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



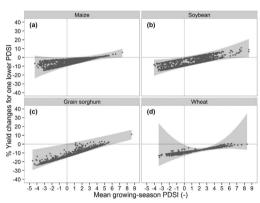
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HIGHLIGHTS

- 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

ARTICLE INFO

Article history:
Received 14 October 2015
Received in revised form 27 January 2016
Accepted 27 January 2016
Available online xxxx

Editor: D. Barcelo

Keywords: Irrigation Drought Adaptation PDSI Kansas

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.

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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 cropspecific 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 countylevel 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,

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