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Assessing future drought impacts on yields based on historical irrigation reaction to drought for four major crops in Kansas

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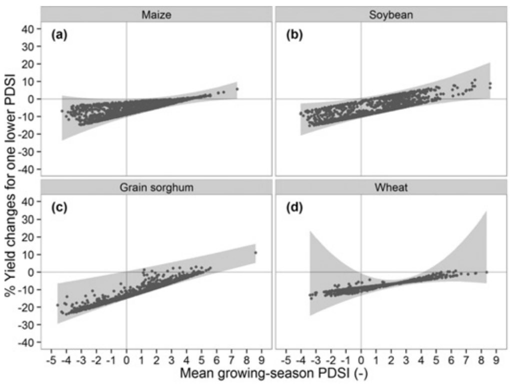
HIGHLIGHTS

- Irrigation water use were quantified for each crop.
- Drought increases summer crop's irrigation but such effect is unclear for wheat.
- Climate change in future will increase irrigation for all crops.
- Yield of summer crops are projected to reduce in future climate scenarios.

GRAPHICAL ABSTRACT



Yield changes for one lower PDSI in Kansas over 1992 – 2012

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ABSTRACT

Evaluation of how historical irrigation reactions can adapt to future drought is indispensable to irrigation policy, however, such reactions are poorly quantified. In this paper, county-level irrigation data for maize, soybean, grain sorghum, and wheat crops in Kansas were compiled. Statistical models were developed to quantify changes of irrigation and yields in response to drought for each crop. These were then used to evaluate the ability of current irrigation to cope with future drought impacts on each crop based on an ensemble Palmer Drought Severity Index (PDSI) prediction under the Representative Concentration Pathways 4.5 scenario. Results indicate that irrigation in response to drought varies by crop; approximately 10 to 13% additional irrigation was applied when PDSI was reduced by one unit for maize, soybean, and grain sorghum. However, the irrigation reaction for wheat exhibits a large uncertainty, indicating a weaker irrigation reaction. Analysis of future climate conditions indicates that maize, soybean, and grain sorghum yields would decrease 2.2–12.4% at the state level despite additional irrigation application induced by drought (which was expected to increase 5.1–19.0%), suggesting that future drought will exceed the range that historical irrigation reactions can adapt to. In contrast, a lower reduction (−0.99 to −0.63%) was estimated for wheat yields because wetter climate was projected in the central section of the study area. Expanding wheat areas may be helpful in avoiding future drought risks for Kansas agriculture.

1. Introduction

Climate change has been reported to slow current crop yield growth in the United States (Kucharik and Serbin, 2008; Lin and Huybers, 2012; Lobell et al., 2014) and results in substantially adverse impacts on future

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agricultural outputs (Schlenker and Roberts, 2009; Ruane et al., 2014). Progressively increasing drought stress in the US, induced by either declining rainfall (Dai, 2013) and higher water demands associated with warmer climate (Lobell et al., 2013), are critical mechanisms constraining yields, testing the ability of the current irrigation infrastructure to adapt to future climate change.

Previous studies investigated the potential ability of irrigation to adapt to future drought using process-based models that simulate crop development under hypothetical irrigation scenarios (Brumbelow and Georgakakos, 2001; Rosenzweig et al., 2014; Ventrella et al., 2012; Moore et al., 2013). For example, Rosenzweig et al. (2014) investigated future climate impacts on global crop yields by assuming two simplified irrigation scenarios (full irrigation and rainfed), and simulated an overall reduction of yields induced by climate change. Ventrella et al. (2012) executed an assessment for wheat and tomato in southern Italy but employed more irrigation scenarios; i.e. assuming irrigation application when soil moisture reaches a certain threshold. Similar analysis can been found in Brumbelow and Georgakakos (2001), who assumed applying irrigation in the model when a ten-day composite moisture stress index was reduced to a certain level. The International Panel on Climate Change Fifth Assessment Report (IPCC AR5, 2014) summarized that those studies must implicitly or explicitly make assumptions about how farmers adjust their practices in response to climate change. However, in reality, farmers have long been interacting with climate to maximize their profits (Zhang et al., 2008; Wreford et al., 2010; OECD, 2012). For example, US data shows that farmers increased irrigation in response to drought while their reactions varied substantially by location (Zhang et al., 2015). This variability reflects not only a consequence of drought severity but also a combined effect of the availability of irrigation water resources and technologies (Dow et al., 2013). Such reactions are difficult to reflect in artificial irrigation scenarios in process-based models, and are often poorly quantified due to the lack of relevant data. Therefore, the regional irrigation water application induced by climate needs to be reasonably estimated so that the impact assessment can be executed based on a realistic response.

A central issue is whether future drought severity would surpass the ability of the current irrigation water supply to maintain crops at the county level and this would have fundamental implications in guiding future irrigation water policy. If future drought is still within the current irrigation adaptive capacity, further investments to upgrade current systems would not be economically justified; conversely, if future drought exceeds current irrigation capacity, then improving irrigation-based adaptive capacity is critical to mitigate future drought impacts. However, quantifying and benchmarking the current irrigation-based adaptation is never easy because most available irrigation data products are not very well characterized in terms of crop-specific information, and the databases are compiled from short periods of records. For example, the most-frequently used irrigation dataset, MIRCA2000 (Portmann et al., 2010) only provides the total irrigated area in the year 2000. To quantify the adaptive effects of irrigation, crop-specific irrigation water application over a long time period is required. A long-term data product is needed to be able to evaluate the actual irrigation reaction to drought and allow the irrigation-based impact on yields to be benchmarked under current climate conditions.

In this study, county-level irrigation datasets for each of the four crops (maize, soybean, grain sorghum, and wheat) for 1992 through 2012 in the state of Kansas in the US were compiled. Based on this dataset, the irrigation reaction to drought for each crop was quantified, providing a basis for actual drought-induced irrigation change. Potential yield changes to future drought were then calculated considering such reactions. The objective of this study was to assess whether the historical irrigation reactions could mitigate future drought impacts on the four major crops in Kansas. A statistical model in conjunction with this dataset was used to investigate the relationship between climate, crop, and irrigation. Currently, a statistical model has been often used to establish the relationship between climate and yield in empirical studies. For example, Lobell et al. (2011) established a multiple regression model to investigate the response of crop yields to air temperature and precipitation for major grain production. Using an empirical statistical model, Schlenker and Roberts (2009) developed a linkage between thermal time accumulation and yields and found harmful impacts of extreme temperatures in US agricultural production. In our study we attempted to quantify this relationship from temperatures; a quantity of combining temperature, precipitation, soil conditions (i.e., drought index), and irrigation. Therefore a two-stage least square regression method was applied to this dataset. This regression method is a widely-used multilevel modeling technique to help quantify the inter-relationship in a hierarchical system as is the case in this study (Angrist and Imbens, 1995).

2. Datasets and methods

2.1. Datasets of irrigation, crop yields, and climate

The irrigation data used in this study were drawn from the Water Information Management and Analysis System (WIMAS) (Kansas Department of Agriculture and Kansas Geological Survey, 2013). The dataset was based on water use annual reports from farmers to the Kansas Department of Agriculture, Division of Water Resources. The crop-specific irrigation data by county for 1992 through 2012 were obtained from the dataset. Even though this dataset is only available for Kansas counties, it provides much more detailed information on irrigation than the other more geographically extensive datasets from which crop-specific information cannot be determined (e.g., USGS, 2013; Portmann et al., 2010).

Following the procedures of previous work using the WIMAS dataset (Kansas Water Office and Division of Water Resources, 2011; Kenny and Juracek, 2013; Wilson et al., 2005), crop-specific irrigation water volume was determined for each county-year pair. Then the irrigation water volume was divided by the harvested area for each crop so that the crop-specific mean seasonal irrigation depth (mm) for each county-year pair could be produced. The harvest area of each crop was derived from the US Department of Agriculture's National Agricultural Statistics Service (NASS, 2013) database. The major reason we used harvested area data rather than irrigated area is that irrigated area changes in each year are caused by different climate moisture conditions occurring in each year. Thus, only using irrigation volume per irrigated area will overlook drought impacts on irrigated areas; hence thereby underestimating drought influences. In addition, the second reason for using harvest area data is the large amount of missing data on irrigated crops in the NASS dataset.

The annual county-level yield data for the four crops in all Kansas counties were collected from the NASS database (NASS, 2013) from 1992 through 2012. In addition, monthly temperature and precipitation data were obtained from the Parameter-elevation Regressions on Independent Slopes Model dataset (PRISM, 2013) and their county-level average values were calculated in ArcGIS software. To better represent drought, the Palmer Drought Severity Index (PDSI) was calculated for each county and month using an algorithm provided by the National Climatic Data Center (2013). Briefly speaking, PDSI was developed by Palmer (1965) to measure the cumulative departure in surface water balance. This index incorporates antecedent and current moisture supply (precipitation) and demand (potential evapotranspiration) into a hydrological accounting system, which is a two-layer bucket-type model for soil moisture calculations. The PDSI is a standardized measure ranging from about -10 (dry) to $+10$ (wet). The PDSI index has been widely used in the US to monitor drought conditions, and a detailed description on the algorithm can be found in Dai (2013). Based on the algorithm, the monthly PDSI over 1931–2012 was calculated, and only the results from 1992 to 2012 were used to match the availability of irrigation data. In calculating the PDSI, the reference climate period was set to the default value in the calculation code (i.e., 1931–1990, 60 years). Using other reference climate periods would not change the year-to-year variation of PDSI and thus would not influence modeling projections in our regression model (see Section 2.2). The available water capacity for the upper and lower soil layers in each county used to calculate PDSI was extracted from the Gridded Soil Survey Geographic Database (Soil Survey Staff, 2013).

Mean growing-season temperature (T) and PDSI were then calculated for each crop growing season. Based on the US Department of Agriculture crop calendar (http://www.usda.gov/oce/weather/CropCalendars/), the growing seasons of the three summer-season crops (maize, soybean, and grain sorghum) were set from May to September. For the winter-season crop (wheat), the growing season was set from September in the previous year to June in the current year.

2.2. Two-stage model and scenario analysis

In this study, changes in irrigation depth for each unit change in PDSI (hereinafter referred to as the irrigation reaction) were quantified and drought impacts on yield with the irrigation reaction were estimated. A two-stage least square regression method was applied for each crops' dataset. The model is written as,

$$\begin{aligned} log(Y_{c,t}) = {} & \alpha_1 IRRI_{c,t} + \alpha_2 IRRI_{c,t}{}^2 + \alpha_3 T_{c,t} + \alpha_4 T_{c,t}{}^2 + \alpha_5 PDSI_{c,t} \\ & + \alpha_6 PDSI_{c,t}{}^2 + \alpha_{7,c} County_c + \alpha_{8,c} County_c * Year_t \\ & + \alpha_{9,c} County_c * Year_t{}^2 + \varepsilon_{c,t} \end{aligned} \tag{1}$$

$$\begin{aligned} \log(IRRI_{c,t}) = {} & \beta_1 PDSI_{c,t} + \beta_2 PDSI_{c,t}{}^2 + \beta_{3,c} County_c + \beta_{4,c} County_c * Year_t \\ & + \beta_{5,c} County_c * Year_t{}^2 + \mu_{c,t} \end{aligned} \tag{2}$$

where $Y_{c,t}$ is crop yield of county c in year t (bu/ac); $IRRI$ is the irrigation depth applied to the crop (mm); T is the mean growing-season temperature (°C); $PDSI$ is the mean growing-season PDSI (−); $County$ is the dummy variable for county, accounting for the difference between counties; $Year$ denotes time for removing technology factors related to time; α and β are the regression coefficients for each term; and ε and μ are the error terms.

The two-stage model first quantifies the actual irrigation reaction to each unit change in PDSI as the first-stage equation (Eq. (2)). Then in the second stage (Eq. (1)), the model-estimated new IRRI replaces the actual values of IRRI in Eq. (1) to compute a regression model for estimating the effects of all predictors on crop yields. For each equation, the quadratic term of variables used to capture the potential nonlinear effect was included. The quadratic terms in Eq. (2) are important for detecting the potential gradual limitation of water resources as climate becomes drier. Unobserved possible nonlinear time trends at the county level were controlled by using county-by-year linear and quadratic terms and unobserved time-constant variations between counties using a county-fixed effect.

The uncertainty of the model and associated estimates was assessed by a bootstrap analysis, which is a common statistical method to estimate the uncertainty of a model (Rubin, 1981). By constructing a number of re-samples and replacing the observed dataset, this analysis evaluated the model accuracy defined by confidence intervals. More specifically, the years were chosen randomly with replacements for 1000 times to estimate the regression coefficients of the model. After that, 1000 sets of regression coefficients were derived which could then be used to calculate yield changes by inputting future drought conditions. Here, the median value and 95% confidence interval of those regression coefficients are reported. The confidence interval not spanning zero indicates that the coefficient is statistically significant.

This model considered irrigation amounts but does not include potential effects of irrigation timing. This is because irrigation schedules were not recorded in the WIMAS dataset, thus it is impossible to include schedule effects into the statistical model. In addition, a six-year

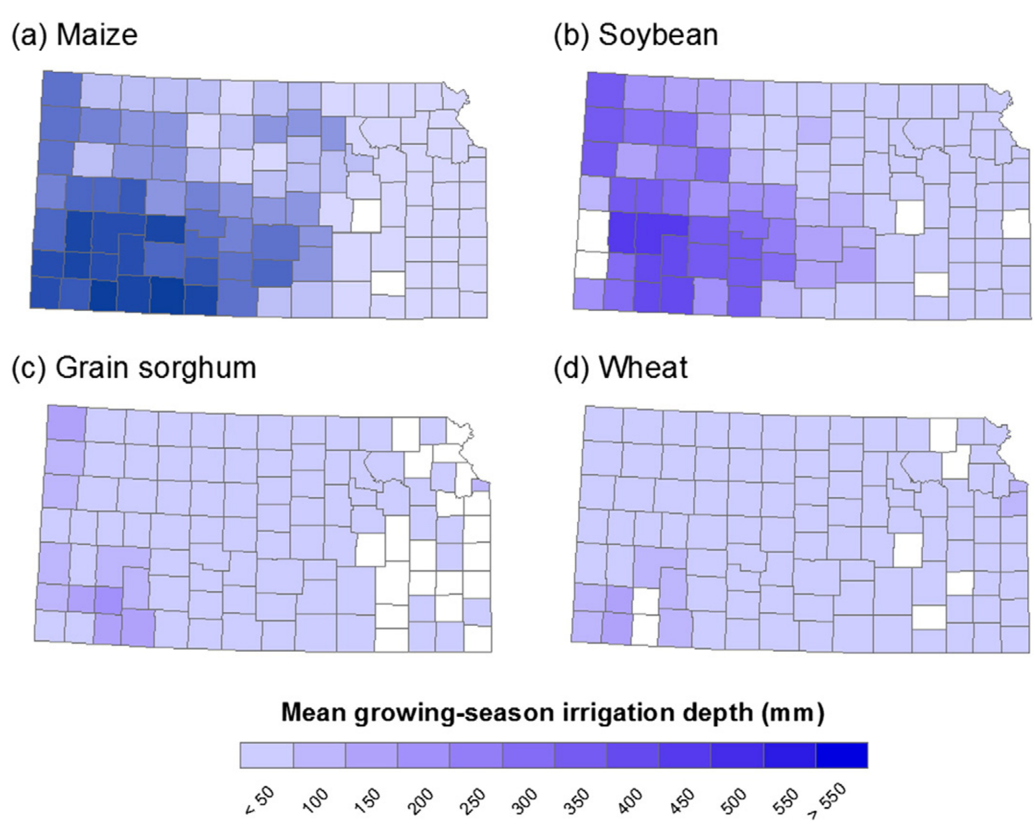

Fig. 1. Mean growing-season irrigation for maize (a), soybean (b), grain sorghum (c), and wheat (d) in Kansas. The blank counties indicate no data.

Table 1
Regression coefficients of the two-stage regression model and the 95% confidence interval estimated by the bootstrap resampling approach.

Crops	Variables	Regression coefficient	95% confidence interval
Maize	Eq. (1)		
	IRRI	0.002	(0.001, 0.004)
	IRRI^2	−1.19E−06	(−2.05E-06, −3.64E−07)
	T	−0.4	(−0.72, −0.08)
	T^2	0.008	(0.001, 0.015)
	PDSI	0.082	(0.068, 0.098)
	PDSI^2	−0.011	(−0.015, −0.007)
	Eq. (2)		
	PDSI	−0.11	(−0.13, −0.09)
	PDSI^2	0.014	(0.004, 0.025)
	Adjusted R^2	0.998	
Soybean	Eq. (1)		
	IRRI	0.004	(0.003, 0.006)
	IRRI^2	−2.84E−06	(−5.06E−06, −1.08E−06)
	T	0.39	(0, 0.78)
	T^2	−0.011	(−0.021, −0.001)
	PDSI	0.092	(0.08, 0.105)
	PDSI^2	−0.01	(−0.013, −0.007)
	Eq. (2)		
	PDSI	−0.11	(−0.13, −0.09)
	PDSI^2	0.002	(0.001, 0.003)
	Adjusted R^2	0.996	
Sorghum	Eq. (1)		
	IRRI	0.004	(0, 0.008)
	IRRI^2	−4.25E−07	(−1.31E−05, −1.12E−08)
	T	1.09	(0.56, 1.67)
	T^2	−0.024	(−0.037, −0.012)
	PDSI	0.14	(0.128, 0.152)
	PDSI^2	−0.015	(−0.019, −0.012)
	Eq. (2)		
	PDSI	−0.12	(−0.15, −0.1)
	PDSI^2	0.001	(0, 0.002)
	Adjusted R^2	0.997	
Wheat	Eq. (1)		
	IRRI	−0.004	(−0.009, 0)
	IRRI^2	1.70E−05	(5.81E−08, 4.03E−05)
	T	−0.13	(−0.26, 0)
	T^2	0.006	(0, 0.012)
	PDSI	0.088	(0.071, 0.105)
	PDSI^2	−0.006	(−0.01, −0.002)
	Eq. (2)		
	PDSI	−0.24	(−0.28, −0.19)
	PDSI^2	0.068	(0.053, 0.084)
	Adjusted R^2	0.995	

experiment in the US found that climatic variability has been the leading influence on seasonal irrigation requirements over irrigation timing (Steele et al., 2000), indicating irrigation scheduling must follow real-time monitoring of crop water use and a preprogrammed irrigation scheduling regime may be not pragmatic.

For supporting the two-stage model approach in this study, the Durbin–Wu–Hausman (Wu, 1973) test of endogeneity was conducted which compare results of consistent but possible less efficient two-stage least squares estimations with those of inconsistent but more efficient ordinary least squares estimations (Davidson and MacKinnon, 1993). When the resulting *p*-value is significantly different from zero, this indicates a preference for the two-stage least squares model, and if there is no significant difference, the ordinary least squares model should be used. Results of the test are presented in supplementary material 1, suggesting the two-stage model is preferred for the four crops.

PDSI predictions based on the IPCC AR5 ensemble mean climate under the Representative Concentration Pathways (RCP) 4.5 scenario as reported by Dai (2013) were obtained. The RCP 4.5 scenario is representative of an intermediate greenhouse gas emission scenario. This data product is based on 14 climate models with a spatial resolution of 2.5 × 2.5 degree. Using the monthly PDSI predictions in Dai (2013), the mean growing season for the four studied crops was calculated for three future climate periods: years 2020–2039, 2040–2059, and 2080–2099. The difference in anticipated growing-season PDSI for the three future time periods relative to the baseline climate (1992–2012) was calculated as the PDSI changes for each crop growing season, and was then input into the two-stage model. Finally, the changes in irrigation and yields due to future droughts can be estimated. This PDSI prediction data product may be coarse at the state level, but this data product is based on the multiple climate model prediction in the newest IPCC AR5. Compared with predictions made by single climate models, multiple climate model prediction is clearly preferred for accurate estimates of future climate trends (Fordham et al., 2012) When finer climate prediction data products become available in the future, the methodology used in this study can be applied and would provide more spatially extensive results.

3. Results

3.1. Crop-specific irrigation in Kansas

The WIMAS data indicate that the 1992–2012 county-level irrigation water depth varies by crop. Greater irrigation depths for maize and

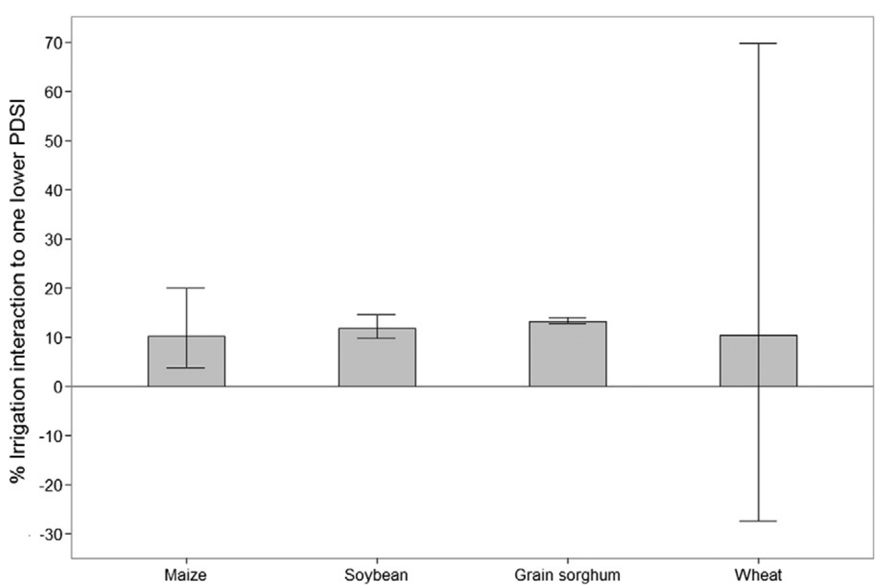

Fig. 2. Percentage irrigation reactions to one lower PDSI over the growing season. The box shows the estimate of the 50th percentile, and the error bars show estimates of the 2.5th to 97.5th percentiles calculated from the bootstrap analysis.

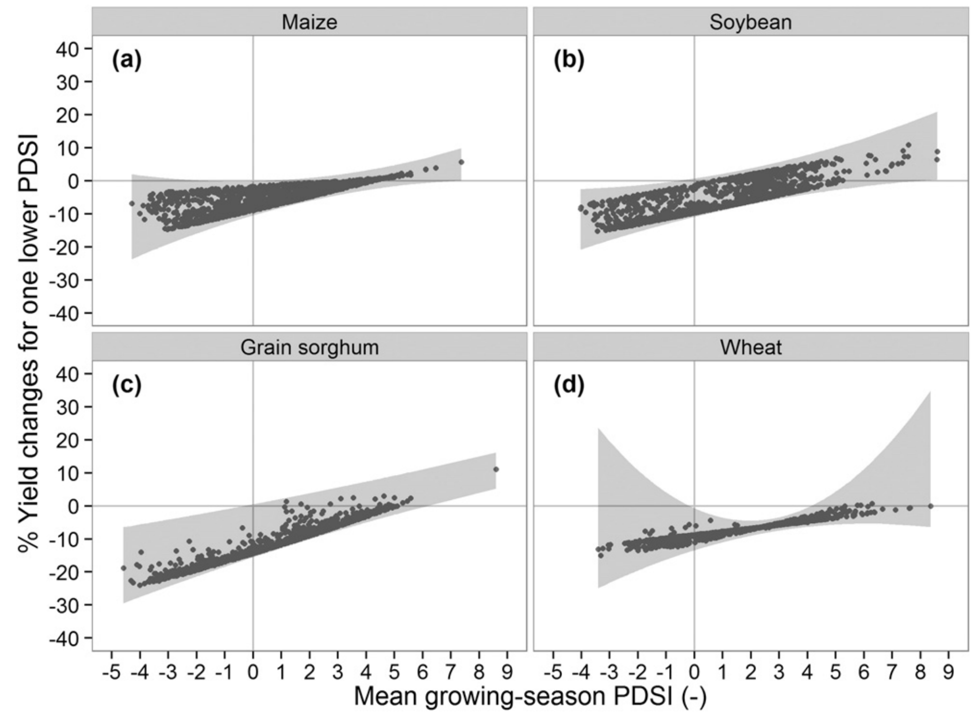

Fig. 3. Model-estimated percentage yield changes for one unit lower PDSI. Black points are the model-estimated percentage yield changes. The shaded areas show the 95% confidence interval in the bootstrap analysis. Results are depicted for maize (a), soybean (b), grain sorghum (c), and wheat (d).

soybean are shown particularly in the western regions (350–550 mm), compared with grain sorghum and wheat (0–200 mm irrigation) (Fig. 1). In addition, substantial variability throughout Kansas is also evident with 2 to 4 times greater irrigation applied in the western region than in the central and eastern regions for maize and soybean (Fig. 1a, b). Spatial distributions of irrigation for grain sorghum and wheat are similar but more uniform (Fig. 1c, d) and such distributions are mainly caused by the uneven precipitation in Kansas.

3.2. Climate and irrigation-based adaptive effects on crop yields

A two-stage regression model was established, and the regression coefficients and their 95% confidence interval suggest a statistically significant effect for each variable (Table 1). Using the model, PDSI was artificially reduced by one unit to evaluate the effect of drought. The model outputs show the degree that irrigation and yields would change per each one unit reduction in PDSI. The model indicates

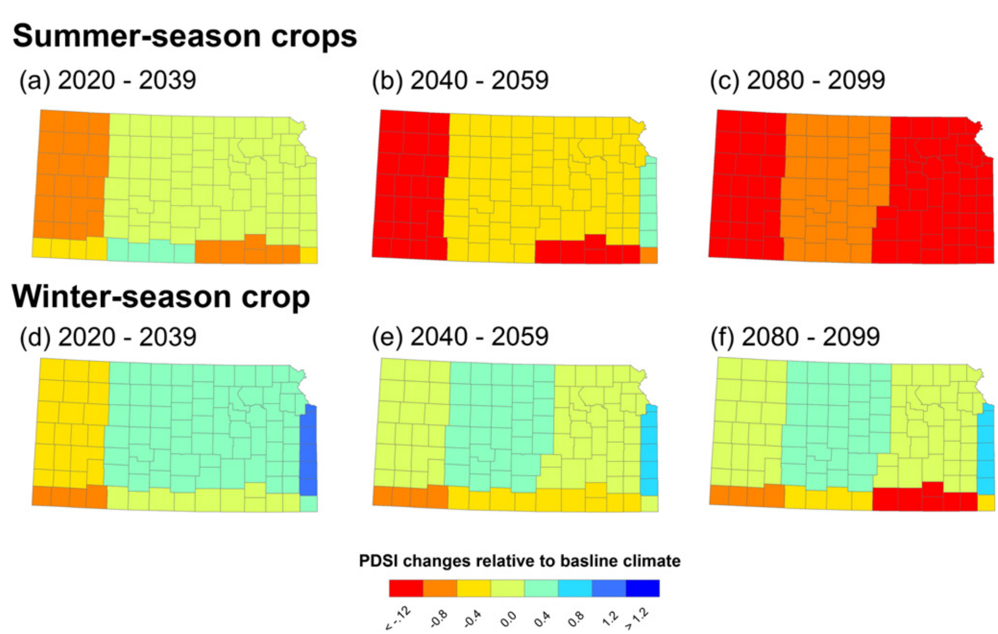

Fig. 4. Changes in PDSI relative to the baseline climate in 2020–2039, 2040–2059, and 2080–2099 for summer growing-season crops (May–Sep., upper panel) and the winter growing-season crop (Oct in the previous year to May in the current year, lower panel).

Table 2
State-level estimated percentage irrigation and yield changes under projected future drought in 2020–2039, 2040–2059, and 2080–2099.

Crops	Time period	Irrigation changes (%)	Yield changes (%)
Maize	2020–2039	9.4 (7.7, 11.5)	−2.2 (−2.6, −1.8)
	2040–2059	14.6 (11.7, 17.9)	−3.6 (−4.2, −3.1)
	2080–2099	19.0 (15, 23.6)	−6.5 (−7.3, −5.6)
Soybean	2020–2039	5.1 (4.3, 6.0)	−2.2 (−2.4, −1.9)
	2040–2059	9.4 (7.9, 11.1)	−4.2 (−4.8, −3.7)
	2080–2099	14.5 (12, 17.1)	−9.4 (−10.5, −8.3)
Grain sorghum	2020–2039	10.3 (8.3, 12.8)	−4.9 (−5.3, −4.5)
	2040–2059	15.1 (12.1, 19.1)	−8.5 (−9.1, −7.9)
	2080–2099	18.9 (15, 24.2)	−12.4 (−13.3, −11.6)
Wheat	2020–2039	9.1 (5.7, 13.5)	−0.63 (−0.86, 0.12)
	2040–2059	6.9 (4.2, 10.2)	−0.75 (−0.98, −0.06)
	2080–2099	9.2 (5.8, 13.3)	−0.99 (−1.57, 5.36)

drought-induced increased irrigation application to offset the resultant water stresses but this varies by crop (Fig. 2). For the three summer-season crops (maize, soybean, and grain sorghum), a one-unit reduction in PDSI would result in approximately a 10–13% increase in irrigation to meet the associated higher water demands, while the irrigation reaction to drought for wheat was about 8% but exhibited considerable uncertainty (Fig. 2).

Fig. 3 illustrates the yield change resulting from a one unit reduction in PDSI assuming the historical pattern of irrigation reactions. At present, maize growing above 4 in the mean growing-season PDSI tends to increase from the drought, whereas maize yields grown below this threshold tend to decline (Fig. 3a). Similar results were found for soybean and sorghum when the PDSI threshold is approximately 4 (Fig. 3b) and 5 (Fig. 3c). For wheat, a reduction in the yields at most sites were projected when PDSI was artificially decreased by 1 unit, with the greatest reduction being around 15% (Fig. 3d).

3.3. Future PDSI changes under the RCP4.5 climate scenario

Using the PDSI scenarios predicted by Dai (2013), a drier climate averaged over the growing season for the three summer-season crops was projected in most counties, where PDSI would decline by 0.0–0.8 for climate in 2020–2039 (Fig. 4a), 0.4–1.2 in 2040–2059 (Fig. 4b), and 0.8–1.2 in 2080–2099 (Fig. 4c), relative to the baseline climate. For wheat, the future drying trend would be concentrated in eastern and western Kansas and a small number of counties in the southern areas where the magnitude of PDSI reduction varies between 0.0 and 0.4 (Fig. 4d–f). In the central region of the state, the climate for the wheat growing season was projected to become wetter with PDSI increasing by 0.0–0.8 in most counties (Fig. 4d–f) during the three twenty-year time periods.

3.4. Changes in yield and irrigation under future drought

Under future drought scenarios, maize irrigation shows a positive change due to drought, with the state level irrigation increased by 9.4% for the climate in 2020–2039, 14.6% in 2040–2059, and 19.0% in 2080–2099 (Table 2). The majority of counties will experience a 0–30% increase in irrigation with the western and eastern regions showing a substantial increase especially for the climates in 2040–2059 and 2080–2099 (Fig. 5a, c, e). Despite the increased irrigation

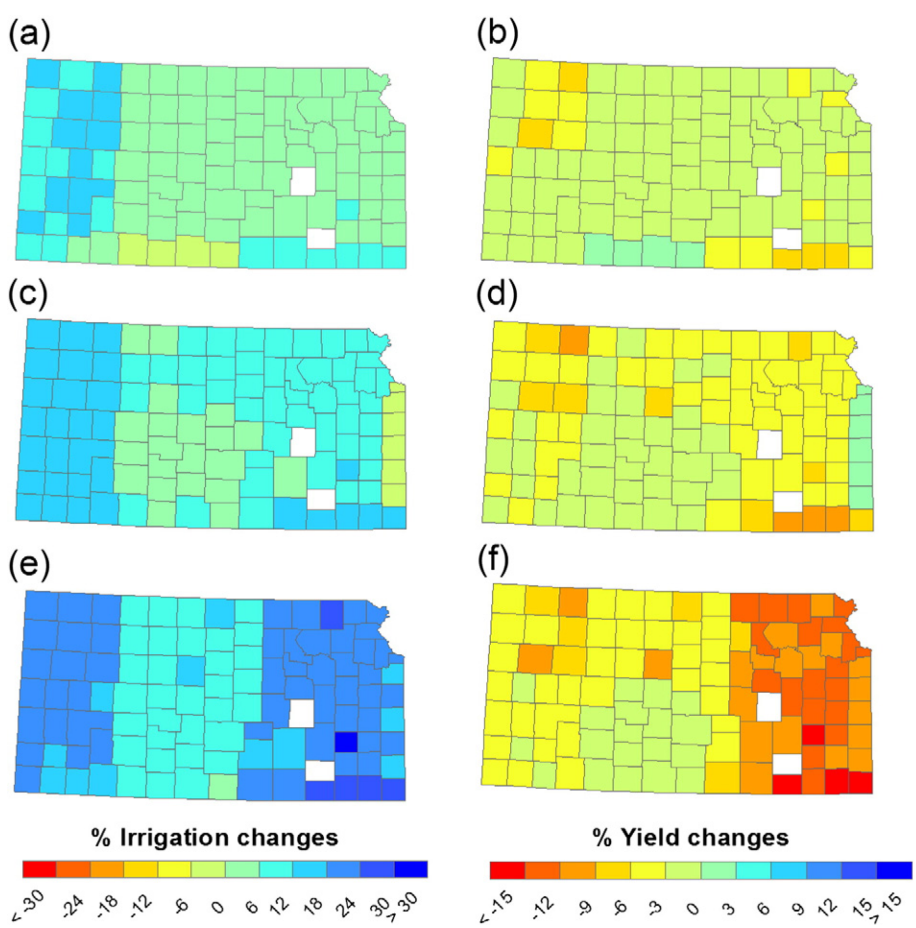

Fig. 5. Model-estimated percentage changes in maize irrigation (left panel), and yield changes (right panel) under three climate scenarios. Results are depicted for 2020–2039 (a, b), 2040–2059 (c, d), and 2080–2099 (e, f).

application under future drought scenarios, the model still projects an overall negative yield change. On the state level, maize yield was projected to decrease by 2.2% for the climate in 2020–2039, 3.6% in 2040–2059, and 6.5% in 2080–2099 (Table 2) relative to the baseline climate. Substantial yield reductions were found in counties in the western and eastern regions especially for the climates in 2040–2059 and 2080–2099 (Fig. 5b, d, f).

Similar changes in yield were estimated for soybeans (Fig. 6). More irrigation was applied due to drier climate in most counties (Fig. 6a, c, e) with state-level irrigation increasing by 5.1% for the climate in 2020–2039, 9.4% in 2040–2059, and 14.5% in 2080–2099 (Table 2). However, the overall soybean yield would still decrease under future climate scenarios: 2.2% for the climate in 2020–2039, 4.2% in 2040–2059, and 9.4% in 2080–2099 (Table 2). There would be 0–3% yield improvement in some southwestern counties but yields in the eastern areas would have substantial reductions in variability between 3 and 15% (Fig. 6b, d, f).

For grain sorghum, around 0–30% more irrigation was applied in reaction to drier climate (Fig. 7a, c, e). At the state level, irrigation was projected to increase by 10.3% for the climate in 2020–2039, 15.1% in 2040–2059, and 18.9% in 2080–2099 (Table 2). However, greater yield losses due to drought were projected for grain sorghum (Fig. 7b, d, f) than for maize and soybean. Yield would decrease by 4.9% in 2020–2039, 8.5% in 2040–2059, and 12.4% in 2080–2099 relative to the baseline level (Table 2).

Because of the different PDSI trends during the wheat growing season (Fig. 3), fundamentally different projections for future changes in irrigation and yield were obtained (Fig. 8). An increase in irrigation was projected but the magnitude is much lower than the other three crops. State irrigation was projected to increase by 9.1% in 2020–2039, 6.9% in 2040–2059, and 9.2% in 2080–2099 (Table 2). This is because irrigation becomes less than the baseline level in the central part of the state (Fig. 8a, c, e). Yields would increase in some eastern counties under the three future climate scenarios (Fig. 8b, d, f), whereas crop yields in some portions of the southern areas would be negatively affected by drought (Fig. 8b, d, f). Reductions in crop yield due to drought are marginal at the state level, with variability between −0.99 and −0.63% (Table 2).

4. Discussion

This study assesses how future drought would affect crop yields in Kansas considering actual farmers' irrigation reactions to drought. The results indicate that more irrigation would be necessary to offset water stresses resulting from drought, and is consistent with a previous study (Zhang et al., 2015). These results further indicate that irrigation responses to drought are dependent on the crop. Increasing irrigation as a reaction to drought is more evident for the three summer-season crops: around 10–13% more irrigation was applied when PDSI was one unit lower than the baseline level. However, there was only an 8% increase in irrigation with one unit reduction in PDSI for wheat with large uncertainty noted (Fig. 2). Since these results were derived from observations, the quantified irrigation reactions are viewed as an overall consequence due to the combined effects of climate, local water policy, and farmers' reactions in order to abate drought.

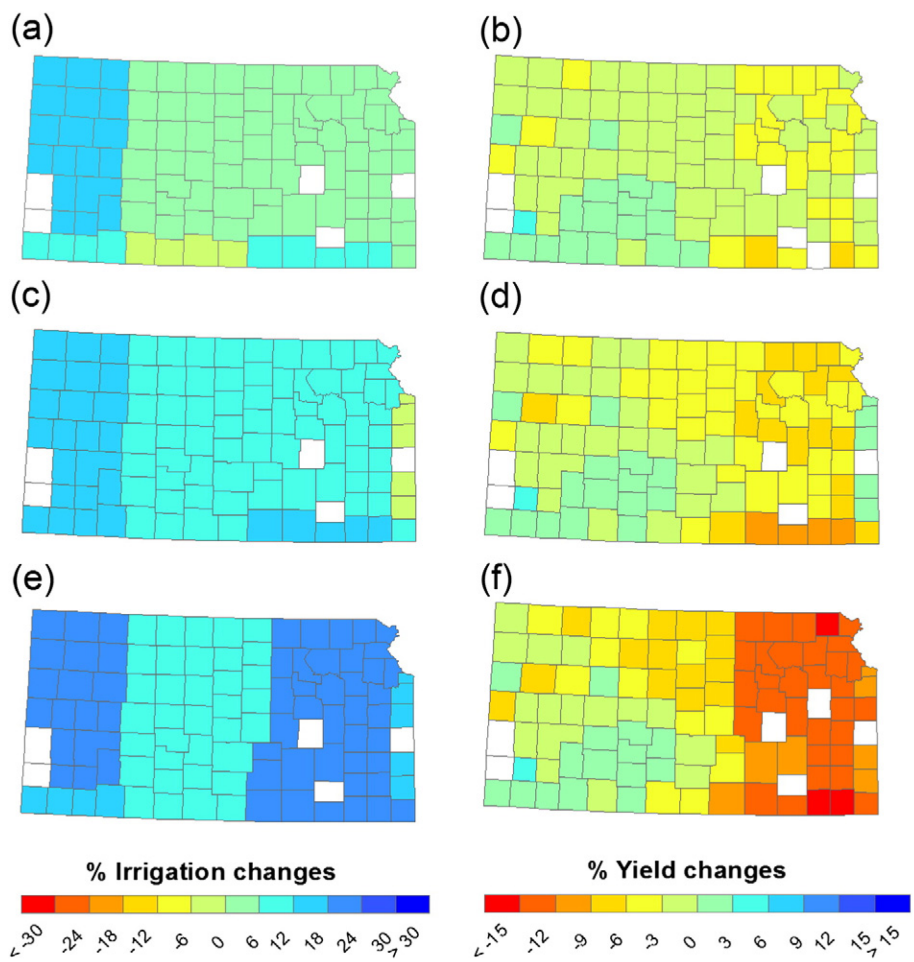

Fig. 6. Model-estimated percentage changes in soybean irrigation (left panel), and yield changes (right panel) under three climate scenarios. Results are depicted for 2020–2039 (a, b), 2040–2059 (c, d), and 2080–2099 (e, f).

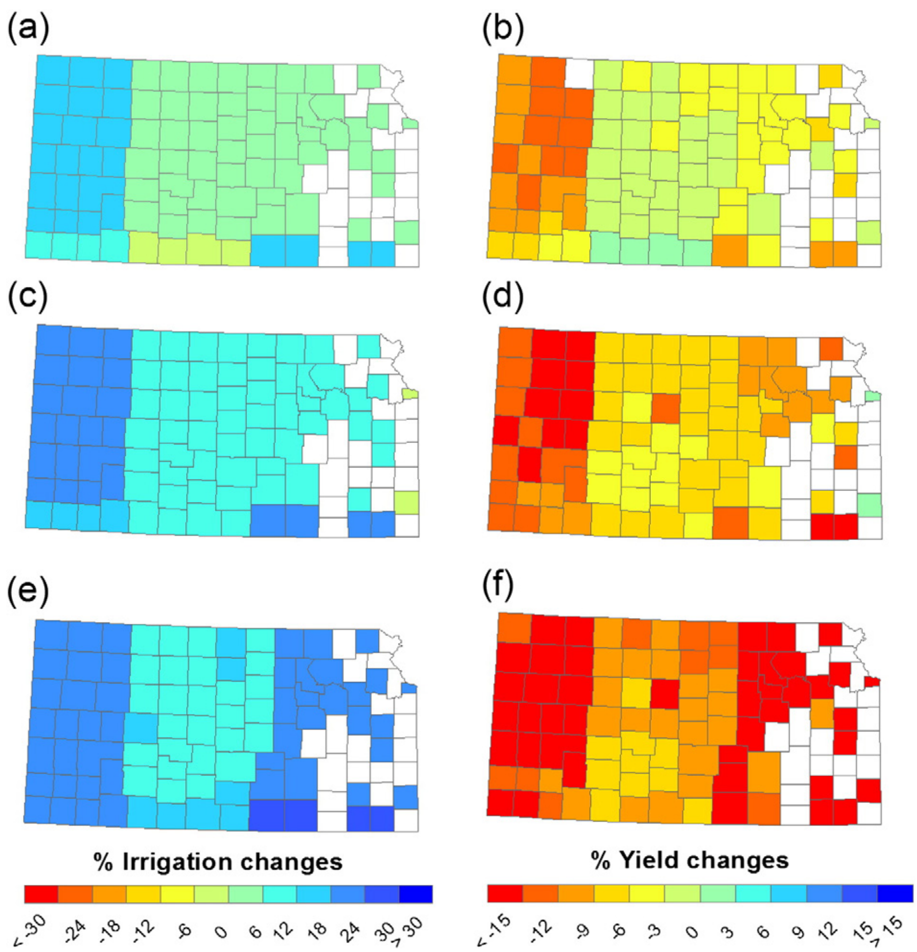

Fig. 7. Model-estimated percentage changes in grain sorghum irrigation (left panel), and yield changes (right panel) under three climate scenarios. Results are depicted for 2020–2039 (a, b), 2040–2059 (c, d), and 2080–2099 (e, f).

Separating crop-specific irrigation is very difficult in many irrigation data products. Earlier modeling studies often assume that full irrigation was applied for the irrigated area to all crops (Deryng et al., 2011; Rosenzweig et al., 2014; Ventrella et al., 2012). However, these results do not support that assumption. Results demonstrate that after undertaking the same degree of water stresses (i.e., one unit reduction in PDSI), the three summer-season crops (maize, soybean, and grain sorghum) would benefit more from the associated irrigation responses than wheat (Fig. 3). This could be ascribed to the lower irrigation response to drought for wheat than the other three crops (Fig. 2). A clear PDSI threshold of yield changes was found for the three summer-season crops. This may be due to less severe water-logging or disease under a very wet climate (i.e., higher PDSI) and higher yields when PDSI was reduced (Zhang et al., 2008, 2010). It is unknown if the results derived in Kansas can be applied to other states in the US. Further investigation is needed to examine existing adaptive priorities for different crops on a broader regional scale.

Historical irrigation reactions were then projected to future drought conditions to evaluate the adaptive effect of current irrigation to future drought. The projection for more severe drought is that irrigation adaptive effects on maize, soybean, and grain sorghum would be inadequate, predicting a yield decline of 2.2–12.4% (Table 2). These results suggest improved irrigation technologies and management as well as additional irrigation water supplies could be critical to Kansas agriculture for drought management. It is important to note that it was assumed that the irrigation reaction to future climate conditions would follow historical patterns. However, an irrigation reaction that is less robust than the historical level is possible since the availability of future agricultural water resources might be reduced due to climate change (Elliott et al., 2014). Additionally, water requirements increase to meet municipal and industrial water demands (Strzepek and Boehlert, 2010) while water resources in the High Plains are currently already in decline (Wen and Chen, 2006; Butler et al., 2013). For these reasons, our model projections are considered conservative. More serious crop damage from drought than estimated here is possible. These findings indicate the need to improve crop resilience to drought in Kansas and demonstrate a need to invest in irrigation infrastructure and relevant technology, particularly for summer-season crops. In contrast, projected reductions in wheat yields under future climate scenarios were very limited (Table 2). This is because wetter climate conditions predicted in the central region of Kansas during the growing season of wheat improve yields (Fig. 4). Therefore, expanding wheat farming may be an option to utilize moisture conditions found during wheat growing season brought on by projected climate change. This wheat farming expansion may help to avoid the future more serious drought during the summer season.

Finally, this study focused only on the effects of drought and associated irrigation responses but this does not include all climate risks such as heat stress (Gourdji et al., 2013). According to this model, yields would decline by 3–13% in response to 1 °C warming (Supplementary material 2); indicating yield would decrease more than presented in this study if heat stresses were to be taken into account.

5. Conclusion

Kansas may face an extensive drought that could be beyond the range of their current irrigation ability if future projections are accurate.

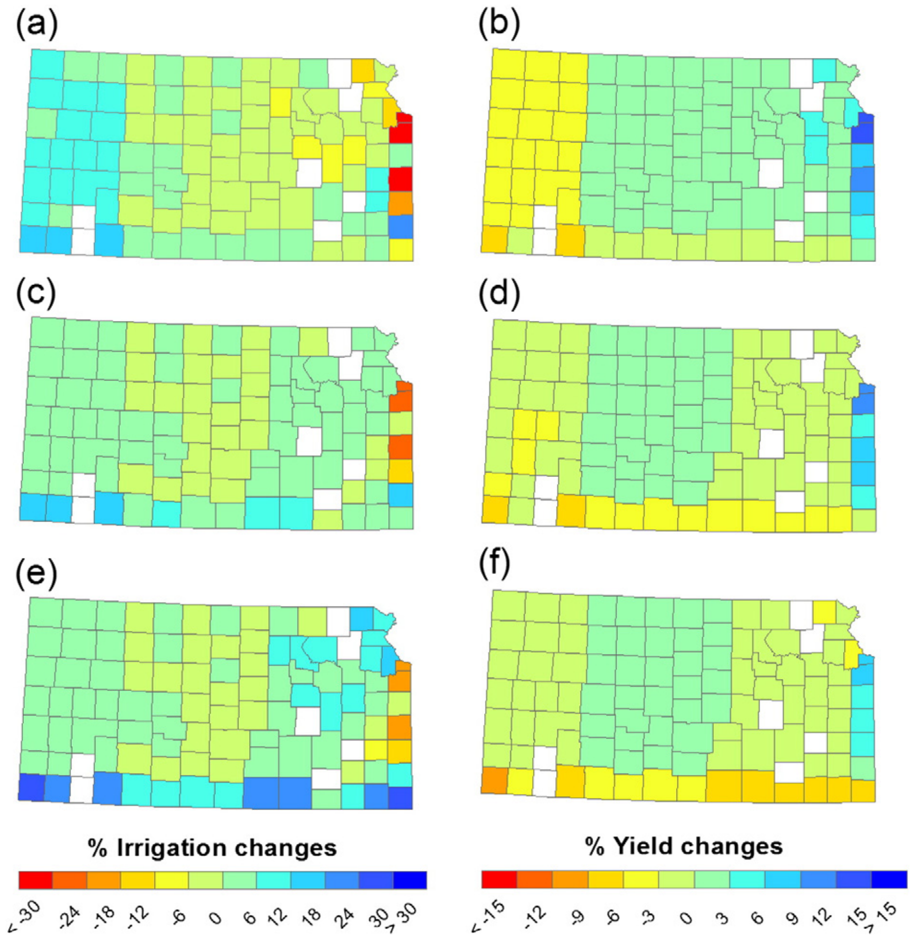

Fig. 8. Model-estimated percentage changes in wheat irrigation (left panel), and yield changes (right panel) under three climate scenarios. Results are depicted for 2020–2039 (a, b), 2040–2059 (c, d), and 2080–2099 (e, f).

Understanding and quantifying knowledge of the historical ability of irrigation to mitigate drought and projecting that information to future drought scenarios could be useful in at least two ways. First, our results provide specific information to local government that can be used to evaluate future drought risks under current irrigation conditions. This research also suggests that the current irrigation reaction can manage future drought risks over the winter season but drought during the summer growing season would exceed the capability of current irrigation practices. Investing in a water-saving crop cultivar and high-efficiency irrigation infrastructure appear to be promising initial priorities needed to abate drought over the summer season in Kansas. Secondly, these results demonstrate that Kansas agriculture could greatly benefit from expanding wheat growing areas thus utilizing the moisture conditions available during wheat growing season.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.scitotenv.2016.01.181.

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