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Impacts of climate change on soybean production under different treatments of field experiments considering the uncertainty of general circulation models

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ABSTRACT

Earth is faced with dramatic changes in the weather systems, which leads to climate change. Climate change affects water resources and crop production. In this study, five and seven general circulation models (GCMs) were respectively collected via the IPCC Fourth and Fifth Assessment Reports. Emission scenarios including B1, A1B, and A2 for AR4 and RCP2.6 and RCP8.5 for AR5 were applied to predict future climate change. The weighting method of mean observed temperature-precipitation (MOTP) was utilized to compute uncertainty related to different climate models. The scenario files made by ΔT and ΔP were applied to the downscaled model of LARS-WG to generate weighted multi-model ensemble means of temperature and precipitation for the period 2020–2039 centered on 2030s. These ensemble means were incorporated into the calibrated AquaCrop model to predict final yield and biomass. In this study, soybean data were applied for four different varieties under three irrigation treatments in field experiments carried out at Karaj Seed and Plant Improvement Institute in two successive years. However, the results of statistical analysis between the model output and observed data for all varieties and irrigation treatments in the calibration year (2010) and validation year (2011) were the same at the 95% confidence level. It is suggested that AquaCrop is a valid model to predict yield and biomass for the study area in the future. Furthermore, comparing future climatic variables to the historical period during the soybean growing season showed enhancement of these variables by the 2030s. The amplitude change of temperature was larger in AR5, whereas the amplitude change of precipitation and CO_2 were larger in AR4. The soybean yield and biomass increased for all treatments in the 2030 s with positive correlation with the climatic variables. The maximum temperature represented the most significant correlation with yield and biomass for almost all treatments. Finally, soybeans might achieve an optimal threshold temperature in the future, leading to yield increases in the 2030s.

1. Introduction

Most parts of Iran are located in arid and semi-arid areas of the world, and Iran's agricultural sectors are highly dependent on water resources and rainfall. The phenomenon of climate change will have consequences such as water scarcity, temperature increase, and high evapotranspiration, which lead to water stress during crop growing periods. Soybean (Glycine max) is a legume crop that is globally popular as an oil seed crop. This legume is a substantial protein source for human feeding and is useful for biofuel feedstock and animal food (Masuda and Goldsmith, 2009).

Crop simulation models, which predict crop yield and biomass (Bannayan et al., 2003), are applicable tools in climate change impacts studies. The AquaCrop model was developed by FAO as a practical model for prediction of attainable yield and biomass for many generic crops under water-limiting conditions. The factors that distinguish this model from other crop models are minimal input parameters and a better balance between simplicity, accuracy, and robustness (Raes

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et al., 2009b; Steduto et al., 2009). The performance of the AquaCrop model to simulate yield response to water stress has been reported by researchers for other crops in different parts of the world, including, for example, teff (Araya et al., 2010), cotton (Farahani et al., 2009; García-Vila and Fereres, 2012; Heidariniya et al., 2012; Hussein et al., 2011), sunflower and potato (García-Vila and Fereres, 2012; Yuan et al., 2013); rice (Amiri et al., 2015), barley (Tavakoli et al., 2015), winter wheat (Heidariniya et al., 2012; Salemi et al., 2011) and wheat (Andarzian et al., 2011; Shrestha et al., 2013). Atmosphere-ocean general circulation models (AOGCMs) are capable of estimating future climate change, especially at globally and continental scales. These numerical models can depict a comprehensive three-dimensional representation of the climate system, illustrating dynamical and physical processes, their interactions, and feedbacks. These models can provide a regional estimation of changes in aerosol concentration and greenhouse gases and their impact on future climate (Randall et al., 2007; Ruosteenoja et al., 2003). The IPCC (Intergovernmental Panel on Climate Change) has published SRES scenarios to survey future developments in the global environment by considering production sources of greenhouse gases and aerosol emissions. Resulting storylines such as A2, A1B, and B1 are respectively the representatives of high, moderate, and low growth rate of future emission scenarios. These emission scenarios, with different technological, social, demographic, economic, and environmental developments in increasingly unalterable ways (IPCC-TGICA, 2007), represent the relationships between the forces driving aerosol emissions and greenhouse gases, especially yearly atmospheric CO_2 concentration and its development during the 21 st century on a global scale. As the climate models became more sophisticated, the latest generation of GCMs were developed by the IPCC in support of the Fifth Assessment Report (AR5) as the fifth phase of the Coupled Model Intercomparison Project (CMIP5). However, as a result of considering land use changes and external forcing such as solar and volcanic forcing at a finer resolution, models were more sophisticated in CMIP5 (Knutti and Sedláček, 2012). Furthermore, the new Representative Concentration Pathway (RCP) with time- and space-dependent trajectories of concentrations of greenhouse gases and other forcing agents are used in CMIP5 as a very low forcing level (RCP2.6), two medium stabilization scenarios (RCP4.5/RCP6) and one very high baseline emission scenario (RCP8.5) (van Vuuren et al., 2011).

Since soybean production plays an important role in Iran for the agricultural and industrial sectors, study of climate change impacts on this crop is important. Moreover, in climate change impacts studies, existing uncertainties should be taken into consideration to produce more accurate outputs. Studies have shown that among different uncertainties, GCM outputs have the most influence on output results (Massah Bavani, 2006; Minville et al., 2008; Prudhomme and Davies, 2007). Notwithstanding the existing studies that have conducted on climate change impacts on different systems along with mitigation and adaptation methods, most studies have concentrated on sensitivity analysis and system vulnerability to one or few climate change scenarios (Alexandrov and Genev, 2003; Brouyère and Dassargues, 2004; Fowler et al., 2004; Gellens and Roulin, 1998; Kamga, 2001; Yates and Strzepek, 1998). Therefore, this study aims to project the weighted multi-model ensemble means as an uncertainty analysis method by applying GCM outputs under three emission scenarios (B1, A1B, and A2) and two Representative Concentration Pathways (RCP2.6, and RCP8.5). Furthermore, although few studies have been done regarding calibration of the AquaCrop model for soybean in this specific area, there is a research gap in comparing different cultivar reactions to water stress. This study predicts future changes on final grain yield and biomass in the study area for the period 2020–2039 centered on 2030 s by considering uncertainty of GCM outputs.

2. Materials and methods

2.1. Study area and experimental treatments

The study area was located in an experimental field of the Karaj Seed and Plant Improvement Institute, Iran (35°47′N, 50°54′E). This area has a cold semi-arid climate with a temperate summer and semi cold winter. The data are derived from two experiments in 2010 and 2011, which were carried out using a completely randomized block design with three replications. The entire cultivated area of soybean was approximately 3750 m^2 for the two experimental years.

AquaCrop version 4.0 (Raes et al., 2012b) was calibrated for year 2010 and validated for year 2011. Four soybean varieties including L17 (V1), Williams*Hobbit (W*H) (V2), M9 (V3), and M7 (V4) were sown on June 27, 2010, and July 4, 2011. Based on genotypes with different length of growing days, the cultivation date varied between the first to third weeks of October. Therefore, July to October were considered the most important months for the length of the crop cycle.

The irrigation method was the furrow system, and water was siphoned at a rate of 0.2 L s^{-1} discharge to deliver water to every furrow. The irrigation period started the first day after sowing, and full irrigation was considered when the water reached to the end of furrow. To perform the irrigation treatments, the cumulative evaporation values from a class-A pan were measured every seven days as a criterion for estimation of applied irrigation amount. Irrigation treatments were defined as without water stress (I1), mild water stress (I2), and severe water stress (I3) by adjusting pan evaporation values to 50, 100, and 150 mm, respectively. Based on these values, irrigation intervals were determined in 7, 14, and 21 days that were respectively assigned to the treatments of (I1), (I2), and (I3). Based on total water input, the irrigation depth, which was applied in the model, was approximately equal to 35 mm for each interval. However, the water stress treatments were conducted after the appearance of five to seven trifoliate leaves. In other words, the irrigation periods for all treatments were the same to the control treatments until five to seven trifoliate leaves. After this growth stage, irrigation treatments were conducted with total applied irrigation amounts of 525 mm (I1), 350 mm (I2), 280 mm (I3) for L17 and W*H, and 455 mm (I1), 315 (I2), and 245 mm (I3) for M9 and M7. Moreover, these irrigation amounts from the calibration year were applied as inputs of AquaCrop for historical and projected future periods.

2.2. AquaCrop model

AquaCrop is a water-driven model designed by yield response in relation to water supply and agronomic practices by using soil water budgeting (Raes et al., 2009b). The specifications of the model including conceptual framework, underlying principles, and distinctive components are discussed by Steduto et al. (2009), whereas the model algorithms and structural detail are described by Raes et al. (2009b). The fundamental equation, propounded by Doorenbos and Kassam in 1979, is shown in Eq. (1) as a basic equation for prognostication of yield response to water (Raes et al., 2009a):

$$\left(\frac{Y_x - Y_a}{Y_x}\right) = k_y\left(\frac{ET_x - ET_a}{ET_x}\right) \tag{1}$$

where Y_x and Y_a are the maximum and actual yield, ET_x and ET_a are the maximum and actual evapotranspiration, and k_y is the proportionality factor between relative yield loss and relative reduction in evapotranspiration.

2.2.1. Input data in the AquaCrop model

Input data, including weather, crop, soil, and field management data, define the crop development environment. Meanwhile, the crop input, as applied to the AquaCrop model, is determined from