Biophysical and hydrological effects of future climate change including trends in CO₂, in the St. Joseph River watershed, Eastern Corn Belt

Abstract

Future climate change has the potential to significantly impact crop growth, both directly due to CO₂ enhancement and indirectly, through temperature and moisture impacts. This work investigates the biophysical and hydrological effects of future climate change, including trends in CO₂, in the St. Joseph River watershed, Eastern Corn Belt. In this study, the Soil and Water Assessment Tool (SWAT) was first modified to take dynamic CO₂ concentration as input. A regional crop leaf development curve from Landsat TM imagery was also used to adjust model performance in corn leaf area development for the historical period. A multi-objective calibration strategy was employed to ensure acceptable simulation of streamflow, seasonal crop growth and interannual crop yield simultaneously. The model was then driven by future climate change and CO₂ data from three Atmosphere-Ocean General Circulation Models (AOGCMs), which are GFDL-CM2.1.1, NCAR-PCM1.3, and UKMO-HADCM3.1, under three Special Report on Emissions Scenarios (SRES) , including B1, A1B and A2 to investigate crop and streamflow response in two future periods: the near future (2021-2050) and the far future (2061-2090). The St. Joseph River watershed is expected to experience more winter and spring precipitation, but slightly decreasing summer precipitation. Due to increasing temperature and decreasing summer moisture, more drought stress is predicted. Both annual total aeration and drought stress are projected to be more variable in both future periods. Although future CO₂ enhancement will benefit the crop growth and final yield by improving radiation use efficiency (RUE) and reducing drought stresses, simulated corn yield still decreased by 6% in the near future period, and 16% in the far future period due to the combined effect of both climate change and CO₂ enhancement. Streamflow redistribution is also predicted in the future. Stream discharge is projected to increase for the whole flow range in the near future period. For the far future period, high flows are expected to decrease, while low flows are expected to increase, indicating more hydrologic drought and flood events in the St. Joseph River watershed.

1. Introduction

Agricultural production is critically dependent on climate conditions. Temperature, precipitation and extreme events such as flooding or drought can seriously affect production, with risks often being higher for smaller farmers and some types of crops (Kling et al., 2003). The US Corn Belt is one of the biggest and most productive agricultural systems globally, with corn production occupying more than 20% of global maize areas. Any yield reduction due to climate variability and climate change may lead to a tighter food market and intensify food crisis (McMichael, 2009).

Mean temperatures in the US Corn Belt have increased by 0.06°C per decade from 1900 to 2010 (Pryor, 2012). Annual precipitation followed a generally increasing trend from 1930 until to the present in this area (Groisman and Easterling, 1994; Andresen, 2012). The increase in the number of heavy precipitation events and number of wet days are two main reasons leading to the increase in precipitation from the 1930's (Kunkel et al., 2003; Grover and Soursounis, 2002).

Increased annual temperature is generally considered to benefit crop production due to the longer growing and reduced frost season (Wuebbles and Hayhoe, 2004). However, the increased summer temperature may be detrimental to yields of corn and soybeans. For example, Thompson (1988) found that the summer warming trend from 1891 to 1936 adversely affected crop yields, while the cooling trend accompanied by increased summer rainfall decreased variability in yield and accounted for a 20% increase in yield from 1936 to 1972. Mishra and Cherkauer (2010) also found that corn and soybean yields in the Midwest are significantly inversely correlated with drought indices and maximum daily air temperature in the grain filling and reproductive growth period.

For the grain fill period, cooler and wetter conditions are favorable for corn and soybean production (Lobell and Asner, 2003). In contrast, if soil is too wet in the spring it adversely affects root metabolism, retards root development, and causes plant wilting after soil submersion (Glinski and Stepniewski, 1983). Delayed planting to avoid wet soil may reduce grain filling time, and reduce crop yield (Arjal et al., 1978). It also increases the risk of exposure to lethal cold temperatures late in the season before grain maturation (Nielsen et al., 2002).

Studies indicate that “cooler and wetter” conditions in summer months and “warmer and drier” condition in spring months are optimal for crop growth in this area. (Rosenzweig et al., 2002; Mishra and Cherkauer, 2010; Pryor, 2012; Wang et al., 2016a) However, projected seasonal changes in precipitation and temperature in this region are likely to lead to sub-optimal conditions for crop growth due to increased temperatures of 3-6 °C by the end of this century (Wuebbles and Hayhoe, 2004), temporally and spatially varied precipitation (Meehl et al, 2007), a shift in the seasonal rainfall distribution to wetter springs (Christensen, 2007), and an increased frequency of intense precipitation events and lower summertime soil moisture levels (Cherkauer and Sinha, 2010).

Many studies have investigated crop responses to possible future climate change in this region. Sinha and Cherkauer (2010) found that the duration of soil frost will decrease late in the century (2070-2099) accompanied by earlier occurrences of last spring frost and later first autumn frost. Southworth et al. (2000) indicate that crops in the northern part of the Midwest will have increased yields under climate change, because of the earlier planting date, but in some locations increased spring moisture will still delay planting despite warmer temperatures (Dohleman and Long, 2009; Rogovska and Richard, 2011). An increase in average temperatures also implies more frequent and intense extreme heat events, which may negatively affect crop

yield (Goldblum, 2009). Possible decreases in summer rainfall during the critical growing periods or longer drought periods will also result in lower summer soil moisture (Mishra et al., 2010), and crop yield reduction (Wuebbles and Hayhoe, 2004). Increased heavy precipitation and flooding also has negative impacts on crop yield; Rosenzweig et al. (2002) predicted 6% corn yield losses due to excessive precipitation and related events by 2030 in the Midwest.

Changes to precipitation and temperature are not the only factors impacting future crop yields; enhanced CO₂ levels in the atmosphere will also affect crop growth. In 2013, CO₂ accounted for about 82% of all U.S. greenhouse gas emissions from human activities (USEPA, 2013). Since CO₂ is the substrate of photosynthesis, increased concentration stimulates photosynthetic rates directly. Crop production responds positively to the increased atmospheric CO₂ concentration, which is termed a “CO₂ fertilization effect” (Oliver et al., 2009). Increased CO₂ concentration reduces the stomatal conductance, which leads to an improved plant-water productivity. As a result, transpiration loss is reduced, and higher soil water content is maintained during the growing season (less drought stress), which improves drought tolerance by delaying the onset of water stress, and finally enhances the biomass production (Long et al., 2004). However, lower transpiration alone will not typically benefit a crop when soil moisture is available. Leakey et al. (2006) found that the productivity and yield of maize were not affected by the open-air elevation of CO₂ concentrations (550 ppm) in the absence of drought in Illinois, USA, although stomatal conductance was reduced by 34% and soil moisture was increased by 31% when compared with corn under ambient CO₂ concentrations (370 ppm).

In summary, crop growth and yield is influenced by precipitation pattern, growing season temperature, and CO₂ concentration. All of these factors directly impact crop water use, either through water availability, atmospheric demand or water productivity, resulting in feedbacks to

the field water balance. As a result, their combined effects and relative importance are difficult to separate and vary from case to case. Therefore, the main objective of this study is to explore the biophysical and hydrologic effects of future climate change accompanied by CO₂ enhancement via a modeling approach. Here the Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998) was applied in the St. Joseph River watershed, located in the Eastern Corn Belt region of the U.S.

SWAT is a semi-distributed, continuous-time ecohydrologic model based on physical principles, but also includes many empirical equations to represent hydrological, hydrochemical and biophysical processes (Gassman et al., 2007; Niraula et al., 2011; Arnold et al., 2012; Wang et al., 2014; Krysanova and White, 2015). SWAT has been under continuous development by the USDA-Agricultural Research Service (ARS) over its 30 year history, with contributions from scientists throughout the world (Williams et al., 2008). The current version of SWAT evolved from the Simulator for Water Resources in Rural Basins (SWRRB) model (Arnold and Williams, 1987), which was inspired by many previous USDA-ARS developed models, including CREAMS (Knisel, 1980), GLEAMS (Leonard et al., 1987), and EPIC (Williams, 1990).

SWAT has been widely used in the St. Joseph River watershed and the larger Maumee River basin to address climate induced change, mostly in hydrology and water quality. For example, Verma et al. (2016) coupled the SWAT model with three AOGCMs for the Intergovernmental Panel on Climate Change (IPCC) A1B scenario in the Maumee River watershed. Their results indicated a 9.7% annual flow increase in late-century (2089-2099) when compared with baseline (1995-2005). Annual suspended solid, total phosphorous and nitrite loadings were also predicted to increase (19.6%, 3.5% and 6.8% respectively). Cousino et al. (2015) also modeled the effect of climate change on flow and water quality using four AOGCMs under four Representative

Concentration Pathways (RCPs) scenarios in the Maumee River watershed. Their results indicated a 20% decrease in total water available for runoff and 17% decrease in sediment loads in Mid-century (2046-2065). Bosch et al. (2014) evaluated the effects of agricultural best management practices (BMPs) in mitigating climate change impacts on water quality in the same area. They predicted a 12% increase in annual streamflow and a 23% increase in sediment yield for the period 2040-2069 under IPCC A1F1 scenario. Enhanced BMP implementation could significantly offset climate induced sediment and nutrient increases.

Previous studies in the Eastern Corn Belt that have used SWAT to study climate change impacts have usually focused on precipitation and temperature change impacts (e.g., Chien et al., 2013), with few studies considering the effect on regional hydrology and crop growth when CO₂ enhancement is also treated as an environmental change factor. Although several studies (Eckhardt and Ulbrich, 2003; Wu et al., 2012; Butcher et al., 2014; Sun et al., 2014) included CO₂ enhancement in SWAT modeling, they focused on quantifying hydrological effects, so crop biophysical responses to changes in both climate and atmospheric CO₂ have not been thoroughly investigated. Further, for many SWAT applications, the calibration strategy fails to examine model performance in simulation crop growth, which is important in the evaluation of evapotranspiration (ET) and soil moisture related to vegetative growth (Arnold et al., 2012; Wang, 2016), as well as for water quality simulations (Nair et al., 2011).

Inspired by these gaps, this study quantifies the biophysical and hydrologic responses to future precipitation change, temperature increase and CO₂ enhancement in an agricultural watershed using SWAT. Specific objectives are to:

- 1) Modify SWAT to take dynamic CO₂ concentration as a model input, which will affect crop development and related hydrological processes.

- 2) Include crop growth calibration in addition to traditional streamflow calibration, to regulate model performance in annual yield and seasonal leaf development, with the help of satellite based LAI curve from Landsat TM imagery.
- 3) Apply the calibrated model in both baseline (1981-2010) and two future periods (2021-2050; 2061-2090) to investigate regional crop growth and streamflow responses due to future climate change and CO₂ enhancement.

2. Methods

2.1 Study Area

The St. Joseph River Watershed (Fig. 1) is located in northeastern Indiana, northwestern Ohio and southeastern Michigan, with a drainage area of 2821 km². Cropland, with coverage of 38% of the watershed area, is the dominant land use/cover type based on the USDA National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL) for 2010. Other land use types in this watershed are pasture (26.6%), forest (13.0%), urban areas (12.5%) and wetland (9.3%). The climate of this region is optimal for corn and soybean production, with long term average (1991-2010) precipitation of 992 mm (Wang et al., 2016b), and annual average air temperature of 9.5 °C . The St. Joseph River watershed is also a relatively flat area; 57% of the watershed has slope less than 2%. The dominant soil type is loam and fine loam, occupying 81% of the watershed area (Feng et al., 2015). Poor drainage dominates this watershed, so tile drainage is widely used to remove excess water which can damage crops, and make fields inaccessible to farm machinery (Smith et al., 2015).

2.2 SWAT Model Overview

Developed by the USDA-ARS, SWAT is widely used to assess the impact of climate variability on hydrologic process and crop production (Luo et al., 2008; Wang et al., 2011; Palazzoli et al., 2015; Niraula et al., 2015). The basic simulation unit for SWAT is the hydrologic response unit (HRU), which is a lumped land area, possessing a unique combination of land use, soil and slope inside each subbasin. At the HRU level, SWAT simulates the hydrologic cycle based on a water balance equation of soil water content including evapotranspiration, surface runoff, infiltration, percolation, shallow and deep aquifer flow (Arnold et al., 1998). A detailed description of SWAT hydrology and water quality simulation components can be found in Neithsch et al. (2009). For this study we used SWAT rev. 488.

SWAT simulates crop growth both under optimal and actual conditions. When no growth stress is considered, daily growth rate or daily biomass accumulation (Δbio ; kg/ha) is regulated by leaf area index (LAI) development, light interception (k_l), photosynthetically active radiation (H_{day} ; MJ m⁻²), and radiation-use efficiency (RUE; 10⁻¹ g/MJ), as follows:

$$\Delta bio = 0.5 * H_{day} * (1 - \exp(-k_l * LAI)) * RUE \quad (1)$$

For annual crops, LAI accumulates following an optimal leaf area development curve for each day. LAI starts to accumulate from the planting date until it reaches the maximum defined LAI for the crop. It remains stable until the senescence point (DLAI) is attained, at which point LAI decreases until plant maturity.

Actual daily growth varies from optimal growth due to various stresses. SWAT considers growth constraints from five aspects: drought, aeration, temperature, nitrogen and phosphorous

stresses. The plant growth factor quantifies the fraction of potential growth achieved on a given day and is calculated as:

$$\gamma_{reg} = 1 - \max(wstrs, astrs, tstrs, nstrs, pstrs) \quad (2)$$

Where γ_{reg} is the plant growth factor (0.0-1.0), $wstrs$ is the water stress for a given day expressed as a fraction of optimal plant growth, $astrs$ is aeration stress, $tstrs$ is the temperature stress, and $nstrs$ and $pstrs$ are nitrogen and phosphorus stresses, respectively. Therefore, the potential LAI and biomass are adjusted daily if any individual stress is greater than 0.0. If there is no stress, then $\gamma_{reg}=1$. In this study, the auto fertilization option was applied to avoid any nutrient stress. The original SWAT drought and aeration stress calculation methods have been replaced with an S-curve method to convert the physical measure of excess or insufficient soil moisture to the aeration or drought stress factor, respectively (Wang et al., 2016a).

2.3 The representation of CO₂ effects in the SWAT model

SWAT considers the biomass production enhancement due to elevated CO₂ concentration in two ways. The direct impact on stimulating photosynthesis is reflected in a change in radiation-use efficiency (RUE) under different ambient CO₂ levels. The relationship used to adjust the RUE for effects of elevated CO₂ (Stockle et al., 1992) is:

$$RUE = \frac{100 * CO_2}{CO_2 + \exp(r_1 - r_2 * CO_2)} \quad (3)$$

where RUE is the radiation use efficiency of the plant (10⁻¹ g/MJ), CO_2 is the concentration of carbon dioxide in the atmosphere (ppmv), and r_1 and r_2 are shape coefficients. For Corn, $r_1=5.7998$ and $r_2=-0.00135$ (Stockle, et al., 1992; Neitsch et al., 2009). According to equation 3, when CO₂ is between 330 and 660 ppmv, RUE increases with increasing CO₂ concentration,

reflecting that plants can accumulate more biomass for the same amount of absorbed energy due to greater carbon intake. Eq. 3 is only suitable for CO₂ concentration from 330 to 660 ppm, as it starts to reverse the effect of CO₂ fertilization at higher concentrations. Thus the equation has been modified for this study so that if CO₂ concentration is greater than 660 ppm, the RUE is constant. Therefore, RUE will not exceed 45.05 (RUE at 660 ppm from eq. 3).

The indirect impact of CO₂ enrichment due to improving plant-water productivity is considered by modifying the canopy resistance term when using the Penman-Monteith equation to calculate potential/actual evapotranspiration. The Penman-Monteith method combines components that account for energy needed to sustain evaporation, the strength of the mechanism required to remove the water vapor and aerodynamic and canopy resistance terms. Based on this method, increased canopy resistance or reduced stomatal conductance leads to a decreased ET. Easterling et al. (1992) proposed the following equation to consider the CO₂ effect on canopy resistance:

$$r_c = \frac{r_l}{(0.5 * LAI) * (1.4 - 0.4 * \frac{CO_2}{330})} \quad (4)$$

where r_c is the canopy resistance (s/m), r_l is the minimum effective stomatal resistance of a single leaf (s/m), and LAI is the leaf area index of the canopy. Increased canopy resistance or reduced stomatal conductance leads to a decreased ET.

2.4 Input Data

2.4.1 Historical climate input

Historical climate input (daily precipitation and air temperature) from 1991 to 2010 is provided from NOAA National Climate Data Center weather stations, as well as weather stations

maintained by the USDA-ARS National Soil Erosion Research Laboratory. Seven precipitation and three temperature stations were selected around or inside the St. Joseph River watershed (Fig.1). Model calibration is based on observed historical climate data.

2.4.2 AOGCM climate input

Three Atmosphere-Ocean General Circulation Models (GFDL-CM2.1.1, NCAR-PCM1.3, UKMO-HADCM3.1), under three Special Report on Emissions Scenarios (SRES) (B1, A1B, A2) were obtained from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project Phase 3 (CMIP3). Though forcing data is also available in Phase 5 of the same project (CMIP5), CMIP3 data was used in this research due to its longer history. The impacts of CMIP3 projections have been widely evaluated in the Midwest USA (Mishra et al., 2010; Schoof et al., 2010; Hayhoe et al., 2010; Cherkauer and Sinha, 2010; Kunkel et al., 2013; Panagopoulos et al., 2015). In addition, previous studies indicated that patterns of temperature and precipitation change are quite similar between CMIP3 and CMIP5 (Panagopoulos et al., 2015; Knutti and Sedlacek, 2013). Climate forcing data were bias corrected and statistically downscaled (Cherkauer and Sinha, 2010) from its original grid resolution (Table 1) to a resolution of 1/8 degree. A quantile mapping method (Wood et al., 2002) was employed as the bias correction and spatial disaggregation technique. Monthly forcing were then temporally disaggregated to daily scale based on resampling of the historic time series, before being utilized as weather input to evaluate climate change effects on crop growth and streamflow. The downscaled and bias-corrected projected daily data is available from 1950 to 2099 for all three models and all three emissions scenarios. Detailed information of AOGCMs and emission scenarios are listed in Table 1.

2.4.3 *CO₂ input*

Historical annual CO₂ concentration and future CO₂ concentration predicted for the three SRES emission scenarios are provided by the IPCC Third Assessment Report - Climate Change (Houghton et al., 2001). Concentration data is provided annually from 1970 to 2100 for each emission scenario. SWAT rev. 488 does not take dynamic CO₂ concentration as input, instead CO₂ concentration is set as a constant 330 ppm. Therefore, the model is unable to correctly reflect crop growth conditions (e.g. RUE in eq. 3, and canopy resistance in eq 4) in the future period when CO₂ concentration is predicted to increase. In order to investigate the effects of future precipitation and temperature change on crop growth, but also explore crop biophysical responses to CO₂ enhancement, dynamic CO₂ concentration were treated as model input. No changes were made to any equations in the SWAT code that use CO₂ concentration. The only change is to provide dynamic CO₂ concentrations as an input, based on which SWAT computes crop growth instead of using the constant value 330 ppm, similar to the work by Wu et al. (2012), and Butcher et al. (2014).

2.5 Model implementation

2.5.1 *Model parameterization and calibration.*

Wang et al. (2016b) developed a regional leaf area development curve based on a time series of Landsat TM5 images. The Cropland Data Layer (CDL) was used to identify the corn pixels in each image, and NDVI was generated for each corn pixel for 11 years (2000-2010). All 11 years of data were merged based on potential heat units (PHU) to generate a normal NDVI-LAI growth curve, which is used to adjust the SWAT potential LAI curve, as shown in Fig. 2. The adjusted potential LAI curve is more regionally specific, and consistent with observed data obtained from Landsat images. Adjusting the seasonal LAI growth curve based on remote

sensing estimates of LAI is helpful to capture intra-annual variability in crop growth in responses to various climate stresses, and reflect reasonable biomass to avoid equifinality in yield estimation (Cavero et al., 2000; Boegh et al., 2004).

Model implementation and initial parameters were based on research from Her and Chaubey (2015). The St. Joseph River watershed was divided into 39 subbasins, with the area of 5000 ha as the stream initiation threshold area. Subbasins were then further divided into 498 hydrologic response units (HRUs) with threshold area proportions of 5% and 10% for land cover and soils. The initial calibration provided by Her and Chaubey (2015) focused on daily streamflow and water quality, without consideration of interannual crop yield variation and seasonal crop growth dynamics. In order to better investigate the synergies between crop growth and the water cycle, biophysical and crop stress parameters (Wang et al., 2016a) were added to the calibration, and seasonal LAI and detrended annual yield were included in the objective functions. We used the best-fit least squares regression method (Goldblum, 2009) to remove crop yield trends caused by improvements in genetics and fertilizer applications.

A multi-algorithm, genetically adaptive multi-objective (AMALGAM) method was used to perform the calibration (Vrugt and Robinson, 2007). Model parameters were auto calibrated by AMALGAM to ensure the capturing of streamflow, seasonal crop growth and interannual crop yield from 2000 to 2010, simultaneously. Most hydrological parameters were left the same as those used by Her and Chaubey (2015), however, those parameters that differ, mostly biophysical and stress parameters, are summarized in Table 2. Including seasonal crop growth and interannual crop yield in the calibration process was helpful to better reflect the surface water budget, especially ET and soil moisture which is closely related to vegetative growth

(Arnold et al., 2012). Water quality simulation can also be improved when crop yield calibration is conducted (Nair et al., 2011).

Daily streamflow at the watershed outlet (USGS 04180500) was used as measured discharge. Seasonal LAI information from the Landsat images was utilized to represent seasonal crop growth. Annual corn yield at the watershed scale was aggregated from county level crop yield (Srinivasan et al., 2010) based on a weighted average to reflect interannual crop yield variability. Nash-Sutcliffe (1970) efficiency was used to evaluate daily streamflow performance, while d-statistics (Willmott, 1982) were employed as indicators of model performance in seasonal LAI growth and inter annual crop yield simulation. The d-statistic reflects the degree to which the simulated variation is a good estimate of the measured variation (Han et al., 2010). It is widely used to evaluate model performance in crop growth (Zeleeke et al., 2011; Yang et al., 2014; Wang et al., 2016a).

Model performance after multi-objective calibration in streamflow is shown in Fig.3, both log (Fig. 3a) and linear (Fig. 3b) scales are used to visualize model performance under low and high flow conditions, respectively. The model did a good job capturing both low and high flow conditions, with a daily Nash-Sutcliffe coefficient (NSC) of 0.82. The d-statistic for LAI is 0.83, and for crop yield is 0.76. After calibration, model performance was validated between 1995 through 1999. Daily Nash-Sutcliffe coefficient of streamflow was 0.86, and the d-statistic for annual crop yield was 0.64. Due to the scarcity of LAI data, there is not a separate validation period to evaluate LAI. Therefore, model performance for all three variables (daily streamflow, seasonal LAI, annual crop yield) are only presented in figures for the calibration period. Our model performance in daily streamflow was deemed as “very good” according to model evaluation guidelines in watershed simulations (Moriiasi et al., 2007). Streamflow performance

after calibration was similar to that of Her and Chaubey (2015), with NSCs of 0.82 and 0.86 for the calibration and validation periods, respectively. Fig. 4 and Fig. 5 depict model performance in seasonal LAI growth and interannual yield variability after calibration, indicating that crop growth was well captured by the calibrated model.

2.5.2 Model application for climate change study.

In order to explore how CO₂ enhancement and future climate change affect crop growth and streamflow, five modeling experiments were designed based on different simulation periods (baseline period:1981-2010, near future: 2021-2050, and far future: 2061-2090) and with/without CO₂ concentration controls as listed below.

1. Baseline experiment: Baseline period daily precipitation and temperature data (1981-2010) plus baseline period (1981-2010) CO₂ concentrations ([CO₂]).
2. Near future experiment: Near future daily precipitation and temperature data (2021-2050) plus near future (2021-2050) CO₂ concentrations ([CO₂]).
3. Near future experiment, with CO₂ control: Near future daily precipitation and temperature data (2021-2050) plus baseline period (1981-2010) CO₂ concentrations ([CO₂]).
4. Far future experiment: Far future daily precipitation and temperature data (2061-2090) plus far future period (2061-2090) CO₂ concentrations ([CO₂]).
5. Far future experiment, with CO₂ control: Far future daily precipitation and temperature data (2061-2090) plus baseline period (1981-2010) CO₂ concentrations ([CO₂]).

Each 30-year simulation experiment has nine runs, indicating nine different climate projections as a function of the three AOGCMs in combination with the three emission scenarios, including the dynamic CO₂ concentrations. Calibrated parameters from section 2.5.1 were used for each experiment.

3. Results and Discussions

3.1 Future climate change and CO₂ enhancement

As shown in Fig. 6, annual precipitation and temperature change prediction are quite different between models and scenarios. Fig. 6 displays variations in average annual temperature and precipitation for the two future periods relative to the baseline period (1991-2010). Both future projections indicate a consistent rise in temperature, but distinct differences in magnitude. For the near future period (2021-2050), the change varied between +0.43 °C and +1.98 °C, with an average value of +1.20 °C, while for the far future period (2061-2090), the range is from +1.42 °C to 3.75 °C, with an average change of 2.79 °C. For precipitation, all of these scenarios experienced an annual increasing precipitation, with average change of +4.7% for the 2021-2050 period, and +7.5% for the 2061-2090 period. The UKMO-HADCM 3.1 model always predicts lower precipitation change but higher temperature increases. In contrast, higher precipitation change but lower temperature change was projected by the NCAR-PCM 1.3 model. Differences in AOGCM performance is due to their different “effective climate sensitivity”. At the time of doubled CO₂ concentration, UKMO-HADCM 3.1 has the highest “effective climate sensitivity”, which is 3.06 °C, while NCAR-PCM 1.3 has the lowest, which is 1.88 °C (Randall et al., 2007). In climate change studies, no single AOGCM is considered to be superior, and it is recommended to use a number of different models (Southworth, 2002). Under the B1 scenario,

all three models predict lower annual precipitation and temperature change than the other two scenarios in both the near future and far future periods.

The monthly temperature and precipitation change based on the three future emission scenarios is illustrated in Fig. 7. Temperature increases are predicted for all months in the near future period (Fig. 7a). Temperature is expected to keep increasing in the far future period under all three scenarios (Fig. 7b). July, August and September are expected to experience greater temperature increases compared to the other months. Most of the time, scenario B1 predicts a smaller increase in temperature when compared with the other two scenarios.

Precipitation change also varies seasonally in the study area. Precipitation increases are predicted in winter and spring months (November to March) for all scenarios in the two future periods, with the magnitude of the increase is highest in the far future period. Marginal variations (could be positive or negative) in precipitation are predicted in June and July. For August, only scenario A2 predicted a moderate increase, on average (around 10%), all other scenarios report marginal precipitation variations. All three scenarios project different precipitation change patterns in September and October. Scenario B1 indicates a moderate decrease in both future periods. For the near future period, scenario A1B indicates moderate decreases in September but moderate increases in October, scenario A2 shows the reverse. For the far future period, both A1B and A2 predict precipitation increases in September and October. Therefore, no clear direction of precipitation change is predicted for the fall months (September and October).

Based on Fig. 6 and 7, the St. Joseph River watershed will more likely experience enhanced air temperature in both future periods, especially during the summer months (July, August, and September). Precipitation is expected to substantially increase in winter and spring, but show little change in summer months (July, June and August). Increased temperature accompanied

with nearly unchanged precipitation in summer months indicates a higher evapotranspiration demand. Therefore, the study area may become much drier in the summer months, which are often critical corn growth periods, and an increase in drought stress during this critical period will lead to final yield reduction.

Fig. 8 depicts the CO₂ concentration prediction from 1970 to 2100 for different SRES scenarios. The A2 scenario has the greatest rate of CO₂ increase. A2 and A1B have quite similar CO₂ concentrations until the year 2050 (522 ppm), when A2 projects a much more rapid increase. The B1 scenario has the lowest concentration among all three SRES emission scenarios, and it reaches a relatively stable concentration (530 ppm) by the year 2080. Unlike the modified model used in this study, SWAT rev. 488 does not consider CO₂ enhancement over time, so CO₂ concentration is kept constant at 330 ppm. Since biomass accumulation and final yield are closely related to RUE (Eq. 1), which is a function of CO₂ level (Eq. 3), Fig. 8b was generated to indicate how corn RUE responds to different CO₂ concentrations. Generally, after model modification, RUE responds to CO₂ increases positively, but when the CO₂ level is over 500 ppm, further CO₂ increases will not cause much further increase in RUE. For this reason, RUE impacts under both the A1B and A2 scenarios are very similar even though their CO₂ concentrations diverge after 2050. This divergence occurs when both scenarios are over 500 ppm CO₂ and SWAT is no longer sensitive to the change. If CO₂ concentration is beyond 660 ppm, RUE will stay constant at 45.05 (RUE at 660 ppm from eq. 3).

3.2 Crop biophysical responses to future climate and CO₂ change

Section 3.1 indicates that future climate change may introduce more drought stress during the crop growing season, which may in turn impact the yield in our study area. However, the enhanced CO₂ is also expected to increase crop yield to some extent. Their combined biophysical

impacts on crop yields are unknown and might be different between the two future periods due to differences in future climate and CO₂ concentration. Therefore, in this section, the biophysical impacts of future climate and CO₂ change are explored.

Fig. 9 exhibits the impacts of climate change and CO₂ enhancement on three crop stresses (aeration, drought and temperature) and final yield based on the different simulation experiments in both the baseline and two future periods. Annual stress for each corn HRU was first computed from the daily time series, and then aggregated to the basin level based on HRU areas. Compared to the baseline period, both annual total aeration (Fig. 9a) and drought stress (Fig. 9b) experienced more variance in both future periods. Furthermore, the variances for both stresses were predicted to increase from the near future to the far future periods. This can be seen from the increase of Q75 (upper quartile, meaning 25% of the data lie above this threshold) and the range (Differences between upper and lower Whisker) of both stresses (Table 3). Limited change in the median value of aeration or drought stress was detected. The impact of CO₂ change on any of the stresses was not appreciable in the near future period. For the far future period, CO₂ enhancement slightly increases the median of annual aeration stress (1.06 vs 0.82), and slightly reduces annual drought stress (10.48 vs. 10.73).

Fig.9c indicates the temperature stress variation for the different simulation experiments. In contrast to aeration and drought stress, climate change effects on temperature stress are quite different. The median value for temperature stress for baseline, near future, and far future periods are 14.71, 8.73, and 6.07, respectively, indicating a decreasing trend in the future periods. This decreasing trend is also accompanied by decreased variation in stress.

The difference in yield for each experiment is caused by the effect of all three stresses. Based on Fig.9d, median crop yield is projected to decrease, the reduction for the near future period is

around 0.5 t/ha, while for the far future period yield loss is 1.2 t/ha. More variance in crop yield is also predicted for both future periods. Larger yield variance in the future is caused by more extremely low yield conditions rather than an increase in high yield occurrences. CO₂ enhancement shows a marginal effect on crop yield (around 0.01 t/ha difference in median value), which is consistent with its influence on growth stresses.

The relationship between growth stresses and crop responses was further investigated by plotting annual yield versus various biophysical stresses (aeration, drought and temperature stresses) for each modeling experiment, as shown in Fig. 10-12. Results indicate an increasing trend in aeration stresses, as seen in the increasing number of years with bigger aeration stress in contrast to the baseline period (Fig. 10). However, there is no clear relationship between aeration stress and crop yield. This is mainly due to the low frequency of aeration stress events during the simulation period. In terms of drought stress (Fig. 11), an inverse correlation was found between yield and annual stress. Compared to the baseline period, the two future periods experienced larger annual stresses, which is also associated with more yield loss. Another interesting point from Fig.11 is the effect of CO₂ on drought stress and yield. When the baseline period CO₂ was used for future periods, it resulted in larger drought stress and more yield reduction, (the gold or purple circles are always to the lower right of their counterpart dots). This indicates that CO₂ enhancement can reduce drought stress and reduce the risk of yield loss. However, the positive influence of CO₂ enhancement on crop growth cannot fully compensate for the negative effect of temperature and precipitation change. The opposite relationship was seen in Fig. 10, where the effect of CO₂ enhancement was to increase aeration stress, with a very slight associated reduction in yield.

Fig. 12 illustrates the relationship between temperature stress and crop yield for the different modeling experiments. Consistent with Fig. 9c, temperature stress decreased in the future period when compared to the baseline period. Decreased temperature stress is caused by the increase in mean temperature. In SWAT, temperature stress is computed based on daily mean temperature, as shown in Fig. 13. For corn, the optimal mean growth temperature is 25 °C. When daily mean temperature is between 20 °C to 30 °C, very limited temperature stress is found. When mean temperature is below 20 °C or over 30 °C, temperature stress increases rapidly. The threshold of high temperature, beyond which heat stress may increase substantially is consistent with other studies (e.g. Schlenker and Robert, 2009). Schlenker and Roberts (2009) found that corn yield decreases sharply, if temperature is over 29 °C. Future temperature increases may help to release stress caused by low temperature (cold condition), however, SWAT does not predict much more stress due to high temperatures, since daily mean temperature over 30 °C is still rare. Fig.12 also indicates that lower temperature stress is accompanied with lower yield. This can be explained by the increasing threat of drought stress. Although a direct temperature stress due to warmer temperatures is not predicted by SWAT, increased temperature does exacerbate the drought stress in summer months, which is more critical to final corn yield (Nielsen, 2008). The reduced temperature stress in the early growing season (cold condition) due to increasing mean temperature cannot compensate for the yield reduction risk due to exacerbated drought stress in summer months. This finding is consistent with other studies (Brown et al., 2000; Hawkins et al., 2013). Brown et al. (2000) applied the erosion productivity impact calculator (EPIC) crop growth model in the Missouri-Iowa-Nebraska-Kansas (MINK) region to study environmental effects of switchgrass and traditional crops under current and future greenhouse-altered climate. They found that higher temperatures would reduce cold stress, but increase heat stress with water

deficit, so climate would still threaten the final corn yield. Hawkins et al. (2013) used an empirical model and AOGCM data to study the heat stress influence on French maize yield. They found that most large maize producing regions could experience a greater number of hot days in 2016-2035, causing an estimated 12% yield loss. However, hot days may become less damaging for yields as precipitation increases. Actually, the increase of temperature itself is not an issue if plenty of soil moisture is provided for corn. Field experiments indicate that no direct damage to photosynthetic capacity was found even when the temperature of the corn plant was raised to 37.8 °C (Nafziger 2011).

To investigate the impact of SRES differences on crop growth, we also compared crop responses under baseline and all three SRES sets of climate projections. Since crop responses in near future and far future period are only different in magnitude, and experience the same direction of change (increasing or decreasing) when compared to baseline (Table 3), we have simplified our discussion by only comparing the baseline with the three SRES for the far future period (2061-2090). Crop stresses and final yield based on different SRES are shown in Table 4. Compared to the baseline period, the median value of annual total aeration and drought stress are expected to increase marginally for all scenarios; the A2 scenario exhibits the biggest change among all three SRES. Temperature stress is expected to decrease substantially for all SRES mainly due to the increase of mean temperature, which is consistent with our results in Fig. 12. Drought stress is expected to become the most important reason causing yield reduction in the far future period. Corn yield is projected to reduce by 11.9%, 19.9% and 24.1% respectively for the B1, A1B and A2 scenarios, respectively. Greater variance in drought and aeration stresses are expected in the far future period, and more noticeable differences are found among the three emission scenarios. For example, the range of drought stress is expected to increase more

dramatically for the A2 scenario (12.0 to 25.2) than the B1 scenario (12.0 to 16.6) with reference to the baseline period. The same trend was observed for Q75 of drought stress as well. The most noticeable increase is predicted under the A2 scenario where the Q75 of drought stress increases from 11.9 in baseline to 15.0 in the far future period. Corn yield is expected to experience more inter annual variation for the A2 scenario as well. The range of corn yield is expected to increase from 2.5 t/ha in baseline to 4.3 t/ha in the far future period under the A2 scenario (73.3% increase), but only to 3.3 t/ha under the B1 scenario (35.9% increase). Therefore, A2 is the worst case among all three SRES for corn growth in the future period. The A2 scenario results in more yield reduction, but also introduces more yield and drought stress variability than the B1 and A1B scenarios.

In conclusion, as a result of future climate change impacts on crop growth stresses, especially the exacerbated drought stress, corn yield in the St. Joseph River watershed is expected to be reduced by 6.4% in the near future period (2021-2050), and 15.7% in the far future period (2061-2090). The greatest impact is found under the A2 scenario, where median yield is expected to be reduced by 24.1%, while interannual yield variability increases by 73.3%. The simulated yield reduction is consistent with other studies in the Eastern Corn Belt. For example, focusing only on rising temperature as one of the environmental factors, Muchow et al. (1990) predicted 4% corn yield reduction in the next 30 years in Midwest USA. Using the CERES-Maize model, Southworth et al. (2000) reported much more yield reduction (10-20%) for medium-season maize in south-central Michigan due to more extreme temperature prediction (+5.1 °C) by the HadCM2GHG AOGCM. Panagopoulos et al. (2015) also employed the SWAT model to explore climate change effects on hydrology, water quality and crop productivity in the Ohio-Tennessee

River Basin. They reported an 8.4% mean yield reduction in the future period (2046 – 2065) based on seven AOGCMs with reference to the baseline period (1981-2000).

3.3 Streamflow response to future climate change and enhanced CO₂

Flow duration curves (Fig. 14) are used to visualize streamflow change under different modeling experiments for the whole range of annual daily flows. Fig. 14a uses a log scale on the horizontal axis to display the streamflow change at low probability of exceedance (PE). A log scale on the vertical axis is used in Fig. 14b to better visualize streamflow change at high flow conditions. Fig. 14c uses linear scale to highlight low flow changes. For the near future period, streamflow volumes are generally predicted to increase for both small and large PE. For the far future period, streamflow is expected to decrease for large PE, while streamflow discharge for small PE will increase. This indicates that more hydrological drought and flooding events are expected to happen in the far future period (2061-2090). This is probably due to the shifted seasonal precipitation pattern in the future, with wetter springs and more intense but less frequent summer storms. Warmer air temperatures coupled with unchanged summer precipitation increases ET in the study region, and in turn reduces flow volumes for low flow conditions (Cherkauer and Sinha, 2010).

We also compared flow duration curve change between the baseline and far future periods under all three SRES (Fig. 15). A redistribution in streamflow is expected for all emission scenarios. Streamflow discharge with small PE (large events) in the far future period is projected to increase when compared to baseline. The largest simulated flood event in the baseline period is 264.3 m³/s, while for the far future period, it is expected to increase to 279.6 m³/s , 290.8 m³/s and 297.9 m³/s respectively for B1, A1B and A2 scenarios. In contrast, streamflow discharge with large PE (small events) is expected to decrease for all three SRES, with moderate decreases

(-21.1%) for the B1 scenario, and large decreases(-47.7%, -44.1%) for A1B and A2 respectively (Fig. 15c). Under the B1 scenario, low flow discharge (PE=0.9) is 5.27 m³/s, which is much higher than A1B (3.49 m³/s) and A2 scenario (3.73 m³/s), but still lower than baseline scenario (6.68 m³/s). Table 5 summarizes the mean annual discharge based on different SRES scenarios. For the near future period, all three SRES scenarios predict an increase in mean discharge. For the far future period, only the B1 scenario predicts an increase trend in mean discharge, while the other two scenarios indicate a slightly decrease in mean discharge.

By comparing the flow duration curves with baseline and future CO₂ concentrations, it can be seen that CO₂ enhancement can increase streamflow in both low PE and high PE conditions. However, the amount of increase is quite marginal and only visible at very low PE conditions (PE < 0.001). For the whole flow range, the mean discharge for the near future period varies from 34.37 m³/s to 34.14 m³/s, so only a 0.67% increase due to CO₂ related crop impacts. The situation for the far future period is similar, with mean discharge increased by 1.3% due to CO₂ enhancement. The increased amount of streamflow is mainly due to the improved plant-water relationship. Enhanced atmospheric CO₂ levels result in reduced stomatal conductance, and therefore decreases the transpiration rate for similar levels of productivity. Reduced ET leaves more water available for streamflow. This finding is consistent with many other studies (Wu et al., 2012; Niu et al., 2013; Butcher et al., 2014), which all predict annual streamflow volume increases of 1%-4% when CO₂ enhancement effects on stomatal conductance are considered by models. However, if LAI response to CO₂ enhancement is also considered by SWAT, streamflow reduction could be expected, mainly due to the resulting increase in ET (Eckhardt and Ulbrich, 2003; Sun et al., 2014).

4. Conclusions

In this research, the SWAT model was used to explore future climate change and CO₂ enhancement effects on corn growth and hydrology in the St. Joseph River watershed, located in the Eastern Corn Belt, U.S. The current SWAT model was first modified to allow input of dynamic daily CO₂ concentration. Remote sensing information was used to generate a regional potential leaf area development curve for parameterization. A multi-objective calibration strategy was conducted to ensure the capturing of daily streamflow, seasonal crop growth and interannual crop yield simultaneously. After calibration, the model was driven by CO₂ concentration, and downscaled, bias-corrected precipitation and temperature from three AOGCMs under three SRES scenarios to study potential biophysical and hydrological impacts in two future periods (2021-2050; 2061-2090).

Based on this work, we can conclude the following:

1. The St. Joseph River watershed will likely experience significant increased precipitation in winter and spring months. But for summer months, a slight decrease or unchanged precipitation is predicted. Air temperature is also expected to rise for all months, but especially for summer months. Increased temperature accompanied with decreased or unchanged precipitation indicates more late summer threat to corn growth due to increased drought stress in the future period.
2. Both total annual aeration and drought stresses are expected to vary more year-to-year in both future periods. No significant change in the median value of aeration or drought stress was detected. Temperature stress is expected to decrease in the future period when compared to the baseline period. This is mainly due to the reduction of

cold stress in the early growing season; however, reduced temperature stress cannot compensate for the yield reduction risk due to exacerbated drought stress in summer months due to temperature increases and precipitation reduction.

3. Future CO₂ enhancement benefits crop growth and final yield by improving radiation use efficiency (RUE) and reducing drought stresses. The improvement in RUE is not significant when the CO₂ level is over 500 ppm. Annual median drought stress is expected to decrease slightly (from 10.7 to 10.5) due to increased CO₂, and median aeration stress is also expected to increase slightly (from 0.8 to 1.1) due to higher soil water content. Therefore, the mitigation impact of CO₂ enhancement on crop yield reduction is not significant. Detrended crop yield is still expected to decrease by 6.1% in the near future period, and by 15.6% in the far future period due to both climate change and CO₂ enhancement. Scenario A2 is the worst case among all three SRES, with greater yield reduction, and more yield variation than the other two SRES.

4. Climate change results in a redistribution in streamflow. Streamflow was predicted to increase for the whole flow range in the near future period, primarily due to precipitation increases. Increases in streamflow due to enhanced crop water productivity are quite low and only visible at very low PE condition (PE < 0.001). For the far future period, high flows are expected to increase, while low flows are expected to decrease, indicating a potential for both more hydrological drought and flood events in St. Joseph River watershed.

To mitigate the negative effect of climate change, especially to reduce the threats from exacerbated drought stress on corn growth in the study region, possible adaptation strategies

should be considered by local stakeholders. Focused efforts to mitigate these projected problems could also be made in breeding and genetics. For example, to develop and market drought-tolerant seeds, and improve the average yields of drought tolerant corn (Lobell et al., 2014). Adaption in management practices is also beneficial for corn growth, such as using earlier planting date (Lobell et al., 2011), or developing water management innovations, including irrigation to alleviate drought stress in critical growth periods (Malcolm et al., 2012).

Acknowledgement

This project is funded by U.S. Department of Energy (DOE), DE-EE0004396 and Purdue Climate Change Research Center (PCCRC).

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Table 1. Details of the General Circulation Models and CMIP3 emission scenarios used for future climate projections. All projection are based on IPCC 4th Assessment Report (Meehl et al., 2007) and SRES (Nakicenovic et al., 2000)

AOGCM		
Model Name	Institution	Grid resolution
GFDL-CM2.1.1	NOAA / Geophysical Fluid Dynamics Laboratory, Princeton University, Princeton, New Jersey, USA	2° * 2.5°
NCAR-PCM1.3	National Center for Atmospheric Research, USA	2.9° * 2.9°
UKMO-HADCM3.1	Research / Met Office, UK	2.75° * 3.75°
SRES		Maximum CO ₂
	Description	
B1	<ul style="list-style-type: none"> • A convergent world with global population that peaks in mid-century and declines thereafter. • Economic structure will change rapidly towards service and information economy, reduction in materials intensity. • Rapid introduction of clean and resource efficient technologies. 	550 ppm
A1B	<ul style="list-style-type: none"> • Has the same global population pattern as b1. • Very rapid economic growth. • Rapid introduction of new and more efficient technologies. 	720 ppm
A2	<ul style="list-style-type: none"> • A very heterogeneous world with continuously increasing global population. • Regionally oriented economic growth that is more fragmented and slower than in other SRES. 	850 ppm

Table 2 Parameter calibration values for streamflow, seasonal LAI and annual corn yield for parameters that differed from those used by Her and Chaubey (2015)

Parameter	Description	Calibrated
CN	Curve number (SF) ^a	-0.245
b1	Aeration stress S-shape transformation parameter 1 ^b	8.1664
b1-b2	Aeration stress S-shape transformation parameter 2	-3.0662
c1	Drought stress S-shape transformation parameter 1	1.835
c1-c2	Drought stress S-shape transformation parameter 2	-3.8133
RUE	Radiation-use efficiency ((kg/ha)/(MJ/m ²))	32.00
BLAI	Maximum potential leaf area index	4.00
HI _{opt}	Harvest Index for optimal growing conditions	0.4823
HI _{min}	Harvest Index under highly stressed growing conditions	0.2901

^a Scale factor (SF) proportionally increases or decreases values of parameters

^b Detailed information about stress parameters can be found in Wang et al., 2016.

Table 3. Statistics for stresses and corn yield based on all modeling experiments.

Statistic	Stress/Yield	Baseline climate and [CO₂]	Near future climate and [CO₂]	Near future climate, baseline [CO₂]	Far future climate and [CO₂]	Far future climate, baseline [CO₂]
Median	Aeration Stress	0.70	0.75	0.67	1.06	0.82
	Drought Stress	9.82	9.91	9.96	10.48	10.73
	Temperature Stress	14.71	8.74	8.74	6.07	6.07
	Corn Yield (t/ha)	7.85	7.37	7.38	6.62	6.63
Q75	Aeration Stress	1.45	2.00	1.94	2.49	2.23
	Drought Stress	11.85	13.29	13.39	13.82	14.12
	Temperature Stress	21.88	11.33	11.33	8.00	8.00
	Corn Yield (t/ha)	8.12	7.71	7.70	7.15	7.16
Range	Aeration Stress	3.42	4.76	4.65	5.76	5.30
	Drought Stress	11.99	18.68	18.93	20.66	21.56
	Temperature Stress	39.81	19.22	19.22	14.46	14.46
	Corn Yield (t/ha)	2.46	3.02	3.05	4.19	4.29

Table 4. Statistics for stresses and corn yield based SRES in Far Future and baseline period

Statistic	Stress/Yield	Baseline climate and [CO ₂]	Far future climate and [CO ₂]		
			B1	A1B	A2
Median	Aeration Stress	0.70	0.84	1.36	1.49
	Drought Stress	9.82	10.32	9.84	10.86
	Temperature Stress	14.71	6.25	5.88	5.37
	Corn Yield (t/ha)	7.85	6.91	6.47	6.29
Q75	Aeration Stress	1.45	2.43	3.21	2.83
	Drought Stress	11.85	12.59	12.03	15.04
	Temperature Stress	21.88	8.68	7.31	7.44
	Corn Yield (t/ha)	8.12	7.37	7.02	6.95
Range	Aeration Stress	3.42	5.48	8.25	6.40
	Drought Stress	11.99	16.60	14.18	25.20
	Temperature Stress	39.81	15.19	13.27	13.58
	Corn Yield (t/ha)	2.46	3.34	3.86	4.26

Table 5. Mean discharge from the five modeling experiments.

	Mean discharge (m ³ /s)				
	Baseline climate and [CO ₂]	Near future climate and [CO ₂]	Near future climate, baseline [CO ₂]	Far future climate and [CO ₂]	Far future climate, baseline [CO ₂]
B1	32.63	33.20	33.01	33.66	33.26
A1B	32.35	34.95	34.70	29.06	28.18
A2	31.71	35.21	34.97	31.00	30.19

Fig. 1 Location and land cover of the St. Joseph River watershed. Land cover is from the USDA NASS Cropland Data Layer for 2010. The location of three USGS gauging stations and seven weather stations are also shown.

Fig. 2 Modification of the default potential LAI growth curve in SWAT using LAI estimated from observations of NDVI over 11 growing seasons.

Fig. 3 Comparison of simulated and observed daily streamflow for the St. Joseph River near Fort Wayne, IN (USGS 04180500) during the calibration period (January 2000 – December 2010): a) log scale and b) linear scale.

Fig. 4 Comparison of simulated and observed corn LAI during the calibration period (2000-2010) averaged over the St. Joseph River watershed.

Fig. 5 Comparison of simulated and observed corn yield (tons/ha) averaged over the St. Joseph River watershed during the calibration period (2000-2010).

Fig. 6 Annual mean temperature and precipitation change from the baseline period (1981-2010) to a) the near future period (2021-2050) and b) the far future period (2061-2090) according to three AOGCMs under three GHG scenarios in St. Joseph River watershed.

Fig. 7 Monthly mean: (a) temperature and (b) precipitation variation between the baseline period (1981-2010) and the near future period (2021-2050); Monthly mean: (c) temperature and (d) precipitation variation between the baseline period (1981-2010) and the far future period (2061-2090) according to the average of three AOGCMs under three GHG scenarios.

Fig. 8 Future changes to CO₂ and radiation use efficiency as estimated by the modified SWAT model.

Fig. 9 Boxplots for annual basin level stress and corn yield for the different modeling experiments: a) Aeration stress, b) Drought stress, c) Temperature stress, and d) corn yield. Box plots for each experiment based on annual average results for the 30 year period as projected by three AOGCMs and three climate change scenarios.

Fig. 10 SWAT estimated corn yield vs. aeration stress for all model experiments

Fig. 11 SWAT estimated corn yield vs. drought stress for all model experiments

Fig. 12 SWAT estimated corn yield vs. temperature stress for all model experiments

Fig. 13 The SWAT modeled relationship between corn temperature stress and mean daily air temperature

Fig. 14 Flow duration curves for all modeling experiments

Fig. 15 Flow duration curves for baseline period (1981-2010) and all three SRES in far future period (2061-2090)