact of rising temperature on wheat grain yield. The positive effect of CO_2 fertilization varied considerably across the five representative locations. For example, wheat grain yield received the least positive effect from CO_2 emission in Khorramabad in the future period (Figs. 2c and 5a3). The length of the wheat growth period decreased more in Khorramabad (decreased by 9.38%) than at the other four representative locations (decreased by 0.97% to 8.64%) under rising temperature conditions (Fig. 5b1–b5), since rising temperature can reduce the length of the wheat growing season. Many scientific reports worldwide have also indicated the negative effect of rising temperature on the length of the crop growing season and consequently on crop grain yield (Asseng et al., 2014; Rahimi-Moghaddam et al., 2019; Ding et al., 2021).

Specifically, the projection results in the current study indicated that great variation in wheat grain yield would occur in the future according to locations, RCPs, future time periods, and GCMs (Figs. 2 and 3). As shown in Figure 4, a much higher variance was explained by locations compared to scenarios and GCMs, which may be due to the large differences in annual cumulative rainfall (from 265.00 mm in Hamedan to 569.10 mm in Kermanshah) and annual mean temperature (ranging from 11.46°C in Hamedan to 18.32°C in Shiraz) across the five representative locations (Table 2). Additionally, the variation in future wheat grain yield was higher at locations with less rainfall (Fig. 2). The highest variation was recorded in Hamedan (Fig. 2), which typically receives less rainfall (265.00 mm) than the other locations (320.90–569.10 mm) (Table 2). Indeed, rainfall plays a much greater role in grain yield change than temperature in dryland environments. In the future, for a specific area with low rainfall, even a tiny variation in rainfall could cause much larger changes in wheat grain yield (Schierhorn et al., 2020). For instance, Hamedan with a semi-arid cold climate had a much lower annual mean temperature (11.46°C) than Shiraz with an arid cold climate (18.32°C) (Table 2), while the change in future wheat grain yield was much larger in Hamedan than in Shiraz (Fig. 2), mainly because of less rainfall in Hamedan (265.00 mm) than in Shiraz (320.90 mm) (Table 2). In a study assessing climate variability impacts on crop yield and irrigated water demand in South Asia (Ahmad et al., 2020), it was reported that in the absence of irrigation, up to 39.00% of the variation in wheat grain yield and 75.00% of the variation in rice yield were associated with rainfall changes at all study locations. Another research (Gupta and Mishra, 2019) investigated rice yield uncertainty in agro-ecological zones of India and highlighted that high temperature and low rainfall may be the reason for great variation in yield in some agro-ecological zones in West India.

In this study, projected seasonal mean temperature and seasonal cumulative rainfall varied substantially with the GCMs and scenarios used, indicating strong uncertainty for future climate conditions in the study area. The proportion of uncertainty, however, differed among scenarios, GCMs, and locations. The highest proportion in all cases was associated with the 29 GCMs and the five representative locations (length of boxplots in Figs. 2a–e and 3). In the arid climate zone (i.e., Shiraz), GCMs showed the largest contribution to uncertainty in projecting future wheat grain yield, followed by scenarios (Fig. 4). This is likely due to high variations in projected seasonal cumulative rainfall among GCMs (Fig. 1b1–b5) combined with a higher increase in future temperature compared to other locations. It is also interesting to note that the uncertainty resulting from GCMs at different representative locations was magnified with increasing emission scenarios (from RCP4.5 to RCP8.5) and farther time periods (from 2030s to 2080s), particularly for rainfall projections. In agreement with these findings, Wang et al. (2018) reported that climate projections from GCMs contributed to large differences in wheat yield, especially in dryland regions of eastern Australia. In their study, GCMs were the largest source of uncertainty in projecting wheat grain yield change. Another study has also indicated that large variation in temperature projection due to GCMs and scenarios would be important in affecting crop yield variability in the future (Asseng et al., 2011). Specifically, Asseng et al. (2011) reported that observed variations in the average growing season temperature of $\pm$2.00°C from 1996 to 2007 in the main wheat growing regions of Australia caused a reduction in grain production of up to 50.00%. Previous studies have also shown that GCMs and scenarios are major sources of uncertainty in quantifying climate change impacts, as GCMs have limited capacity for predicting climate extremes and inter-annual climate variations, which would ultimately lead to false representation of climate change impacts on crop yield (Osborne et al., 2013; Asseng et al., 2014; Araya et al., 2015; Kassie et al., 2015). This is related to the structure of GCMs, particularly when applied to project future conditions in various regions with contrasting climate types (warm-dry, cool-dry, warm-wet, cool-wet, and temperate) located at different altitudes (Ruane and McDermid, 2017; Ahmad et al., 2020). Therefore, the ensemble use of a wide range of GCMs should be prioritized to narrow uncertainty when assessing wheat grain yield under future climate change, particularly in dryland environments characterized by large fluctuations in rainfall and temperature.

Moreover, scenarios (RCP×future time period) made an important contribution to uncertainty in projecting future wheat grain yield changes at all semi-arid climate locations (i.e., Hamedan, Sanandaj, Kermanshah, and Khorramabad), and higher rainfall along with elevated CO_2 concentration resulted in a considerable increase in wheat grain yield compared to the arid climate location (Fig. 2). These findings are in accordance with those of Masutomi et al. (2009), who pointed out that higher CO_2 concentration may bring higher uncertainty in projecting climate change effects on rice yield in the 2080s in Southeast Asia, and the average change in rice production varied with and without CO_2 fertilization across all scenarios and GCMs.

The current findings further revealed that the GCMs IPSL-CM5A-LR, IPSL-CM5A-MR, MIROC-ESM, CanESM2, and HadGEM2-AO contributed substantially to the total uncertainty in projecting climate change impacts on wheat grain yield, while IPSL-CM5B-LR, CCSM4, and BNU-ESM produced moderate effects and can be used to project future climate conditions in similar environments worldwide, especially in the absence of computational facilities capable of processing large amounts of data from simulation experiments (GCM×RCP×future time period×location) (Fig. 3). Overall, GCMs and scenarios have been determined to be the major sources of uncertainty in projecting climate change impacts on wheat growth and grain yield, though the magnitude of uncertainty is highly dependent upon climate.

4.2 Limitations

The current study aimed to assess the major sources of uncertainty (GCMs, locations, and scenarios) in projecting climate change impacts on wheat grain yield. However, many other sources of uncertainty exist when investigating climate change impacts on crop production, including crop models (e.g., model inputs, parameters, and structure) (Asseng et al., 2013), downscaling approaches (Khan et al., 2006), genotypes and management options (e.g., irrigation regime, nitrogen application, and sowing date) (Ojeda et al., 2021), and soil types (e.g., plant available water capacity) (Wang et al., 2018). For example, a review of 277 articles from 1991 to 2019 across 82 countries (460 locations) reported that uncertainty in projecting climate change impacts on crop yield related to model parameters and model structure comprised 28.00% and 20.00% of studies, respectively (Chapagain et al., 2022). In another study using the APSIM, MONICA (Model for Nitrogen and Carbon in Agro-ecosystems), and SIMPLACE (Scientific Impact Assessment and Modelling Platform for Advanced Crop and Ecosystem Management) crop models, Kamali et al. (2022) investigated the main drivers of uncertainty regarding management practices (water allocation strategies, three sowing dates, and three maize cultivars) in projecting irrigated maize yield under historical conditions and under scenarios of rising temperature and altered irrigation water availability in southern Spain. They concluded that irrigation strategy was the main driver of uncertainty in projecting crop yield (accounting for 66.00% of variance). They also reported that under rising temperature, both crop model and cultivar choice contributed to uncertainty in projecting crop yield as importantly as irrigation strategy. Generally, studies focusing on uncertainty in all parameters and inputs simultaneously are still lacking (Chapagain et al., 2022).

It should also be mentioned that the current research was conducted only under water-limited conditions. Other factors such as nitrogen (Wang et al., 2018) and phosphorus (Engebretsen et al., 2019) can also affect the uncertainty of projected wheat grain yield in the future. Accordingly, it is suggested that the simultaneous effects of all environmental (i.e., soil and climate), genetic, and management (e.g., sowing date, plant density, irrigation, and nitrogen fertilizer) factors should be considered when analyzing sources of uncertainty in projecting future wheat grain yield.

5 Conclusions

In this study, we quantified three sources of uncertainty in projecting future wheat grain yield under climate change based on 29 GCMs, six scenarios (RCP4.5_{2030}s, RCP8.5_{2030}s, RCP4.5_{2050}s, RCP8.5_{2050}s, RCP4.5_{2080}s, and RCP8.5_{2080}s), and five representative locations with different climate types (Shiraz, Hamedan, Sanandaj, Kermanshah, and Khorramabad). Our results indicated that the increase in projected future wheat grain yield under different RCPs and future time periods at all representative locations was largely associated with the rise in CO_2 concentration in upcoming periods.

Most of the variation in projected future wheat grain yield can be explained by locations, followed by scenarios and GCMs, depending on the climate of each location. At the arid climate location (Shiraz), the biggest source of uncertainty in predicting future wheat grain yield was associated with GCMs, mainly due to high variations in projected seasonal cumulative rainfall among GCMs. Accordingly, it seems that multi-GCM ensembles should be prioritized to adequately address and reduce uncertainty when projecting wheat grain yield under climate change conditions, particularly in arid climate regions. At all semi-arid climate locations (Hamedan, Sanandaj, Kermanshah, and Khorramabad), scenarios were the biggest source of uncertainty in projecting future wheat grain yield changes. Our findings also revealed that IPSL-CM5B-LR, CCSM4, and BNU-ESM produced moderate effects in projecting climate change impacts on wheat grain yield and can be used to project future climate conditions in similar environments worldwide, especially in the absence of computational facilities capable of processing large amounts of data from simulation experiments (GCM×RCP×future time period×location). Furthermore, only one crop model (APSIM-wheat) was used in the current study to simulate climate change impacts on wheat grain yield. Accordingly, potential sources of uncertainty resulting from crop models (such as model structure and parameters), downscaling approaches, adaptation options (irrigation regime, nitrogen application, sowing date, and cultivar), and soils should be considered in future studies. It is worth noting that calibrating crop models for the effects of CO_2 on photosynthesis and transpiration of local cultivars is important, as there is evidence of widespread genotypic variability in the response of these processes to CO_2.

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Appendix

Table S1 Summarized results of APSIM model evaluation (adapted from Rahimi-Moghaddam et al., 2021)

Trait	R^2	d-index	nRMSE (%)	MBE	N
Days to flowering (d)	0.85	0.92	5.2	1.3	45
Days to maturity (d)	0.78	0.89	6.8	2.1	45
Grain yield (t/hm^2)	0.72	0.86	12.5	0.3	78
Soil moisture (cm^3/cm^3)	0.68	0.81	8.9	–0.02	156

Note: R^2, coefficient of determination; d-index, Wilmot's index of agreement; nRMSE, normalized root mean square error; MBE, mean bias error; N, number of observations.

Note: Figure translations are in progress. See original paper for figures.