Climate change impact on meteorological, agricultural, and hydrological drought in central Illinois

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This paper investigates the impact of climate change on drought by addressing two questions: (1) How reliable is the assessment of climate change impact on drought based on state-of-the-art climate change projections and downscaling techniques? and (2) Will the impact be at the same level from meteorological, agricultural, and hydrologic perspectives? Regional climate change projections based on dynamical downscaling through regional climate models (RCMs) are used to assess drought frequency, intensity, and duration, and the impact propagation from meteorological to agricultural to hydrological systems. The impact on a meteorological drought index (standardized precipitation index, SPI) is first assessed on the basis of daily climate inputs from RCMs driven by three general circulation models (GCMs). Two periods and two emission scenarios, i.e., 1991–2000 and 2091–2100 under B1 and A1Fi for Parallel Climate Model (PCM), 1990–1999 and 2090–2099 under A1B and A1Fi for Community Climate System Model, version 3.0 (CCSM3), 1980–1989 and 2090–2099 under B2 and A2 for Hadley Centre CGCM (HadCM3), are undertaken and dynamically downscaled through the RCMs. The climate projections are fed to a calibrated hydro-agronomic model at the watershed scale in Central Illinois, and agricultural drought indexed by the standardized soil water index (SSWI) and hydrological drought by the standardized runoff index (SRI) and crop yield impacts are assessed. SSWI, in particular with extreme droughts, is more sensitive to climate change than either SPI or SRI. The climate change impact on drought in terms of intensity, frequency, and duration grows from meteorological to agricultural to hydrological drought, especially for CCSM3-RCM. Significant changes of SSWI and SRI are found because of the temperature increase and precipitation decrease during the crop season, as well as the nonlinear hydrological response to precipitation and temperature change.


1. Introduction

Droughts continue to be a major natural hazard, both within the United States and internationally. On average, 35%–40% of the area of the United States has been affected by severe droughts in recent years [Wilhite and Pulwarty, 2005]. Of the 46 U.S. weather-related disasters between 1980 and 1999 causing damage in excess of $1 billion, eight were droughts. Among these, the most costly national disaster was the 1988 drought, with an estimated loss of $40 billion [Ross and Lott, 2003].

Mounting evidence of global warming confronts society with a pressing question: Will climate change aggravate the risk of drought at the regional or local scale?

According to the Fourth Assessment Report recently released by the Intergovernmental Panel on Climate Change (IPCC), droughts have become longer and more intense, and have affected larger areas since the 1970s; the land area affected by drought is expected to increase and water resources availability in affected areas could decline as much as 30% by mid-century. In particular, U.S. crops that are already near the upper end of their temperature tolerance range or depend on heavily used water resources could suffer with further warming [IPCC, 2006]. Unfortunately, there is still much uncertainty in the climate projections which are needed to assess drought risk [National Research Council (NRC), 2006]. The difficulty lies in the fact that general circulation models (GCMs) which are used to project global climate change cannot adequately resolve factors that might influence regional climates [Hayes et al., 1999], and the reliability for extreme events is not as good as for climate averages at the continental scale. Various methods have been developed to downscale precipitation from GCMs [Johnson and Sharma, 2011; Bárđossy and Pegram, 2011]. Using multiple GCMs, Burke and Brown [2008] assessed the impact of climate change on worldwide drought on the basis of multiple drought
indicators, i.e., the standardized precipitation index (SPI), the precipitation and potential evaporation anomaly, and the soil moisture anomaly, as well as the Palmer Drought Severity Index [Burke et al., 2006]. Few studies have explicitly incorporated various uncertainties of regional climate change into drought risk estimates at the local level.

The first question to be addressed in this paper is the assessment of the impact of climate change on drought severity, duration, and frequency at the watershed scale. We utilize a physically based dynamical downscaling technique using a regional climate model with three different GCMs and different emission scenarios to represent a spectrum of possible climate projections. Dynamical downscaling involves nesting a regional climate model (RCM) [Leung et al., 2004] within a GCM. RCMs can provide the necessary spatial and temporal downscaling steps required to make the use of GCM outputs feasible for the case study and for quantifying the drought indices.

The second objective of this paper is to understand the propagation of climate change impacts across a cascade of various levels of droughts from meteorological, to agricultural, hydrological, and economic systems. Are certain types of droughts more sensitive to projected climatic change and variability than others and would the change amplify or diminish as the impact of climate change propagates across different levels of drought indices? Understanding where climate change impact will be most significant could potentially identify which sector is most sensitive to the change of drought severity, duration, and frequency. Understanding the propagation through nonlinear hydrologic and agronomic processes among drought indices could also identify threshold behaviors across drought indices; for example, the change of agricultural drought severity will be dramatic once the meteorological drought change reaches a certain level. Recent empirical and theoretical studies suggest that the presence of extreme nonlinearity and thresholds in water availability or other environmental variables may form important constraints on economic decision-making for agriculture [Schlenker and Roberts, 2006], ecosystems [Brozović and Schlenker, 2007], and industrial water users [Brozović et al., 2007]. The impact triggered by meteorological drought may accumulate from meteorological to socioeconomic responses.

The Salt Creek watershed in East-Central Illinois is used as a case study area. The watershed, ~217 km southwest of Chicago, is a typical watershed in the Midwest where agriculture is the dominant activity (Figure 1). The primary crops are corn and soybeans planted in rotation. The Salt Creek is a tributary to the Sangamon River, which in turn is a tributary to the Illinois River. The drainage area of the Salt Creek watershed is 4786 km². Approximately 89% of the watershed is agricultural, with 80% cultivated crops and 9% rural grassland. One major urban area, the city of Bloomington, is located in the watershed.

Overall, our aim in this paper is to investigate the climate change impact on drought by addressing two questions: How reliable is the assessment of climate change impact on drought based on the state-of-the-art climate change projections and downscaling techniques? Will the impact be at the same level from meteorological, agricultural, and hydrologic perspectives? To deal with uncertainty involved in climate change projection, the impact on a meteorological drought index is first assessed on the basis of daily climate inputs from RCMs driven by three GCMs in the current and a future period with two emission scenarios. The climate projections are fed to a calibrated hydro-agronomic model for the Salt Creek watershed in Central Illinois; the outputs of the model are then used to evaluate the impact of climate change on agricultural drought and hydrological drought. The intensity, duration, and frequency (IDF) of the various drought events are examined through IDF curves. Finally, an assessment of the drought impact on crop yield in the study area is presented. In the remainder of the paper, we describe the methodology, followed by results, discussions, and conclusions.

2. Methodology

2.1. Regional Climate Model (RCM)

This study is based on high-resolution RCM simulations driven by output from historic and future simulations of three GCMs, i.e., the U.S. Department of Energy and National Center for Atmospheric Research Parallel Climate Model (PCM) [Washington et al., 2000], the Community Climate System Model, version 3 (CCSM3) [Collins et al., 2006], and a global atmosphere-only model (HadAM3P) derived from the atmospheric GCM of the Hadley Centre GCM (HadCM3) [Pope et al., 2000; Johns et al., 2003]. These GCMs have different climate sensitivities, which...
represent the increase of global mean temperature when the CO₂ concentration in the atmosphere doubles. As shown in Table 1, PCM and CCSM3 belong to low climate sensitivity models, and HadCM3 is characterized by high climate sensitivity [Kunkel and Liang, 2005]. The former models are at the low end and the latter is in the upper half of the range across all available GCMs [Liang et al., 2008].

Given the relatively coarse scale resolution of GCM simulations (e.g., with a spatial resolution of ~300 km), the RCM, with a horizontal grid spacing of ~30 km, conducts dynamical downscaling integrations and provides improved mesoscale projections for assessing potential climate change impacts at the regional scale. The RCM that provides the climate change projections to this study is a climate extension of the fifth-generation Pennsylvania State University-Nation Center for Atmospheric Prediction (PSU-NCAR) Mesoscale Model (CMM5), version 3.3 [Dudhia et al., 2000]. The CMM5 is an improved version of the model of Liang et al. [2001], and important modifications include incorporation of more realistic surface boundary conditions and cloud cover prediction from an updated global reanalysis [Liang et al., 2004]. It has been demonstrated that CMM5 has considerable downscaling skill over the United States, producing more realistic regional details and overall smaller biases than the driving reanalyses or GCM simulations [Liang et al., 2004, 2006]. The simulation of CMM5 is based on the cumulus parameterization scheme by Grell [1993], which provides superior performance in downsampling U.S.–Mexico precipitation seasonal-interannual variations [Liang et al., 2007]. Hereafter, the three nested GCM-RCM are denoted as PCM-RCM, CCSM3-RCM, and HadCM3-RCM, respectively. Each model is simulated for a period of 10 years under each emission scenario (Table 1).

The historic simulation corresponds to the coupled-model intercomparison project “20th Century Climate in Coupled Models” scenario (20C3M) [Covey et al., 2003], driven by historically accurate forcings, including anthropogenic emissions of greenhouse gases and aerosols, indirect effects on atmospheric water vapor and ozone, and natural changes in solar radiation and volcanic emissions. The baseline simulations for PCM-RCM, CCSM3-RCM, and HadCM3-RCM are 1991–2000, 1990–1999, and 1980–1989, respectively, which have been used as the baseline periods for climate change impact assessment by Liang et al. [2008] and Anderson et al. [2010].

The future simulation is forced by the IPCC Special Report on Emission Scenarios (SRES) [Nakicenovic et al., 2000]. The two PCM emission scenarios are A1Fi (high, effective CO₂ concentration of ~970 ppm by 2100) and B1 (low, ~550 ppm by 2100), respectively; the two CCSM3 emission scenarios are A1Fi and A1B (middle, ~720 ppm by 2100), respectively; the two HadCM3 emission scenarios are A2 (moderately high, 860 ppm by 2100) and B2 (moderately low, ~620 ppm by 2100), respectively. The future simulation period for PCM-RCM is 2091–2100, and for CCSM3-RCM and HadCM3-RCM is 2090–2099. The 3-hourly outputs from the RCMs under each scenario are used as inputs into a process-based hydro-agronomic model to assess the impacts of climate change on the various types of droughts. The bias analysis of RCMs in the study region has been conducted by Liang et al. [2001, 2006]. The performance on the precipitation and temperature is improved by the RCMs compared to the driven GCMs.

### 2.2. A Hydro-agronomic Model

The soil and water assessment tool (SWAT) is adopted to derive the drought indices using the outputs of the RCMs. SWAT is a semidistributed and process-based watershed scale model. The model includes climate, hydrology, nutrients, erosion, crop growth, main channel processes, and flow routing components, and it can be used to predict the impact of climate change and land management practices on water, sediment, and agricultural yields in large complex watersheds with varying soils, land use, and management conditions over long periods of time [Arnold et al., 1998] (details are available at [http://www.brc.tamus.edu/swat](http://www.brc.tamus.edu/swat)). The reason for choosing the SWAT model was its ability to simulate crop growth and agricultural management practices since this is essential to assess the impact of climate change on agricultural and economic drought [e.g., Ficklin et al., 2009]. The SWAT model has been calibrated for the Salt Creek as another motivation [Ng et al., 2010]. The 3-h precipitation, minimum and maximum temperature, relative humidity, wind speed, and solar radiation from the RCMs are aggregated into daily values and fed into the SWAT model which runs at the daily timescale. The baseline years for the three RCMs (i.e., PCM-RCM, CCSM3-RCM, and HadCM3-RCM) are 1991–2000, 1990–1999, and 1980–1989, respectively; as noted above, the future period for PCM-RCM is 2091–2100 and 2090–2099 for both CCSM3-RCM and HadCM3-RCM.

The calibration and validation of the Salt Creek watershed model are based on observed daily streamflow, monthly riverine nitrate load, and annual corn and soybean yields from various sources. Four U.S. Geological Survey (USGS) gages, i.e., Greenview (site number 05582000), Cornland (05579500), Waynesville (05580000), and Rollell (05578500), are located in the watershed. Monthly riverine nitrate load at the watershed outlet at Greenview is obtained from the Illinois Environmental Protection Agency; the annual corn and soybean yields data are obtained from the USDA National Agricultural Statistics Service database. The calibration and validation periods are from 1988 to 1995 and from 1996 to 2003, respectively. Six rain gage stations from the climate database of the SWAT model are used during the calibration period. The calibration is conducted at the daily time step. The
details of the SWAT model set up and calibration for Salt Creek watershed can be found from Ng et al. [2010].

2.3. Drought Indices

[14] The literature is filled with numerous drought indices that have been developed and validated for various regions of the globe. Keyantash and Dracup [2002] classified droughts into three physical types: meteorological drought resulting from precipitation deficits, agricultural drought identified by total soil moisture deficits, and hydrological drought related to a shortage of streamflow. In this study, given that precipitation deficits can lead to the decrease of soil moisture and streamflow deficits, and subsequently contribute to economic and agricultural losses, we incorporate an economic assessment component as a fourth level of drought. Thus, to investigate the impact of projected climate change on drought at different levels, we select four indices to represent four different categories, namely, meteorological, agricultural, hydrological, and economic.

2.3.1. Meteorological Drought

[15] A well known meteorological drought index is the standardized precipitation index (SPI) [McKee et al., 1993], which has the advantages of flexibility, simplicity, adaptability to other hydroclimatic variables, and suitability for spatial comparison [Santos et al., 2010]. The SPI is used to measure precipitation shortage on the basis of the probability distribution of precipitation at different timescales. For example, to obtain the 1-month SPI, the distribution of monthly precipitation, which is typically similar to a gamma distribution [Wilks and Eggleston, 1992], is calculated for each month separately. For the case of weekly SPI, which also follows a gamma distribution [Wu et al., 2005], SPI is computed at the weekly temporal scale using a 4 week average precipitation to replace the value of the present week, and so on moving to the next week, i.e., a 4 week moving window is used for the statistics. In this setting it is possible that overlap exists between two drought events, and then the counts of drought events may not be independent. For a given value of precipitation, the cumulative probability for the gamma distribution is transformed to a standard normal distribution. Then, the SPI value is the z-value of the standard normal distribution corresponding to the cumulative probability [McKee et al., 1993]. The transform ensures that all distributions have a common basis. The detailed description and the computer programs used to calculate SPI can be found at the National Drought Mitigation Center web site (available online at http://www.drought.unl.edu/monitor).

2.3.2. Agricultural and Hydrologic Droughts

[16] In this study, the agricultural drought index is represented by a standardized soil water index (SSWI), which is computed using a similar procedure to the SPI calculation, but applied to the soil moisture time series obtained from the SWAT model simulation. The procedure for calculating the SSWI includes the following four steps: (1) the time series of watershed averaged soil water content in the baseline period (10 years) is obtained from the SWAT model output; (2) the soil water content and runoff are fitted to probability distributions; (3) the fitted distributions are used to estimate the cumulative probability of the soil moisture value of interest (either from the baseline year or from the future climate scenario); (4) the cumulative probability is converted to the z-value of a normal distribution with zero mean and unit variance. The standardized runoff index (SRI) proposed by Shukla and Wood [2008] is used to represent the hydrological drought. SRI is computed using a procedure similar to the SPI and SSWI calculations.

2.3.3. Economic Drought

[17] Crop yield is used as a monetary measure to quantify the economic impact associated with each of the projected climate change scenarios. Crop yield is linked to the three previously described drought indices (SPI, SSWI, and SRI). The crop yield is an annual value while the other drought indices are weekly. Given that each climate scenario is only 10 year long, the sample size of the crop yield is 10 instead of 520 (52 weeks in 1 year × 10 years) for the other three drought indices. This limits our ability to derive an economic drought indicator in a similar fashion to the three other indices. Thus, we limit our economic analysis to provide an economic assessment under both current (baseline) climatic conditions and future climatic projections. Two crops are grown in the case study, i.e., corn and soybeans which are rotated by year.

[18] In this study, the connections among the various types of indices are implemented through the SWAT simulation model, allowing for a unified framework of comparison among the indices under the impact of climate change. Note that the model is calibrated in terms of streamflow using the USGS observations for the baseline period. All the drought indices in the future periods are computed with respect to the baseline conditions, i.e., the fitted distributions, through which the drought index values are computed for both baseline and future years, is constructed on the basis of the baseline years. The weekly precipitation in the baseline years is fitted by a gamma distribution; runoff is fitted by a lognormal distribution; for soil water content (θ), a lognormal distribution is fitted to \( \theta' = \theta_{\text{max}} - \theta \), where \( \theta_{\text{max}} \) is maximum soil water content.

[19] Next, we describe a consistent approach to quantify the impacts of climate change projections on drought characteristics, such as intensity, duration, and frequency.

2.4. Intensity-Duration-Frequency Curve of Drought

[20] Drought characteristics include onset, end, intensity, duration, frequency and magnitude [Dracup et al., 1980], and areal extent [Andreadis et al., 2005]. These drought characteristics can be quantified for any drought indicator. Following the concept of establishing intensity-duration-frequency (IDF) curves for rainfall, commonly used in hydrological design standards, we derive the IDF curves for droughts using a similar approach. Unlike rainfall events, droughts tend to persist for much longer duration. Thus, drought intensity can be defined as the average drought severity or magnitude (measured as SPI, SSWI, or SRI) over a particular duration (here in weeks). These IDF curves are specific to the case study, but in general can describe how drought characteristics change under climate change scenarios. The following procedures are employed in this study for deriving the drought IDF curves for the baseline years and the future years:

[21] 1. Determine the temporal scale for computing the drought indices. For both baseline and future years, the available data are the 10 year daily time series of precipitation, soil moisture, and streamflow. In this study, the weekly
values of these variables are used to compute the corresponding drought indices.

2. Identify the drought events. SPI values between 0 and −0.99, −1.00 and −1.49, −1.50 and −1.99, and less than −2.00 are defined as mild drought, moderate, severe, and extreme drought, respectively [McKee, 1993]. In this study, drought events with intensity I less than −1.0 are presented.

3. Perform drought frequency analysis. Given duration and intensity, the number of drought event (N) is counted during the 10 year period of baseline or future years.

4. Construct the intensity-duration-frequency curve of drought for the baseline period and the future period (2090–2100) under the two emission scenarios from each nested GCM-RCM.

It should be noted that given only the 10 year period for future projections available for this study, our analysis is limited to short-term instead of long-term droughts that may last for multiple years. To assess the uncertainty introduced by using 10 year simulations of the future, drought analysis is conducted on the basis of historical climate data during three 10 year periods (i.e., 1971–1980, 1981–1990, and 1991–2000).

2.5. Drought Characteristics of the Case Study Watershed

Coupling the climate change scenarios with the hydro-agronomic model to calculate the drought indices and their characteristics as discussed above, we proceed to address our research questions about the impact of climate change on various drought indices and their characteristics. We start with the construction of each of the drought index time series underlying each of the climate change scenarios. For both baseline and future periods, the daily average values of climate variables including precipitation from one grid point (Figure 1) are used as the input of the SWAT model. As we can see in Figure 1, four RCM grid points are within the Salt Creek watershed, and the values of the climate variables from individual RCMs are almost identical over these grid points. Moreover, the historical observation of climate variables is point-based, therefore the climate time series from one grid point is used for the impact assessment.

The time series of SPI, SSWI, and SRI drought indices are constructed using (1) daily precipitation output from each of the nine scenarios of GCM-RCM and emission scenarios, as well as the baseline scenario; and (2) the daily outputs of soil water content and streamflow from the SWAT simulation model, which uses a number of sub-watersheds (100 for the case study area) in a semidistributed form. The following procedures are undertaken: The weekly SPI is computed from the daily meteorological data during the 10 year period from the RCMs and historical data. Recall that the weekly SPI is computed using a 4 week moving average of the precipitation time series. The SSWI is based on the averaged soil water content over the entire watershed, and the SRI is based on the runoff at the outlet of the watershed.

3. Results and Discussion

Three GCM-RCM models are used to assess current and future conditions under two different emission scenarios, respectively. The temperature is predicted to increase under all the scenarios, but the variability of the precipitation projection is significant. The mean monthly precipitation and temperature changes are shown in Figures 2 and 3, respectively. The PCM-RCM predicts increased monthly precipitation from March to September, while CCSM3-RCM and HadCM3-RCM...
HadCM3-RCM predict decreased precipitation from July to October and increased precipitation from April to June.

Comparing the time series for the three indices (SPI, SRI, and SSRI), the variability of SPI is more significant with weaker persistence compared to both SSWI and SRI. This is because the rainfall variability has been partially filtered through the hydrological system of vegetation, topography, and soil. The SPI, SSWI, and SRI time series are used for the following statistical analyses: exceedance probability, IDF curves, extreme drought events, and propagation of drought from meteorological to agricultural and hydrological systems.

Before assessing the projected change of drought, the variability of drought characteristics is analyzed on the basis of three 10 year historical drought indices during 1971-2000. Figure 4 shows the IDF curves and the most severe drought intensity. The number of meteorological drought events varies moderately but the agricultural and hydrological variability is minimal. The most severe meteorological drought is more serious in 1981–1990 than in the other two periods; the variability of severe agricultural and hydrological droughts is not significant.

3.1. Projected Change of IDF Curves

Figure 5 shows the projected change of IDF curves from the three GCM-RCMs. In general, the number of drought events decreases with the increase of drought duration for all the drought indices and all the GCM-RCM scenarios. But if the IDF curves are compared between baseline and future projections, the difference varies with GCM-RCM and drought indices. For a given drought duration, the number of drought events increases from baseline to the future for most scenarios. The frequency change from CCSM3-RCM is the most significant especially for SSWI and SRI. The frequency increase of certain levels of drought is more significant for the high emission scenarios. For example, for SRI with duration of 2 weeks, the number of drought events increases from 46 under the baseline to 169 under the A1B scenario, and the number is up to 326 under the A1Fi scenario. Emission scenarios may not be the sole factor contributing to the difference because of limited record length of data from RCMs. For CCSM3-RCM, the number of drought events increases from SPI to SSWI and to SRI. For example, under A1Fi the number of drought events with \( D = 1 \) week is 112, 261, and 356, respectively.

3.2. Projected Change of Extreme Drought Events

The IDF curves can be used to analyze extreme drought events, which in practice can be more significant for drought management. Table 2 shows the longest duration for drought intensity less than \( -1 \) with the three drought indices. The longest duration increases from baseline to the future, except for SSWI from PCM-RCM. For example, from PCM-RCM, the longest duration for SPI increases from 6 weeks under baseline to 8 weeks under B1, and 10 weeks under A1Fi; from CCSM3-RCM, the longest duration for SRI is, 30 weeks for low emission and 40 weeks for high emission, which is about 3 times the baseline. Although in general longer drought durations are observed for the higher emission scenarios (Table 2), some fluctuations occur given the relative short length (10 years) of the study period for each scenario.

The most severe drought (i.e., the most negative drought intensity) is assessed for various durations up to 52 weeks, and the results are shown in Figure 6. The climate change impact on the most severe drought is significant based on CCSM3-RCM compared with PCM-RCM and...
HadCM3-RCM. Moreover, the impact on the most severe agricultural and hydrological droughts is more dramatic than for the meteorological drought under the CCSM3-RCM scenarios. From Figure 6, the change for SRI on the basis of CCSM3-RCM is the most significant one compared with other drought indicators and RCMs. Table 3 shows the change of drought intensity with a duration of 20 weeks. For example, for CCSM3-RCM under A1Fi, the intensity of the most severe drought increases from $0.88$ to $1.70$ for SPI, from $1.40$ to $2.53$ for SSWI, and from $2.27$ to $4.55$ for SRI.

### 3.3. Propagation of Drought From Meteorological to Agricultural to Hydrological Systems

The climate change impact on meteorological, agricultural, and hydrological drought differs even under the same GCM-RCM with the same emission scenario. The change in the number of drought events in terms of all the three drought indices in two emission scenarios is small for PCM-RCM (Figure 7, top), moderate for the HadCM3-RCM (Figure 7, bottom), and significant for the CCSM3-RCM (Figure 7, middle). From Figure 7, the propagation of climate change impact on meteorological drought to agricultural drought and hydrological drought can be assessed. The $y$-axis in Figure 7 represents the change from baseline in number of drought events in 1 year denoted as $N_d$ yr$^{-1}$. In general, agricultural drought (SSWI) and hydrological drought (SRI) are more sensitive to climate change than meteorological drought (SPI). This can be explained by the nonlinear response of soil moisture and runoff to the precipitation and temperature changes. From Figure 2, the precipitation change from CCSM3-RCM is very different from those with the other two models (i.e., decreasing in summer and increasing in postvegetation season); the temperature increase (Figure 3) during summer is especially strong for CCSM3-RCM. For example, the temperature increases 9°C during July under emission scenario A1Fi. The drought impact from CCSM3-RCM shows greater changes from SPI to SSWI to SRI for the drought under both emission scenarios. For example, for $I < -1$ and $D = 1$, the number of drought events per year under A1Fi are 6, 21, and 30 for SPI, SSWI, and SRI, respectively. For HadCM3-RCM, the SSWI is more sensitive to climate change than both SPI and SRI under both emission scenarios. Therefore, the significant change on agricultural and hydrologic drought can be explained by the temperature increase and precipitation decrease during the crop season, as well as the nonlinear hydrologic system.

![Figure 4](image-url)
Figure 5. The number of drought events for (top) SPI, (middle) SSWI, and (bottom) SRI per 10 years during baseline and future periods under two emission scenarios. Drought events are indentified for $I < -1$. 
Table 2. The Longest Duration (by Weeks) of Drought Events

<table>
<thead>
<tr>
<th>Drought Indicator</th>
<th>Emission Scenario</th>
<th>PCM-RCM</th>
<th>CCSM3-RCM</th>
<th>HadCM3-RCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPI</td>
<td>Baseline</td>
<td>6</td>
<td>8</td>
<td>10</td>
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<td></td>
<td>High</td>
<td>10</td>
<td>13</td>
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<td></td>
<td>Low</td>
<td>8</td>
<td>11</td>
<td>8</td>
</tr>
<tr>
<td>SSWI</td>
<td>Baseline</td>
<td>12</td>
<td>18</td>
<td>22</td>
</tr>
<tr>
<td></td>
<td>High</td>
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<tr>
<td></td>
<td>Low</td>
<td>8</td>
<td>31</td>
<td>26</td>
</tr>
<tr>
<td>SRI</td>
<td>Baseline</td>
<td>13</td>
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<tr>
<td></td>
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<td>15</td>
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<tr>
<td></td>
<td>Low</td>
<td>26</td>
<td>30</td>
<td>24</td>
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</tbody>
</table>

*Drought events here are defined by thresholds of intensity $I < -1$, and are assessed by SPI (standardized precipitation index), SSWI (standardized soil water index), and SRI (standardized runoff index).

3.4. Crop Yield Assessment

[35] From the outputs of the SWAT model, the climate change impact on the crop yield can be assessed. Since there is only one crop yield in a year, the sample size is 10 for the 10 year period and is not sufficient to conduct the frequency analysis on the economic drought index.

[36] Figure 8 shows the box plots of the corn and soybean yield under the baseline and the future projections with two emission scenarios and the three GCM-RCMs. The yield of both corn and soybean decreases even for the PCM-RCM. The yield decreases less with the low emission scenario than the high emission scenario. The most significant decrease of corn and soybean yield is the case of a higher emission scenario (A1Fi) from CCSM3-RCM, where the average annual corn yield is 8.9 t ha$^{-1}$ under baseline but 7.4 t ha$^{-1}$ in the future under A1Fi, i.e., decreasing by 1.5 t ha$^{-1}$. The average annual soybean yield is 2.8 t ha$^{-1}$ under baseline and 1.4 t ha$^{-1}$ under A1Fi, i.e., decreasing by 1.4 t ha$^{-1}$. In the three 10 year simulations, the difference of the average annual corn yield is 0.43 t ha$^{-1}$ and 0.02 t ha$^{-1}$ for soybeans. The yield decrease among different RCMs and emission scenarios varies significantly. Two-sample Kolmogorov-Smirnov tests are conducted for the following null hypothesis: The yields for the current and future climate are from the same continuous distribution. At the 5% significance level, the test rejects the null hypothesis except the B1 scenario of PCM-RCM for corn and soybean and the B2 scenario of HadCM3-RCM for corn. Thus, when quantifying the impact of climate change on crop yield, assessing the uncertainty of model and emission scenarios is an important step to demonstrate the level of uncertainty associated with the results.

4. Conclusions

[37] In this paper, regional climate change projections on the basis of dynamical downscaling through regional climate models are used to assess drought frequency, intensity, and duration, and the impact propagation from meteorological, to agricultural and hydrological sectors. The RCMs are driven by three GCMs which have low and high climate sensitivities and two emission scenarios. For a given GCM-RCM, a higher emission scenario results in a larger impact on the various droughts. However, different GCM-RCMs predict different changes of drought properties including intensity, duration, and frequency even under the same or slightly different emission scenario; the change of the IDF curves from baseline to future varies with GCM-RCMs and drought indices. For a given drought intensity and duration, PCM-RCM predicts little change of drought frequency. However, HadCM3-RCM predicts a moderate increase of drought frequency and CCSM3-RCM predicts a significant increase of drought frequency.

[38] The combination of climate sensitivity and emission scenarios determines the future drought predictions. However, the impacts are complicated. Even though the climate sensitivity of HadCM3 is the highest among the three GCMs, the impacts from HadCM3-RCM with two moderate emission scenarios (A2 ~860 ppm and B2 ~620 ppm) is less significant than those from CCSM3-RCM with a moderate emission scenario (A1B, 720 ppm). PCM and CCSM3 have very similar levels of climate sensitivity (2.1°C versus 2.2°C), but under the same emission scenarios (A1Fi, B1), PCM-RCM projects drought characteristics that differ little from the baseline, while CCSM3-RCM projects a large difference. Actually, the differences of the outputs from GCMs go beyond the level of climate sensitivity; different model structure and parameterization probably contribute largely to different regional climate change projections. Recalling the precipitation change projections shown in Figure 2, the three GCM-RCMs (especially PCM versus the other two) show very different results. Moreover, emission scenarios are more complex than a single value for emission amount; regionally varying economic development paths and spatial distribution of emissions should also be taken into account when comparing the outcomes from the emission scenarios.

[39] Meteorological drought impacts (represented by SPI) are amplified in agricultural and hydrological impacts because of the increased temperature and decreased precipitation during the crop season, as well as the nonlinear hydrological responses to precipitation and temperature change. From the results, the agricultural section is more sensitive to the climate change impact, probably because of the soil moisture reduction caused by the significant increase of temperature. Therefore, the temperature increase is an important factor to the change of drought characteristics. The uncertainty in the RCM and emission scenarios propagates through these systems and could be confounding the results.

[40] In general, although climate models still offer inconsistent results, in this study two GCM-RCM models (CCSM3 and HadCM3) indicate that IDF curves of short-term droughts (i.e., 1–4 weeks) are likely to increase in frequency and severity. The PCM-RCM results show insignificant differences from baseline conditions. To further advance our understanding of the potential impact of climate change on drought characteristics, greater efforts are needed to reduce the uncertainties in predictions of GCMs.

[41] We also recognize the shortcoming due to use of only a 10 year record length. This is because of the extreme computational requirements of running a RCM over long periods for many scenarios (GCMs and emissions). We tried to alleviate this problem by using a short drought duration (weekly). We expect that the methodology and general results presented here would be valuable for promoting longer term RCM simulations that would be feasible if computational limitations are overcome.
Figure 6. The severest meteorological droughts under given durations are assessed during the baseline and future periods under two emission scenarios. The drought event is represented by (top) SPI, (middle) SSWI, and (bottom) SRI.
Table 3. Change of Intensity of the Most Severe SPI (Standardized Precipitation Index), SSWI (Standardized Soil Water Index), and SRI (Standardized Runoff Index)\(^a\)

<table>
<thead>
<tr>
<th>Drought Indicator</th>
<th>PCM-RCM</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Baseline</td>
<td>A1Fi</td>
<td>B1</td>
<td>Baseline</td>
<td>A1Fi</td>
</tr>
<tr>
<td>SPI</td>
<td>0.99</td>
<td>−1.08</td>
<td>−1.38</td>
<td>−0.88</td>
<td>−1.70</td>
</tr>
<tr>
<td>SSWI</td>
<td>−1.10</td>
<td>−1.09</td>
<td>−1.02</td>
<td>−1.40</td>
<td>−2.53</td>
</tr>
<tr>
<td>SRI</td>
<td>−1.64</td>
<td>−1.82</td>
<td>−2.01</td>
<td>−2.27</td>
<td>−4.55</td>
</tr>
</tbody>
</table>

\(^a\)For the duration of 20 weeks, the SPI, SSWI, and SRI was between the baseline and future periods for the various RCM-driven simulations.

Figure 7. The change of the total number of meteorological, agricultural, and hydrologic drought events of intensity \(I < -1\) and (left) duration \(D = 1\) week and (right) \(D = 2\) weeks are assessed based on climate projection from (top) PCM-RCM, (middle) CCSM3-RCM, and (bottom) HadCM3.
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References

Figure 8. The box plots of simulated (top) corn and (bottom) soybean yields during baseline and future periods under two emission scenarios from PCM-RCM, CCSM3-RCM, and HadCM3-RCM. In each box, the central point is the mean value, the central mark (horizontal line) is the median, the lower and upper edges of the box are the 25th and 75th percentiles, respectively, and the whiskers extend to the most extreme data points.


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