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# Soybean Yield in Future Climate Scenarios under Low Irrigation Conditions: (Case Study: Pars Aabad of Moghan Plain, Iran)

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**ABSTRACT**

Using the AquaCrop model, this research simulated the grains and biological yields of soybean cultivars (M9, Zan and Williams) under different irrigation treatments and future climatic conditions. To this end, whether data of the LARS-WG model were used as input data related to 1970-2010 period in Parsabad of Moghan Plain using AOGCM of HadCM3 based on scenarios of AR4 (A1B, A2 and B1) and NCAR based on scenarios of AR5 (RCP2.6 and RCP 8.5) to study periods of 2011-2030 and 2046-2065. Results showed, compared to the historical period, the statistical periods of 2011-2030 and 2046-2065 would show increases in average monthly minimum temperatures for all scenarios. These periods would also reveal decreases in average monthly maximum temperatures as well as average monthly precipitations for scenarios of RCP8.5, A2, A1B, RCP2.6, and B1, as well as scenarios of B1, RCP2.6, RCP8.5, A2, and A1B, respectively. According to the findings of RMSE and NMRSE, the AquaCrop was a good model for performance evaluation and simulation. The values of grain and biological yield would increase more for A1B and RCP8.5 than for the other scenarios during future periods. These findings indicate that soybean is an acceptable plant for the future climate of Parsabad of Moghan. In conditions of sufficient water and deficient water, Williams and Zan, respectively, exhibited lesser growth reduction and higher grain and biological yields than M9.

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## 1. Introduction

Iran is a part of the arid and semi-arid regions of the world; therefore, water is the most important element for the sustainable production of agricultural products. The plant's water requirement depend on several factors, such as cultivars, climatic and agronomic operations (Asgharipour and Mosapour, 2016). Soybean (*Glycine max*) belongs to the leguminosae family grown mainly worldwide and in Iran. This legume is one of the most valuable crops in the world since it is used not only as an oilseed crop and a feed for livestock and aquaculture but also as nutritionally valuable food for human consumption (Masuda and Goldsmith, 2009).

Agriculture is an extremely vulnerable sector to climate change. Concerns about global climate change have emerged over the past decades and, international efforts have begun to solve this major problem (Ibrahim *et al*., 2016; Asgharipour *et al*., 2016). Today most of the information available on future climate change status is derived from simulations performed by Atmosphere-Ocean Global Circulation Models (AOGCMs). In these models, the relationships describing the behavior of the atmosphere based on a three-dimensional grid representing the horizontal surface of the earth and the vertical height of the atmosphere are dissolved. The computational cells of these models are beyond the reach of the study region. To overcome this problem, it

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is necessary to downscale the outputs of these models before they can be used by studies that evaluate the effects of climate change and compare them with observational data (Alison *et al*., 2004; Amiri et al., 2020).

Nowadays, it is common to use statistical downscaling models (e.g., LARS-WG) to model climate behavior in different parts of the world. Given the wide effects that climate change has on the agricultural sector, different parts of the world have begun to carry out exhaustive research for many years to adapt agriculture to this phenomenon. Such researches are also a vital task in Iran to implement substantial administrative plans. Since the results of meteorological generators are merely valid in the test areas, their application to other areas requires secondary tests and validation proportional to the data provided by the regional meteorological stations. The most widely used statistical downscaling method is meteorological generating methods. The most popular meteorological generator model is the LARS-WG model, which can be applied in different regions and under multiple scenarios based on meteorological inputs (Mitchell, 2003).

Since its inception, the IPCC has published a series of assessment reports that are regarded as the most authoritative sources of evidence on climate change. The IPCC has so far published the first, second, third, and fourth assessment reports. The AR4 Report on Climate Change (A1B, B1, B2, A1, and A2) was published in 2007, with emphasis on more than 95% of human participation in climate change. According to the AR4, assuming that a solution is not applied, all climate change forecasting models indicate a continuous increase in temperature caused by an increase in GHGs emissions and the great contribution of human intervention to all these changes. In 2014, the IPCC Working Groups submitted the Fifth Climate Change Assessment Report and are currently completing and approving the Synthesis Report (SYR). The IPCC has used the new RCP scenarios (RCP-2.6, RCP-4.5, RCP-6, and RCP-8.5) as the representatives of various GHGs trajectories in AR5. The new emission scenarios have four key trajectories named after Forcing Radiative up to 2100 (IPCC, 2014).

Plant models can be used to examine the impact of climate change on crop production. By producing daily data for future years, the results of these downscaling models can be considered as inputs of plant models to estimate the yield of crops under climate change in the coming decades (Jones, 2000). The AquaCrop model is among those used to simulate crop growth through the use of long-term series of past climate data (Voloudakisa *et al*., 2014). Researchers have introduced several models in recent decades to simulate plant growth and the transport of solutes in the soil. The accuracy of these models depends largely on the accuracy of the required input data.

If these models are accurately calibrated and validated, the expected crop yield can be calculated used them to estimate, irrigation planning and evaluation of irrigation management scenarios, without the time and space limitations involved in field trials. The model has a high simulation capacity while using a relatively small number of directly measurable parameters. Simplicity, the need for minimal input data, and acceptable accuracy are the benefits of using this model. The AquaCrop model focuses on the plant's response to water. This model helps project managers, consultants, irrigation engineers, and farmers to increase water productivity (Raes *et al*., 2012). The AquaCrop model applies to a wide range of crops, including fodder, vegetables, cereals, fruits, oils, and tubers (Steduto *et al*., 2009). It is worth noting that the model with the default values is applicable to all plants, but some parameters are universal and must be defined regionally for the model (Droogers and Kite, 2001). The effectiveness of the AquaCrop model in simulating the performance of multiple crops under drought and salinity conditions has been well established by many researchers. Ahmadzadeh Araji et al. (2018) investigated the performance of the Aquacrop model in three soybean cultivars under different irrigation treatments and multiple climatic conditions. They reported that the model can simulate grain and biological yield in present and future climatic conditions in different irrigation treatments. García-Vila et al. (2009) applied the AquaCrop model to optimize the amount of cotton irrigation in southern Spain. The results showed that the model simulated the grain and biomass yield, and the efficiency of water use for cotton with a coefficient of determination greater than 90%. In addition, the accuracy of the model to estimate biomass yield was higher than other parameters.

By forecasting the yield of Roshan and Ghods wheat cultivars under different soil moisture and salinity

profiles in the Birjand region, Khorsand et al. (2014) assessed the efficiency of the AquaCrop model. The results showed that the model had an average relative error of 2.98 and 4.28% in the prediction of yield for the Roshan and Ghods cultivars, respectively. Rodríguez Díaz et al. (2020) by examining the effects of climate change on water needs in the watershed of the Jodalquier River in Spain showed that the water demand of a crop season will increase by 15 to 20% in the 2050s. Haverkort and Verhagen (2019) examined the effect of climate change on potatoes in northern Europe and concluded that climate change will prolong the growing season of potato in this region. Rosenzweig and Parry (2019) predict that the length of plant growth in Iran will be greatly reduced. Cereal production will also fall by 40 to 50 percent in rainfed agriculture.

Ardabil province ranks second in the country in soybean production after Golestan province. Almost all soybean production in Ardabil province is done in Parsabad of Moghan region due to its unique climatic characteristics (Aghighi Shahverdi *et al*., 2015).

Investigating the impact of future climate change on the development and production of soybeans is critical in Iran due to the importance of producing this crop as the most important oilseed plant, as most studies to far have only evaluated select scenarios focused on a single variety of soybean (e.g., Ghorbani *et al*., 2014; Rio *et al*., 2015; Bao *et al*., 2015; Mohanty *et al*., 2016). One of the most common and most reliable tools used to investigate and evaluate climate change prediction in future decades is the General Circulation Model (GCM), the outputs of which have been downscaled by using statistical methods and is somehow close to real data. One of these models is LARS-WG that uses daily climatic parameters in a station such as precipitation, number of sunny hours, and minimum and maximum temperatures to simulate data for the future by utilizing available time series. Therefore, three objectives are discussed in this paper. The first objective is to forecast the future climate of Moghan using LRS-WG in three AR4 and two AR5 scenarios. In addition, due to the lack of research in the Moghan area to predict the yield of different soybean cultivars, the second objective is to evaluate the predictive power of the AquaCrop model for grain and biological yield in current and future Moghan weather conditions and three irrigation conditions among three early soybean cultivars (M9, Williams, and Zan). The final third aim predicts the effects of future climate changes on the final grain and biological yields of three soybean cultivars during 2011-2030 and 2046-2065 by considering GCM products.

## 2. Materials and methods

### *2.1. Study area and experimental treatments*

The experimental site is located in a field of Parsabad of Moghan Plain, Iran (latitude 39°20′-39°42′ N and longitude 47°30′-48°10′ E). This area is known as a semi-arid climate with an annual average rainfall of 271 mm and an average annual temperature of 15 °C. The average values of climatic data in Parsabad of Moghan Plain for the growing period are summarized in Table 1.

**Table 1. The climatic data of the experimental in a field of Parsabad of Moghan during the years of the study**

| Climatic data | | Months | | | |
|---|---|---|---|---|---|
| | Year | July | August | September | October |
| Average temperature (°C) | 2015 | 28.6 | 28.2 | 23.8 | 17.7 |
| | 2016 | 26.9 | 27.6 | 23.8 | 16.3 |
| Precipitation (mm) | 2015 | 7.9 | 0.0 | 9.6 | 52.1 |
| | 2016 | 1.8 | 2.7 | 77.8 | 45.0 |
| Evaporation (mm) | 2015 | 254.4 | 243.3 | 142.0 | 46.7 |
| | 2016 | 261.0 | 260.9 | 108.8 | 65.4 |

The data were derived from a two-year experiment organized in split-plots based on a randomized complete block design with three replications performed in 2015 and 2016. The treatments were four irrigation regimes including full irrigation, and irrigation cutting at vegetative, flowering and seed filling growth stage as main plot and three cultivars as subplot. AquaCrop Version 5.1 based on regional conditions was calibrated for 2015 and validated for 2016. The three varieties of soybean used herein included M9 (V1), Williams (V2), and Zan (V3) (M9 is a mutant of Clark variety): early maturation (Growth period or time of maturity = 110 days), indeterminate, multi-branch, high yield, resistant to falls and stock lodging with violet flowers; Williams: Fairly early (growth period or time of maturity = 120 days), maturity group 3, indeterminate, high yield, single branch with white flowers; and Zan: early (growth period or time of maturity = 115 days), maturity group 3, indeterminate, high yield, single branch with violet flowers (Jamali *et al*., 2011). The varieties were sown on

July 14, 2015 and July 17, 2016. Therefore, the period from July to the end of October of both years was considered as a crop cycle.

Table 2 summarized some of the physicochemical traits of the experimental soil. According to the results of the soil tests and the requirements of the soybean plant, 70 kg of urea fertilizer per hectare (as initiator) and 250 kg of triple superphosphate were added to the soil. Potassium nano fertilizer (27% $K_2O$, 10 kg $ha^{-1}$) was also used to meet the need for potassium. Control of weed was done manually from the initial stages of growth until the appearance of the pods. Avant (a.i. 1.5 kg $ha^{-1}$) and Hexaflumuron (a.i. 2 kg $ha^{-1}$) were also used for pest management. The amount of water needed for each plot in the crop years of 2015 and 2016 was presented in Table 3.

**Table 2. Soil physical and chemical characteristics of clay loam soil in the experimental fields**

| Depth (cm) | Texture | K (mg/kg) | P (mg/kg) | Organic matter (%) | pH | EC (dS/m) | PWP (Vol %) | FC (Vol %) | TAW (mm/m) | BD (g/cm$^3$) | SHC (mm/day) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0-50 | Clay | 400 | 4.5 | 0.82 | 7.1 | 0.81 | 15 | 26 | 115 | 1.40 | 380 |

PWP: Permanent Wilting Point, FC: Field Capacity, TAW: Total available water, BD: Bulk Density and SHC: Saturated hydraulic conductivity

**Table 3. The amount of water needed for each plot in the crop years of 2015 and 2016 (Total growth period)**

| Crop year | Soybean water requirement for Moghan area* | Normal irrigation (m$^3$.h$^{-1}$) | 80% ETc | 60% ETc | 40% ETc |
|---|---|---|---|---|---|
| 2015 | 7600 | 7666 | 6133 | 4600 | 3066 |
| 2016 | 7700 | 7703 | 6162 | 4622 | 3082 |

*Source: Ministry of Agriculture, 2016

Each experimental plot consisted of four rows of 5 m in length. The inter- and intra-row spaces were 0.6 and 0.05 m. After blocking, the main plots were separated by two m of space to avoid water leaks. In this experiment, the seeds of different soybean cultivars (prepared by Moghan Oil Company) were sown manually on June 25. Soybeans were treated with *Rhizobium japonicum* at a rate of 25 g 7 kg of seed. In this study, the irrigation interval was variable and the irrigation time was determined based on vegetation indices and evaporation of the pan. For this purpose, the data of daily evapotranspiration from pan (ETp) was obtained from the Moghan Research Center and soybean evapotranspiration (ETc) calculated based on the Eq. 1:

$$ETc = Kc.\ Kp.\ ETp \qquad (1)$$

Where ETc is crop evapotranspiration, Kc is specific crop coefficient, and Kp and ETp are coefficients of evaporation pan and evaporation rate of pan, respectively.

The specific crop coefficient was obtained using Fig. 1 The coefficient of evaporation pan was also calculated by FAO publication No. 24 according to Doorenbos and Pruitt (1977) (based on the average daily wind speed (km $day^{-1}$) at 2 m high, average daily relative humidity in percentage, and the distance of the pan from the vegetation that was considered 30 m and in this study was 0.75). When the cumulative evapotranspiration reached the level of irrigation, the irrigation using furrow method was performed again.

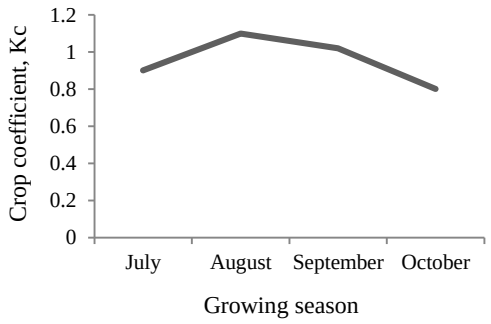


**Figure 1. Variation of the crop coefficient (Kc) for soybeans during growing season**

As mentioned above, irrigation regimes have been described as without water stress, mild water stress (80% ETc (water requirements or evapotranspiration in mm), moderate water stress (60% ETc), and severe water stress (40% Etc) based on the division of Ribas-Carbo et al. (2005). Also, irrigation intervals were 10 days regarding the regional custom. Following the

emergence of five to seven trifoliate leaves, the irrigation regimens were conducted. In addition, the irrigation quantities from the years of calibration and validation were used as source for the predicted historical and future phases of the AquaCrop model.

*2.2. Input data in the AquaCrop model*

The input data of the model is divided into four categories: climatic data, vegetation data, soil data, and management data, including irrigation management and farm management. Climate data: Climate data consists of four parts: daily reference evapotranspiration, daily minimum and maximum temperature, daily precipitation values and average annual concentration of $CO_2$ concentration. Statistical data from the Ultan Moghan weather station was used to calculate ETo using the Penman-Monteith method (Allen *et al*., 1998). Atmospheric $CO_2$ concentrations were calculated using the default values of the model. In addition, the emission scenarios of AR4 and AR5 were chosen from the IPCC data available in the AquaCrop database to make predictions about the future. Vegetation parameter data and soil properties were used as inputs to the model through Tables 4 and 2, respectively.

**Table 4. Input data of soybean crop parameters used in the AquaCrop model**

| Description | Values | | | Units | Remarks |
|---|---|---|---|---|---|
| | M9 | Williams | Zan | | D |
| Base temperature | 5 | 5 | 5 | ˚C | D |
| Upper temperature | 30 | 30 | 30 | ˚C | D |
| Canopy growth coefficient | 0.25 | 0.25 | 0.25 | % day$^{-1}$ | C |
| Maximum canopy cover | 0.95 | 0.95 | 0.93 | % | C |
| Canopy decline coefficient | 0.17 | 0.17 | 0.16 | % day$^{-1}$ | C |
| Water Productivity normalized | 16 | 16 | 15 | g.m$^{-2}$ | C |
| Soil water depletion factor for canopy expansion – Upper threshold | 0.15 | 0.15 | 0.15 | - | D |
| Soil water depletion factor for canopy expansion – Lower threshold | 0.65 | 0.65 | 0.65 | - | D |
| Shape factor for water stress coefficient for canopy expansion | 3 | 3 | 3 | - | C |
| Soil water depletion fraction for stomata control – Upper threshold | 0.50 | 0.50 | 0.50 | - | D |
| Shape factor for water stress coefficient for stomata control | 3 | 3 | 3 | - | D |
| Soil water depletion factor for canopy senescence – Upper threshold | 0.70 | 0.70 | 0.70 | - | D |
| Shape factor for water stress coefficient for canopy senescence | 3 | 3 | 3 | - | D |
| Minimum effective rooting depth | 0.30 | 0.30 | 0.30 | m | M |
| Maximum effective rooting depth | 0.60 | 0.60 | 0.60 | m | M |
| Days from sowing to emergence | 6 | 6 | 6 | day | M |
| Days from sowing to start senescence | 86 | 88 | 85 | day | M |
| Days from sowing to maturity | 100 | 100 | 100 | day | M |
| Days from sowing to flowering | 36 | 36 | 35 | day | M |
| Length of the flowering stage | 25 | 25 | 24 | day | M |
| Building up of HI starting at flowering | 70 | 71 | 67 | day | C |
| Reference harvest index (HI0) | 29 | 30 | 29 | % | C |

C: Calibrated, D: Default, M: Measured

*2.3. Model prediction accuracy*

Accuracy of model prediction was calculated based on the most relevant statistical indices, including root mean square error (RMSE), root mean square error normalized (RMSEn), the coefficient of determination ($R^2$), and the mean absolute error (MAE). Agreements between simulated and observed biomass and grain yields are represented by those indices. The relationships between these indexes are expressed by the following formula (Eqs. 2-5):

$$RMSE = \left[\frac{\sum_{i=1}^{n}(Pi-Oi)^2}{n}\right]^{1/2} \quad (2)$$

$$RMSEn = 100\frac{RMSE}{Omean} \quad (3)$$

$$MAE = 1/n\sum_{n=i}^{n}|Pi - Oi| \quad (4)$$

$$R^2 = \frac{\sum_{i=1}^{n}(Pi-\overline{Oi})^2}{\sum_{i=1}^{n}(Oi-\overline{Oi})^2} \quad (5)$$

Where Pi is simulated values, Oi is observed values, Omean is observed average data, and n is the several measurements.

RMSE (Eq. 5) values should be close to 0 for good model performance; high RMSE values suggest bad model performance. RMSEn is an indicator for showing relative variations between observations and predictions on a percentage scale. The RMSEn values would be great if they are less than 10%, good if they

are between 10 and 20%, fair if they are between 20 and 30%, and poor if they are greater than 30%. $R^2$ varies between 0 to 1. Therefore, it is clear that $R^2$ values close to 1 indicate less variation of error and those greater than 0.5 are usually considered acceptable on watershed scales (Vara Prasad *et al*., 2005; Raes *et al*., 2012).

*2.4. Simulation of future climate by the LARS-WG*

LARS-WG V.5.5 software was utilized to statistically downscale the data of the HADCM3 model of the general atmospheric circulation for AR4 scenarios and NCAR for IPCC AR5. Table 5 summarizes the important characteristics of the general circulation model used in this study. Minimum temperature, maximum temperature, precipitation and radiation, hours of future climate, and the database of the Moghan-Oltan meteorological station (Synoptic station code: 40700, Height: 72.6cm, Latitude: 39.36 and Longitude: 47.47 located in the northwest of the country and north of the province of Ardebil) were used for the creation of daily temperature data. In general, the LARS-WG model generates data in three steps: data calibration, data validation, and generation, and/or simulation of meteorological data for future periods.

**Table 5. Global Climate Models from IPCC, AR4 and IPCC, AR5 incorporated into the LARS-WG stochastic weather generator version 5.5.**

| Center | Model | Spatial Resolution | Emission Scenario | RCP |
|---|---|---|---|---|
| UK Meteorological Office | HADCM3 | 2.5 × 3.75° | SRA1B, SRA2, SRB1 | - |
| Meteorological Research Institute Japan | NCAR | 1.88°×2.50° | - | 2.6, 8.5 |

**Table 6. characteristics of scenario AR4 (IPCC, 2007)**

| Scenario | The main hypothesize in the scenario | | Co2 (ppm) 2011-30 | Co2 (ppm) 2046-65 | Co2 (ppm) 2081-100 |
|---|---|---|---|---|---|
| B1 | The world with sustainable development | Changes in economic structures, along with improved environmental awareness | 410 | 492 | 538 |
| A1B | The rich world | This scenario is characterized by rapid economic growth (2 % growth) | 418 | 541 | 674 |
| A2 | Isolated world | Cultural characteristics of different regions are distinguished | 414 | 545 | 754 |

There are several methods to predict and simulate the future climate, the most comprehensive of which are GCM models. The purpose of these models is to simulate all the three-dimensional characteristics of the climate and, therefore, the most complete atmospheric models to predict the future. GCM models are based on physical laws expressed by mathematical relationships. These relationships dissolve in a three-dimensional grid on the surface of the Earth and in the middle and upper layers of the atmosphere. To simulate the Earth's climate, the main climatic processes (atmosphere, ocean, surface, ice, and biosphere) are simulated in separate sub-models. All sub-models of the atmosphere, the ocean, the surface of the Earth, the ice and the biosphere come together to form general atmospheric circulation models. Due to their complexity, these models inevitably run in spaces of high dimensions, so they cannot be used in smaller dimensions, such as the surface of a city and the catchment area, and are very different from reality.

The model obtains the baseline time observation data and, by examining them, extracts the statistical features of the data. The QTEST procedure for the statistical reference period is then applied to validate the robustness and durability of the model in order to reproduce a set of synthetic results during the reference period. Finally, to determine the efficiency of the model in data restoration, these results are compared with observation statistics. In fact, this model generates daily and stationary meteorological parameters by receiving meteorological data for the period and the results of the general atmospheric circulation model in the same period as current and future statistical periods. To validate the model, the data from the previous scenario of climate change are compared with the observed data. After validating the capacity of the

model, the final stage is extracted according to the target scenarios (three IPCC AR4 scenarios and two IPCC AR5 scenarios) for future periods of daily data that include radiation, minimum temperature, maximum temperature and precipitation. Table 6 provides a summary of the characteristics of the mentioned scenarios of AR4 (A1B, A2 and B1). Unlike the Special Report on Emission Scenarios (SRES) in the Fourth Assessment Reporting Models, the fifth assessment report uses the representative of the greenhouse gas concentration trace lines as presented in Table 7.

**Table 7. characteristics of scenarios RCP (2.6 and 8.5: Representative Concentration Pathway in various Greenhouse Gases) (Van Vuuren et al., 2011)**

| Scenario | Forcing Radiative (W/m2) | CO2 Concentration (ppm) |
|---|---|---|
| RCP2.6 | Peak at 3 W/m2 and then decline | 490 ppm before 2100 and then decline |
| RCP8.5 | Rising up to 8.5 W/m2 by 2100 | 1370 ppm by 2100 |

**Table 8. Evaluation results of grain yield and biomass**

| Characteristics | N | X observation | X simulation | RMSE | RMSEn (%) | P (t) | $R^2$ |
|---|---|---|---|---|---|---|---|
| Grain yield | 12 | 2016 | 2157 | 268 | 13 | 0.30* | 0.88 |
| Biomass | 12 | 5881 | 6215 | 643 | 10 | 0.32* | 0.83 |

Notes: number of observations (N), correlation coefficient between simulated and observed values (R2), Pvalue from the paired t-test [P (t)], absolute root mean square error (RMSE), normalized root mean square error (RMSEn), (*) means that significant at 0.05 level and ns (non-significant).

*2.5. Future grain and biological yields, and comparison of treatments*

For each scenario of emissions, the values of combined means and multi-model temperature sets for the periods 2011-2030 and 2046-2065 were applied to the AquaCrop system to predict the grain and biological yield values for three cultivars and four levels of irrigation. Subsequently, average annual values of yield and biomass were compared in five emission scenarios for the future periods with the corresponding values obtained for the historical period. Finally, tolerance to stress TOL = Yp−Ys; (Rosielle and Hamblin, 1981)

Where Yp is the yield of stress-free cultivation and Ys is the stressed crop yield of a given cultivar. This index was used to assess the response of soybean cultivars to drought stress. The susceptibility index of less than one indicates that the genotype is more droughts tolerant. Higher TOL values indicate a relatively greater susceptibility of genotypes to stress. Therefore, a low TOL value is an appropriate criterion for the selection of desirable genotypes (Blum, 1988).

## 3. Results and discussion

*3.1. Model evaluation*

The statistical variables intended to evaluate (calibration and validation) the model in terms of grain and biological yield simulations over two years are shown in Table 8. The results showed that Root-Mean-Square Deviations (RMSEs) were equal to 268 $kg.ha^{-1}$ and 643 $kg.ha^{-1}$ for grain and biological yields for 2015 and 2016, respectively. The values of RMSEn were 13% and 11% for grain and biological yields, respectively. The linear regression model between measured and simulated values of grain and biomass yield is shown in Figs 2. and 3.

The results of the aforementioned analysis showed $R^2$ values of 0.84 and 0.73 for the grain and biological yields, respectively. In addition, 85% of grain and biological yield points are within the limits of line 1:1 and ± 20% of the standard deviation of the measured grain and biological yields. There were no statistically significant differences between the results of the model output and the observed data. The prediction accuracy of the model with respect to grain and biological yields was evaluated using the following statistical indices (Table 8): According to Table 8, the RMSEn values for grain and biological yield are 13 and 10%, respectively. The t-test values for grain and biological yield were 30% and 32%, respectively. In addition, R2 values for grain and biological yield were 88% and 83%, respectively. The results of the evaluation of the model by RMSEn showed that the model has an excellent capacity (≤10%) to predict grain yield and a good capacity (10-20%) to predict biological yield. The t-tests indicate that there is no significant difference

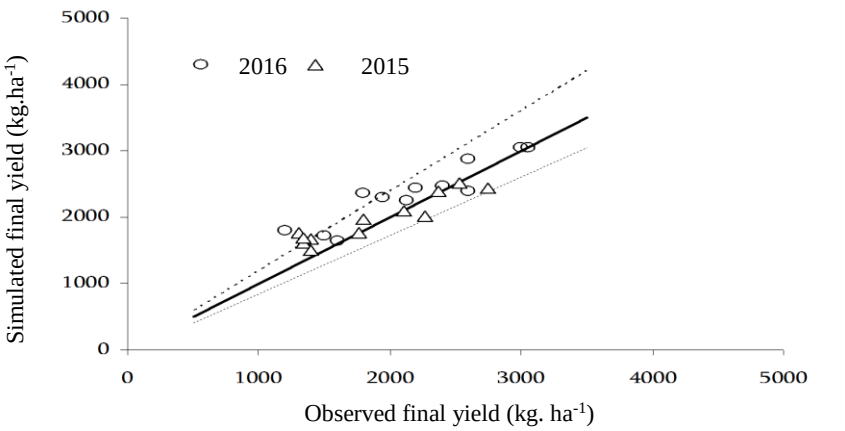


**Figure 2. Regression model between simulated and observed final yield for soybean in future climate scenarios under low irrigation conditions in Parsabad of Moghan. The dotted line is 1:1.**

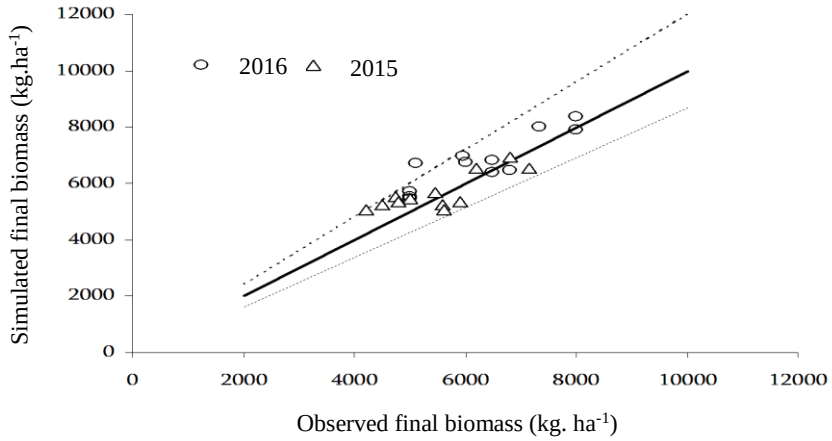


**Figure 3. Regression model between simulated and observed final biomass for soybean in future climate scenarios under low irrigation conditions in Parsabad of Moghan. The dotted line is 1:1.**

between predicted and observed values for grain and biological yield.

The model calibration used for the region based on the experiments conducted years ago was determined with the present irrigation treatments on common cultivars and by the research team. The estimated grain yields and biomass of different soybean varieties revealed a model error of less than 10% in the prediction of grain yields and biomass. Therefore, the model has the ability to simulate the effects of irrigation treatments on soybean cultivars. Table 9 shows the results of the statistical analysis of the observational and output data of the model for 2015 (validation).

The prediction accuracy of the model with respect to grain and biological yields were evaluated using the following statistical indices: According to Table 9, the RMSEn values for grain and biological yield were 14 and 11%, respectively. Also, t-test values for grain and biological yield were 20% and 19%, respectively. In addition, R2 values for grain and biological yield were 90% and 77%, respectively. The values of RMSEn demonstrate that the model has a good performance (10-20%) for both grain and biological yields. The results of the evaluation of the model by RMSEn showed that the model has a good capacity (10-20%) to predict grain and biological yield. The t-tests indicate that there is no significant difference between the predicted and observed values for grain and biological yield.

However, the results of the observed and simulated data indicated that Aquacrop model could predict grain and biological yields under water stress in Parsabad of Moghan plain, which is in accordance with those of Ahmadzadeh Araji et al. (2018), Silva et al. (2018) and

Giménez et al. (2017). Although the AquaCrop model is a good option to predict the grain and biological yield of the Parsabad of Moghan, it was characterized by errors in drought stress. That is consistent with the research by Ahmadzadeh Araji et al. (2018). Recently, Silva et al. (2018) has reported that yield values for soybean grown in Motopiba region, Brazil, varied from 3.5 to 4.4 ton $ha^{-1}$. They claimed that the yield values simulated by the Aquacrop model and those measured in the field were similar for both cultivars ($R^2$=0.92, RMSEn = 10%, MAE = 10%).

**Table 9. Evaluation results of grain yield and biomass in three soybean varieties under different irrigation levels in the calibration years of 2015 and 2016.**

| Characteristics | N | $X_{observation}$ | $X_{simulation}$ | RMSE | RMSEn (%) | P (t) | $R^2$ |
|---|---|---|---|---|---|---|---|
| (2015) | | | | | | | |
| Grain yield | 12 | 1862 | 1951 | 235 | 13 | 0.30* | 0.88 |
| Biomass | 12 | 5496 | 5665 | 557 | 10 | 0.32* | 0.83 |
| (2016) | | | | | | | |
| Grain yield | 12 | 2169 | 2362 | 294 | 14 | 0.20* | 0.90 |
| Biomass | 12 | 6265 | 6765 | 719 | 11 | 0.19* | 0.77 |

Notes: number of observations (N), correlation coefficient between simulated and observed values ($R^2$), Pvalue from the paired t-test [P (t)], absolute root mean square error (RMSE), normalized root mean square error (RMSEn), (*) means that significant at 0.05 level and ns (non-significant).

*3.2. LARS-WG, model evaluation*

Table 10 represents the results of the statistical evaluation of meteorological characteristics and real data simulated by the model for the historical period. The RMSEs obtained were small and the smaller values of this index, the smaller the differences between the observed values and the predicted values of the meteorological factors generated by the LARS-WG model. To evaluate the capacity of the LARS-WG model to simulate the climate of the region, the model performed statistical tests at the study station. T-test was employed to test the congruence of the average monthly precipitation and the monthly average of maximum/minimum daytime temperatures. F-tests were performed to evaluate the variance of monthly precipitations. Before using the model results, the model ability should be considered in the climate simulation of rainfall and temperature data in the study station. For this purpose, a comparison of the means and the test for comparison of variances were made using F and t-tests, respectively in the study station (Table 11). For each series, the table shows the ratios of the number of non-significant tests (5%) to the total number of tests. In other words, a *p*-value less than the level of significance (5%) rejects the null hypothesis assuming that the simulated data are congruent with the real data because there were no significant differences between the observed data and those of 11-month temperatures simulated by the model with a confidence interval of 95%. In addition, the results of *F*-test statistics showed that none of the months of the year exhibited significant differences between the observed data and the data simulated by the model with a confidence interval of 95%. According to the results, the LARS-WG model is suitable for modeling meteorological characteristics and can be used to simulate data related to future periods. The high capacity of the LARS-WG model to simulate meteorological characteristics has also been verified by Ahmadzadeh Araji et al. (2018) and Sun et al. (2015).

**Table 10. LARS-WG model evaluation indicators**

| Parameter | MAE | RMSE | $R^2$ |
|---|---|---|---|
| Minimum temperature | 0.1450 | 0.1887 | 0.9995 |
| Maximum temperature | 0.2107 | 0.2511 | 0.9995 |
| Radiation | 0.1634 | 0.2355 | 0.9972 |
| Precipitation | 4.0557 | 5.5066 | 0.8899 |

Comparisons between changes in GCM production in different emission scenarios and RCPs during five significant growing months (July-October) in the historical period are shown in Table 12 Given the results obtained, minimum temperature, maximum temperature, and $CO_2$ rates increased in the first (2011-2030) and the second (2014-2065) periods compared to the historical period. Rashidian (2017) used LARS-WG software and HADCM3 model for 2011-2030 to compare historical periods. Their results showed that the amount of precipitation in Semnan province will increase by 4.4% and the temperature by 1.9% with respect to the reference and observation data. Therefore, we will see an increase in temperature in the coming decades for the province under study. The

results showed reductions in precipitation rates in both future periods compared to the basic rate. In addition, the results indicated that the scenarios of RCP2.6 and RCP8.5 exhibited minimum and maximum temperatures, respectively, in both future periods. Based on the results obtained, scenario B1 would have the greatest decrease in rainfall rates during the first and second future periods. In addition, the largest increase in $CO_2$ rates would be related to scenario A2 in both future periods.

**Table 11. Climatic variables in Parsabad of Moghan region, Iran**

| | Climatic variables | | | |
|---|---|---|---|---|
| | Average Monthly Precipitation | Variance Monthly Precipitation | Monthly average minimum temperature | Average monthly maximum temperature |
| | t- test | F-test | t- test | t-test |
| January | 0.99 | 0.17 | 0.52 | 0.29 |
| February | 0.99 | 0.34 | 0.90 | 0.29 |
| March | 0.55 | 0.21 | 0.18 | 0.91 |
| April | 0.37 | 0.52 | 0.34 | 0.77 |
| May | 0.33 | 0.71 | 0.04 | 0.43 |
| June | 0.34 | 0.74 | 0.23 | 0.84 |
| July | 0.15 | 0.22 | 0.25 | 0.83 |
| August | 0.34 | 0.09 | 0.60 | 0.13 |
| September | 0.09 | 0.64 | 0.29 | 0.30 |
| October | 0.79 | 0.69 | 0.56 | 0.49 |
| November | 0.61 | 0.55 | 0.48 | 0.14 |
| December | 0.42 | 0.83 | 0.39 | 0.44 |

**Table 12. Climatic variables over the soybean growing season for the historical period (1970–2010) and the GCM outputs during 2011-2030 and 2046-2065 under different emission scenarios.**

| Period | Min-Temp (˚C) | Max-Temp (˚C) | Precipitation (mm) | $CO_2$ (ppm) |
|---|---|---|---|---|
| 1970-2010 | 14.1 | 33.0 | 289.0 | 336.2 |
| 2011-2030 (RCP 2.6) | 14.3 | 33.1 | 253.3 | 426.4 |
| 2011-2030 (RCP 8.5) | 14.7 | 33.3 | 252.3 | 441.3 |
| 2011-2030 (B1) | 14.5 | 33.0 | 251.7 | 433.1 |
| 2011-2030 (A1B) | 14.6 | 33.2 | 271.1 | 420.0 |
| 2011-2030 (A2) | 14.6 | 33.2 | 260.2 | 455.6 |
| 2046-2065 (RCP 2.6) | 16.7 | 37.2 | 252.0 | 436.0 |
| 2046-2065 (RCP 8.5) | 16.9 | 37.4 | 255.2 | 446.0 |
| 2046-2065 (B1) | 16.8 | 37.2 | 250.7 | 443.0 |
| 2046-2065 (A1B) | 16.9 | 37.5 | 244.6 | 440.0 |
| 2046-2065 (A2) | 16.9 | 37.4 | 251.3 | 460.3 |

**Table 13. Correlation between climatic variables and averaged yield and biomass of three varieties under different irrigation levels.**

| Averaged yield and biomass of three varieties | Min-Temp | Max-Temp | Precipitation | CO2 |
|---|---|---|---|---|
| Yield under normal irrigation (I) | 0.860* | 0.975** | 0.640 | 0.90* |
| Yield under weak water stress (I2) | 0.880* | 0.970** | 0.660 | 0.91* |
| Yield under mild water stress (I3) | 0.850 | 0.980 | 0.780 | 0.88* |
| Yield under sever water stress (I4) | 0.730 | 0.660 | 0.900** | 0.44 |
| Biomass under normal irrigation (I1) | 0.830* | 0.963** | 0.660 | 0.91* |
| Biomass under weak water stress (I2) | 0.886* | 0.960** | 0.673 | 0.90* |
| Biomass under mild water stress (I3) | 0.875 | 0.966** | 0.635 | 0.90* |
| Biomass under sever water stress (I4) | 0.770 | 0.550 | 0.920** | 0.86 |

N=6.

* Means that significant at the 0.05 level, ** significant at the 0.01 level.

*3.3. Future grain and biological yields, and impacts of climate change*

The annual yield averages for the historical and future periods (2011-2030 and 2046-2065) in emission scenarios of AR4 and AR5 are shown in Figs. 4 and 5, respectively. The average grain yield for future periods within all emission scenarios under control (100% water requirement) and weak water stress (80% water requirement) suggests that Williams, M9, and Zan will have the largest increase. On the other hand, the predicted grain yield under mild water stress (60% water requirement) and severe water stress (40% of water requirement) revealed that M9 and Zan had the highest rise, followed by Williams. Based on TOL, Williams, followed by M9 and Zan in all the emission and RCPs scenarios during the historical period, was the most drought-resistant cultivar under conditions of poor water stress. However, in severe and mild water stress conditions, the most tolerant cultivar was Zan, followed by M9 and Williams in all the emission and RCPs scenarios in the historical period. Therefore, Zan is more tolerant of drought stress than the other two cultivars.

The biological yield averages for the historical and future periods (2011-2030 and 2046-2065) in emission scenarios of AR4 and AR5 are shown in Figs. 6 and 7, respectively. The average biomass for future periods within all emission scenarios under the control and weak water stress treatments indicated that Williams, M9, and Zan had the highest increase. In addition, the predicted biomass under conditions of mild and severe water stress showed that Zan had the highest increase, followed by M9 and Williams.

*3.4. Evaluation of the impact of climate variables on soybean production*

Table 13 shows the correlations between the climatic variables and the averages of grain and biological yields for three soybean cultivars and four different irrigation regimes. Based on the results, in conditions of normal irrigation and mild water stress, grain values and biological yield show significant positive correlations with minimum/maximum temperatures and $CO_2$ rates. However, such a correlation can also be seen between values of grain and biological yields and rainfall rates in both mild and severe stress conditions. Therefore, the results showed a vital role for the precipitation figures in the improvement of plant growth and performance in water scarcity conditions.

According to Figs. 4-7, the greatest increase in values of grain and biological yield was predicted in the scenarios of A1B, RCP8.5, A2, B1, and RCP2.6 in descending order. In addition, the relationship between the maximum temperature with the grain and the biological yield (Table 13) under normal irrigation and low stress treatments is very high. This is in accordance with the results in Table 12, which showed the temperature rise in the RCP8.5, AB, A2, B1 and RCP2.6 scenarios.

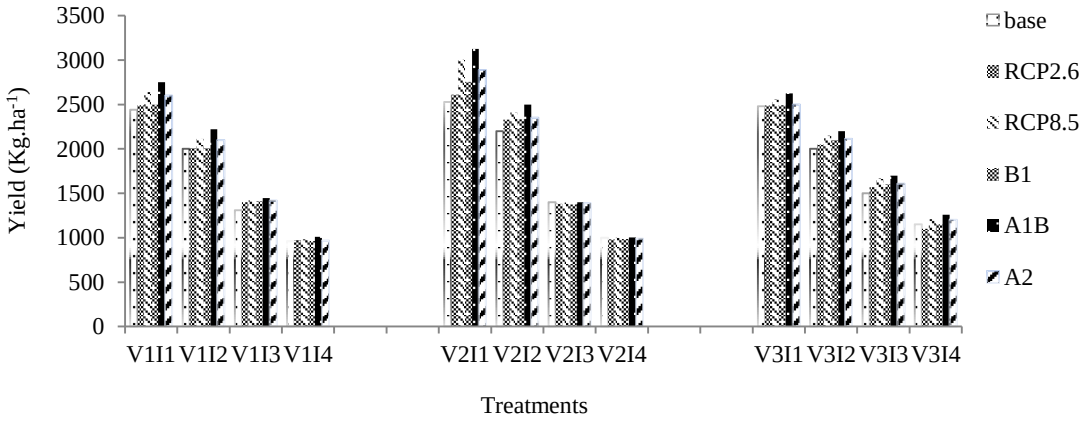


**Figure 4. Soybean Yield of different treatments in the historical period (base: 1970-2010) and predicted future period 2011-2030 according to the AR4 and AR5 emission scenarios. RCP stands for Representative Concentration Pathway. B1, A1B and A2 are future climate scenarios.**

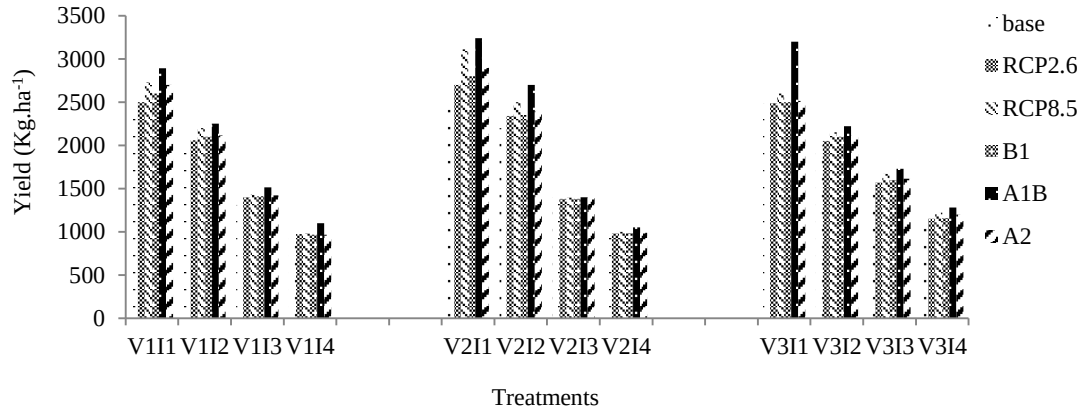


**Figure 5.Yield of different treatments in the historical period (base: 1970-2010) and predicted future period 2046-2065 according to the AR4 and AR5 emission scenarios. RCP stands for Representative Concentration Pathway. B1, A1B and A2 are future climate scenarios.**

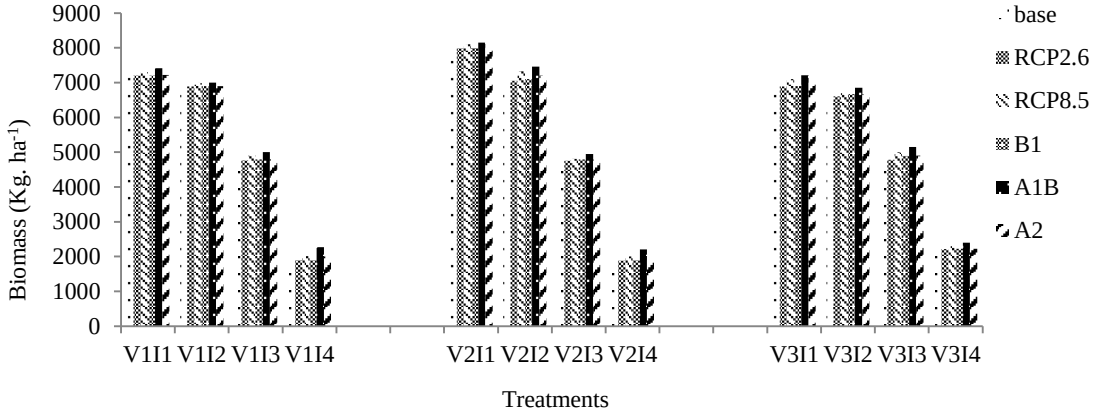


**Figure 6. Biomass of different treatments in the historical period (base: 1970-2010) and predicted future period 2011-2030 according to the AR4 and AR5 emission scenarios. RCP stands for Representative Concentration Pathway. B1, A1B and A2 are future climate scenarios.**

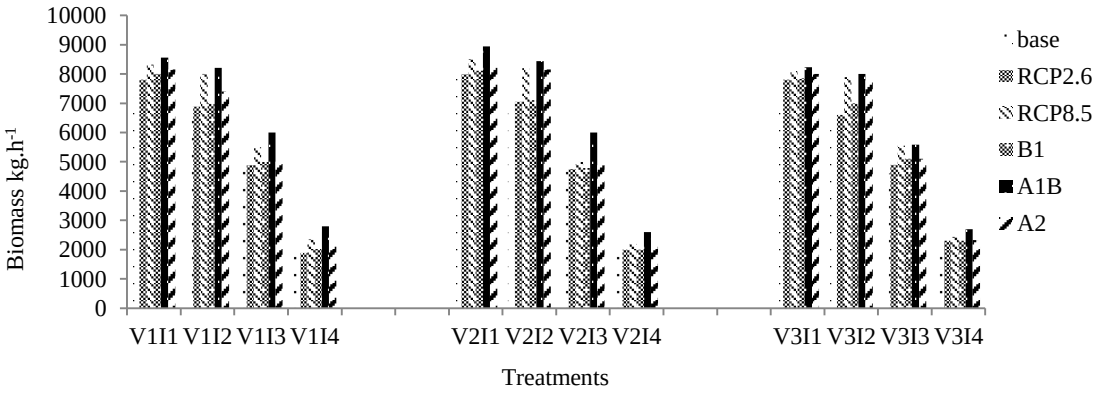


**Figure 7. Biomass of different treatments in the historical period (base: 1970-2010) and predicted future period 2046-2065 according to the AR4 and AR5 emission scenarios. RCP stands for Representative Concentration Pathway. B1, A1B and A2 are future climate scenarios.**

Table 14 shows average monthly temperatures in the reproductive stage of soybean and throughout the growing season during historical and future periods, demonstrating optimal temperatures for the future growth of this plant. For all scenarios in the two future periods (2011-230 and 2046-2065), the results (Table

14) indicated that, compared to the historical period, average temperatures would rise by 2-3 °C in the reproductive stage and by 1-2 °C throughout the growing season. Since several studies have suggested a temperature range between 25 °C and 29 °C for the reproductive stage of soybean (Brevend and Egli, 2003; Jones., *et al*. 2009) an average temperature increase of 2-3 °C in this phase would take place in favor of soybean plants because it is not beyond the normal temperature range. On the other hand, the higher $CO_2$ rates cancel out the negative effects of the partial increase in temperature and improve soybean grain and biological yields.

**Table 14. Monthly mean temperature and monthly averaged in reproductive stage and the entire growing season for the historical period (1970–2010) and future periods (2011-2030 and 2046-2065) at different emission scenarios.**

| Mean temperature (°C) | July | August | September | October | Reproductive stage (Aug–Sep) | Growing season (July–Oct) |
|---|---|---|---|---|---|---|
| 1970-2010 | 26.50 | 25.50 | 20.50 | 17.50 | 23.00 | 22.50 |
| 2011-2030 (RCP 2.6) | 27.04 | 26.10 | 24.12 | 18.50 | 25.11 | 23.94 |
| 2011-2030 (RCP 8.5) | 28.00 | 27.21 | 25.35 | 18.30 | 26.28 | 24.71 |
| 2011-2030 (B1) | 27.90 | 27.50 | 25.10 | 18.30 | 26.30 | 24.70 |
| 2011-2030 (A1B) | 27.93 | 26.50 | 24.50 | 18.10 | 25.50 | 24.25 |
| 2011-2030 (A2) | 27.45 | 26.52 | 24.40 | 18.25 | 25.46 | 24.15 |
| 2046-2065 (RCP 2.6) | 28.15 | 27.85 | 24.30 | 18.60 | 26.07 | 24.72 |
| 2046-2065 (RCP 8.5) | 30.04 | 29.11 | 25.70 | 19.41 | 27.40 | 26.06 |
| 2046-2065 (B1) | 28.50 | 28.00 | 24.50 | 18.63 | 26.25 | 24.90 |
| 2046-2065 (A1B) | 30.00 | 29.00 | 25.50 | 19.00 | 27.25 | 25.87 |
| 2046-2065 (A2) | 29.50 | 28.75 | 25.50 | 19.00 | 27.12 | 25.68 |

After evaluating the effects of climate change on soybean plants in the city of Pampa, Argentina, Travasso et al. (2009) showed that average temperatures and $CO_2$ rates would increase in all the scenarios studied. They reported that an increase in $CO_2$ rate along with a rise in average temperature was favorable for soybean plants, improving their yield by 3%. Tacarindua et al. (2013) argued that high temperatures reduced the number of pods per plant by 16-30%. The reduction in yield caused by the increasing temperature was attributed to a decrease in the duration of the grain filling period.

On the other hand, increases in $CO_2$ concentrations in all temperature degrees result in a higher yield because larger amounts of photosynthetic material are assigned to the grains. Temperatures higher than the favorable limits however, diminish the positive effects of $CO_2$ on the plants (Wheeler *et al*., 1996). For wheat, Wilcox and Makowski (2014) argued that the negative effects of increasing temperatures would be offset by increases in $CO_2$ concentrations. They explained that increasing $CO_2$ concentrations would improve plant performance by increasing photosynthesis rates and water use efficiency. Ohe et al. (2007) reported that increasing temperatures more than normal ranges during the stages of soybean growth led to a 30% reduction in the plant yield. By investigating the effects of changes in temperatures and $CO_2$ concentrations on soybean in the future climate in Gorgan Plain, Nehbandani and Soltani 2016 concluded that a temperature increase of 3 °C would lead to an increase of 30 $g.m^{-2}$ in the grain yield. Rising temperatures of 3-8 °C reduced irrigation requirements by 90 mm due to the lower number of days elapsed until maturity. Under these conditions, the grain yield decreased by 130 $g.m^{-2}$ because of shortened plant growth period and increased number of days when the temperature exceeded the favorable limits for the plants. Zhang and Nearing (2005) examined the effects of climate change on winter wheat yield. They reported that wheat yield would increase in the future period (2070-2099) and that the yield of winter wheat would change due to interactions between increasing temperatures (negative effect) and rising carbon dioxide.

## 4. Conclusion

Obviously, changes in minimum and maximum temperatures, precipitation, and rates of $CO_2$ during the future periods (2011-2030 and 2046-2065) will influence the growth, and grain and biomass yields of

soybean. Much research has been done in most regions of Iran on the impact of planting density, planting dates, fertilizer and water management under current climatic conditions on soybean growth and yield. Also, related studies are absent for Parsabad of Moghan Plain. The present research, however, examined changes in soybean growth and yield for the future periods under Moghan plain conditions to the atmosphere general circulation models and evaluating the outputs of LARS-WG downscaling model. According to TOL, short-growing cultivars are the most tolerant in water stress conditions of weak (Williams), mild (M9), and severe (Zan). Zan, M9, and Williams exhibited the highest to lowest increases (in descending order) in grain and biological yields for the four irrigation levels under the projected climate change. However, when selecting the right cultivar for each year, in addition to adapting to climatic conditions and limited water, other conditions, such as fertilizer requirements, resistance to biotic stress, etc., should be considered. According to the climate change predicted in this study, the increase in the maximum temperature significantly and positively affects the soybean grain and biological yield, except for severe stress. Precipitation also has a positive effect on the final yield. It is obvious that the increase in grain and biological yields in the coming decades (2011-2030 and 2046-2065) in the studied scenarios. However, due to physiological mechanisms, heat stress during the reproductive stage can significantly decrease plant performance. Therefore, it is imperative to take into account precipitation, minimum and maximum temperatures, and $CO_2$ rates during flowering and yield formation stages to predict plant yield. Since the study region is partly considered a hot and humid region of Iran, soybean growth and yield will improve provided that there is sufficient water supply under the future climate in Parsabad of Moghan Plain resulting from an average temperature rise of 2-3 ºC along with increasing $CO_2$ rates.

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