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SENSITIVITY OF MAIZE YIELD POTENTIAL TO REGIONAL CLIMATE IN THE SOUTHWESTERN U.S.

S. H. Kim, B. Myoung, D. H. Stack, J. Kim, M. C. Kafatos

ABSTRACT. *The sensitivity of maize yields to the regional climate in the Southwestern U.S. (SWUS) has been investigated by using the Agricultural Production Systems sIMulator (APSIM) model in conjunction with meteorological forcings [daily maximum and minimum temperature (T_{max} and T_{min}), precipitation, and radiation] from the North American Regional Reanalysis (NARR) dataset. Sensitivity experiments showed that potential crop production responded nonlinearly to variations in T_{max}, T_{min}, and downwelling solar radiation at the surface. Mean annual yield potential (Y_p) was changed by -3.0 and 1.79 Mg ha^{-1} for the +1 and -1 standard deviations (σ) of T_{max} variation for entire the SWUS. The impact of T_{min} changes were opposite to that of T_{max}, with 2.84 and -5.11 Mg ha^{-1}, respectively. Radiation changes only affected Y_p decreases by 3.02 Mg ha^{-1} in the -1 σ case. Yield sensitivity varied geographically according to regional mean climate states. For warmer areas of the SWUS, including southern California and Arizona, maize productivity responded positively to a lower T_{max} and higher T_{min}. For cooler regions, such as northern California and high-elevation Nevada, a higher T_{max} and higher T_{min} were favorable for higher yields. The T_{min} effect (e.g., cold surges) was larger during the planting period, and the T_{max} effect (e.g., heat waves) was larger in the growing season. Downwelling solar radiation at the surface also played an important role in coastal regions and the Central Valley of California.*

Keywords. *Climate change, Crop models, Regional impacts, Yield potential.*

Global agricultural production has increased with developments in agricultural systems and technology, such as new cultivars, nutrients, pesticides, and investment in irrigation systems (Cassman, 1999; Cassman et al., 2003; Brisson et al., 2010; Grassini et al., 2011; Olesen et al., 2007). In the coming decades, demands for agricultural products will continue to grow due to population increase, changes in diet, and other industrial demands. The current world population of over 7 billion people is anticipated to reach 9 billion by the mid-21st century. With socioeconomic development, food consumption patterns have also changed from starch-based staples to meat and dairy products (Godfray et al., 2010; Kastner et al., 2012). Recently, policymakers have mandated biofuels for environmental benefits such as lower greenhouse gas (GHG) emissions and energy security by reducing dependency on imported petroleum (Farrell et al., 2006). For example, the U.S. requires an increase in renewable fuel standards (RFS) to 36 billion gallons per year by 2022, as stipulated by the Energy Independence and Security Act (EISA). The European Union (EU) produced 10 billion liters of biodiesel in 2013, about 40% of global production, and is expected to produce 15 billion liters by 2022 (OECD, 2014). According to the Food and Agriculture Organization of the United Nations (FAO), a 60% increase in demand for agricultural products is projected by 2050 due to these reasons (IIASA, 2012).

Agricultural productivity strongly depends on local climate conditions determined by meteorological parameters, mainly temperature and precipitation. It has been suggested that as much as 80% of agricultural productivity may be determined by regional weather and climate for rainfed production systems (Fageria, 1992). Increased atmospheric CO_2 concentrations due to anthropogenic emissions and associated global warming trends have accelerated over the past few decades. For instance, according to the 2012 Global Climate Reports from the National Oceanic and Atmospheric Administration (NOAA, 2012), 2012 was the 10th warmest year for recorded global mean temperature since 1880, and the annual mean temperature marked the 36th consecutive year above the 20th century average. Quantitative effects of the trend in global warming vary widely according to region (e.g., IPCC, 2007, 2013). Therefore, assessing the potential impact of global climate change and variation on regional agricultural systems has become crucial for ensuring global food security (IPCC, 2013).

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The Southwestern U.S. (SWUS) is an important agricultural region for the country, with the highest agricultural output coming from California (CA). According to the 2007 Census of Agriculture (USDA, 2007), CA had the largest value of agricultural products sold ($33.9 billion) in the U.S., about 11.4% of total national value. In addition to agriculture's importance to the economy and food security, ecosystems in the region display interesting characteristics and include a great variety of land cover types (deserts, semi-arid regions, agricultural areas, large urban centers, mountains, and coastlines). Plants and crops in arid and semi-arid regions such as the SWUS exist near their physiological limits. Thus, even a slight change in regional temperatures and/or precipitation due to climate change can have a substantial impact on natural ecosystems and agricultural production. Future climate projections for the SWUS region, including CA, Arizona (AZ), and Nevada (NV), indicate that the greatest warming will occur in summers, leading to more frequent severe droughts (Fields et al., 2007) and a higher likelihood of reduced harvests (USGCRP, 2009). Thus, an ability to integrate increased regional climate variability with agricultural production is essential for securing agricultural production in this region as well as for food security for the U.S. and the world.

The simplest way to increase crop production is to expand cropland under predicted abiotic stress caused by future climate change. However, cultivable land and resources for agriculture are currently pressed to their limits. Moreover, converting forests or grasslands to croplands for biofuel increases GHG emissions instead of reducing them (Searchinger et al., 2008). Therefore, increasing agricultural production by increasing the yields of current cropland is a more appropriate way to meet the food demands of the coming decades. Global mean crop yield has increased, but yield trends show a wide geographical variation (Cassman et al., 2003; Grassini et al., 2011; Van Ittersum and Cassman, 2013). Trends indicate that the yields of specific crops in some countries barely increase as technology and knowledge become saturated. To ensure global food security, it is necessary to find agriculturally underperforming regions for additional investment. For high-performing regions with advanced agricultural systems, such as the SWUS, assessing yield changes under anticipated future climate change and associated variation is required for food security.

The "yield gap" is defined as the difference between the actual yield (Y_a) and potential yield (Y_p) that can be achieved using current technology and optimal management practices, respectively. Yield gap analyses are widely used to assess food security issues (Van Ittersum and Cassman, 2013). Potential yield (Y_p) is determined only by climate variables, such as solar radiation and temperature, with non-limiting nutrients, water, and controlled biotic stresses (Evans, 1993). Therefore, assessing Y_p is crucial to evaluating the climate impact on crop productivity in specific regions. Several methods have been used to estimate Y_p. Statistical methods based on surveys, yield contests, or experiments are severely limited, as it is not clear whether yield values are affected by stresses from biotic or abiotic processes. Recently, remote sensing data have been employed in yield gap studies because they provide relatively higher temporal and spatial resolution (Lobell, 2013). The data show the current state of crop development; thus, they are more reliable for estimating Y_a than Y_p. Another method is to use crop models. Estimating Y_p using physically based crop models is perhaps the best approach for specific regions because it is based on biophysical crop processes that reflect crop responses to environmental factors in the region of interest. Moreover, models incorporate a number of management factors, such as planting date, that are crucial for crop yields (Lobell et al., 2009; Van Ittersum et al., 2013). Process-based crop models, such as the Agricultural Production Systems sIMulator (APSIM; Keating et al., 2003), CERES (Ritchie et al., 1998), and Decision Support System for Agrotechnology Transfer (DSSAT; Jones et al., 1998, 2003), have been widely used to simulate both actual yield estimates and yield gap analysis (Chauhan et al., 2013; Mastrorilli et al., 2003; Lv et al., 2015).

In this study, a crop model was used to investigate the impacts of climate variability on maize productivity on a regional scale, especially for the SWUS. APSIM was selected in this study because it performed well among the major crop models participating in the Agricultural Model Intercomparison and Improvement Project (AgMIP; http://www.agmip.org). Because crop development and yield react nonlinearly to variations in climate drivers (Porter and Semenov, 2005), the interannual and geographical variations of these drivers, extreme temperatures in particular, are of great interest for their effects on climate variability and change. Thus, evaluating Y_p using crop models at a regional scale, where climate characteristics are constantly changing from daily to interannually, is essential for fully assessing the response of crop production to climate variability.

Climate data are essential in assessing the impact of climate variability on Y_p. Weather stations can provide accurate local meteorological history, but their spatial coverage is often too coarse to resolve variations in regional climate characteristics. Moreover, most of these sites are located within major cities, far from agricultural lands, and their temperature records can, for example, be contaminated by urban heat island effects. For evaluating the response of agricultural systems to climate change on a regional scale, high-resolution reanalysis data based on skillful numerical modeling in conjunction with quality-controlled observations are an important source of meteorological forcing data. As such, the National Centers for Environmental Prediction (NCEP) North American Regional Reanalysis (NARR) data were employed to drive the APSIM crop model to understand the connection between climate variability and regional agricultural processes in the SWUS.

DATA AND METHODOLOGIES

DESCRIPTION OF CROP MODEL

The APSIM model (http://www.apsim.info) calculates the yield of a specific crop by simulating interactions among plants, animals, soil, climate, and management practices (Asseng et al., 1998; Holzworth et al., 2006; Keating et al., 2003; McCown et al., 1996). APSIM is well documented, freely distributed, open source, scriptable, and modular, and it has been continuously developed to enhance its capability. This allows for flexible and multiple applications to a variety of crops and regions, making it ideal for scaling up to regional domains.

APSIM has been well validated in multiple field experiments for various regions over a wide range of environments (Liu et al., 2013; Lyon et al., 2003; Archontoulis et al., 2014; Harrison et al., 2014; Chauhan et al., 2013; Dixit et al., 2011) and has been used to study the potential impact of climate variability on crop productivity (Asseng et al., 2013b; Liu et al., 2012; Liu et al., 2014). The APSIM maize module determines the period of developmental stage in terms of accumulated thermal time. Thermal time (growing degree days) is estimated using a linear relationship (e.g., see fig. 1(b) in Wilson et al., 1995) calculated with 3 h temperatures interpolated from daily maximum temperature (T_{max}) and minimum temperature (T_{min}). The thermal time durations for the subsequent phases are dependent on cultivar-specific values.

APSIM's modules are essentially point-scale models representing the system at a single point in space. As a part of the current project, we developed ApsimRegions, an automated modeling framework that allows APSIM to be run over a large domain with thousands of points (Stack and Kafatos, 2013; http://www.apsimregions.org). Using this framework, users can simultaneously feed APSIM with multiple datasets of climate, soil, and management practices to cover a wide geospatial range at regional scales.

The maize module in APSIM has five phenological parameters: thermal time from emergence to the end of the juvenile stage, flowering to maturity, flowering to start of grain, maximum number of grains per head, and grain growth rate. Traditional crop model calibration requires a large amount of detailed field experiment data to adjust the phenological parameters. Unlike the Corn Belt in the Midwestern U.S., few maize modeling studies have been performed throughout the SWUS (Lee et al., 2011). Consequently, site-specific observational datasets are absent from previous studies, except for general county-level information on management practices. The study region covered numerous individual farms in several states, and each farm may have used different cultivars, planting/harvest dates, and experienced a unique local microclimate. Therefore, a conventional model calibration method using a few points cannot represent the entire study region. Because it was not practical to calibrate for each individual farm, we examined generic cultivars and configurations that characterized climate impact over a broader region, following the Global Yield Gap Atlas protocols (http://www.yieldgap.org). As the protocol suggested for simple calibration, we tested the harvest dates of six cultivars implemented in APSIM (fig. 1). All six cultivars were in the range of the actual harvest dates (USDA, 2010), and phenology-related model coefficients of the cultivars were expected to be optimized across the study region. The cultivars were validated with observed yield data for each county to determine the cultivars for this study (fig. 1). Among the cultivars, Pioneer 3237 was selected based on its performance during four years of simulation, and parameters were not modified in this low-level calibration process. The cultivar is suitable for maximum yield in dryland and irrigated systems, and thus it could be used in our study region (https://www.pioneer.com/web/site/australia). Recently, Van Ittersum et al. (2013) proposed a model calibration and validation procedure for global-scale crop modeling studies. They suggested that if the model was calibrated and validated in a similar climate, then the same model can be used in the same climate zone.

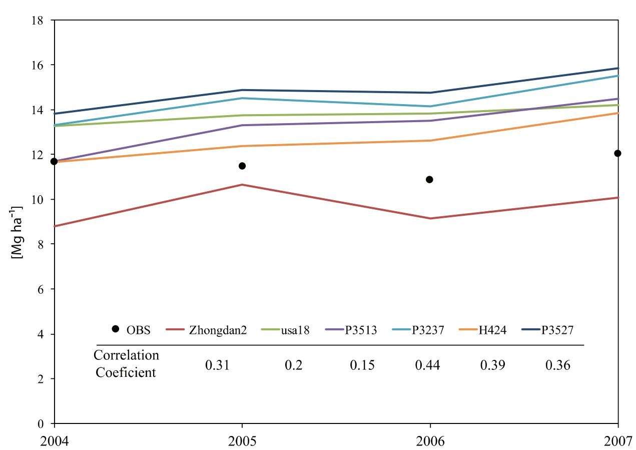

Figure 1. Black dots indicate actual yields (Y_a) and solid lines represent the yield potential (Y_p) of each cultivar (Zhongdan2, USA 18 leaf, Pioneer 3513, Pioneer 3237, Hycorn 424, and Pioneer 3527). The numbers below the legend show the correlation coefficient between Y_a and Y_p for each cultivar. A four-year period (2004-2007) was selected for which actual yield data were available for most of the counties in SWUS. The trend is similar among the cultivars, but the yields are different. Pioneer 3237 was selected for this study because it showed better performance in interannual variation (i.e., the highest correlation coefficient) and provided the second largest yield.

Crop Model Input Data

The soil type was selected for each grid point based on the HC27 generic soil profiles database (HarvestChoice, 2010; Koo and Dimes, 2013). The soil profiles were derived from a 9 km resolution global database called the Harmonized World Soil Database (IIASA, 2012) by matching the location of soil with one of the 27 soil profiles based on three criteria: soil texture, water content classification, and organic carbon content. HC 27 soil profiles have been widely used in a large number of regional and global crop modeling studies (Dourte et al., 2014; Müller and Robertson, 2014; Cenacchi and Koo, 2011; Bryan et al., 2011; Nelson et al., 2009).

In addition to the soil type, management decisions such as cultivar, irrigation, and planting practices play a crucial role in determining crop yields (Moen et al., 1994). To minimize crop stress through management practices, following the definition of Y_p, optimal management practice setups were applied. The generic type of hybrid maize, P3237, released by Pioneer Hi-Bred International USA, was selected for the simulation. Key modeling features of the cultivar include a maximum number of grains per head of 850, base temperature of 8°C, thermal time from flowering to maturity of 980°C day, and a grain growth rate of 8 mg grain^{-1} d^{-1}. Irrigation was applied to maintain the 95% soil water-holding capacity, as used in previous studies (e.g., Lee et al., 2009). Unlimited use of nitrogen fertilizer was also assumed

Table 1. Description of sensitivity tests.

Abbreviation	Description of Data
CTRL	Control run in which all climate variables are varied for 21 years.
STMX	Adding standard deviation of maximum temperature; other variables remain the same as CTRL.
STMN	Adding standard deviation of minimum temperature; other variables remain the same as CTRL.
SRAD	Adding standard deviation of radiation; other variables remain the same as CTRL.
MAXT	Only maximum temperature is varied with time (1991-2011); other variables are held constant (21-year daily mean).
MINT	Only minimum temperature is varied with time (1991-2011); other variables are held constant (21-year daily mean).
RADN	Only radiation is varied with time (1991-2011); other variables are held constant (21-year daily mean).

by applying 25 kg ha^{-1} of nitrogen at a depth of 30 mm if the nitrogen in the soil was less than 50 kg ha^{-1} at a depth of 50 mm. Other management practices in the region were obtained from cost and return studies of maize in the San Joaquin Valley for 2008 (UC Davis, 2013), including specific row spacing (76.0 cm), planting depth (3 cm), and crop density (8 plants m^{-2}).

Sowing Date

A number of previous climate impact studies were based on fixed sowing dates for the entire analysis period. The main reason for using a fixed estimated date is the lack of data, which reflects interannual variation at regional or national scales. The proxy sowing date can be problematic in yield gap studies. The sowing date not only changes every year but is also highly dependent on geographical location and varies widely, from February to August in the SWUS according to region. Potential yield (Y_p), the maximum possible yield under optimal management conditions, requires an optimal sowing date. Maize yields are highly sensitive to planting dates; however, data on observed planting dates are not available for the study domain. Thus, the optimal planting dates were calculated at each point using Monte Carlo simulations for maximum yields. This was done by simulating yields at each grid point with 25 different sowing dates in one-week intervals from 1 February to 1 August, resulting in 25 separate runs for every year of a 21-year period (1991-2011). The planting dates that generated the maximum Y_p were identified for each grid point and for each year; subsequently, they were averaged over the 21-year period. The yield-maximizing planting dates obtained in this way were then used for each year in the simulation.

Climate Data

The climate variables for driving APSIM include T_{max} and T_{min}, solar radiation (*Rad*), and precipitation. Potential yield (Y_p) is the yield of a crop cultivar under non-limiting water supply; thus, precipitation was not a key factor in this study. The water-limited potential yield (Y_w) that is important in rainfed regions is defined in a similar way to Y_p but is also limited by water supply. The daily data for the 21-year period were obtained from NARR, which provides a dataset with high spatial and temporal resolutions, 32 km and 3 h, respectively (Mesinger et al., 2006; http://www.esrl.noaa.gov/psd/). A regularly spaced grid of 958 points was used to cover the study area. NARR has been generated using the NCEP Eta model in conjunction with observational data from satellites, surface stations, and gridded station precipitation data and is regarded as one of the most accurate regional-scale historical weather datasets for North America.

Historical Data

County-level yield data for the study region were collected from the USDA National Agricultural Statistics Service (http://quickstats.nass.usda.gov). Six counties in CA (Glenn, Sacramento, San Joaquin, Shutter, Solano, and Yolo) and four counties in AZ (Cochise, Graham, Maricopa, and Pinal), the most active maize-growing counties that have the longest records, were selected for this study. The counties in CA have a full 21 years of records (1991-2011). Records for AZ are shorter; records of 15 to 18 years length were available during the 21-year period.

Experimental Design

The effect of climate variability on maize Y_p in the SWUS was examined in a sensitivity experiment as climate change or variability varied regionally within the study domain. Instead of simply applying specific numbers for the climate variables, standard deviations were calculated based on regional climatology. Using the 21 years of NARR data, the standard deviations (σ) of daily meteorological variables were calculated at each grid point during the growing season. The mean standard deviations were 3.56°C for T_{max}, 3.13°C for T_{min}, and 2.73 kg s^{-2} for *Rad*.

The sensitivity of maize yield was calculated from yields simulated with daily meteorological forcing time series, one from the observed values (CTRL in table 1) and three synthesized by adding $\pm 1.0\ \sigma$ and $\pm 0.5\ \sigma$ to the observed values (STMX, STMN, and SRAD in table 1). The yield calculated with the observed meteorological forcing (CTRL) was the control against which the sensitivity of yields based on the three synthetic forcings was calculated.

To assess the relative contributions of T_{max}, T_{min}, and *Rad* to the interannual variation of maize Y_p, three additional meteorological forcing datasets were generated to drive APSIM (MAXT, MINT, and RADN in table 1). In each of these sets, the interannual variation of only one variable was included while the other two variables were held constant at their 21-year mean values.

To investigate whether annual maize yields were significantly controlled by extreme temperature events, both extremely hot and cold days were examined. Hot days were defined as the number of days when T_{max} exceeded the 70th, 80th, 90th, and 95th percentiles during the growing season (April to October) at all grid points belonging to each agricultural district (table 2). Cold days were defined as the number of days when T_{min} was below the 1st, 10th, 30th, and 40th percentiles during the same period.

Table 2. Description of selected agricultural districts.

	Agricultural District			
	Sacramento Valley (CA)	San Joaquin Valley (CA)	Southern (AZ and CA)	Northeast Nevada (NV)
Counties	Colusa, Glenn, Sacramento, Solano, Sutter, Tehama, and Yolo	Fresno, Kern, Kings, Madera, Merced, San Joaquin, Stanislaus, and Tulare	Cochise, Graham, Maricopa, Pina, and Yuma (AZ), and Imperial (CA)	Elko, Eureka, and White Pine

RESULTS

CROP MODEL VALIDATION

The simulated Y_p using APSIM was evaluated with the county-level Y_a records from USDA-NASS. Table 3 and figure 2 show that the averaged Y_a was about 70% to 90% of the averaged Y_p during the 21-year study period. The overall average of the ratio was 81%. A previous study by Lobell et al. (2009) concluded that 80% is a typical value under irrigated systems in a developed country. In their model simulations, an averaged ratio of Y_a and Y_p at 18 sites in the U.S. Corn Belt was 75% between 2004 and 2005. A recent study using the same crop model reported a mean ratio of 89% from 123 field-year observations between 2005 and 2007 across Nebraska in the western U.S. Corn Belt (Grassini et al., 2011). The Global Yield Gap Atlas shows that the ratio ranges from 70% to over 90% in the U.S. (http://www.yieldgap.org). These previous studies show a range of 70% to 90%. The 80% plateau of the ratio, Lobell et al. (2009) argued, is based on a global-scale mean value with an econometric perspective. They also pointed out that it is possible for technology to exceed the 80% ratio. They did not specify the reason for an 80% maximum, but Pioneer (2015) describes possible reasons. A maximized yield close to Y_p does not always guarantee a better profit margin (e.g., see fig. 1 in Pioneer, 2015). Maximum profit is obtained by optimizing inputs, such as fertilizer and irrigation, and weed and pest control rather than maximizing investments. Therefore, farmers would not aim for contest-winning yields (close to Y_p) as opposed to maximum profit. The ratio range of 70% to 90% in APSIM simulations is still a realistic value and is well matched by previous studies. The results suggest that APSIM estimated Y_p reasonably well for the study region.

Table 3. Averaged Y_a: Y_p ratio for each county.

County	Y_a:Y_p Ratio
Cochise	89.7%
Glenn	92.2%
Graham	72.7%
Maricopa	70.0%
Pinal	69.0%
Sacramento	85.9%
San Joaquin	78.0%
Shutter	85.7%
Solano	82.8%
Yolo	87.6%

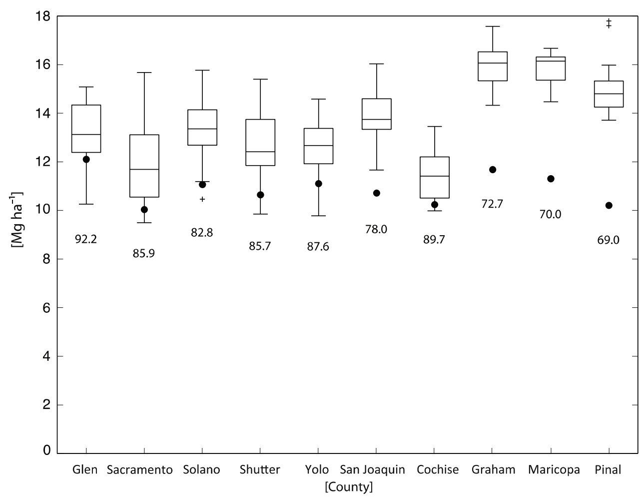

Figure 2. Box plots showing distribution of simulated yield potential (Y_p) for the 21-year study period. Black dots are averaged observed yields (Y_a) at selected counties in CA (Glenn, Sacramento, Solano, Shutter, Yolo, and San Joaquin) and AZ (Cochise, Graham, Maricopa, and Pinal). Numbers below box plots are Y_a: Y_p ratios (%) for each county.

CLIMATE SENSITIVITY OF APSIM CROP YIELDS

The effect of climate variability on maize production in the SWUS was examined in a sensitivity experiment by adding ±1 σ to the observed values (STMX, STMN, and SRAD in table 1). Results from the sensitivity study (fig. 3) show that the simulated maize yield is highly sensitive to variation in these climate conditions. The mean annual maize yield across the entire study area shows that a lower T_{max} (-1 σ) is a favorable condition for higher maize yields in the SWUS (fig. 3a). Mean yield differences between CTRL and STMX were -3.0 and 1.79 Mg ha^{-1} for the +1 σ and -1 σ T_{max} varia-

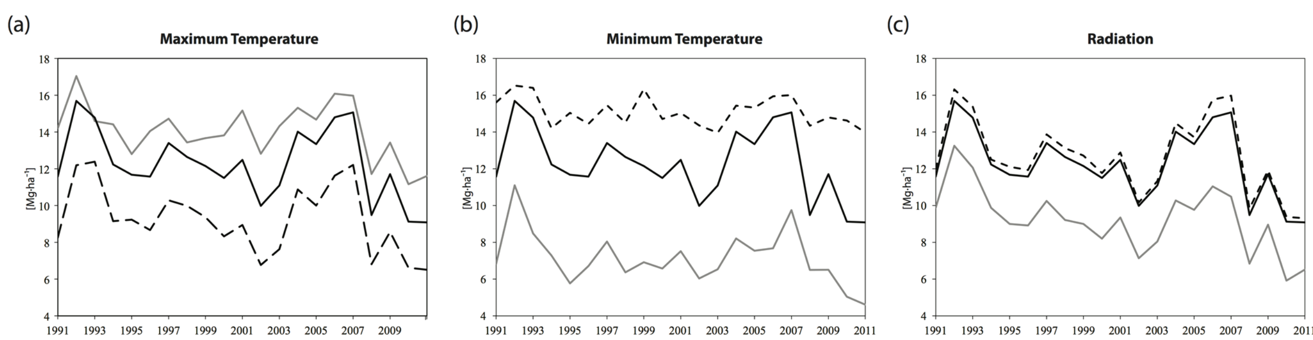

Figure 3. Averaged maize yields across the entire SWUS with multiple σ of (a) maximum temperature, (b) minimum temperature, and (c) radiation. Solid black solid line is control, dashed black line is +1 σ, and solid gray line is -1 σ.

tions, respectively. STMN showed that the effects of T_{min} on maize yield were opposite to that of T_{max}; the calculated yields were enhanced as T_{min} increased (fig. 3b). For the implemented temperature, forcing varied from +1 σ to -1 σ, and the calculated yields varied by 2.84 and -5.11 Mg ha^{-1}, respectively. Yield response was more sensitive to lower T_{min} than higher T_{max}. In the SRAD experiment, only the -1 σ case significantly affected maize yields (fig. 3c); the regional mean yield decreased by 3.02 Mg ha^{-1}, about 25% in CTRL. A notable yield reduction by smaller SRAD implied the presence of a threshold insolation value for maize to grow effectively. In addition, the results showed that T_{min} and T_{max} were the dominant drivers in determining maize yield in the SWUS; surface insolation effects were significant only when thresholds were not met. The most significant impact on mean maize yields in the SWUS was lower T_{min}, which decreased yields by over 41%.

The sensitivity of maize yield to these climate variables varied regionally (fig. 4). As T_{max} increased, the yield decreased (and vice versa) in most of the region, as shown in figure 4a (and 4b). Exceptions were found in northern CA, the Sierra Nevada, central and northeastern NV, and northeastern AZ. Due to high latitude, high elevation, or both, these regions have lower mean temperatures than other regions. Thus, higher T_{max} provided more favorable conditions for increasing maize yield. Similarly, due to a cooler climate, higher (or lower) T_{min} was associated with higher (or lower) yields in these regions, as shown in figure 4c (and 4d). An increase in T_{min} was also favorable for yields in warmer climate regions, such as the Central Valley and most of southern CA and southwestern AZ. Figure 4 also emphasizes that the yield response to T_{min} change was more sensitive than the response to T_{max} change in cooler regions, and the yield response to T_{max} change was larger than the response to T_{min}

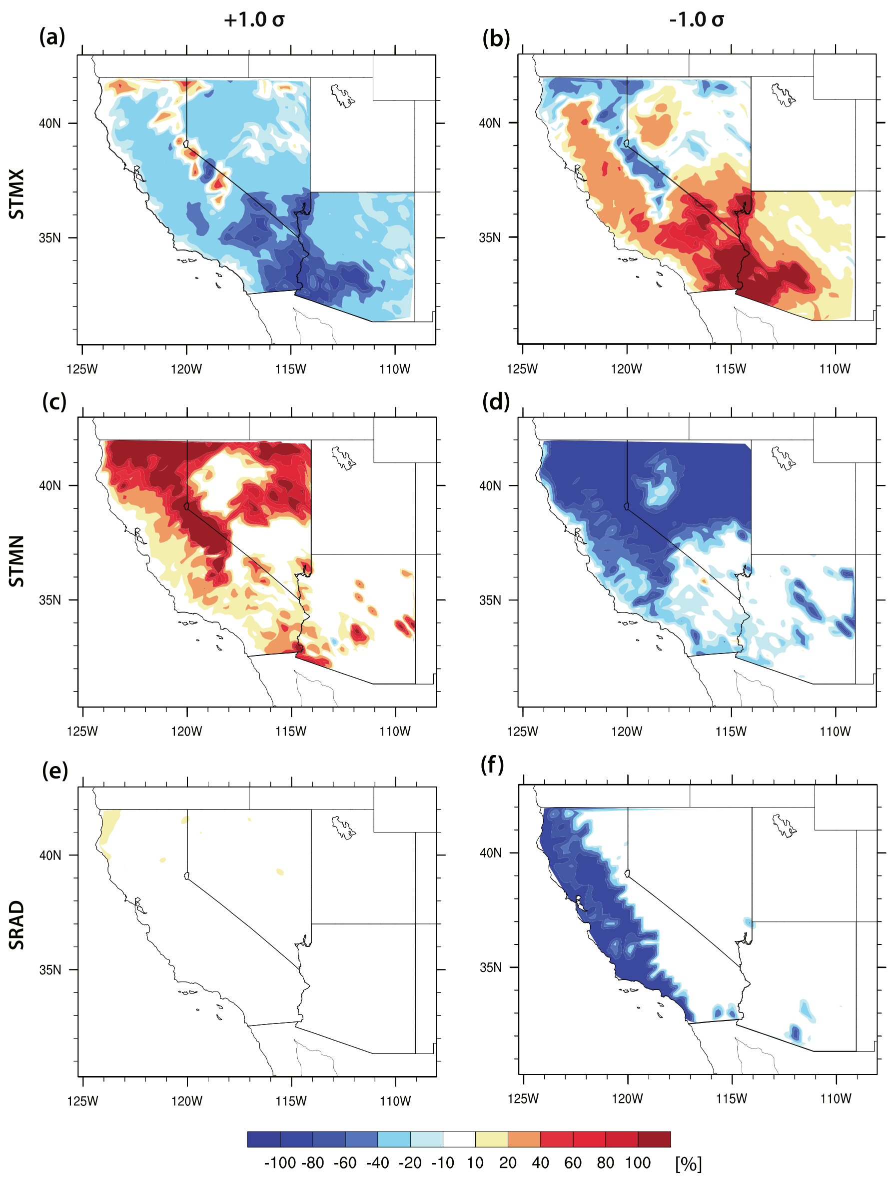

Figure 4. Differences in yields between CTRL and +1.0 σ of (a) STMX, (c) STMN, and (e) SRAD and between CTRL and -1.0 σ of (b) STMX, (d) STMN, and (f) SRAD.

change in warmer regions. These differences in yield sensitivity were primarily because of local climate differences in temperature and the physiological limits of crop type.

The SRAD experiment also showed a distinct spatial response to insolation changes. As shown in the time series of radiation sensitivity for the entire study region (fig. 3c), significant differences existed only in the negative sigma case. Figure 4f shows that lower yields in the SRAD run occurred in the coastal and Central Valley regions of CA, where the amount of insolation was strongly affected by local climate, specifically by the occurrence of boundary layer stratus clouds and fog during the growing season. The mean 21-year insolation in this region was lower than in other regions by as much as 3 MJ m^{-2} during the growing season. The relatively lower annual insolation in these regions caused a substantial response to the variation in insolation.

INTERANNUAL VARIATIONS OF MAIZE YIELDS AND DOMINANT CLIMATIC DRIVERS

The sensitivity experiment in the previous section suggested that maize yield was highly dependent on these three climatic variables. Thus, interannual variation in these variables will affect interannual variation in maize yield. Figure 5 shows the results of an experiment in which only one climate variable underwent interannual variation while the other two variables remained at the 21-year mean annual cycle (MAXT, MINT, and RADN in table 1). Both MAXT and MINT showed strong interannual variations (figs. 5a and 5b), but RADN remained largely the same (fig. 5c), indicating that the effects of interannual variation of insolation on maize yield in the SWUS were negligible. Compared with CTRL (dashed lines in fig. 5), the yield in MINT is closer to CTRL than the yield in MAXT. In addition, the interannual variability in MINT was similar to CTRL except for 1999. The relatively lower yields of MINT than CTRL in that year seem to be associated with T_{max} (e.g., 1999 had the highest yields in the MAXT experiment).

To evaluate the contribution from each climate variable, the two highest (1992 and 2007) and lowest (2008 and 2011) yield years (figs. 3 and 5) were selected from CTRL. In 1992, warmer conditions in the cooler climate regions (e.g., northern CA, the Sierra Nevada, and northern Nevada) substantially increased the yields in these regions (fig. 6a). The opposite was found in 2011 in which both lower T_{max} and T_{min} in these cooler regions reduced yields (fig. 6b). This result suggests that above-normal T_{max} and T_{min} promoted maize production in relatively cool regions, as pointed out in previous sections. In 2007 and 2008, temperature tendencies in both cooler and warmer regions contributed to yield characteristics. In the highest yield year (2007), higher T_{min} occurred in the cooler regions, while higher T_{min} and lower T_{max} were observed in the warmer regions (e.g., the coastal regions, Central Valley, and southern domain; fig. 6c). All these conditions were favorable for higher yields. Similarly, but with reversed signs, anomalous temperature trends of both T_{min} and T_{max} were unfavorable for yields in 2008. Figure 6d shows higher T_{max} for most of CA, especially in the Central Valley, that significantly decreased yields. Lower T_{min} in northeast NV and western AZ also contributed to lower yields.

The results shown in figure 6 indicate that T_{min} and T_{max} greatly contributed to the variation in maize yields throughout the SWUS on the interannual time scale, depending on geographical locations with varied local climates. In regions with a relatively warmer climate, such as the Central Valley and southern CA and AZ, lower T_{max} and higher T_{min} provided optimal conditions for growing maize. In regions with a relatively cool climate, such as northern CA and NV and northeastern NV, higher T_{max} and higher T_{min} were favored for higher yields. Thus, mean climate variables have to be carefully employed when assessing an agricultural response to climate change, as regional climates in the SWUS and their impact on crops have both strong spatial and temporal variation, as shown in figure 6.

IMPACT OF EXTREME TEMPERATURE EVENTS ON YIELD IN MAIZE GROWING REGIONS

Despite a substantial potential yield across the mountain and desert regions, actual maize production occurs mainly in CA's Central Valley and in southern AZ, where a warm climate dominates. For more in-depth study of these regions, case studies were performed for the Sacramento Valley, San Joaquin Valley, and southern CA and AZ regions based on the agricultural districts where counties grow maize and for which at least ten years of USDA data were available from 1991 to 2011. For comparison with a region of cooler climate, northeast NV was included in the analysis (table 2). Results of the sigma sensitivity study for the three agricultural districts indicated that all three districts responded similarly to temperature variations, i.e., higher yields for lower T_{max} and higher T_{min} (fig. 7). In general, sensitivity to T_{max} was stronger than sensitivity to T_{min}. In addition, the yield variation of STMN was smallest in the Southern district, which seemed to be due to the warmer climate. The main

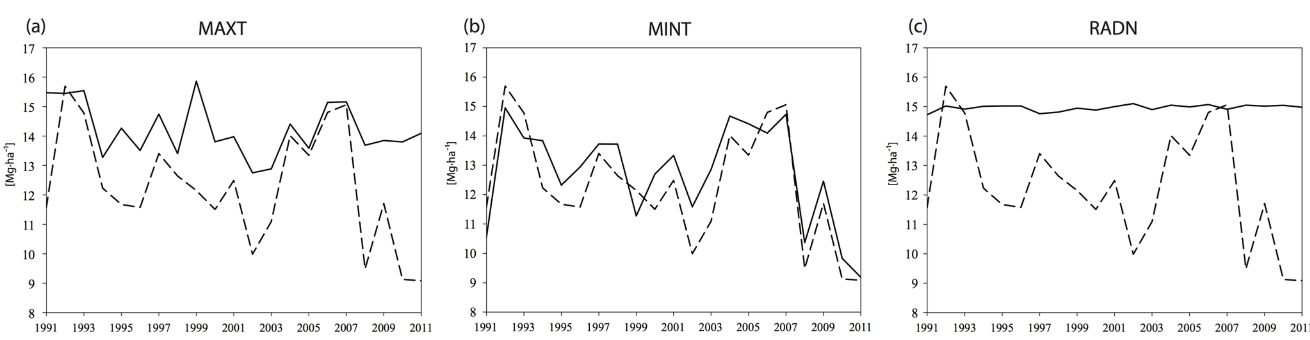

Figure 5. Maize yield potential for (a) MAXT, (b) MINT, and (c) RADN. Dashed line is CTRL, and solid line is time series.

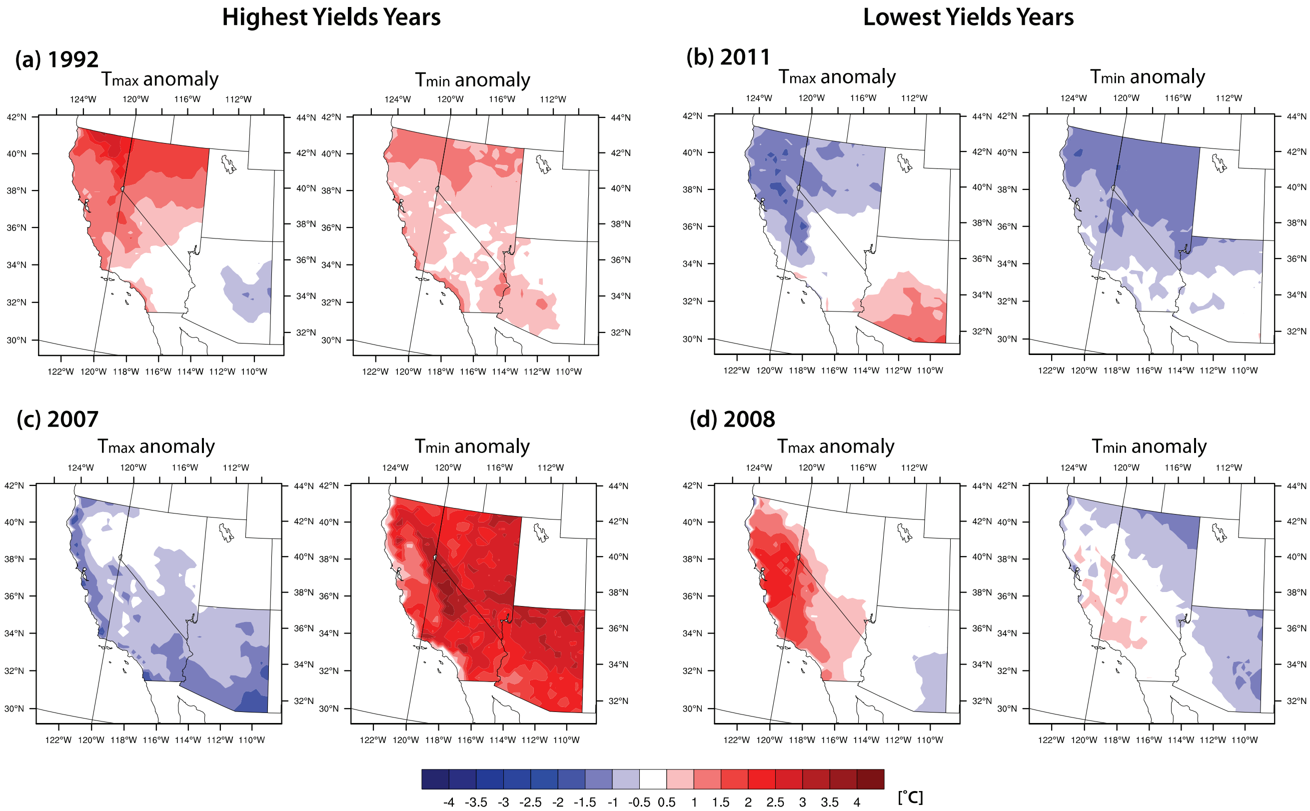

Figure 6. Maximum and minimum temperature anomalies for (a) 1992, (b) 2011, (c) 2007, and (d) 2008. The years 1992 and 2007 had the highest yields, and 2008 and 2011 had the lowest yields.

reason behind the adverse impact of T_{max} and T_{min} on maize yield is that maize is susceptible to both heat and cold stress; thus, its mortality increases during heat waves or cold surges (Lobell et al., 2011; Thakur et al., 2010).

Next, a correlation analysis was performed between the number of hot/cold days and the area mean of the annual yields in each district for the 21 years. Figure 8 shows the correlation coefficients with different thresholds for hot and cold days. The results indicate that the higher the number of hot/cold days, the lower the yield in warm climate regions (i.e., Sacramento Valley, San Joaquin Valley, and Southern), which is indicated by strong negative correlations for both hot and cold days. Negative relationships were stronger for

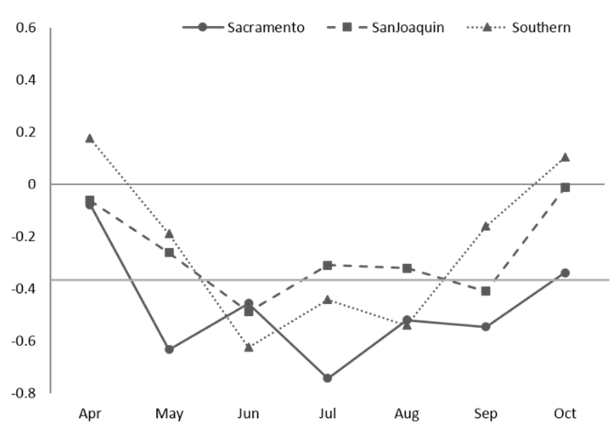

Figure 7. Monthly correlations for 21 years (1991-2011) between the number of hot days in each month and annual mean yield in three agricultural districts. Solid gray line indicates 95% confidence level.

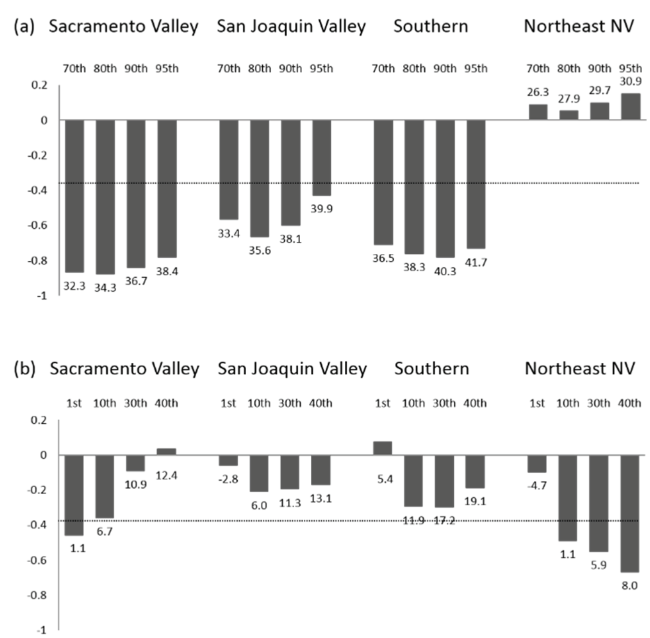

Figure 8. Correlations for 21 years (1991-2011) between (a) the number of hot days during the growing season (Apr.-Oct.) in each year and the annual mean yield in each district with four different threshold percentiles (70th, 80th, 90th, and 95th) and (b) the number of cold days with four different threshold percentiles (1st, 10th, 30th, and 40th). Numbers below the bars indicate actual temperatures (°C) corresponding to the thresholds. Solid lines indicate 95% confidence level.

hot days (fig. 8a) than for cold days (fig. 8b) and were significant at the 95% confidence level for all three districts and for all thresholds. Thresholds with the highest correlation varied with districts between the 80th and 90th percentiles and with a temperature range between 34°C and 40°C. For cold days, the highest correlations slightly exceeded the 5% significance level only in Sacramento Valley, consistent with the strong sensitivity for T_{min} in that district (not shown). However, it should be noted that the correlations at some individual grid points were much higher than those at the district level. This implies that both hot days and cold days were critical for the interannual fluctuation in maize yields.

In the cold climate region of northeast NV, the negative effect of hot days on yield did not exist, and a weak positive relationship was found (fig. 8a). As seen from the temperature range for the various thresholds (26.3°C to 30.9°C) in northeast NV, this region was not hot enough to be significantly affected by heat waves. However, strong negative relationships with cold days were observed, as in warm climate regions (fig. 8b). Again, the cold climate in this region may be responsible for the strong sensitivity to extreme cold events.

Hot days occurred most frequently from June to September, as shown in the 21-year climatology of temporal distribution of hot days (with the thresholds of the highest correlations in fig. 8) for each district (fig. 9). As expected, cold days occurred mostly in the early growing season (April and May) and late growing season (September and October). Particularly in northeast NV, hot days were more concentrated in July and August (fig. 9d), and cold days were more evenly distributed during the growing season, except in July and August (fig. 9h). In order to test which months were most critical to the interannual variation of yield with respect to hot and cold days, the same correlation analysis was repeated as in figure 9 but for each month rather than for the entire growing season. As summarized in table 4, the maximum correlation of yield and number of hot days occurred

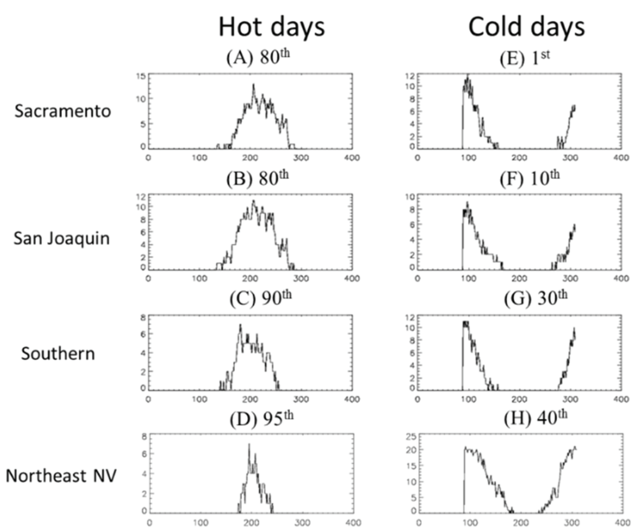

Figure 9. The 21-year (1991-2011) climatology of temporal distribution of hot days (A, B, C, and D) and cold days (E, F, G, and H) per grid. The thresholds are those of the highest correlations in figure 8. The *y*-axis is the number of the hot or cold days during the growing season.

Table 4. Month of the highest correlation between the number of hot or cold days and maize yield. The 70th (30th) threshold percentile was used for the hot (cold) days. Months for hot days in northeast Nevada are not shown due to the insignificant correlation.

Agricultural District	Hot Days	Cold Days
Sacramento Valley	July (-0.74)	April (-0.49)
San Joaquin Valley	June (-0.49)	April (-0.28)
Southern	June (-0.63)	May (-0.48)
Northeast Nevada	-	June (-0.53)

in July for the Sacramento Valley and in June for the San Joaquin Valley and Southern region. Especially in the Sacramento Valley, relatively high correlations persisted for six months from May to October (not shown). The month with the highest correlation for cold days indicated that cold days in the early growing season (April and May) played a more critical role than those at the end of the growing season when maize crops were in their mature stage (September and October). More specifically, maize yield was most sensitive to cold days in May for the Southern region but in April for both the Sacramento Valley and San Joaquin Valley. In northeast NV, a frequent occurrence of extreme cold events in June was most adverse to maize yield.

Summary and Discussion

In this study, sensitivity of the simulated maize Y_p using APSIM in conjunction with meteorological forcing from NARR was assessed for the SWUS on regional scales. Despite limitations in the observational data, such as the unknown accuracy of observed yields and limited management data, compared to the observed crop yields, the APSIM simulations projected Y_p reasonably well across the study region.

Our sensitivity analysis demonstrated that climate drivers can substantially and nonlinearly affect potential crop productivity. In the SWUS, the effects of insolation were noticeable only when insolation was substantially below a threshold value. These effects were limited to the coastal and Central Valley regions of CA. Potential maize yields were most sensitive to T_{min} and T_{max}, with the response to the climate drivers reversed depending on local mean climates. T_{min} was a critical driver across the cooler climate regions in the northern and/or high-altitude regions of CA and NV. In the most active maize-growing regions with warmer climates, lower T_{max} and higher T_{min} were generally beneficial for increasing yield. In these regions, it was found that extremely hot conditions in the peak growing season (June and July) and extremely cold conditions in spring (April and May) adversely affected maize yields. These results implied that future maize yields in the SWUS could be estimated using projected regional climate data.

Recently, process-based crop models have been widely used for climate change impact studies (Rötter et al., 2011). Uncertainties exist at each stage of crop model simulation, and it is crucial to quantify these for end-users and stakeholders. For the above-mentioned reasons, recent assessment studies of climate change impact have tried to take account of such uncertainty by using multiple models and/or statistical methods (Iizumi et al., 2009; Tao et al., 2009; Tebaldi and Lobell, 2008; Bassu et al., 2014; Araya et al., 2015). The climate modeling community has widely used multi-model ensemble approaches to assess model uncertainties. Few studies have been performed on uncertainty analysis using multiple crop models because of the difficulties in systematic comparison among crop models (Asseng et al., 2013a). However, there have been a few attempts to integrate multi-modeling approaches, such as the Global Gridded Crop Model Intercomparison (GGCMI) project (Rosenzweig et al., 2014; Bassu et al., 2014). Bassu et al. (2014) pointed out that multi-model ensemble simulation provides better results by reducing individual model variability even with simple model calibration. The recently (October 2010) launched Agricultural Model Intercomparison and Improvement Project (AgMIP; www.agmip.org), aims to build a transdisciplinary modeling framework to produce more robust results of climate impact on crop yields. This project has contributed to quantifying modeling uncertainties as well as improving model performance. Compared to the multi-modeling approaches, our single-model analysis may have a higher level of uncertainty. Quantifying the uncertainties was beyond the scope of this study, but a possible uncertainty was estimated with sensitivity tests of management decisions (fig. 10). Meanwhile, our results can contribute to AgMIP projects as an ensemble member, and our modeling framework can be applied in other crop models in future studies.

In this study, future climate projections based on emission scenarios were not directly employed; however, this work can still provide significant information for assessing the impact of future climate change on agricultural productivity. According to the most recent model projection by Coupled Model Intercomparison Project Phase 5 (CMIP5), a projected mean increase in temperature of 1.7°C to 5.6°C is expected by the end of this century depending on scenarios

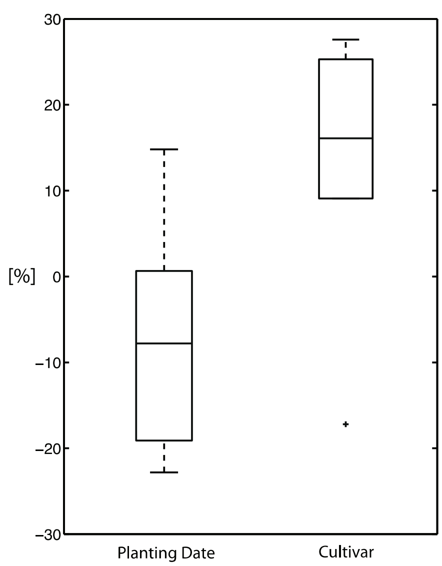

Figure 10. Sensitivity tests were performed to estimate the uncertainty of simulated yield potential (Y_p) due to management decisions as a percentage of actual yield (Y_a) for 21 years. For planting date, we tested 25 different dates in one-week intervals from 1 February to 1 August. For cultivar sensitivity, we tested six cultivars (Pioneer 3527, Pioneer 3237, Pioneer 3513, USA 18 leaf, Hycorn 424, and Zhongdan2). The results imply that the selection of planting date is crucial for a reasonable Y_p and Y_a ratio. The cultivar sensitivity test shows that all cultivars except one were in a reasonable range.

in the SWUS (Taylor et al., 2012; USGCRP, 2014). The mean temperature changes tested in this study were 3.56°C and 3.13°C for T_{max} and T_{min}, respectively. Thus, the results from this sensitivity study can be used to obtain the qualitative impact of climate change on maize Y_p, mainly via temperature changes. Recent climate modeling projections show not only a shifted mean temperature but also increased temperature variability, resulting in a higher frequency of extreme weather events (USGCRP, 2014). The SWUS is expected to experience more frequent heat waves but less frequent or severe cold waves. The negative correlation between heat waves and Y_p in warm climate regions implies that extreme temperature events must be considered in studies on the impact of future climate change on potential crop yield.

Our study did not consider crop water stress because agricultural systems in the SWUS mostly use irrigation. However, water resources in this region can be limited during extreme climate events. The prolonged and severe drought in CA since 2012 has significantly affected agricultural systems. According to Howitt et al. (2015), the shortage of surface water for irrigation was replaced by 6 million acre-feet of groundwater in 2015. These groundwater pumping rates are excessive and unsustainable. The current groundwater levels are 100 feet lower than previous records. This has caused land surface subsidence of more than 20 feet, and the surface level has continuously sunk by one foot per year in parts of the San Joaquin Valley (Farr et al., 2015). This may be an example of future agricultural systems under water stress. Future projections of precipitation show that changes are spatially inhomogeneous in the SWUS (USGCRP, 2014). Higher temperature has a significant impact on water resources in the SWUS, which are strongly dependent on the snowpack at high elevations (Shukla et al., 2015). Increasing temperature trends, especially higher temperatures in the spring, affect early snowmelt and consequently the early peak of streamflow. This, in turn, affects the timing and volume of runoff and eventually limits agricultural water resources. According to a recent report by IPCC (2014), regional-scale to global-scale projections of drought remain relatively uncertain, but drier conditions in the SWUS are consistently projected. Therefore, future crop yield studies in the SWUS need to consider water stress due to frequent drought events as well as extreme heat events.

Process-based crop models simulate the phenology of each crop cultivar and growth-related factors using sophisticated management practices at the farm level. Due to the one-dimensional model structure, crop modeling does not have the capability of contemplating regional-scale water constraints, nor of diagnosing adaptation strategies. Thus, an integrated approach to both agricultural and hydrologic systems is crucial for evaluating the impact of weather on agricultural productivity and the water cycle, especially in arid to semi-arid regions that are dependent on irrigation. A recent study has attempted to link water resources and agricultural systems in the Central Valley of CA using the Water Evaluation And Planning (WEAP) model and a process-based crop model (Winter et al., 2013). This pilot exploration started in a region of CA, but the methodology can be employed on a larger scale, such as the SWUS, in future studies.

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