Vulnerability of maize production under future climate change: possible adaptation strategies

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Abstract

BACKGROUND: Climate change can affect the productivity and geographic distribution of crops. Therefore, evaluation of adaptive management options is crucial in dealing with negative impacts of climate change. The objectives of this study were to simulate the impacts of climate change on maize production in the north-east of Iran. Moreover, vulnerability index which indicated that how much of the crop yield loss is related to the drought was computed for each location to identify where adaptation and mitigation strategies are effective. Different sowing dates were also applied as an adaptation approach to decrease the negative impacts of climate change in study area.

RESULTS: The results showed that the maize yield would decline during the 21st century from −2.6% to −82% at all study locations in comparison with the baseline. The result of vulnerability index also indicated that using the adaptation strategies could be effective in all of the study areas. Using different sowing dates as an adaptation approach showed that delaying the sowing date will be advantageous in order to obtain higher yield in all study locations in future.

CONCLUSION: This study provided insight regarding the climate change impacts on maize production and the efficacy of adaptation strategies. © 2016 Society of Chemical Industry

Keywords: adaptation; DSSAT; LARS-WG; maize; vulnerability index

INTRODUCTION

Climate change is one of the major concerns for all of communities throughout the world and has come to the forefront of scientific problems.1 The average global temperature has increased in recent decades because of human activities and has been expected to continue rising in the near future.2 According to the fourth report by the Intergovernmental Panel on Climate Change (IPCC) the annual average global temperature increased about 0.74 ± 0.18 °C during the 1906–2005 period.3 A warming of 0.2 °C per decade is also predicted for the next two decades.4 Hence, several studies have been carried out in different parts of the world to highlight these changes and variability.3,5 In this regard, the historic trend (1960–2005) of mean annual temperature for Iran indicated that annual increase of temperature was about 0.05 °C with the highest mean annual air temperature recorded (16.3 °C) in 2001.6

The agricultural and food systems represent the most vulnerable sectors to climate variability. Undoubtedly, crop production is going to be affected by climate change and also food security of a nation depends on how crop yield responds to climate variability.7 Because of the socio-economic importance of these two systems, it is fundamental to assess the effect of future climate change on crop productivity.8 Climate changes generally impose negative impacts on agricultural production especially in hot and dry areas,9 but in some areas, mainly those located above 55° latitude will have positive effects.10 During recent decades, the issues of climate variability and climate change impacts on agricultural and crop production have been used in many scientific studies.11,12 On the other hand, crop growth simulation models have been developed as one of the useful tools to project these effects in last decades. These models have been widely used in different studies related to crop production or resources management.13 The outputs of crop simulation models when run with future projected weather data under climate change scenarios, generated by general circulation models, can be used to predict the effects of climate variability on crop production.14 Among these models, the Decision Support System for Agrotechnology Transfer (DSSAT) is an extensive decision support system including a set of crop simulation models that applies not only to predicting the impacts of climate variability on crop productivity but also can estimate the best genetic options and management under climate change scenarios.15 Guo et al.,16 using the HadCM3 model under A2 and B2 scenarios, projected that the average of maize and wheat yield will increase by 3.2% and 9.8%, respectively, without CO2 fertilisation in the North China Plain. Tao and Zhang17 revealed that maize yield may decrease, on average, from 13.2% to 9.1% during the 2050s, relative to 1961–1990. The study conducted by Meza et al.18
showed that climate change could affect crop development, and will reduce the length of its growing cycle. Tojo Soler et al.\textsuperscript{19} investigated the effects of different weather and planting dates on maize yield in Brazil with CERES-Maize, and indicated that a later planting date will decrease 55\% on average yield under rainfed conditions and 21\% under irrigated conditions, and almost accelerate the harvest date by 45 days. However, Mall et al.\textsuperscript{20} demonstrated that delaying the sowing dates would be beneficial for increasing soybean yields under climate change condition at all the locations in India. Alexandrov and Hoogenboom\textsuperscript{1} also indicated that the yield of maize and winter wheat will decrease under a current level of CO\textsubscript{2} (330 ppm), precipitation deficit and high temperature due to a shorter crop growing season.

Adaptation and mitigation could be intended as direct and indirect intervention to reduce or prevent damages due to the climate change, respectively. Although, adaptation and mitigation may be different, both are important components to overcome the negative impacts of climate variability on crop yield and commonly apply as complementary strategies. In general, to reduce the irreversible impacts of climatic fluctuation in vulnerable regions where agriculture is most sensitive, many adaptation strategies were suggested, including: altered crop rotation, changing cultivars, more efficient water use, altering the timing or location of cropping activities, development of new agricultural areas and improving the effectiveness of pest, disease and weed management.\textsuperscript{3} So, improving responses to climate change by designing appropriate adaptation and mitigation solutions or choosing effective adaptation and mitigation strategies could be a critical challenge for farmers over the coming decades. Results of many studies suggested that the impacts of climate change without using adaptation and mitigation strategies may create considerable problems related to agricultural production and economies.\textsuperscript{21} On the other hand, various studies have been conducted to investigate the role of the agronomic mitigation or adaptation strategies to climate change.\textsuperscript{20,22,23} However, it should be noted that the efficacy of adaptation and mitigation strategies in each region is different and no single approach can give the required information for adapting agriculture in a changing climate, hence it is possible to use the vulnerability index to identify which areas and/or years have higher or lower response to these strategies and which adaptation and mitigation efforts are likely to be most effective and thus how one may prioritise them.\textsuperscript{24} In general, vulnerability index was described as the ratio of a crop failure index (detrended yield for that year divided by the actual harvest for the year) to a drought index (mean growing season rainfall divided by the actual rainfall in a season) which indicated that how much of the crop yield loss in each region and/or year is related to the drought.\textsuperscript{24}

Iran has diverse climate conditions (from arid to humid), but most areas in this country commonly have arid and semi-arid climates with annual average precipitation of 250 mm. Most of the annual precipitation falls from October through April.\textsuperscript{25} Maize (\textit{Zea mays} L.) is one of the most widely grown grain crop in the world and Iran. According to the FAO Statistics (2013) (http://faostat.fao.org) there were 425 000 ha under maize cultivation with 2.54 million tones production in Iran, with 99.5\% of it under irrigation and this crop is grown almost all over the country under varied soil and climatic conditions. The objectives of this study were to simulate the impacts of climate change on maize production in the north-east of Iran. Moreover, vulnerability index was computed for each location to identify where adaptation and mitigation strategies are effective. Different sowing dates were also applied as an adaptation approach to decrease the negative impacts of climate change in study area.

**MATERIALS AND METHODS**

**Study area, weather and yield data**

The present study was conducted in three locations in the north-east of Iran (Khorasan Razavi province) named as Mashhad, Sabzevar and Torbat heydariyeh which are located between 35° 16’ and 36° 16’ N latitudes, 57° 39’ and 59° 38’ E longitudes, respectively (Fig. 1). The north-east of Iran commonly faces a highly fluctuating climate and rainfall in this area is rare from July to September.\textsuperscript{26} In this study, historical daily weather data for each region including maximum and minimum temperature (°C), precipitation (mm) and solar radiation (MJ m\textsuperscript{-2} d\textsuperscript{-1}) were obtained as baseline data for the 1983–2010 period from local synoptic stations. For the similar time period the maize yield data also were obtained from the agriculture ministry.

**General Circulation Models, downscaling model, and scenarios**

Due to low spatial resolution of General Circulation Models (GCMs), outputs should be downscaled and two methods including dynamical and statistical downscaling are commonly in use.\textsuperscript{27} Statistical downscaling has more advantages and ability compared with dynamic downscaling especially when lower cost and faster evaluation of climatic variables is required. This downscaling method can be carried out by the common statistical methods such as regression or by the weather generator models such as Long Ashton Research Station Weather Generator (LARS-WG) model.\textsuperscript{2} The LARS-WG model is a stochastic weather generator that generates synthetic daily time series of solar radiation, precipitation, maximum and minimum temperature of any length which correspond to the observed climate statistics at a single site.\textsuperscript{28} This weather generator uses the Fourier series for temperature modelling and also Markov chain and semi-empirical distribution methods for precipitation and radiation simulation, respectively.\textsuperscript{29} The following three emissions scenarios from the major families of SRES emissions scenarios have been used to project the future data. The A1B scenario represents the fastest growing economies in the world, maximum population growth in the middle of this century and high-performance technology based on a balanced energy mix.\textsuperscript{30} The A2 scenario includes very heterogeneous environmental conditions, high population growth...
rate, negligible economic development and slow technological change.31 Moreover, the B1 scenario describes a convergent world with a global population that peaks in mid-century and rapid changes in economic structures toward a service and information economy.32

In this study, several statistics criteria were computed to evaluate the accuracy of the simulated data. The coefficient of determination (\( R^2 \)) was calculated to compare simulated temperature, precipitation and radiation with measured values [Eqn (1)]. The index of agreement (\( D \)) was used as a standardised measure of the degree of model prediction error and varies between 0 and 1 so that a value of 1 indicates a perfect match, and 0 indicates no agreement at all [Eqn (2)]. The mean squared deviations (MSD) also was computed to evaluate the model error and forecasts accuracy, in addition this index represents the forecast overall deviation of observations [Eqn (3)]. Finally, the mean absolute error (MAE) was calculated to estimate the mean absolute error function for the forecast and the eventual outcomes. In other words it is a quantity used to measure how close forecasts or predictions are to the eventual outcomes [Eqn (4)]:

\[
R^2 = \frac{\sum_{i=1}^{n} (S_i - \bar{S})(O_i - \bar{O})^2}{\sum_{i=1}^{n} (S_i - \bar{S})^2 \sum_{i=1}^{n} (O_i - \bar{O})^2}
\]

\[
D = 1 - \frac{\sum_{i=1}^{n} (S_i - O_i)^2}{\sum_{i=1}^{n} (|S_i| + |O_i|)^2}
\]

\[
MSD = \frac{\sum_{i=1}^{n} (S_i - O_i)^2}{n}
\]

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |O_i - \bar{O}|
\]

where \( S \) and \( O \) are simulated and observed data, respectively, \( \bar{S} \) and \( \bar{O} \) are the mean of simulated and observed data, \( S_i = (S_i - \bar{S}) \), \( O_i' = \left( O_i - \bar{O} \right) \), and \( n \) is the number of observations.

The LARS-WG was finally used to produce daily data series for three projection decades (2020s, 2050s and 2080s) using two GCM models including GFCM21 and INCM3 developed in the Geophysical Fluid Dynamics Lab and Institute for Numerical Mathematics in Russia, respectively.33,34 For evaluating the precision of these two GCM models in climatic data simulation \( R^2 \) [Eqn (1)], MAE [Eqn (4)] and RRMSE [Eqn (5)] also were computed:

\[
RRMSE = \sqrt{\frac{\sum_{i=1}^{n} (O_i - S_i)^2}{n}} \left( \frac{100}{\bar{O}} \right)
\]

where \( S \) and \( O \) are simulated and observed data, respectively, \( \bar{O} \) is the mean of observed data and \( n \) is the number of observations.
Crop model

The Decision Support System for Agrotechnology Transfer (DSSAT) is one of the most widely used crop simulation models (for more than 20 different crops) in the world.\(^\text{35}\) The DSSAT model is derived from the CERES and CROPSIM and also more than 120 studies conducted by DSSAT models from North America to Africa.\(^\text{35,36}\)

This crop model simulates plant growth and development as a function of daily weather, soil condition and crop management. Plant growth is calculated on a daily basis and biomass allocation is a function of the stage of plant growth and development and also depends on the amount of available biomass for growth. All the processes of growth and development have been dynamic and are influenced by environmental factors and characteristics of plant varieties. Weather conditions also will be available in the climate file providing daily data. Commonly, the description of plant development is expressed based on the thermal unit. Moreover, plant growth potential is a function of visible radiation and absorbed radiation depend on the leaf area index (LAI). Different factors such as row spacing, plant density and light use efficiency also have direct effect on potential output. In this model, empirical equation has been used for processes of growth phenology, canopy development, organ formation, photosynthesis, allocation of assimilates and soil water content. Hence, the model is able to simulate climate effects on soil moisture and nitrogen, growth and yield.\(^\text{37}\)

In this study, the CERES-Maize model (in DSSAT ver. 4.5), which is one of the most popular and high visibility models, has been used in order to carry out the simulation of maize characteristics. The cropping system model was previously calibrated and validated at the study areas for maize-Single Cross 704.\(^\text{38}\) For simulating the maize growth and yield also it was assumed that the crop was free from any insect, pest and disease effects. Moreover, \(135 \text{ kg N ha}^{-1}\) was applied twice and irrigation was set as automatic to avoid yield differences due to inadequate nitrogen or inefficient water management.

Vulnerability index

Vulnerability refers to the degree that agricultural systems may experience harm due to drought (rainfall anomaly), hence vulnerability assessment is an effective way to realise the impacts of climate change on these systems.\(^\text{39}\) Vulnerability index was described as the ratio of a crop failure index to a drought index [Eqn (6)].\(^\text{24}\) The crop failure index is the detrended yield for that year divided by the actual harvest for the year.\(^\text{24}\) In general, an increase in crop yield from year to year may be explained by gradual improvements in technology, while other variables such as weather conditions, pests and diseases, input availability are all fairly constant or under control, thus the goal of detrending is to get a good long-year record of yields (http://cmboxuserguide). In other words, detrended yield removes the effect of increased technology or consistent misreporting and demonstrates an ‘expected harvest’ based on a long-term trend and the hypothesis is that an upward (downward is not very likely) trend in yields caused by the factors mentioned above is eliminated from the statistics. Detrending yield requires two steps. The first step involves the fitting of a smooth curve through the yield statistics and the second step includes obtaining yield anomalies as the difference between the yield in each year and average of observed long-term yield. On the other hand, the drought index is the mean growing season rainfall
in which regions or years was large relative to the size of drought. It must be considered that the value of vulnerability index above 1.5 is related with sufficiently high vulnerability that no significant adaptation takes place. In this study the crop failure index and drought index were calculated based on baseline data (1983–2010) and the Minitab17 software was used to compute the detrended yield data for this baseline time period.

**Adaptation strategies**

In this study sowing time was evaluated as an agronomic adaptation option. The optimal sowing dates for maize could be considered at three different times, including spring cultivation (from the middle of March to June), summer cultivation (from July to August) and winter cultivation (February). However, due to changes in climate these dates can change over time. In most locations of these study areas, maize sowing date normally occur within the middle of May to the middle of June. Hence, current sowing date (15 June) for each location based on the local information was considered and two planting dates (29 May and 29 June) were chosen for different locations. The phenological stages, leaf area index and potential grain yield was simulated for current and future (2020s, 2050s and 2080s) climatic conditions which was projected by two GCMs (GFCM21, INCM3) under three scenarios (A1B, A2 and B1).

### RESULTS

#### LARS-WG model validation

The LARS-WG model was evaluated using four statistical criteria to determine the reliability of simulated climate data. The results generally indicated adequate accuracy for simulation the climatic data in the study areas (Table 1). The evaluation of two GCMs in climatic data simulation also showed the similar results (Table 2 and Table 3).

#### Maize production

The simulated phenological stages, maximum leaf area index and grain yield (kg ha\(^{-1}\)) of maize in current planting date (15 June) for baseline and changes in potential yields with GFCM21 and INCM3 under A1B, A2 and B1 scenarios in three periods for Sabzevar. (Table 5) was tested with vulnerability index using both GCMs under all scenarios and time periods showed a

Table 5. Simulated phenological stages, maximum LAI and grain yield (kg ha\(^{-1}\)) of maize in current planting date (15 June) for baseline and changes in potential yields with GFCM21 and INCM3 under A1B, A2 and B1 scenarios in three periods for Sabzevar.

<table>
<thead>
<tr>
<th>GCM model</th>
<th>Scenario</th>
<th>Decade</th>
<th>Anthesis day</th>
<th>Maturity day</th>
<th>Yield (kg ha(^{-1}))</th>
<th>LAI max</th>
</tr>
</thead>
<tbody>
<tr>
<td>GFCM21</td>
<td>Baseline</td>
<td>2020</td>
<td>47</td>
<td>75</td>
<td>6950</td>
<td>4.07</td>
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<tr>
<td>A1B</td>
<td>2020</td>
<td>45</td>
<td>73</td>
<td>5358</td>
<td>3.70</td>
<td></td>
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<tr>
<td></td>
<td>2050</td>
<td>44</td>
<td>70</td>
<td>2731</td>
<td>3.24</td>
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<tr>
<td></td>
<td>2080</td>
<td>43</td>
<td>69</td>
<td>1381</td>
<td>2.71</td>
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</tr>
<tr>
<td>A2</td>
<td>2020</td>
<td>45</td>
<td>73</td>
<td>5080</td>
<td>3.68</td>
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<tr>
<td></td>
<td>2050</td>
<td>44</td>
<td>71</td>
<td>3165</td>
<td>3.31</td>
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<tr>
<td></td>
<td>2080</td>
<td>43</td>
<td>67</td>
<td>1270</td>
<td>2.42</td>
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<tr>
<td>B1</td>
<td>2020</td>
<td>45</td>
<td>73</td>
<td>5167</td>
<td>3.70</td>
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<tr>
<td></td>
<td>2050</td>
<td>45</td>
<td>72</td>
<td>3465</td>
<td>3.47</td>
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<tr>
<td></td>
<td>2080</td>
<td>44</td>
<td>70</td>
<td>2755</td>
<td>3.24</td>
<td></td>
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<tr>
<td>INCM3</td>
<td>A1B</td>
<td>2020</td>
<td>45</td>
<td>73</td>
<td>4791</td>
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<tr>
<td></td>
<td>2050</td>
<td>44</td>
<td>71</td>
<td>2733</td>
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<td>44</td>
<td>69</td>
<td>1788</td>
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<tr>
<td>A2</td>
<td>2020</td>
<td>45</td>
<td>73</td>
<td>5319</td>
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<td>45</td>
<td>72</td>
<td>2888</td>
<td>3.33</td>
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</tr>
</tbody>
</table>

where \(Y_i\) is detrended yield, \(H_i\) is the actual harvest, \(R_i\) is the actual rainfall in a season.

\[
\text{vulnerability index} = \frac{\text{crop failure index}}{\text{drought index}} = \frac{(\hat{Y}_i/H_i)}{(R_i/R_i)} \tag{6}
\]

### Adaptation strategies

In this study sowing time was evaluated as an agronomic adaptation option. The optimal sowing dates for maize could be considered at three different times, including spring cultivation (from the middle of March to June), summer cultivation (from July to August) and winter cultivation (February). However, due to changes in climate these dates can change over time. In most locations of these study areas, maize sowing date normally occur within the middle of May to the middle of June. Hence, current sowing date (15 June) for each location based on the local information was considered and two planting dates (29 May and 29 June) were chosen for different locations. The phenological stages, leaf area index and potential grain yield was simulated for current and future (2020s, 2050s and 2080s) climatic conditions which was projected by two GCMs (GFCM21, INCM3) under three scenarios (A1B, A2 and B1).
negative trend in comparison with the current situation in these locations except in Sabzevar under B1 scenario using INCM3 model in 2020s (Tables 4, 5 and 6). The days to anthesis in Mashhad, Sabzevar and Torbat heydariyeh were changed by $-1$ to $-6$, $+2$ to $-5$ and $-1$ to $-7$ days compared to baseline in each region based on the different models, scenarios and times, respectively (Tables 4, 5 and 6). The physiological maturity period was also shorter for both GCM models and under all scenarios and time periods (Tables 4, 5 and 6). Moreover, in the most cases the longest and shortest periods for both phenological stages were obtained under B1 and A2 scenarios using both GCMs.

**Maximum leaf area index**

The prediction of this feature under the climate change and across all models, scenarios and times revealed that the maximum leaf area index would decline in all of the study locations in the future (Tables 4, 5 and 6). The highest change in the maximum LAI was obtained in Sabzevar which altered from 3.79 to 2.42 related to B1 scenario of INCM3 in 2020s and A2 scenario of GFCM21 in 2080s, respectively (Table 5).

**Grain yield**

The simulated grain yield of maize was lower in all study locations using INCM3 and GFCM21 models under all scenarios and time periods compared to baseline (Tables 4, 5 and 6). The highest variations in maize yield were predicted for Sabzevar ($-6.7\%$ to $-82\%$) and Mashhad ($-2.6\%$ to $-43\%$), moreover the moderate fluctuation was obtained in Torbat heydariyeh ($-2.6\%$ to $-25.2\%$) from 2020s towards 2080s. The lowest reduction was simulated in 2020s under A1B scenario of GFCM21 in Mashhad (8493 kg ha$^{-1}$), and also under B1 scenario of INCM3 in Sabzevar (6485 kg ha$^{-1}$) and Torbat heydariyeh (8805 kg ha$^{-1}$), whereas the highest reduction for these three regions (4962, 1225 and 6766 kg ha$^{-1}$ respectively) was related to A2 scenario of INCM3 model in 2080s (Tables 4, 5 and 6).

**Vulnerability index**

The vulnerability index was computed for each year and study location (Fig. 2) and then the mean value of the vulnerability index across the full time series for Mashhad, Sabzevar and Torbat heydariyeh were obtained as 0.84, 0.91 and 0.66, respectively. The results showed that the adaptation efforts and appropriate strategies are likely to be effective in these regions. Furthermore, due to the changes of crop failure index and drought index in the baseline period for each area found that these indicators had high frequency and values in the recent years compared to earlier years, which resulted from the rainfall anomaly and high temperature in these areas and caused more sensitivity to climate change and higher vulnerability of maize yield to drought (Fig. 3). The results also revealed that the high crop failure index and minor drought index leads to high vulnerability index, while the low crop failure index and major drought index result in low vulnerability index (Fig. 3). Hence, according to these results Mashhad and especially Sabzevar indicates more vulnerability in comparison with Torbat heydariyeh.

![Figure 2. The estimated values of vulnerability index (VI) for baseline period at study locations.](image)

![Figure 3. Time series of annual crop failure index and drought index for study locations.](image)
Vulnerability of maize production

Figure 4. The effect of varying planting dates on maize anthesis day and physiological maturity day using GFCM21 and INCM3 models under A1B, A2 and B1 scenarios in Mashhad, Sabzevar and Torbat heydariyeh in three periods. dap, days after planting.

scenarios and locations compared to baseline (Fig. 4a). This duration increased in Mashhad and Torbat heydariyeh for the planting date of 29 May (Fig. 4a), while the longest duration was obtained for 15 June in Sabzevar (current sowing date) (Table 5). Moreover, this trait commonly decreased for the planting date of 15 June in all of the study areas (Fig. 4a, Table 5). The highest change in physiological maturity period was obtained in Torbat heydariyeh by +2 to –18 days in comparison with the baseline, also this period was altered from +2 to –14 days in Mashhad and 0 to –13 days in Sabzevar (Fig. 4b). Overall, the simulation results illustrated that physiological maturity period increased for the planting date of 29 June and decreased for the planting date of 29 May in all of the study locations (Fig. 4b, Table 4). The longest period for both phenological stages also was simulated under A1B and B1 scenarios in 2020s and the shortest period was obtained under A2 scenario in 2080s with using both GCM models.

The highest maximum LAI was predicted for the sowing date of 29 May in the 2020s and under A1B scenario of GFCM21 and B1 scenario of INCM3 in Mashhad (5.1), A1B scenario of INCM3 in Torbat heydariyeh (5.13) and B1 scenario of INCM3 in Sabzevar.
The range of changes for maize grain yield also was projected from +8% to −55%, +16% to −85% and +4% to −40% in Mashhad, Sabzevar and Torbat heydariyeh based on different planting dates, time periods and scenarios in study locations, respectively (Fig. 5b). The highest predicted grain yield obtained for the planting date of 29 June, while the lowest yield was simulated for the planting date of 29 May in all locations (Fig. 5b). The highest simulated yield in Mashhad (9390 kg ha\(^{-1}\)) and Torbat heydariyeh (9437 kg ha\(^{-1}\)) was related to B1 scenario of INCM3 in 2020s and in Sabzevar was obtained (8075 kg ha\(^{-1}\)) under A1B scenario of GFCM21 in 2020s, however the A2 scenario of INCM3 (in Mashhad and Torbat heydariyeh) and A2 scenario of GFCM21 (in Sabzevar) showed the lowest grain yield in 2080s (3875 kg ha\(^{-1}\), 5419 kg ha\(^{-1}\) and 1008 kg ha\(^{-1}\), respectively) (Fig. 5b). In addition, the maximum and minimum range of changes with respect to the different planting dates occurred in Sabzevar and Torbat heydariyeh, respectively. The simulation results showed that in the most cases earlier
planting dates decreased maize grain yield since the anthesis stage was faced with the higher temperatures, while the latest planting date increased the yield.

**DISCUSSION**

The aim of this study was to investigate the impacts of climate variability based on GFCM21 and INCM3 models under A1B, A2 and B1 scenarios on maize production in future and the efficacy of adaptation strategies to mitigate the effects of climate change. The results of climate model evaluation indicated that LARS-WG had appropriate prediction for climatic data and this is in agreement with several studies.6,27,29 So, this model was used to produce daily climatic data as one stochastic growing season for each projection period using different GCM models and scenarios. The results of GCM evaluation also showed adequate accuracy for climatic data simulation in the study areas which confirm the reliability of simulated data.

The simulated results revealed that the maize yield would decline in response to climate change during future century from −2.6% to −82% at all study locations in comparison with the baseline. The reduction of maize yield under different climatic scenarios has been reported in various studies.17,18 Moreover, the same trend in phenological stages and maximum leaf area index was obtained. It seems these issues are associated with increase in air temperature and decreases in precipitation that is projected in the future.29 So, increasing of temperature caused an increase in development rate of the crop and a decrease in growth period which result in yield reduction. Generally, A2 scenario indicated a more negative impact on maize yield and growth for the future climate in different time periods and under both GCMs, while the B1 scenario showed more optimal conditions. The IPCC report revealed that mean annual warming under A1B and A2 scenarios was more than the B1 scenario in future climate change condition, therefore the higher yield reduction of maize under A2 scenario could be due to higher temperature and shorter growth period in this scenario.3

The result of vulnerability index demonstrated that using of adaptation strategies could be effective in order to reduce the impacts of climate variability on maize productivity in all of the study areas. Similar results were also obtained by Challinor et al.24 and Simelton et al.39 Hence, the use of different sowing dates as an adaptation approach found that delaying the sowing date will be advantageous in order to mitigate the adverse effects of climate change by avoiding thermal stress at the growth period and obtain higher yield in all of the study areas in next decades. There are many studies which have focused on the efficiency of agronomic adaptation and mitigation approaches in relation to climate-induced yield losses in different locations.20,22,23,38

**CONCLUSIONS**

Changing climate could decrease maize production in the future conditions in the north-east of Iran (Khurasan Razavi province). The simulated phenological stages, maximum LAI and grain yield of maize would be decreased by future climate change. The vulnerability index (vulnerability index) indicated that using of adaptation strategies could be effective in all of the study locations. Consequently, the use of different sowing dates as an adaptation approach found that the latest planting date (29 June) resulted in less damage to maize grain yield rather than other planting dates (29 May and 15 June) due to mitigation of temperature effects, especially in the anthesis stage.

**REFERENCES**


