Measuring Agricultural Drought And Uncertainty In Future Drought Projections

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MEASURING AGRICULTURAL DROUGHT AND UNCERTAINTY IN FUTURE DROUGHT PROJECTIONS

by

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ABSTRACT

Drought is a devastating, recurring, and widespread natural hazard that affects natural habitats, ecosystems, and economic and social sectors. Within the agricultural sector, droughts can reduce soil-water availability, affect water and soil quality, contribute to crop failures and pasture losses, and severely reduce crop yield. Effective drought quantification and early warning are critical for drought risk adaptation. Moreover, future drought risks could be exacerbated due to climate change. Modeling how climate change might influence future drought risks is of great importance in natural resources and water resources planning management. This dissertation has three parts. 1) The first part compares and evaluates six trend simulation models to simulate the nonlinear trend and two decomposition models to remove the nonlinear trend from the yield time series. Study results find that a locally weighted regression model, coupled with a multiplicative decomposition model, is the most appropriate data self-adaptive detrending method, which allows spatial visualization of drought impact on corn yield in US by highlighting six historical major drought events. 2) The second part develops a new agriculturally-based drought index, called the Integrated Scaled Drought Index (ISDI). This index incorporates important components controlling agricultural drought, such as vegetation, temperature, precipitation, and soil moisture. The robustness and usefulness of this index is validated by multiple data sources. This index integrates the benefits of numerical model simulation and remote sensing technology to account for interannual variability of drought for the longest possible time-frame in the satellite era. 3) The third part focuses on identifying hotspots
and uncertainty in agricultural drought projections by analyzing surface soil moisture outputs from CMIP5 multi-model ensembles (MMEs) under RCP2.6, RCP4.5, RCP6.0, and RCP8.5 scenarios. This part investigates the MME annual and seasonal percentage change of surface soil moisture and examines the change in duration, frequency, severity, and spatial extent of severe agricultural drought. This part also quantifies and partitions three sources of uncertainty associated with these drought projections: internal variability, model uncertainty, and scenario uncertainty, and examines the spatiotemporal variability of annual and seasonal signal to noise (S/N) change in soil moisture anomalies across the globe and for different lead times.
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CHAPTER 1 INTRODUCTION

Drought is a devastating, recurring, and widespread natural hazard that affects natural habitats, ecosystems, and economic and social sectors, such as agriculture, transportation, industry, and urban water supply (Heim 2002). Compared with other natural hazards occurring within finite periods and resulting in apparent destruction, such as tornadoes, hurricanes and earthquakes, drought develops and builds slowly, often without visually obvious damaging impacts (Ding, Hayes and Widhalm 2011). Drought can prolong a longer time period with a gradual accumulation of deficits in precipitation and water supply and followed by a trail of impacts in various economic sectors (AMS 2013). The magnitude of drought impacts depends on various factors, including timing, duration, and severity, as well as a region’s vulnerability, sensitivity, and adaptive capacity (Wheaton et al. 2008).

Drought is a very costly natural hazard and has had large economic impacts on the United States. According to the NOAA’s National Centers for Environmental Information (NCEI)’s “Billion-Dollar Weather and Climate Disasters Summary” (NOAA 2016), from 1980-2016, the CPI-adjusted economic losses ($220.3B) from drought account for roughly 19.1% of total losses from major weather events. In the United States, only tropical cyclones are more costly.

Drought affects the natural environment and various societal sectors in different ways, and thus has many definitions. The World Meteorological Organization (WMO 1986) has defined drought as a sustained, extended deficiency in precipitation. The American
Meteorological Society (AMS 2013) has identified drought as not just a simple moisture deficit, but also a result of a complex interplay between natural precipitation deficiencies, or excessive evapotranspiration during varying time periods and different areal extents, and the demands of human and environmental water use that may be exacerbated by inefficiencies in water distribution, planning, and management.

Generally, drought can be classified into four types based on its duration and impacts: meteorological drought, agricultural drought, hydrological drought, and socioeconomic drought (AMS 1997, Heim 2002). Meteorological drought, agricultural drought, and hydrological drought are defined by physical, hydrometeorological, or biological parameters, while socioeconomic drought focuses on the impacts of drought on society (AMS 2013). Agricultural drought is of primary interest in this study. Agricultural drought usually occurs at a critical time during the growing season resulting in declining soil moisture and crop failure (Heim 2002, Mishra and Singh 2010). Agricultural drought affects both irrigated and dryland crop production, as well as livestock industries that rely on no-irrigated pastures or surface runoff (AMS 2013). It usually lags meteorological drought, depending on prior surface soil layer moisture (Heim 2002).

Within the agricultural sector, droughts reduce soil-water availability, affect water and soil quality, increase risks of wildfire and pest infestation, and contribute to crop failure and pasture loss. Droughts can severely affect crop growth and reduce yield, threatening food security. The 1930s Dust Bowl (three major waves: 1934, 1936, and 1939-1940), with its sustained deficient rainfall, high temperatures, and high winds, reduced the yield of wheat and corn by as much as 50% (NOAA 2003, Warrick 1984). The 1950s drought reached its greatest spatial extent in 1954, when crop yields in some areas dropped by as
much as 50% (NOAA 2003). The 1987-1989 drought caused estimated total losses of $39B in energy, water, ecosystems, and agriculture (Riebsame, Changnon Jr and Karl 1991) and resulted in about a 30% reduction in US corn production (Rosenzweig et al. 2001). About 80 percent of agricultural land experienced drought in 2012, making the 2012 drought the most extensive since the 1950s (USDA 2013). The 2012 drought resulted in widespread harvest failures of the corn, sorghum and soybean and caused agriculture damage up to be $30B (NOAA 2016). Such studies have chronicled total agricultural losses during individual event. However, quantifying and comparing drought losses across time and space are challenging because crop yields and productions are controlled by many factors, including scientific and technological advances (e.g., improvements in plant genetics, fertilizer, pesticides, and irrigation facilities), as well as weather and climate factors. The long-term nonlinear and non-stationary increasing trend in crop yield is mainly caused by science and technology advances. There are few studies have compared these losses across events in the long-term because of challenges associated with changing technology and other non-climatic and non-environmental influences on yield.

Moreover, despite tremendous improvements in technology and in crop yield potential, food production and food security remain highly dependent on weather and climate variability (Rosenzweig et al. 2001). The impact of an extreme weather event depends not only on the severity of the event itself, but also on the vulnerability and exposure of the human and natural systems that experience it (Lesk, Rowhani and Ramankutty 2016). Similar extreme weather could have differing effects depending on the vulnerability of the exposed system (e.g., irrigation systems and technology would mitigate such vulnerability) (Lesk et al. 2016). The historical droughts had a very large impact on
agricultural in the United States. Thus, drought monitoring, an early warning system, and water resources management are critical for agricultural production and drought risk adaptation. Effective drought quantification and monitoring can mitigate losses. The identification and quantification of drought events is difficult, since there are several definitions, such as meteorological drought, agricultural drought, hydrological drought, and socioeconomic drought (American Meteorological Society 1997; Heim 2002), and varying criteria to estimate the start and end of drought events.

In addition to measuring the current droughts, understanding how climate change might influence the future drought risks at regional scale is also of great importance to decision makers and stakeholders. Future drought impacts could be exacerbated by climate change (Mishra and Singh 2011, AMS 2013). The six-month period from January to June of 2016 set records as the planet's warmest half-year in the modern temperature record, which dates to 1880, with an average temperature 1.3 degrees Celsius (2.4 degrees Fahrenheit) warmer than the late nineteenth century. Meanwhile, five of the first six months set records for the smallest monthly Arctic sea ice extent since consistent satellite records began in 1979 (Lynch 2016). The global temperature and Arctic sea ice are continuing their decades-long trends of change (Lynch 2016). It is extremely likely that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcing together (IPCC 2013). However, the most dangerous consequence of climate change is not the change in averages but the overall increase of extreme events. Future climate changes can alter hydrometeorological patterns on local to regional scales. It is generally agreed that, with increased water vapor in the atmosphere, associated with rising
global temperature especially at lower latitudes, the global hydrological cycle intensifies and the occurrences of both droughts and floods increase in some regions (IPCC 2007). The climate change directly alters precipitation amount, intensity, frequency and type. Warming associated with climate change accelerates land surface drying and increases the potential incidence and severity of droughts; heating increases evaporation and provides adequate surface moisture to the atmosphere, leading to more intense precipitation events (IPCC 2007). The warmer climate therefore increases risks of both drought and floods.

Changes in the frequency, intensity, and duration of droughts would have significant impact on the water management, natural resources, agriculture, and aquatic ecosystems (Mishra and Singh 2009). In the context of climate change, it is important for decision makers to understand how future droughts might change on the regional scale in the future in order to develop adequate adaptation and mitigation strategies (Heinrich and Gobiet 2012). However, there is still considerable uncertainty in drought projection in the future (IPCC 2013). Understanding and modeling uncertainty in drought projection are of great importance in natural resource and water resource planning management.

This dissertation covers three important themes in agricultural drought research from drought impacts to drought quantification to drought projections. The three studies respectively aim at: (1) comparing the respective advantages and disadvantages of six trend simulation models to simulate the nonlinear trend and two decomposition models to remove the nonlinear trend from the yield time series, providing a long-term spatial visualization of drought impact on agriculture across large regions, and identifying spatial patterns of vulnerability of corn to drought in United States; (2) developing a new agriculturally-based drought index which integrates both climate information and satellite-
based observation and considers important components controlling agricultural drought: vegetation conditions, temperature, precipitation, and soil moisture; (3) investigating annual and seasonal percentage change of surface soil moisture, examining the change in duration, frequency, severity, and spatial extent of severe agricultural drought, quantifying the three sources of uncertainty due to internal variability, model uncertainty, and scenario uncertainty, and employing signal-to-noise analysis to understand how large the expected change is compared with the uncertainty in the 21st century projections under RCP2.6, RCP4.5, RCP6.0, and RCP8.5 scenarios in the framework of CMIP5.
CHAPTER 2 LITERATURE REVIEW

2.1 DROUGHT QUANTIFICATION AND MONITORING

2.1.1 Station-based drought indices

Traditionally, drought monitoring was mainly based on in-situ meteorological data obtained from weather stations.

2.1.1.1 Palmer Drought Severity Index (PDSI)

PDSI is a widely-used drought index based on the supply-and-demand concept of the water balance. Its formulation uses long term historical precipitation and temperature data, and available soil water content (Palmer 1965a). PDSI generally ranges from -6 to +6, with negative values denoting dry spells and positive values indicating wet spells. Internal “memory” in PDSI calculations, make it a relevant measure for time scales between 9 and 12 months. PDSI is considered to be useful primarily for agricultural drought and other water uses that are sensitive to soil moisture (Guttman 1998). To facilitate operational application of the PDSI, Heddinghaus and Sabol (1991) modified the rules of accumulation during wet and dry spells and created Palmer Modified Drought Index (PMDI). The PDSI and its variations, such as the Palmer Hydrologic Drought Index (PHDI), Palmer Modified Drought Index (PMDI), and Palmer Z index have been widely used for drought monitoring and water resources management decisions.
2.1.1.2 Palmer Z index

The Palmer Z index is the Z component of the PDSI computation. Palmer Z index reflects monthly departure of the moisture from normal for each month, as determined by the Palmer soil water balance model. It can be also expressed as "Moisture Anomaly Index". Palmer Z index is a short-term drought index, which can respond to a month of above-normal precipitation even during periods of drought.

2.1.1.3 Surface Water Supply index (SWSI)

The SWSI was primarily developed to monitor abnormalities in surface water supply sources. It is based on monthly non-exceedance probability from available historical records of reservoir storage, streamflow, snow pack, and precipitation (Shafer and Dezman 1982). Snowpack, streamflow, precipitation, and reservoir storage are the four inputs required to calculate SWI. During summer months, SWI is calculated only by streamflow, precipitation, and reservoir storage, while during winter month, streamflow is replaced by snowpack (Wilhite and Glantz 1985).

2.1.1.4 Standardized Precipitation Index (SPI)

The SPI was developed to quantify precipitation deficit for a desired period. The precipitation accumulations are fitted to a probability distribution which is then transformed to a normal distribution from which deviations from normal can be computed (McKee, Doesken and Kleist 1993, Edwards 1997). The SPI is comparable over both space and time. It is calculated based only on precipitation data and can be computed over any duration desired by a user. Zero values reflect the median of the precipitation distribution, -3 indicates a very extreme dry spell, and +3 indicates a very extreme wet spell.
The SPI has various advantages over the PDSI, including fewer input data requirements, a spatially invariant interpretation, and flexible time scales (Guttman 1998). Short term SPI can help detect soil moisture conditions related to agriculture drought because soil moisture responds to precipitation anomaly on a relatively short time scale. Relatively longer scale SPI can help detect ground water and reservoir storage deficits because groundwater and reservoir reflect long term precipitation anomaly. The most appropriate measures for agricultural drought are 3- and 6-month SPI values (Rouault and Richard 2003).

2.1.1.5 Standardized Precipitation Evapotranspiration Index (SPEI)

Vicente-Serrano, Begueria and Lopez-Moreno (2010) proposed the Standardized Precipitation Evapotranspiration Index (SPEI) based on precipitation and temperature data to include the effect of temperature variability on drought assessment. The SPEI combines changes in evaporative demand caused by temperature fluctuation with the simplicity of calculation and multiscalar nature of SPI (Vicente-Serrano et al. 2010). For this reason, the SPEI is particularly suited for detecting, monitoring, and exploring the consequences of global warming on drought conditions (Vicente-Serrano et al. 2010).

While the SPI is calculated using monthly (or weekly) precipitation data, the SPEI uses the monthly (or weekly) difference between precipitation and potential evapotranspiration (PET), representing a simple climatic water balance. The difference between precipitation and PET can be accumulated at different time scales following the same procedures as SPI. Since the purpose of including PET is to provide a relative temporal estimation, the use of a simple or complex method to calculate PET all provide similar results when a drought index is calculated (Mavromatis 2007, Vicente-Serrano et
al. 2010). The simplest Thornthwaite approach (Thornthwaite 1948) is used to calculate PET, which only requires monthly mean temperature. Generally, a two-parameter gamma or a three-parameter Pearson type III distribution is used to model the precipitation accumulation of different time scales (Guttman 1999, McKee et al. 1993), while the log-logistic distribution is found to be the most suitable distribution to model the precipitation minus PET values (Vicente-Serrano et al. 2010). The probabilities of precipitation minus PET values are then transformed into the quantile of a normal distribution with mean of zero and standard deviation of one by using inverse normal (Gaussian) distribution function following the method used to calculate SPI. The SPEI is particularly suitable for identifying and assessing the climate change impact on future drought risks. Vicente-Serrano et al. (2010) suggested that increase in water demand as a result of temperature increase will affect the future occurrence, intensity, and magnitude of droughts.

2.1.2 Remote sensing based drought monitoring

2.1.2.1 Normalized Difference Vegetation index (NDVI)

There existed many remote sensing drought indices, among them, the Normalized Difference Vegetation index (NDVI) is the most commonly used for ecosystem and drought monitoring. The NDVI was first proposed by Rouse Jr et al. (1974) which is the normalized reflectance difference between the near infrared (NIR) and visible red band. The chlorophyll A and B within vegetation leaf have high peak absorption at visible red radiation and spongy Mesophyll cells have an optimum reflection region in NIR wavelengths. The NDVI data are good surrogate measures of the physiologically functioning surface greenness level of a region. Greater NDVI indicate greater
photosynthetic capacity of vegetation canopy (Tucker 1979). NDVI have been widely used for drought monitoring and assessment during the last decades (Peters et al. 2002).

\[ NDVI = \frac{\rho_{\text{NIR}} - \rho_{\text{RED}}}{\rho_{\text{NIR}} + \rho_{\text{RED}}} \]

Where \( \rho_{\text{NIR}} \) and \( \rho_{\text{RED}} \) represent the spectral reflectance of near infrared band and visible red band respectively.

### 2.1.2.2 The Vegetation Condition Index (VCI)

The Vegetation Condition Index (VCI) was developed by Kogan (1995a) to scale NDVI. The interannual variations of NDVI contain both weather and ecosystem components. By linearly scaling NDVI values from zero (minimum NDVI) to 1 (maximum NDVI) for each grid cell and each week, the ecosystem component of NDVI can be separated from its weather component. The VCI can approximate the weather-related component in NDVI. This index showed excellent ability to detect and measure the time of drought onset, intensity, duration and impact on vegetation which not only for well-defined, prolonged, strong and wide-spread drought, but also for localized, short-term and ill-defined drought (Kogan 1995a, Kogan 1995b).

\[ VCI = \frac{(NDVI - NDVI_{\text{min}})}{(NDVI_{\text{max}} - NDVI_{\text{min}})} \]

Where \( NDVI_{\text{max}} \) and \( NDVI_{\text{min}} \) are the multiyear maximum and minimum NDVI respectively for each week and each pixel.

### 2.1.2.3 Temperature Condition Index (TCI)

In addition to VCI, the Temperature Condition Index (TCI) was developed to provide additional information to determine temperature-related vegetation stress (Kogan 1995b). Contrary to NDVI, high temperature indicates unfavorable or drought conditions, while low temperature indicates mostly favorable conditions.
\[ TCI = \frac{T_{\text{max}} - T}{T_{\text{max}} - T_{\text{min}}} \]

Where \( T \), \( T_{\text{max}} \), and \( T_{\text{min}} \) are the weekly temperature, its multiyear maximum, and its multiyear minimum respectively, calculated for each pixel. Temperature is derived from the thermal band.

2.1.2.4 Vegetation Health Index (VHI)

The Vegetation Health Index (VHI) combines temperature and precipitation from VCI and TCI to assess drought conditions:

\[ VHI = \alpha \cdot VCI + \beta \cdot TCI \]

Where \( \alpha \) and \( \beta \) represent different weights. Generally, \( \alpha \) is equal to 0.7 and \( \beta \) is equal to 0.3. The weights can be reexamined depending on the validation datasets. The TCI can distinguish drought and non-drought events and can monitor both drought and excessive wetness. Initially, most of NDVI, TCI and VCI drought monitoring were based on the data obtained from the Advanced Very High Resolution Radiometer (AVHRR) sensor. NDVI data calculated from AVHRR sensor is available from 1981 to present which makes time series remote sensing based drought monitoring possible.

2.1.2.5 Normalized Difference Water Index (NDWI)

Additional remote sensing based drought indices have been developed with the availability of hyperspectral remote sensing data, such as MODIS (Moderate Resolution Imaging Spectroradiometer), a key instrument aboard the Terra (EOS AM) and Aqua (EOS PM) satellites. The Normalized Difference Water Index (NDWI), derived from NIR and shortwave Infrared (SWIR) channel, is proposed by Gao (1996). The SWIR channel can reflect change of water content via absorption of water content and NIR can reflect vegetation vigor via high optimum reflection by spongy Mesophyll cells. The NDWI is
sensitive to changes in liquid water content in the vegetation canopy and is less sensitive to atmospheric aerosol scattering effects (Gao 1996). NDWI is influenced by desiccation and wilting in the vegetation canopy, that may be more sensitive than NDVI for drought monitoring, but NDWI is complementary to, not a substitute for NDVI (Gao 1996). Gu et al. (2007) found that NDWI values exhibited a quicker response to drought conditions than NDVI through a five year analysis for drought assessment over central Great plain of US.

\[
NDWI = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}}
\]

Where \(\rho_{NIR}\) and \(\rho_{SWIR}\) represent the spectral reflectance of the near infrared band and the shortwave infrared band respectively. The band channels vary with sensor. If MODIS data are used, 860 nm (band 2) will be used as NIR and 1240 nm (band 5), 1640 nm (band 6), or 2130 nm (band 7) will be used as SWIR.

2.1.2.6 Normalized Difference Drought Index (NDDI)

Based on NDVI and NDWI, Gu et al. (2007) proposed normalized difference drought index (NDDI). The NDDI has stronger response to summer drought and is a more sensitive drought indicator.

\[
NDDI = \frac{NDVI - NDWI}{NDVI + NDWI}
\]

2.1.2.7 Normalized Multi-band Drought Index (NMDI)

Based on a sensitivity study by Wang et al. (2008), the reflectance of each MODIS SWIR band responds differently to soil moisture and leaf water content variation. Thus, Wang and Qu (2007) proposed another new drought index, the Normalized Multi-band Drought Index (NMDI). NMDI used NIR band centered at 860 nm channel (band 2) as reference which is insensitive to leaf water content changes and two liquid water absorption SWIR channels centered at 1640 nm (band 6) and 2130 nm (band 7) as the soil and
vegetation moisture sensitive band. NMDI provided solutions to separate vegetation moisture and soil moisture by amplifying one signal and minimizing the other (Wang and Qu 2007).

\[ NMDI = \frac{\rho_{860nm} - (\rho_{1640nm} - \rho_{2130nm})}{\rho_{860nm} + (\rho_{1640nm} + \rho_{2130nm})} \]

Where \( \rho_{860nm} \), \( \rho_{1640nm} \), and \( \rho_{2130nm} \) represent the spectral reflectance of a satellite sensor centered at 860nm, 1640nm, and 2130nm respectively. Strong differences between \( \rho_{1640nm} \) and \( \rho_{2130nm} \) absorption bands in response to soil and leaf water content give this combination potential to monitor water content for both soil and vegetation.

2.1.2.8 Scaled Drought Condition Index (SDCI)

Most recently, Rhee, Im and Carbone (2010) has proposed a new remote sensing drought index, the Scaled Drought Condition Index (SDCI), for monitoring agricultural drought in both arid and humid regions. This index combines three standardized scaled remote sensing variables, the land surface temperature (LST) data, NDVI data from MODIS sensors, and precipitation data from Tropical Rainfall Measuring Mission (TRMM) satellite. This study has proved that SDCI performed better than existing indices such as NDVI and Vegetation Health Index (VHI) in both arid and humid regions through validation against in-situ PDSI, Z-index, and SPI of different time scales and United States Drought Monitor (USDM) maps (Rhee et al. 2010).

\[ SDCI = \frac{1}{4} \times scaled\ LST + \frac{2}{4} \times scaled\ TRMM + \frac{1}{4} \times scaled\ NDVI \]

2.1.2.9 Microwave Integrated Drought Index (MIDI)

Zhang and Jia (2013) proposed a new multi-sensor microwave remote sensing drought index, the Microwave Integrated Drought Index (MIDI), for monitoring short-term drought, especially meteorological drought over semi-arid regions. This index combines
three variables, Tropical Rainfall Measuring Mission (TRMM) derived precipitation, Advanced Microwave Scanning Radiometer for EOS (AMSR-E) derived soil moisture (SM), and AMSR-E derived land surface temperature (LST) and linearly scales each variable from 0 to 1 for each pixel based on absolute minimum and maximum value over time.

\[ MIDI = \alpha \times \text{scaled TRMM} + \beta \times \text{scaled SM} + (1 - \alpha - \beta) \times \text{scaled LST} \]

Each variable is linearly scaled from 0 to 1 for each pixel based on the absolute minimum and maximum values over time. The MIDI used weights of 0.5, 0.3, and 0.2 for scaled TRMM, scaled SM, and scaled LST respectively were recommended to be an optimum microwave remote sensing drought index in monitoring short-term drought, especially for meteorological drought after testing several sets of weights against in-situ drought index (Zhang and Jia 2013).

2.2 NATIONAL WIDE DROUGHT MONITORING SYSTEM

The United States has invested considerable effort on drought monitoring, producing several national wide monitoring systems.

Table 2.1 Drought monitoring system in the United States

<table>
<thead>
<tr>
<th></th>
<th>Time span</th>
<th>Temporal Resolution</th>
<th>Data</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>United States</td>
<td>Jan., 2000-</td>
<td>Weekly</td>
<td>Climatic, hydrologic and soil conditions as well as reported impacts and observations from more than 350 contributors</td>
<td>The U.S. Drought Monitor is the most widely used drought monitoring reference. USDM is jointly produced by the National Drought Mitigation Center at the University of Nebraska-Lincoln, the United States Department of Agriculture, and the National Oceanic and Atmospheric Administration. The U.S. Drought</td>
<td><a href="http://droughtmonitor.unl.edu">http://droughtmonitor.unl.edu</a></td>
</tr>
<tr>
<td>States Drought Monitor</td>
<td>present</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vegetation Drought Response Index (Brown et al. 2008)</td>
<td>May, 2007-present</td>
<td>Bi-weekly</td>
<td>Remote sensing - typically via satellites, radar or aerial photography, mainly based on NOAA's AVHRR satellite instrument, as well as climate data (PDSI, SPI, etc.), and other biophysical information such as land cover/land use type, soil characteristics, and ecological setting</td>
<td>VegDRI are produced by the National Drought Mitigation Center (NDMC) in collaboration with the US Geological Survey's (USGS) Center for Earth Resources Observation and Science (EROS), and the High Plains Regional Climate Center (HPRCC). VegDRI maps are produced every two weeks and provide regional to sub-county scale information about drought's effects on vegetation. The VegDRI maps deliver continuous geographic coverage over large areas, and have inherently finer spatial resolution about 1-km² resolution than other commonly available drought indicators such as the U.S. Drought Monitor.</td>
<td><a href="http://v">http://v</a> egdri.u nl.edu/</td>
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<td>------------------------------------------------------------------------------</td>
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</tr>
<tr>
<td>STAR - Global Vegetation Health Products</td>
<td>Jan., 2005-present</td>
<td>Weekly</td>
<td>AVHRR satellite data</td>
<td>Global and Regional Vegetation Health (VH) products is a NOAA/NESDIS system estimating vegetation conditions, health and the related products. This product contains several Vegetation Health Indices (VHI) derived from the radiance observed by the Advanced Very High Resolution Radiometer (AVHRR) onboard the NOAA-7, 9, 11, 14, 16 and 18 afternoon polar-orbiting satellites. The VH products can be</td>
<td>http:// <a href="http://www.s">www.s</a> tar.nes dis.noa a.gov/smcd/e mb/vci /VH/in dex.ph p</td>
</tr>
<tr>
<td>Service</td>
<td>Frequency</td>
<td>Source</td>
<td>Details</td>
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<td></td>
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<tr>
<td>The Evaporative Stress Index (ESI)</td>
<td>Weekly</td>
<td>Geostationary Operational</td>
<td>The Evaporative Stress Index (ESI) describes temporal anomalies in evapotranspiration (ET), highlighting areas with anomalously high or low rates of water use across the land surface. Here, ET is retrieved via energy balance using remotely sensed land-surface temperature (LST) time-change signals. LST is a fast-response variable, providing proxy information regarding rapidly evolving surface soil moisture and crop stress conditions at relatively high spatial resolution. The ESI also demonstrates capability for capturing early signals of “flash drought”, brought on by extended periods of hot, dry and windy conditions leading to rapid soil moisture depletion.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>National Weather Service Precipitation</td>
<td>Daily</td>
<td>Radar and rain gauges</td>
<td>NWS Precipitation Analysis combines information from radar and rain gauges to produce maps of estimated rainfall totals. Checkboxes below the map allow you to tailor your view and to choose time periods back to 2005. Maps can show actual precipitation totals, normal, departure from normal, and percent of normal precipitation. They can show either the continental U.S. and Puerto Rico or one state at a time for different time periods back to 2005. Layers, such as topography,</td>
<td></td>
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<tr>
<td>Service Analysis Web service</td>
<td></td>
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<td><a href="http://water.weather.gov/precip/">http://water.weather.gov/precip/</a></td>
<td></td>
</tr>
<tr>
<td>2005-present</td>
<td></td>
<td></td>
<td>used as proxy data for monitoring vegetation health, drought, soil saturation, moisture and thermal conditions, fire risk, greenness of vegetation cover, vegetation fraction, leaf area index, start/end of the growing season, crop and pasture productivity, etc.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
population, counties, rivers, states, and highways can be turned off and on. Users can download precipitation data and shape files. There are also useful links to weather forecasts, drought and snow information. The precipitation pages are updated every day, around 9:30 a.m., 12:30 p.m. and 4:30 p.m. Eastern Standard Time.

| Groundwater and Soil Moisture Conditions from GRACE Data Assimilation (Houborg et al. 2012, Zaitchik, Rodell and Reichle 2008) | Monthly | NASA's Gravity Recovery and Climate Experiment (GRACE) satellites and integrated with other observations | Scientists at NASA’s Goddard Space Flight Center generate groundwater and soil moisture drought indicators each week. They are based on terrestrial water storage observations derived from GRACE satellite data and integrated with other observations, using a sophisticated numerical model of land surface water and energy processes. The drought indicators describe current wet or dry conditions, expressed as a percentile showing the probability of occurrence within the period of record from 1948 to the present, with lower values (warm colors) meaning dryer than normal, and higher values (blues) meaning wetter than normal. These are provided as both images and binary data files. | http://drought.unl.edu/monitoring_tools/NASA_GRACE_Data_Assimilation.aspx |

2.3 CLIMATE CHANGE IMPACT ON FUTURE DROUGHT RISKS

During recent years, researchers have used General Circulation Model (GCM) and Regional Climate Model (RCM) output to investigate potential changes impact on the frequency, duration, and intensity of drought.

SPI is the most commonly used index because it requires fewer inputs and can be interpreted similarly across space. Loukas, Vasiliades and Tzabiras (2008), Mishra and
Singh (2009), and Vidal and Wade (2009) used SPI and all found that drought severity and drought extent increases under the emission scenarios that they used.

Projected drought changes depend on which index is used. For example, Dubrovsky et al. (2009) found that SPI changes indicate decreased drought risk in summer and increased risk in both winter and spring. By contrast, PDSI changes indicate an increased drought risk at all stations for all seasons and for all climate change scenarios. This study showed that PDSI is more appropriate than SPI to assess the potential impact of climate change on future droughts, because drought depends on both precipitation and temperature.

Some other drought indices have also been employed to investigate the climate change impact on drought due to different applications, such as Standardized Runoff Index (SRI) (Jung and Chang 2012), Precipitation Index Percent of Normal (PNPI) and Agricultural Rainfall Index (ARI) (Sayari et al. 2013).

Several new variants of drought indices or new applications have been proposed to make the drought index more appropriate for climate change impact on drought risk analysis. Dubrovsky et al. (2009) introduced the concept of relative SPI and PDSI (rSPI and rPDSI). The rSPI and rPDSI relate either to a different station allowing for inter-station comparison or to a different period allowing for period comparison (e.g. climate change impact assessment). Russo et al. (2013) proposed a nonstationary SPI, which is similar to rSPI, but uses a nonstationary Gamma distribution. It can model the entire time series without splitting the data into shorter periods. Mishra and Singh (2009) combined SPI of different time scales and severity-area-frequency (SAF) curves together. This methodology can help us investigate and visualize climate change impact on all three characteristics of drought (severity, spatial extent, and return period) at the same time.
CHAPTER 3 DETRENDING CROP YIELD DATA FOR SPATIAL VISUALIZATION OF DROUGHT IMPACTS IN THE UNITED STATES, 1895-2014

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3.1 ABSTRACT

Historical drought events have had severe impacts on United States agriculture, but attempts to quantify and compare these impacts across space and time have been challenging because of the nonlinear and non-stationary nature of the crop yield time series. Here, we address this challenge using long-term state- and county-level corn yield data from 1895 to 2014. We apply and compare six trend simulation models – simple linear regression, second order polynomial regression, centered moving average, locally weighted regression, spline smoothing, and empirical mode decomposition – to simulate the nonlinear trend, and two decomposition models – an additive decomposition model and a multiplicative decomposition model – to remove the nonlinear trend from the yield time series. Our comparison of each method evaluates their respective advantages and disadvantages with respect to applicability across time and space, efficiency, and robustness. We find that a locally weighted regression model, coupled with a multiplicative decomposition model, is the most appropriate data self-adaptive detrending method. Detrended crop yield minus one represents the percentage lower or higher than normal yield conditions, termed “crop yield anomaly”. We then apply this detrending method and perform Pearson correlation analysis to show the quantitative relationship between state-level corn yield anomalies and multiple drought indices. We find that the 3-month Standardized Precipitation Index (SPI) in August and Palmer Z-index in July correlate most closely with corn yield anomalies. This correlation is higher east of the 100° W meridian, where irrigation is not as extensively used. Finally, we show how the detrending process allows spatial visualization of drought impact on corn yield in US using gridded August 3-month SPI values with examples from six major droughts on corn yields. Our focus on
comparing detrending methods produces a methodology that can aid analysis of agricultural yield for both empirical and modeling studies connecting environmental and climate conditions to crop productivity.

Keywords: Detrending method; Crop yield anomaly; Locally weighted regression model; Drought index; Gridded Standardized Precipitation Index

3.2 INTRODUCTION

Drought is a devastating, recurring, and widespread natural hazard that affects natural habitats, ecosystems, and economic and social sectors, such as agriculture, transportation, industry, and urban water supply (Heim 2002). The magnitude of drought impacts depends on various factors, including timing, duration, and severity, as well as a region’s vulnerability, sensitivity, and adaptive capacity (Wheaton et al. 2008), which makes quantification of overall drought impacts difficult. Within the agricultural sector, droughts reduce soil-water availability, affect water and soil quality, increase risks of wildfire and pest infestation, and contribute to crop failures and pasture losses. Droughts can severely affect crop growth and reduce yield, threatening our food security. Despite tremendous improvements in technology and in crop yield potential, food production and food security remain highly dependent on weather and climate variation (Rosenzweig et al. 2001).

Droughts have had large economic impacts on US agriculture. From 1980 to 2014 alone, CPI (Consumer Price Index) - adjusted drought losses are estimated at $206B (NOAA 2016). The 1930s Dust Bowl (three major waves: 1934, 1936, and 1939-1940), with its sustained deficient rainfall, high temperatures, and high winds, reduced the yield
of wheat and corn by as much as 50% (NOAA 2003, Warrick 1984). The 1950s drought reached its greatest spatial extent in 1954, when crop yields in some areas dropped as much as 50% (NOAA 2003). The 1987-1989 drought caused estimated total losses of $39B in energy, water, ecosystems, and agriculture (Riebsame et al. 1991) and resulted in about a 30% reduction in US corn production (Rosenzweig et al. 2001). About 80 percent of agricultural land experienced drought in 2012, making the 2012 drought the most extensive since the 1950s (USDA 2013). The 2012 drought resulted in widespread harvest failures of the corn, sorghum and soybean and caused agriculture damage up to be $30B (NOAA 2016). Such studies have chronicled total agricultural losses during individual event. However, few studies have compared these losses across events because of challenges associated with changing technology and other non-climatic influences on yield.

The impact of an extreme weather event on agriculture depends not only on the severity of the event itself, but also on the time of the event and the vulnerability of the natural systems that experience it (Lesk et al. 2016, van der Velde et al. 2012, IPCC 2012). Similar extreme weather could have differing outcomes depending on the crop development stages and the vulnerability of the exposed system (e.g., irrigation and technology would mitigate such vulnerability to drought) (Lesk et al. 2016, van der Velde et al. 2012). Thus, identifying the spatiotemporal variation of the drought impacts on agriculture and constructing a quantitative relationship between drought and agriculture losses could provide policy makers and stakeholders with scientific information regarding which agricultural areas are most vulnerable and sensitive to drought.
Figure 3.1 Corn yield time series from 1895 to 2014 in Arizona, Iowa, Nebraska, South Carolina, and Texas (Units: kg/ha) (Corn yield data were obtained from USDA’s National Agricultural Statistics Service; corn yields are calculated from corn production for grain divided by corn area harvested for grain.)

Quantifying and comparing drought losses across time and space are challenging because crop yields and productions are controlled by many factors, including scientific and technological advances (e.g., improvements in plant genetics, fertilizer, pesticides, and irrigation facilities), as well as weather and climate factors. The overall trend is of increasing yield, mainly caused by technological advances; the high-frequency fluctuations are mainly caused by weather and climate factors (Figure 3.1). All of these factors make long-term crop yield data inherently nonlinear and non-stationary (varying mean and standard deviation) (Figure 3.1). This renders comparison and spatial visualization of drought impact on agriculture difficult. For example, the 1950s droughts (peaking in 1954) and the 2012 drought are two historical major events. It is difficult to quantitatively extract and compare the impacts of these two droughts on agriculture merely from the original
crop yield maps because of yield differences caused by technological advances and spatial patterns of agricultural production (Figure 3.2). Modeling and spatial visualization of drought impacts on agriculture require appropriate distinctions between the high frequency fluctuations caused by the climate variability and the long-term trend caused by technological factors. This study explores and introduces a process of identifying the long-term trend, appropriately detrending yield data, and separating out a meaningful climate effect on crop yield.

Figure 3.2 Spatial visualization and comparison of original corn yield in 1954 and 2012 (Units: kg/ha)

Detrending technology statistically removes the long-term mean changes from the time series. The trend should be removed before other basic applications are implemented, such as computing the correlation function (Wu et al. 2007). Most previous studies detrended crop yield using a specific predetermined function, such as a simple linear regression model or a second order polynomial regression model against time. For example, Quiring and Papakryiakou (2003) applied a simple linear regression model to detrend wheat yield data; the resulting residuals were used to determine the most appropriate drought indices for measuring agricultural drought in the Canadian prairies. Trnka et al. (2007) applied a second order polynomial regression model to detrend yield data to

However, the simple linear regression model and second order polynomial regression model used in previous studies are not suitable to detrend long-term crop yield in this study. Such predetermined functions cannot accommodate nonlinearity seen in the crop yield time series, as illustrated by data from five select states (Figure 3.1). Additionally, the detrending process must be done across space, involving yield data for dozens of states and thousands of counties. Predetermined functions also lack sufficient flexibility and capability to remove many different nonlinear trends from the data, because trends vary across space (Figure 3.1). Furthermore, potential future climate changes in mean and variability, combined with technological changes, could introduce additional nonlinearity and non-stationarity to crop yield data in the long-term. Thus, a data self-adaptive detrending method that can automatically follow the underlying pattern of the nonlinear crop yield time series is needed.

This study compares six trend simulation methods and two decomposition models, and evaluates their respective advantages and disadvantages with respect to applicability across time and space, efficiency, and robustness. We explore an appropriate data self-
adaptive detrending approach that can automatically simulate the long-term nonlinear and non-stationary yield trend caused mainly by technology advances and thus remove the trend to isolate interannual fluctuations caused mainly by weather and climate factors. By applying this approach to detrend and standardize the corn yield data, we construct a quantitative relationship between drought and agriculture losses and compare drought impacts on corn yield across time and space through spatial visualization from 1895 to 2014 by highlighting six major historical drought events.

3.3 DATA SOURCE AND METHODOLOGY

3.3.1 Agriculture data

Long-term agriculture statistics were obtained from USDA’s National Agricultural Statistics Service (NASS), which maintains a comprehensive databases of land use, farm income, crop production and yield, livestock, and commodity prices at national, regional, state, and county levels (USDA 2014). Since the mid-1950’s, NASS estimates have been derived from area frame surveys which identify cultivated areas from remotely-sensed imagery, followed by stratified sampling in random field locations. This method is complemented by farmer interviews within regions of highest cultivation. NASS collects information from several sources, of which the sample surveys are the most important. Further detail on sampling methods and uncertainty analysis is available elsewhere (Davies 2009, Prince et al. 2001, USDA 1983, USDA 1999, USDA 2006, USDA 2012, USDA 2016). We examined corn yield because corn is the most widely produced crop in United States. We compared detrending methods and demonstrated spatial visualizations of
drought impacts on corn yield from 1895 to 2014 for 48 states and 2398 out of 3108 counties with at least 30-year corn yield data across the conterminous United States.

3.3.2 In-situ drought indices

State-level drought indices—including the monthly Palmer Drought Severity Index (PDSI), Palmer Hydrological Drought Index (PHDI), Palmer Z-index, Modified Palmer Drought Severity Index (PMDI), 1-month SPI (Standardized Precipitation Index), 2-month SPI, 3-month SPI, 6-month SPI, 9-month SPI, 12-month SPI, and 24-month SPI—from 1895 to 2015 were obtained from NOAA’s National Centers for Environmental Information (ftp://ftp.ncdc.noaa.gov/). NCEI employs a climatologically-aided interpolation method to interpolate station data to composite grids; climate divisional and state values were computed as the area-weighted average of the composite gridpoints (Vose et al. 2014).

PDSI was developed by Palmer (1965a), which is based on the supply-and-demand concept of the water balance equation by using precipitation, temperature and available water content (AWC) of the soil. Its variations include the Palmer Z index (Palmer 1965a), which measures short-term departure of moisture from normal; PHDI (Palmer 1965a), which is used for water supply monitoring; and PMDI (Heddinghaus and Sabol 1991), which is designed for real time operational purposes. The categories of drought intensity for PDSI, PHDI and PMDI are: 0 to -0.49 (near normal), -0.50 to -0.99 (incipient drought), -1.00 to -1.99 (mild drought), -2.00 to -2.99 (moderate drought), -3.00 to -3.99 (severe drought), and ≤ -4.00 (extreme drought). The categories of drought intensity for Palmer Z index are: 0 to -1.24 (near normal), -1.25 to -1.99 (mild to moderate drought), -2.00 to -2.74 (severe drought), and ≤ -2.75 (extreme drought). SPI was developed by McKee et al.
(1993) to quantify precipitation deficit for different time scales. More information about drought indices can be found in the reviews of Heim (2002), Mishra and Singh (2010), and WMO and GWP (2016).

We calculated 4-km gridded SPI values across the conterminous United States using 4-km PRISM (Parameter-elevation Relationships on Independent Slopes Model) precipitation data set (Daly et al. 2008) from 1895 to 2014 for the spatial visualization purpose in section 3.4. SPI values were computed following the method of McKee et al. (1993). For each pixel, monthly precipitations can be accumulated into different time scales (e.g. 1-month, 2-month, 3-month, 6-month, 9-month, 12-month, and 24-month). For zero precipitation accumulation, the probability was computed using the frequency of zero precipitation accumulation. For non-zero precipitation accumulation, a two-parameter gamma distribution was fitted by using the maximum likelihood estimation (MLE) method. Then, the probability of zero and non-zero precipitation accumulation together was transformed into the quantile of a normal distribution with mean of zero and standard deviation of one by using inverse normal (Gaussian) distribution function. The resulting value is SPI. The different time scales for SPI are computed to address various types of drought: the shorter time scales are appropriate for meteorological drought and agricultural drought, the longer time scales are for hydrological drought (Heim 2002, McKee et al. 1993). McKee et al. (1993) has defined drought intensities for values of the SPI into four categories: 0 to -0.99 (mild drought), -1.00 to -1.49 (moderate drought), -1.50 to -1.99 (severe drought), and ≤ -2.00 (extreme drought).
3.3.3 Detrending method

We compared six different detrending methods for removing the increasing trend from corn yield. The first step of detrending is to simulate the trend inherent in the data. The trend simulation methods included a simple linear regression model, a second order polynomial regression model, a moving average model, a locally weighted regression model (LOWESS), a smoothing spline model, and an empirical mode decomposition model (EMD). After trend simulation, we applied and compared two decomposition models to detrend the data. These methods were applied separately for each state and each county. All data processing and spatial visualization used the R programming language and its related packages.

3.3.3.1 Trend simulation method

3.3.3.1.1 Simple linear regression model

A simple linear regression model is the simplest and most commonly used statistical method to identify a linear trend. By visual inspection, if the trend is linear, a simple linear regression fitting would be sufficient to simulate the trend. The resulting trend is a straight line fitted to the data. Simple linear regression model can be fitted against time using the method of least squares.

\[ Y_t = \beta_0 + \beta_1 t \]

Where \( Y_t \) is the crop yield at time \( t \); time \( t \) is the predictor; and \( \beta_0 \) and \( \beta_1 \) are the coefficients.

3.3.3.1.2 Second order polynomial regression model

A second order polynomial regression model is also commonly used in trend simulation (Trnka et al. 2007, Goldblum 2009, Hlavinka et al. 2009). A second order
polynomial regression model is appropriate if a quadratic trend present in the crop yield time series. This model accounts for the positive trend in annual crop yield that occurs because of increasing fertilization, plant genetics, and technological innovation and then declines because of economic transformation in the farming sector (Hlavinka et al. 2009, Chloupek, Hrstkova and Schweigert 2004). A second order polynomial regression model can be fitted against time using the method of least square.

\[ Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 \]

Where \( Y_t \) is the crop yield at time \( t \); time \( t \) is the predictor; and \( \beta_0, \beta_1, \text{and} \beta_2 \) are the coefficients.

3.3.3.1.3 Moving average model

Moving average models can be used to smooth the irregular roughness and high-frequency variation to identify overall pattern and trend in a time series. The moving average model is data self-adaptive. Unlike linear regression models, moving average models do not provide a specific model, but they detect local trends that simple linear regression models cannot. There are two simple kinds of moving average models: backward moving average (BMA) models, wherein all values for previous years are averaged for specific time spans, and centered moving average (CMA) models, wherein the values are averaged both before and after the current time. BMA models introduce an artificial time shift between the original data and the moving average (Bashan et al. 2008). CMA models are preferred because they eliminate this artificial effect. As the time span of moving average increases, the trend becomes smoother. Here, CMAs at time spans of 5 years, 10 years, 15 years, and 20 years are calculated to identify the trend. Formulas for each time span are as follows:
5 years: \( mY_t = \frac{1}{5} Y_{t-2} + \frac{1}{5} Y_{t-1} + \frac{1}{5} Y_t + \frac{1}{5} Y_{t+1} + \frac{1}{5} Y_{t+2} \)

10 years: \( mY_t = \frac{1}{20} Y_{t-5} + \sum_{j=-10}^{4} \frac{1}{10} Y_{t+j} + \frac{1}{20} Y_{t+5} \)

15 years: \( mY_t = \sum_{j=-15}^{7} \frac{1}{15} Y_{t+j} \)

20 years: \( mY_t = \frac{1}{40} Y_{t-10} + \sum_{j=-10}^{9} \frac{1}{20} Y_{t+j} + \frac{1}{40} Y_{t+10} \)

Where \( Y_t \) is the original crop yield at time \( t \); and \( mY_t \) is the moving averaged crop yield at time \( t \).

3.3.3.1.4 Locally weighted regression model

The locally weighted regression model (LOWESS) is a widely used non-parametric regression smoothing and memory-based method proposed by Cleveland (1979) and further developed by Cleveland and Devlin (1988). LOWESS involves a regression model based on a weighted least squares method that uses a local point of interest and assigns more weights to neighboring points near the point of interest and less weights to points farther away. The regression model can be linear or polynomial. Locally quadratic fitting performs better when the regression surface has substantial curvature (Cleveland and Devlin 1988). LOWESS requires a weight function and fraction of points in the neighborhood (\( f \)) parameter (neighborhood size). Here, the weight function is a tri-cube weight function, and the weight for any specific point in the neighborhood is determined by the distance between that point and the point of interest.

Here, we use locally weighted quadratic fitting. In this procedure, we let \( 0 < f \leq 1 \) and let \( r \) be \( fn \) rounded to the nearest integer (\( n \) is total data points). The integer \( r \) is the number of points used to estimate the point of interest \( t_i \). Let \( d_{max} \) be the time difference between \( t_i \)
and the $r$th nearest neighbor. For each $t_i$, the weight function $W$ are defined for all $t_k$ ($k = 1, \ldots, n$) as follows

$$w_{t_k}(t_i) = \begin{cases} 1 - \left| \frac{t_k - t_i}{d_{\text{max}}} \right|^3 & \text{for} \ |t_k - t_i| \leq d_{\text{max}} \\ 0 & \text{otherwise} \end{cases}$$

For each $t_i$, the estimates $\hat{\beta}_0(t_i)$, $\hat{\beta}_1(t_i)$, and $\hat{\beta}_2(t_i)$ of $\beta_0(t_i)$, $\beta_1(t_i)$, and $\beta_2(t_i)$ are fitted by method of weighted least squares with weight function $W$ to minimize

$$\sum_{k=1}^{n} w_{t_k}(t_i)(Y_{t_k} - \beta_0(t_i) - \beta_1(t_i)t_k - \beta_2(t_i)t_k^2)^2$$

Thus, the fitted value $\hat{Y}_{t_i}$ at time $t_i$ using locally weighted quadratic fitting is

$$\hat{Y}_{t_i} = \hat{\beta}_0(t_i) + \hat{\beta}_1(t_i)t_i + \hat{\beta}_2(t_i)t_i^2$$

As the fraction of points in the neighborhood ($f$) increases, more points will be included in the regression of the point of interest and the regression will become more global. More detailed information about LOWESS can be found in Cleveland (1979) and Cleveland and Devlin (1988). Setting the parameter $f$ is a critical issue in LOWESS. Cross validation provides an appropriate method to determine the optimum parameter $f$. In this study, $f$ was determined by the $k$-fold cross validation method, which is a data self-adaptive automatic method (Stone 1974). The original sample data are randomly partitioned into $k$ mutually disjoint equal-sized groups. Each time, one group is left out for validation and the remaining $k-1$ groups are used as training data for prediction. With $k$ iterations, all sample data are used for both training and validation and each group is used once as validation data. The averaged prediction error (mean absolute error) of $k$ times is used for cross-validation statistics. The parameter $f$ with the minimum averaged prediction error is used as the optimum parameter. The R function “crossval” in the R package “bootstrap” was
used for cross-validation implementation for LOWESS method (Efron and Tibshirani 1993).

3.3.3.1.5 Smoothing spline model

Spline functions have been applied extensively for interpolation. A k-th order spline is a piecewise continuous polynomial function of degree k and has continuous derivatives of order 1, 2, … and k-1, at its knot points. Splines are superior to polynomials for approximating disjointed or episodic functions, where ordinary polynomials are inadequate (Cook and Peters 1981). Reinsch (1967) developed an algorithm for spline smoothing to extract the underlying function from unwanted experimental noise. Spline smoothing uses a penalized least squares criterion to control for overfitting by shrinking the effect of the standard sum-of-square functions for a regression spline and adding the roughness “penalty” regularization function (differentiable function) (Eubank 1988).

Cubic smoothing spline model is the most commonly used method and will be used in this study. Let $Y_i$ be crop yield at time $t_i$, modeled by function $Y_i = f(t_i) \ (i = 1, 2, \ldots, n)$. The smoothing spline estimate $\hat{f}$ of the function $f$ is defined to minimize

$$\sum_{i=1}^{n} (Y_i - f(t_i))^2 + \lambda \int_{t_1}^{t_n} (f''(t))^2 \, dt$$

The smoothing parameter $\lambda$ is a tuning parameter governing the trade-off between the goodness of fit and smoothness of the curve. As $\lambda$ approaches zero, the smoothing spline emphasizes goodness of fit and the curve converges to the traditional interpolation spline passing through each of the data points. As $\lambda$ approaches positive infinity, the smoothing spline emphasizes smoothness and the curve converges to a straight line of ordinary linear regression (Eubank 1988). The most important issue for spline smoothing
is to find an objective criterion for choosing the optimum value of the smoothing parameter $\lambda$. Wahba and Craven (1978) proposed the generalized cross validation (GCV) method for spline smoothing; it is the method currently recognized as optimal for parameter selection.

### 3.3.3.1.6 Empirical mode decomposition model

Huang et al. (1998) have developed an empirical mode decomposition (EMD) method for analyzing nonlinear and non-stationary data. The method decomposes a complicated data set into different “intrinsic mode functions” (IMF) based on the local characteristic time scale of the data. The method is intuitive, direct, and adaptive (Huang et al. 1998). An intrinsic mode function satisfies two conditions: (1) in the whole data set, the number of extrema and the number of zero crossings must be either equal or differ at most by one; (2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero (Huang et al. 1998). The IMFs represent the oscillation mode imbedded in the data and are extracted systematically in a sifting process. The sifting process identifies the local maxima and minima to extract from the highest-frequency oscillation to lowest-frequency oscillation systematically until the residual component becomes a constant, a monotonic function where no more complete IMF can be identified, or the residue becomes so small that it is less than the predetermined value of substantial consequence (Huang et al. 1998, Wu et al. 2007). Finally, a data set will be decomposed approximately into $\log_2 n$ IMFs, with $n$ being the number of data points (Wu et al. 2007) and the decompose equation is as follows:

$$Y(t) = \sum_{j=1}^{m} c_j + r_m$$

Where $m$ is the total number of IMFs; $c_j$ is the $j$th IMF; and $r_m$ is the residual component.
More detailed information about EMD method can be found in Huang et al. (1998), Huang et al. (2003) and Wu and Huang (2004).

3.3.3.2 Decomposition model

After simulating the trend by appropriate statistical models, a decomposition model is applied to remove the simulated trend and obtain the detrended data. There are two methods to do this:

The simplest method is an additive decomposition model. Generally, the composition of fluctuations and trend is assumed to be additive. The detrended data result from subtracting the values of the trend line from the original data, creating a time series of residuals. The unit of the residuals is the same as the original data. An additive decomposition model is appropriate when the variation is relatively constant over time.

Another method is a multiplicative decomposition model, wherein the detrended data result from computing the ratio of the original data to the values of the trend line. The detrended data are dimensionless and indicate percentage differences compared to the values of the trend line. A multiplicative decomposition model is appropriate when the variation is not constant through time. The multiplicative decomposition model can remove the variance associated with the trend.

3.3.4 Quantitative measures of trend fitting

Six basic quantitative measures of trend fitting were used in this study: root mean square error (RMSE), mean absolute error (MAE), coefficient of efficiency (E), index of agreement (d), modified coefficient of efficiency (E1), and modified index of agreement (d1).
Root mean square error (RMSE) and mean absolute error (MAE) have been widely used as standard statistical metrics to measure model performance. Nash and Sutcliffe (1970) defined the coefficient of efficiency (E) as the proportion of the initial variance accounted for by a model. It ranges from minus infinity to 1.0 with higher values indicating better agreement. Willmott (1981) proposed the index of agreement (d) to represent 1 minus the ratio between the sum of squared errors (SSE) and the “potential error” (PE). It ranges from 0.0 to 1.0 with higher values indicating better agreement between the model and observation. Both d and E represent an improvement over the widely used coefficient of determination (R^2). R^2 describes the degree of collinearity between the observed and simulated values, but this measure is limited by its insensitivity to additive and proportional differences between observations and model simulations (Willmott 1981, Legates and McCabe 1999, Legates and Davis 1997). Both d and E can detect differences in the observed and model simulated means and variances.

Further, Willmott (1984) and Legates and McCabe (1999) argued that both d and E are sensitive to outliers because errors and differences are inflated when their values are squared. Based on original d and E, Willmott et al. (1985) and Legates and McCabe (1999) proposed a more generic form of d and E and advocated the use of the modified index of agreement (d_1) and the modified coefficient of efficiency (E_1). The advantage of d_1 and E_1 is that the errors and differences are given appropriate weighting, not inflated by their squared values (Legates and McCabe 1999).
Table 3.1 Equation of quantitative measures of trend fitting

<table>
<thead>
<tr>
<th>Equation</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Root Mean Square Error $RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$</td>
<td>Mean Absolute Error (MAE) $MAE = \frac{1}{n} \sum_{i=1}^{n}</td>
</tr>
<tr>
<td>(RMSE)</td>
<td>Error (MAE)</td>
</tr>
<tr>
<td>Coefficient of Efficiency $E = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}<em>i)^2}{\sum</em>{i=1}^{n} (y_i - \bar{y})^2}$</td>
<td>Modified Coefficient of Efficiency $E_1 = 1 - \frac{\sum_{i=1}^{n}</td>
</tr>
<tr>
<td>(E)</td>
<td>(E₁)</td>
</tr>
<tr>
<td>Index of Agreement $d = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}<em>i)^2}{\sum</em>{i=1}^{n} (</td>
<td>\hat{y}_i - \bar{y}</td>
</tr>
<tr>
<td>(d)</td>
<td>(d₁)</td>
</tr>
</tbody>
</table>

Where $y_i$ represents the i-th observed value; $\hat{y}_i$ represents the i-th model simulated value; $\bar{y}$ represents the observation mean for the entire period.

3.4 RESULTS

3.4.1 Detrending methods comparison

3.4.1.1 Trend simulation methods comparison

Figure 3.3 shows the corn yield time series from 1895 to 2014 in Illinois and South Carolina, as well as the trend simulation results by six models. Both the corn yield time series in Illinois and South Carolina show a prominent nonlinear increasing trend dominates the long-term crop yield time series. The trend is largely due to technological
development and increasing inputs, and is most pronounced after 1950. The series also show high-frequency variation, largely due to weather-related factors, that increases with time. In order to isolate the interannual variability, it is necessary to remove the technology trend from the time series to standardize crop yield.

Because the technology trend is nonlinear, a simple linear regression model does not explain the change of corn yield in Illinois (Figure 3.3-1(a)) and South Carolina (Figure 3.3-2(a)) well and is not logical or reasonable for detrending long-term crop yield data. A quadratic trend improves the relationship in Illinois (Figure 3.3-1(b)), but it still cannot capture the slowly increasing trend from 1895 to 1960 in South Carolina (Figure 3.3-2(b)). A second order polynomial regression model fit the trend well for several states (e.g., Idaho, Illinois, Maryland, Michigan, and Minnesota), but not in many others. These pre-selected models lack sufficient flexibility to remove the non-stationary and nonlinear trend for all states and all counties.

Visual inspection of corn yield suggests that a 20-year CMA model is necessary to smooth the irregularities in the time series (Figure 3.3-1(c) and Figure 3.3-2(c)). A moving average model requires a predetermined time span to do the moving average operation. However, the determination and the choice of time span for a moving average model is subjective. In addition, a boundary problem arises when using the CMA model. A 20-year CMA model requires 10-years of data before and after the year of interest. As the data point moves to the earliest or latest years, the first 10 and last 10 data points, respectively, lack enough data to be estimated and are assigned as missing values (Figure 3.3-1(c) and Figure 3.3-2(c)). Furthermore, one missing value occurring in the time series can cause 20 additional data points to be assigned as missing values for the moving average trend curve.
But, even if no missing values exist in the time series, a 20-year CMA still sacrifice 20 data points at the earliest and latest data points of the time series. The centered moving average model is of no use or biased near the boundary of the time series.

Figure 3.3 Trend simulation methods comparison: (a) simple linear regression model; (b) second order polynomial model; (c) centered moving average model of 5-year, 10-year, 15-year, and 20-year timespans; (d) locally weighted regression model; (e) smoothing spline model; (f) empirical mode decomposition model (the upper six figures are Illinois and the lower six figures are South Carolina; data: corn yield from 1895 to 2014 in Illinois and South Carolina)
By contrast, LOWESS models can be fitted with neighboring points near the boundary of the time series and the boundary points can be estimated instead of being assigned as missing values. LOWESS models can be either linear or polynomial. Locally weighted quadratic fitting performs better when the regression surface has substantial curvature (Cleveland and Devlin 1988), like that of corn yield through time. Here, we use locally weighted quadratic fitting in this study. In the LOWESS method, choice of the parameter \( f \) (fraction of points in the neighborhood) is very critical. As \( f \) increases from 0.1 to 1, the scale of the trend changes from local to global (Figure 3.3-1(d) and Figure 3.3-2(d)). With an \( f \) parameter of 1, LOWESS includes all of the data in the time series, and it is actually a polynomial regression model performed on the whole time series (Cleveland and Devlin 1988). Here, we used a ten-fold cross-validation process to optimize the choice of \( f \) (Breiman and Spector 1992). The ten-fold cross-validation process was repeated 100 times and the average parameter \( f \) was used as the optimum value for each state and county.

One assumption of the LOWESS methodology is that the fitted function should follow the underlying patterns of the data providing a nearly unbiased estimation (Cleveland and Devlin 1988). Visual inspection for trending fitting of state-level corn yield demonstrates that the fitted trend using the optimum \( f \) parameter corresponds to the underlying time series pattern, such as Illinois (Figure 3.3-1(d)) and South Carolina (Figure 3.3-2(d)).

For the smoothing spline model, we used generalized cross validation (GCV) to optimize the smoothing parameter. The trend curve simulated by the smoothing spline model also follows the corn yield time series closely in Illinois (Figure 3.3-1(e)) and South Carolina (Figure 3.3-2(e)), and this model performs well for most corn yields at the state level. However, for counties with shorter records, the fitted smoothing spline passes
through all data points and converges to a traditional interpolation spline that no longer smooths the data, losing its ability to fit the long-term trend caused by technological advances (examples of four counties are shown in Figure 3.4).

![Smoothing spline trend simulations for (a) Butte, California; (b) Lake of the Woods, Minnesota; (c) Wyoming, Pennsylvania; (d) Fairfield, South Carolina (smoothing spline converges to traditional interpolation spline)](image)

Figure 3.4 Smoothing spline trend simulations for (a) Butte, California; (b) Lake of the Woods, Minnesota; (c) Wyoming, Pennsylvania; (d) Fairfield, South Carolina (smoothing spline converges to traditional interpolation spline)

For the empirical mode decomposition (EMD) model, the residual component is a monotonic function or a function containing only a single extrema from which no more oscillatory IMFs can be extracted (Huang et al. 1998). The residual component can represent the overall trend, which is determined intrinsically and is neither linear nor quadratic (Wu et al. 2007). The definition of the residual component in EMD method is almost identical to the definition of the trend when the data span in the trend covers the
whole data length (Wu et al. 2007). Visual inspection suggests that the residual component of an EMD model simulated the trend well following the intrinsic data pattern through time in 35 out of 48 states, such as Illinois (Figure 3.3-1(f)) and South Carolina (Figure 3.3-2(f)). In another 11 states, the trend should include the residual component and the lowest-frequency IMF that contains physically meaningful information. In the remaining two states, the trend should include the residual component and the two lowest-frequency IMFs to represent the trend.

3.4.1.2 Quantitative measure of trend fitting results

Table 3.2 Quantitative measures of trend fitting results

<table>
<thead>
<tr>
<th>Model</th>
<th>RMSE</th>
<th>MAE</th>
<th>E</th>
<th>d</th>
<th>E_1</th>
<th>d_1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple Linear Regression Model</td>
<td>1219.19</td>
<td>1041.38</td>
<td>80.48%</td>
<td>94.25%</td>
<td>57.06%</td>
<td>77.30%</td>
</tr>
<tr>
<td>Second Order Polynomial Regression Model</td>
<td>743.37</td>
<td>545.49</td>
<td>92.20%</td>
<td>97.90%</td>
<td>77.32%</td>
<td>88.29%</td>
</tr>
<tr>
<td>20-year Centered Moving Average Model</td>
<td>554.31</td>
<td>375.42</td>
<td>93.36%</td>
<td>98.20%</td>
<td>81.01%</td>
<td>90.37%</td>
</tr>
<tr>
<td>Locally Weighted Regression Model</td>
<td>559.56</td>
<td>374.85</td>
<td>94.79%</td>
<td>98.60%</td>
<td>83.60%</td>
<td>91.72%</td>
</tr>
<tr>
<td>Spline Smoothing Model</td>
<td>531.85</td>
<td>357.10</td>
<td>94.97%</td>
<td>98.66%</td>
<td>84.19%</td>
<td>92.01%</td>
</tr>
</tbody>
</table>
Table 3.2 shows the average values of the 48 states for six quantitative measures of trend fitting to provide an overall perspective of trend fitting for those six trend simulation methods. For state-level data, in all six measures, simple linear regression models are the poorest fitting model, while second order polynomial regression models provide a closer fit to the observed data when compared with simple linear regression models. The other four methods all perform much better than simple linear regression models and second order polynomial regression models, fitting state-level corn yield with similar accuracy.

The modified index of agreement ($d_1$) ranges from 0 to 1.0, while modified coefficient of efficiency ($E_1$) ranges from minus infinity to 1.0. The modified index of agreement ($d_1$) is more convenient for interpretation (Legates and McCabe 1999), and thus we calculated the county-level $d_1$ to compare the county-level trend fitting for different methods (Figure 3.5). EMD model is not included in county-level analysis, because the choices of residual components and the IMFs of EMD model to fit the trend are not consistent for different counties and EMD model needs visual inspection and manual applications, which is not practical for thousands of counties. Further, the counties where the smoothing spline converges to an interpolation spline will be excluded from calculation of $d_1$ because an interpolation spline connects all data points and renders a useless fit for the technological trend (Figure 3.4). The county-level $d_1$ for the other four methods are
shown in (Figure 3.5(a-d)); those for the smoothing spline are shown in (Figure 3.5(e)) where about 600 counties are excluded because of this convergence. Figure 3.5 shows that the $d_1$ of locally weighted regression models are higher than with the simple linear regression models, second order polynomial models, and 20-year centered moving average models. The $d_1$ of locally weighted regression and smoothing spline are close. Given the limitation of smoothing spline model on shorter records, locally weighted regression models represent the best-trend fit for county-level corn yield data in terms of modified index of agreement ($d_1$).

![Figure 3.5](image)

Figure 3.5 County-level modified index of agreement ($d_1$) in the United States for five trend simulation methods: (a) simple linear regression model; (b) second order polynomial regression model; (c) 20-year centered moving average model; (d) locally weighted regression model; (e) smoothing spline model

3.4.1.3 Decomposition model comparison

The studies conducted by Hlavinka et al. (2009), Quiring and Papakryiakou (2003), Trnka et al. (2007), Goldblum (2009) and Mishra and Cherkauer (2010) assumed an
additive composition of fluctuations and trends, and used residuals subtracted from the regression line as the detrended data to represent crop departure from normal. However, we found evidence to suggest that this may not be a sound assumption for long-term corn yield time series in this study.

Figure 3.6 Comparison of additive decomposition model and multiplicative decomposition model (the upper two figures are Illinois and the lower two figures are South Carolina; data: corn yield from 1895 to 2014 in Illinois and South Carolina; trend simulation method: locally weighted regression model)

After applying an additive decomposition model to remove the trend from the time series, the variance of detrended corn yield in both Illinois and South Carolina increases with time (Figure 3.6). As corn yield and associated variance increase with time, the variance of the differences between original crop yield and simulated trend also increases. Thus, a multiplicative decomposition model is more appropriate because the variance of the detrended data is adjusted to the magnitude of crop yield, becoming more stationary through time (Figure 3.6). Here, detrended crop yields minus one represent the percentages
lower or higher than normal crop yield conditions (i.e. extreme events don’t occur); these values are denoted as “crop yield anomalies”. Therefore, after implementing an appropriate trend simulation method, we applied a multiplicative decomposition model to detrend corn yield.

3.4.2 Final detrending model choice

Our choice of a detrending model is based on performance, efficiency, and robustness. The analysis above demonstrates the sub-par performance of the simple linear regression and second order polynomial regression models. Further, the centered moving average model is of no use and/or is biased near the boundaries of the time series, as well as being strongly limited by missing values. The empirical mode decomposition model performs well for state-level corn yield data, but, as discussed in section 3.4.1.1, the choice of residual component and the IMFs is not consistent across the United States, requiring visual inspections and manual applications. Employing EMD to detrend multiple crop types in thousands of counties is time consuming and not practical. The smoothing spline model performs well for state-level corn yield where the records are long, but it does not perform well for shorter records. For counties with shorter data records (e.g., fewer than 60 years), the smoothing spline converges to interpolation spline and connects all data points together, rendering it useless for this application (Figure 3.4). The spline smoothing model is not robust to data with shorter records for fitting the trend caused by technological advances. The locally weighted regression model can automatically follow the underlying pattern of the non-linear and nonstationary corn yield time series and provide good trending fitting for both state-level and county-level corn yield. Thus, the locally weighted regression model coupled with multiplicative decomposition model is the preferred method
here to detrend the corn yield for both state-level and county-level, and is then employed in the following analysis.

3.4.3 Correlation analysis between detrended crop yield and multiple drought indices

Corn has five main phenological stages: emerged, silking, dough, dent, and mature (USDA 2009), and yield sensitivity to drought varies with stages. Corn is most sensitive to water stress during the early reproductive stage (tasseling, silking, and pollination) (Kranz et al. 2008). Droughts occur during silking period tend to desiccate the silks and pollen grains, causing poor pollination and resulting in the greatest yield reduction (Kranz et al. 2008, Berglund, Endres and McWilliams 2010). We performed Pearson correlation analysis to examine the best drought indices to correlate with corn yield anomalies for spatial visualization purpose in section 3.4 and to demonstrate the spatial patterns of the correlations.

3-month SPI in August and Z-index in July show the highest correlation with corn yield anomalies among all of the drought indices (Figure 3.7). Since the 3-month SPI in August is calculated from June, July, and August precipitation totals, it corresponds most closely to tasseling, silking, blister, milk, dough and dent stages. The phenology of corn explains why corn yield anomalies correlate most closely with 3-month SPI in August. As the time scale of SPI increases from 3-month to 24-month, the correlation coefficient decreases (Figure 3.7). This indicates that time scale of 3-month for SPI is appropriate for agricultural drought monitoring.
Figure 3.7 Correlation maps of multiple drought indices by month with corn yield anomalies at state level (For example, the map in the second row and second column shows correlations between the 2-month SPI in July and corn yield anomalies at state level)

For shorter time scales drought indices (1-month SPI, 2-month SPI, and Z-index), the corn yield anomalies are most highly correlated with drought indices in July (Figure
3.7), suggesting that July is the most critical single month when averaged across the United States, because July approximately corresponds to the early reproductive stage (tasseling/silking) in most states. In some southern states (e.g., Texas), where corn planting and harvesting time are earlier (USDA 2010), corn yield anomalies are most highly correlated with 1-month SPI, 2-month SPI and Z-index in June.

PDSI, PHDI, and PMDI show the highest correlation with corn yield anomalies in August among all seasons and perform better than the SPI at 6-month and longer time scales, but are inferior to the SPI at 3-month and shorter time scales as well as to the Z-index (Figure 3.7).

The two maps showing the highest correlations (Z-index in July and 3-month SPI in August), indicate that the corn yield anomalies are more highly correlated with drought intensity east of 100° W meridian than west of it (Figure 3.7). This occurs because areas west of the 100° W meridian typically use irrigation (Schlenker and Roberts 2009). Those areas east of 100° W meridian usually do not, leaving them more susceptible to drought.

3.4.4 Spatial visualization of drought impact on crop yield

We used this detrending approach to compare corn yield responses to drought across six major drought years: the droughts of 1936, 1954, 1980, 1988, 2002, and 2012. We used only counties in the conterminous United States with at least 30 years of data (counties in white are either counties do not produce corn, or counties with missing data for a particular drought, or counties with too short records). The corn yield time series for each state and each county was detrended separately using a locally weighted regression model coupled with a multiplicative decomposition model. The values shown in maps (Figure 3.8) are corn yield anomalies. Since the 3-month SPI in August and the Z-index in
July show the highest correlation with corn yield anomalies, we used the gridded 3-month SPI in August calculated from the 4-km gridded PRISM data as a reference of drought severity.

The maps of state-level corn yield anomalies generally correspond well with the county-level maps (Figure 3.8). The county-level maps clearly show more detailed crop information than the state-level maps (Figure 3.8). The state-level and county-level maps complement each other to reflect crop yield anomalies information.

The crop yield anomalies were calculated by adjusting to the magnitude of the crop yield itself, which indicates percentage lower or higher than the crop yield of normal conditions. This methodology lets us compare drought impacts across space and time. The 1936 drought had the greatest impact on corn yield in the Midwest and western parts of the south central United States, where corn yields fell by 50% and more (Figure 3.8). The impact of the 1954 drought showed up mainly in West South Central, East South Central, and South Atlantic, where the corn yield was reduced by 40% to 50% (Figure 3.8). The 1980 drought was similar in both magnitude and spatial extent to the 1954 drought. The 1988 drought’s impact on corn yield was most evident in the Midwest, East South Central, and South Atlantic, where the corn yield reduced by 30% to 40% (Figure 3.8). The 2002 drought had its greatest impact in the Middle Atlantic and South Atlantic, where the corn yields of Maryland, New Jersey, Ohio, Pennsylvania, Delaware, South Carolina, and Virginia were reduced by 30% to 40% (Figure 3.8). The impact of the recent 2012 drought was most strongly seen in the corn yield in the Midwest and East South Central, where the corn yields were 30% lower than normal in Illinois, Indiana, and Tennessee, and were 40% to 50% lower in Kentucky and Missouri (Figure 3.8).
Figure 3.8 Spatial visualization of state-level and county-level corn yield anomalies accompanied with gridded August 3-month SPI in the United States for six historical drought years: 1936, 1954, 1980, 1988, 2002, and 2012 (column (a): gridded August 3-month SPI calculated from PRISM data; column (b): state-level corn yield anomalies; column (c): county-level corn yield anomalies)

Comparisons between August 3-month SPI and corn yield anomalies for these six severe droughts show a strong correspondence between dryness and lower-than-normal corn yield for areas east of 100° W, however, this correspondence is weak for areas west of 100° W because of agricultural irrigation (Figure 3.8). The areas where corn yield greatly reduced during these six droughts correspond to the areas that experienced severe drought without access to irrigation.
The magnitudes of corn yield reductions in 1936, 1954 and 1988 correspond to the impacts reported in the literatures cited in the introduction part (NOAA 2003, Warrick 1984, Rosenzweig et al. 2001). This result partially illustrates the effectiveness and robustness of the selected detrending method.

3.5 CONCLUSION

This study identifies the appropriate data self-adaptive detrending method to standardize and detrend the corn yield by comparing multiple detrending methods, in order to compare drought impacts on corn across both space and time. We compared six trend simulation methods using six quantitative measures of trend fitting, and found that the simple linear regression and second order polynomial regression models have the poorest fit. Of the other four methods, the centered moving average model is limited by its boundary problems. Employing the EMD model to detrend crops for thousands of counties is time consuming and impractical because the choices of the residual component and IMFs to represent the trend are not consistent for different counties and different states and require visual inspections and manual applications. Smoothing spline models do not perform well for counties with shorter data records (e.g., fewer than 60 years) and in this case, a smoothing spline model connects all data points and converges to a traditional interpolation spline, which is useless in trend fitting for this application. We also compared two decomposition models and found that multiplicative decomposition model to be more appropriate for detrending crop yield because the variance of the detrended crop yield is adjusted according to the magnitude of crop yield and becomes more stationary over time. Thus, the locally weighted regression model, coupled with multiplicative decomposition model, is the most appropriate data self-adaptive method to detrend the crop yield.
This study represents the first long-term spatial visualization of drought impact on corn across large regions and identifies spatial patterns of vulnerability of corn to drought in United States. Our approach standardized the corn yield allowing a quantitative measure of relationship between drought and corn yield and spatial visualization of drought impacts on corn yield. We performed Pearson correlation analysis between corn yield anomalies and multiple drought indices during growing seasons. Z-index in July and 3-month SPI in August are the best two drought indices to correlate with corn yield anomalies among all of the drought indices. The corn yield anomalies are more highly correlated with drought indices for states east of the 100° W meridian than the west of it where agriculture is often supported by extensive irrigation. Six major drought years (1936, 1954, 1980, 1988, 2002, and 2012) were selected for the spatial visualization of drought impact on corn yield. Gridded 3-month SPI calculated from PRISM data were used to represent drought severity. The state-level and county-level maps of corn yield anomalies can capture the spatial variability of lower-than-normal corn yield caused by droughts. Lower-than-normal corn yield corresponds strongly with dryness east of 100° W, but weakly to its west. The impacts of the six historical droughts on corn yield were described and compared, and generally corresponded with what were reported in literatures. This also illustrates the effectiveness and robustness of the selected detrending method.

3.6 DISCUSSION

Our detrending approach is not limited to corn, but relevant to other crops as well. We applied the same approach for soybeans. Strong correspondence was shown between dryness and lower-than-normal soybean yield in 1980 (Figure 3.9). The 1980 drought
showed its impact on soybean yield mainly in West South Central, East South Central, and South Atlantic and Kansas (Figure 3.9).

Figure 3.9 Spatial visualization of state-level and county-level soybean yield anomalies accompanied with gridded August 3-month SPI in 1980: (a) gridded August 3-month SPI in 1980 calculated from PRISM data; (b) state-level soybean yield anomalies in 1980; (c) county-level soybean yield anomalies in 1980

Our detrending approach is also not limited to drought analysis. Crop yield anomalies can occur for reasons other than drought (e.g., flooding, extreme short-term weather events, pest infestation, and disease). This study successfully separated out environmental and weather factors from other technological factors. By identifying crop yield anomalies, our approach can also be used, for example, to assess the effect of excessive moisture and flooding on crop yield. The Great Flood of 1993, occurring from April to September along the Mississippi and Missouri rivers and their tributaries, killed at least 48 people and caused approximately $20B in flood-related damages (Johnson, Holmes and Waite 2004). Corn yields in Midwest along the Mississippi and Missouri rivers were lower than normal (Figure 3.10), mainly because of the flooding. The August 3-month SPI showed that, in contrast with the excessively wet conditions in Midwest, the Southeast experienced a severe drought (Figure 3.10). The corn yields in the Southeast were also lower than the normal (Figure 3.10), mainly due to the drought and heat wave.
Figure 3.10 Spatial visualization of state-level and county-level corn yield anomalies accompanied with gridded August 3-month SPI in 1993: (a) gridded August 3-month SPI in 1993 calculated from PRISM data; (b) state-level corn yield anomalies in 1993; (c) county-level corn yield anomalies in 1993

Our approach provides one way to assess the impact of drought on crop yield, which could be useful in helping policy makers and stakeholders develop effective risk adaptation strategies and management plans to alleviate the impact of extreme weather on the agricultural sector. Furthermore, our approach successfully isolates weather and climate factors and filters the effect of technological advances. Others have demonstrated the potential for crop production and yield prediction combining climate variables from GCMs and indices of observed antecedent sea surface temperature, warm water volume, and zonal wind patterns (Koide et al. 2013). Other example of locally weighted regression models have demonstrated skills for short-term forecasting (Lall et al. 2006). The method applied in this paper could also be used for short-term forecasts on the effect of technological changes on crop yield. As GCMs begin to demonstrate some success in decadal prediction (Meehl et al. 2014, van Oldenborgh et al. 2012), our method could be combined with such forecasts for predicting crop yield. Finally, the crop yield anomalies derived by this approach can also be used in the analysis of climate change impacts on agriculture.
3.7 ACKNOWLEDGEMENT

This work was supported by the National Oceanic and Atmospheric Administration (NOAA) Climate Program Office (grant number NA060AR4310007) to the Carolinas Integrated Sciences and Assessments. Here, we also wish to thank Karen Beidel for editorial assistance and suggestions.
CHAPTER 4 MAPPING AGRICULTURAL DROUGHT BASED ON THE LONG-TERM AVHRR NDVI AND NORTH AMERICAN REGIONAL REANALYSIS (NARR) IN THE UNITED STATES, 1981-2013

4.1 ABSTRACT

To provide a long-term perspective of drought variability from 1981 to present, we develop a new agriculturally-based drought index called the Integrated Scaled Drought Index (ISDI). This index integrates Normalized Difference Vegetation Index (NDVI) from AVHRR NDVI data (available from 1981 to present), land surface temperature (LST), precipitation (PCP), and soil moisture (SM) data from NCEP North American Regional Reanalysis (NARR) project (available from 1979 to present). This new agriculturally-based drought index incorporates important components controlling agricultural drought, particularly soil moisture, for which there are limited in-situ observations through time and across space. The optimum weights for each component of the ISDI are determined by Pearson correlation analysis with commonly used in-situ drought indices, such as the Palmer Drought Severity Index (PDSI), the Palmer Modified Drought Index (PMDI), Palmer’s Z-index, and the Standardized Precipitation Index (SPI) at different time scales. Resulting ISDI maps are also visually compared with USDM and VegDRI maps for empirical validation. ISDI shows strong agreement with these two national-wide drought monitoring systems. ISDI also shows strong linear correlations with corn yield anomalies in July and with soybean yield anomalies in August and strong spatial correspondence with county-level corn/soybean yield anomalies during major drought events. These results illustrate the robustness and usefulness of ISDI. This agriculturally-based drought index integrates the benefits of numerical model simulation and remote sensing technology to account for interannual variability of drought for the longest possible time-frame in the satellite era. This long-term drought index provides a longer historical perspective of
drought impacts since 1981. It can be generalized to incorporate other satellite data or in-situ observation and has the potential for operational drought monitoring and assessment.

4.2 INTRODUCTION

Drought is a devastating, recurring, and widespread natural hazard with complicated socioeconomic, environmental, and ecological impacts (AMS 1997). Droughts is a costly hazard in the United States historically, in which CPI-adjusted drought losses exceeded 223.8 billion dollars from 1980-2016, roughly accounting for 20% of all losses from major weather events (NOAA 2016). Within the agricultural sector, drought affects soil moisture availability and contributes to crop failures and pasture losses, posing risks on food security.

Drought impacts depend on the timing, severity, and duration of the events, and on resilience. Drought monitoring and early warning are critical for agricultural production and risk adaptation as effective drought quantification can mitigate losses. Of course, identifying and quantifying drought events is difficult due to its complex and diverse nature, reflected in its many definitions (e.g., meteorological, agricultural, hydrological, and socioeconomic), and the varying criteria used to estimate its severity (AMS 1997, Heim 2002, IPCC 2013). Appropriate quantification of drought for a variety of applications (e.g., agricultural drought or hydrological drought) requires consideration of a wide range of contributing processes (Sheffield et al. 2004, Wilhite 2000).

Drought monitoring mainly has been based on in-situ drought indices calculated from station-based, or areally-based meteorological data. The Palmer Drought Severity Index (PDSI) is based on the supply-and-demand concept of water balance equation using precipitation, temperature, and available water content of the soil (Palmer 1965b).
PDSI and its variations, such as the Palmer Z index (Palmer 1965b), Palmer Hydrologic Drought Index (PHDI) (Palmer 1965b), and Palmer Modified Drought Index (PMDI) (Heddinghaus and Sabol 1991) have been widely used for drought assessment and water resources management decisions. Shafer and Dezman (1982) proposed the Surface Water Supply Index (SWSI) to monitor abnormalities in surface water supply using historical records of streamflow, snow pack, precipitation, and reservoir components. The Standardized Precipitation Index (SPI) was developed to quantify precipitation deficit for different time scales based on only precipitation data (McKee et al. 1993). Compared with PDSI, SPI requires less data, has flexible time scales, and is spatially invariant (Guttman 1998). Recently, Vicente-Serrano et al. (2010) proposed the Standardized Precipitation Evapotranspiration Index (SPEI) based on precipitation and temperature data, which incorporates an evapotranspiration component into the calculation of SPI and is appropriate for detecting drought changes in the context of global warming (Vicente-Serrano et al. 2010).

Satellite remote sensing data have also been used to quantify drought when in-situ weather station observations are not available (Rhee et al. 2010, Kogan 1995a), resulting in several remote-sensing-based drought indices. Among them, Normalized Difference Vegetation Index (NDVI) proposed by Rouse Jr et al. (1974) has been widely for drought monitoring (Peters et al. 2002). NDVI is can effectively reflect the physiologically functioning surface greenness level. Higher NDVI values represent greater photosynthetic capacity of the vegetation canopy (Tucker 1979). However, NDVI contains both weather-related and ecosystem components (Kogan 1995a). Kogan (1995a) proposed the Vegetation Condition Index (VCI) by linearly scaling NDVI values from 0 to 1 for each
grid to separate the weather-related components from the ecosystem components. NDVI is influenced by multiple environmental factors, such as extreme weather events (drought and excessive wetness), pests, plant diseases, and fires. To distinguish drought effects from other environmental factors, related climate information from satellite observation or in-situ observation could be integrated with NDVI data (Kogan 1995b). In addition to VCI, thermal band based Temperature Condition Index (TCI) was developed to provide additional information to distinguish vegetation stress caused by drought events from excessive wetness and other factors (Kogan 1995b). The linear combination of VCI and TCI results in Vegetation Health Index (VHI), reflecting both temperature and precipitation conditions (Kogan 1995b).

With the development of hyperspectral remote sensing, such as the Moderate Resolution Imaging Spectroradiometer (MODIS), additional remote-sensing-based drought indices have been developed. Gao (1996) proposed the Normalized Difference Water Index (NDWI) to detect moisture status of vegetation canopy based on the Near Infrared (NIR) channel reflecting vigor of vegetation and the Shortwave Infrared (SWIR) channel reflecting changes of water content. Based on NDVI and NDWI, Gu et al. (2007) proposed Normalized Difference Drought Index (NDDI) and demonstrated a quicker and stronger response to summer drought compared with NDVI and NDWI. Wang and Qu (2007) developed the Normalized Multi-band Drought Index (NMDI) based on the sensitivity findings that the two MODIS SWIR bands respond differently to soil moisture and vegetation moisture variations. NMDI provided solutions to separate vegetation moisture from soil moisture by amplifying one signal and minimizing the other (Wang and Qu 2007).
More recently, Rhee et al. (2010) proposed the Scaled Drought Condition Index (SDCI) for monitoring agricultural drought in both arid and humid regions. This index combines three standardized scaled remote sensing variables together – the Normalized Difference Vegetation Index (NDVI), the land surface temperature (LST) from MODIS sensors, and precipitation from the Tropical Rainfall Measuring Mission (TRMM) satellite. Through validations against in-situ drought indices and United States Drought Monitor (USDM) maps, Rhee et al. (2010) demonstrated that SDCI performed better than NDVI, NMDI, NDDI, and VHI in both arid and humid regions. However, since MODIS and TRMM data are only available since 2000 and 1997 respectively, and TRMM data only cover tropical and subtropical regions, SDCI has short duration and limited spatial coverage. The formulas of several remote sensing drought indices are shown in Table 4.1.

### Table 4.1 Formulas of remote sensing drought indices

<table>
<thead>
<tr>
<th>Drought Indices</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI</td>
<td>(\frac{\rho_{\text{NIR}} - \rho_{\text{RED}}}{\rho_{\text{NIR}} + \rho_{\text{RED}}})</td>
</tr>
<tr>
<td>VCI</td>
<td>(\frac{\text{NDVI} - \text{NDVI}<em>{\text{min}}}{\text{NDVI}</em>{\text{max}} - \text{NDVI}_{\text{min}}})</td>
</tr>
<tr>
<td>TCI</td>
<td>(\frac{T_{\text{max}} - \text{LST}}{\text{LST}<em>{\text{max}} - \text{LST}</em>{\text{min}}})</td>
</tr>
<tr>
<td>VHI</td>
<td>(\alpha \cdot \text{VCI} + \beta \cdot \text{TCI})</td>
</tr>
<tr>
<td>NDWI</td>
<td>(\frac{\rho_{\text{NIR}} - \rho_{\text{SWIR}}}{\rho_{\text{NIR}} + \rho_{\text{SWIR}}})</td>
</tr>
<tr>
<td>NDDI</td>
<td>(\frac{\text{NDVI} - \text{NDWI}}{\text{NDVI} + \text{NDWI}})</td>
</tr>
<tr>
<td>NMDI</td>
<td>(\frac{\rho_{\text{NIR}} - (\rho_{1640\text{nm}} - \rho_{2130\text{nm}})}{\rho_{\text{NIR}} + (\rho_{1640\text{nm}} - \rho_{2130\text{nm}})})</td>
</tr>
<tr>
<td>SDCI</td>
<td>((1/4)\cdot\text{scaled LST}+(2/4)\cdot\text{scaled TRMM}+(1/4)\cdot\text{scaled NDVI})</td>
</tr>
</tbody>
</table>

Where \(\rho\) represents spectral reflectance; \(\alpha\) and \(\beta\) represent the weights.
Vegetation indices naturally lend themselves to agricultural drought measurement, but could be enhanced with information from other variables, such as precipitation, evapotranspiration, temperature, and soil moisture (AMS 2013). Soil moisture is a very important indicator of agricultural drought as it reflects antecedent precipitation, evapotranspirative losses, and determines available water supply for healthy plant growth (WMO 1975, Keyantash and Dracup 2002, AMS 1997). Yet it is one of the least observed variables in the US and elsewhere globally (Sheffield et al. 2004). Because there does not exist a comprehensive, large-scale, and long-term network of in-situ soil moisture measurement (Keyantash and Dracup 2002) and shallow observation depths of remote sensing based soil moisture conditions (Leeper et al. 2016), the use of simulated soil moisture from numerical models provides a viable alternative (Sheffield et al. 2004). Numerical models can compute the soil moisture by simulating water balance of the soil column using precipitation, air temperature, soil temperature, soil porosity, and infiltration as inputs (Keyantash and Dracup 2002). The commonly used and high-resolution reanalysis dataset, North American Regional Reanalysis (NARR) simulates soil moisture and serves as a good source of information for long-term soil moisture conditions. Leeper et al. (2016) demonstrate that soil moisture data from NARR could capture the timing, intensity, and spatial extent of 2012 drought using standardized soil moisture anomalies, when compared against in-situ soil moisture observations from the United States Climate Reference Network (USCRN). In the United States, there are several nation-wide drought monitoring systems, such as the United States Drought Monitor (USDM), and related indices (e.g., Vegetation Drought Response Index (VegDRI) and the Evaporative Stress
These drought monitoring systems have provided national wide drought measurements since 2000.

To cover the longest time-frame during the satellite era, to learn more about year-to-year variability in growing conditions and the consequent impacts on agriculture, and to incorporate one of the most important variables in agricultural drought modeling, we develop a new agriculturally-based drought index that integrates satellite-based observations of vegetation state and climate information from reanalysis dataset. We use the NDVI from NOAA’s AVHRR sensor to take advantage of this longest NDVI time series from 1981 to present and its large area coverage. We combine this with land surface temperature (LST), precipitation (PCP), and soil moisture (SM) data from the NCEP NARR project (available 1979 to present), producing a sound, consistently blended, agriculturally-based drought index that accounts for interannual variability for the longest possible time-frame during the satellite era. Such an index can not only provide insights for historical drought impacts assessment, but also be generalized to incorporate other satellite data or in-situ observation and guide current or future agricultural drought monitoring.

4.3 DATA SOURCES

4.3.1 North American Regional Reanalysis (NARR) data

Precipitation, land surface temperature, and total soil moisture content data were extracted from NARR (http://www.emc.ncep.noaa.gov/mmb/rreanl/) produced by National Centers for Environmental Prediction (NCEP) (Mesinger et al. 2006). NARR is a regional reanalysis in North America, which contains temperatures, precipitation, wind, soil moisture, radiation, evaporation, etc. This dataset provides a long-term climatology
spanning from 1979 to present over North America at a spatial resolution of 32 km and
temporal resolution of 3 hours. NARR uses a recently operational version of the NCEP
regional Eta model and the Noah land-surface model and assimilates high-quality
observational data, including radiosondes, hourly precipitation (with PRISM correction),
surface observations, aircraft, geostationary satellites, etc. (Mesinger et al. 2006). This
dataset is superior to NCEP/NCAR Global Reanalysis (GR), especially due to an advance
in modeling and additional assimilation of precipitation and radiance (Mesinger et al. 2006).
NARR has the potential to represent extreme events, such as floods, droughts, and their
driving mechanisms (Mesinger et al. 2006).

NARR has been widely used for understanding weather and climate variability
across North America. Ruiz-Barradas and Nigam (2006) used NARR data to investigate
the hydroclimate variability over the Great Plains. Mo and Chelliah (2006) used NARR
products to produce PMDI to monitor drought in the US. Karnauskas et al. (2008) used
NARR and 40-yr European Centre for Medium-Range Weather Forecasts (ECMWF) Re-
Analysis (ERA-40) to construct a PDSI dataset. Vivoni, Tai and Gochis (2009) used NARR
to investigate the mechanisms and effects of initial soil moisture on precipitation,
streamflow, and evapotranspiration during the monsoon in New Mexico. Becker, Berbery
and Higgins (2009) used NARR to examine the seasonal characteristics of precipitation
and related physical mechanisms over the US. Choi et al. (2009) used the NARR
temperature and precipitation data for hydrological modeling with SLURP (Semi-
distributed Land Use-based Runoff Processes). Gao, Carbone and Guo (2015) used NARR
data to assess and evaluate the performance of North American Regional Climate Change
Assessment Program (NARCCAP) in simulating the precipitation extremes in the US.
4.3.2 Remote sensing data

NDVI data were obtained from the Global Inventory Monitoring and Modeling System (GIMMS) project to represent the vigor, robustness, and photosynthetic capacity of vegetation. The GIMMS project carefully assembles NDVI data from different AVHRR sensors and accounts for different deleterious effects, such as calibration losses, orbital drift, and volcanic eruptions. The third generation GIMMS NDVI from AVHRR sensors is bimonthly spanning from the period from July 1981 to December 2013 with a spatial resolution of 1/12° lat/lon across the globe. The GIMMS NDVI dataset was downloaded from Ecological Forecasting Lab at NASA Ames Research Center (http://ecocast.arc.nasa.gov/).

4.3.3 Land use/cover data

The National Land Cover Database (NLCD) product with 30m spatial resolution were used to extract the land areas of Grassland/Herbaceous (class 71), Pasture/Hay (class 81), and Cultivated Crops (class 82). We used the NLCD 2001 (Homer et al. 2007) database because this baseline is in the middle of our study period.

4.3.4 In-situ drought index

We obtained in-situ drought indices, including the PDSI, PMDI, Palmer Z index, 1-month SPI, 2-month SPI, 3-month SPI, 6-month SPI, 9-month SPI, and 12-month SPI from 1895 to present from NOAA’s National Centers for Environmental Information (NCEI) (ftp://ftp.ncdc.noaa.gov/). These indices at the climate divisional spatial scale were primarily used for derivation and validation of the potential new drought index.
4.3.5 Agriculture statistics

We obtain the state-level and county-level corn and soybean yield data from 1981 to 2013 from USDA’s NASS Quick Stats tools (USDA 2014). We used corn and soybean yield to validate and test the potential use of the new index.

4.4 METHODOLOGY

4.4.1 Scaled drought indices

Precipitation (PCP), soil moisture (SM), NDVI, and land surface temperature (LST) were scaled according to their historic absolute minimum and maximum values in each pixel following Kogan (1995a) and Kogan (1995b) (Table 4.2). For each pixel, the scaling process was performed for each month since the climate conditions and vegetation states are not homogenous across months. Scaling NDVI can separate climate variability from ecosystem components (Kogan 1995b). Scaling climate variables can discriminate the weather and climate variability from spatial heterogeneity. Thus, the maximum precipitation and soil moisture values are scaled to 1 for the wettest case; the minimum precipitation and soil moisture are scaled to 0 for the driest case. Scaled LST was used to provide additional information for vegetation stress and to determine temperature-related drought vegetation stress (Kogan 1995b). Contrary to NDVI, high temperature indicates unfavorable or drought conditions, while low temperature indicates mostly favorable conditions (Kogan 1995b). Thus, the maximum LST is scaled to 0 and the minimum LST is scaled to 1. The scaling method can make those variables representing drought conditions comparable across space and time. These four variables (precipitation, soil moisture, NDVI, and LST) are linearly combined using different weights to form a new agriculturally-based drought index: Integrated Scaled Drought Index (ISDI).
Table 4.2 Formulas of scaled drought indices

<table>
<thead>
<tr>
<th>Drought Indices</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scaled NDVI</td>
<td>( \frac{\text{NDVI} - \text{NDVI}<em>{\text{min}}}{\text{NDVI}</em>{\text{max}} - \text{NDVI}_{\text{min}}} )</td>
</tr>
<tr>
<td>Scaled LST</td>
<td>( \frac{\text{LST}<em>{\text{max}} - \text{LST}}{\text{LST}</em>{\text{max}} - \text{LST}_{\text{min}}} )</td>
</tr>
<tr>
<td>Scaled PCP</td>
<td>( \frac{\text{PCP} - \text{PCP}<em>{\text{min}}}{\text{PCP}</em>{\text{max}} - \text{PCP}_{\text{min}}} )</td>
</tr>
<tr>
<td>Scaled SM</td>
<td>( \frac{\text{SM} - \text{SM}<em>{\text{min}}}{\text{SM}</em>{\text{max}} - \text{SM}_{\text{min}}} )</td>
</tr>
<tr>
<td>ISDI</td>
<td>( \alpha \times \text{Scaled NDVI} + \beta \times \text{Scaled LST} + \gamma \times \text{Scaled PCP} + \lambda \times \text{Scaled SM} )</td>
</tr>
</tbody>
</table>

Where NDVI represents Normalized Difference Vegetation Index from GIMMS AVHRR NDVI dataset; LST, PCP, and SM represent land surface temperature, precipitation, and soil moisture from NARR dataset; \( \alpha, \beta, \gamma, \) and \( \lambda \) represent the weights of single scaled variable to form the Integrated Scaled Drought Index (ISDI) and \( \alpha + \beta + \gamma + \lambda = 1 \); \( \text{NDVI}_{\text{min}}, \text{LST}_{\text{min}}, \text{PCP}_{\text{min}}, \) and \( \text{SM}_{\text{min}} \) indicate the minimum values of NDVI, land surface temperature, precipitation, and soil moisture for each pixel and each month; \( \text{NDVI}_{\text{max}}, \text{LST}_{\text{max}}, \text{PCP}_{\text{max}}, \) and \( \text{SM}_{\text{max}} \) indicate the maximum values of NDVI, land surface temperature, precipitation, and soil moisture for each pixel and each month.

NARR data are in GRIB format on a Lambert-conformal grid. Climate variables from NARR were resampled using piecewise linear interpolation to spatial resolution of 1/12° lat/lon as GIMMS NDVI. NARR data and AVHRR NDVI data were all projected to UTM Zone 14N.
4.4.2 Correlation analysis with in-situ drought indices

We systematically created fifteen different sets of weights for four variables (PCP, SM, NDVI, and LST). We determined optimum weights by performing Pearson correlation analysis between ISDI of different weights and multiple in-situ drought indices – Palmer Z-index, PDSI, PMDI, 1-month SPI, 2-month SPI, 3-month SPI, 6-month SPI, 9-month SPI and 12-month SPI – at the climate divisional scale. Each of the 344 conterminous United States climate divisions was assumed to be climatologically homogeneous in the validation process. NARR data and AVHRR NDVI data were spatially averaged over 344 climate divisions to facilitate correlation analysis between in-situ drought indices and ISDI of different weights. Two coastal climate divisions do not have soil moisture information from NARR data and are excluded from the testing and validation process. In order to be comparable and consistent across space and time, the whole CONUS from 1981 to present share the same optimum weight.

4.4.3 Correlation analysis with crop yield data

Drought can have significant impacts on agriculture and crop yield variabilities are highly correlated with drought severity (Mishra and Cherkauer 2010, Trnka et al. 2007, Quiring and Papakryiakou 2003). Here, we used the corn and soybean yield, to quantitatively validate the potential use of ISDI. State-level corn and soybean yield time series are detrended by locally weighted regression model (LOWESS) to remove the nonlinear and non-stationary increasing trend caused by technological advances (Lu, Carbone and Gao 2017). This detrending approach allows us to successfully separate out environmental and weather factors from other technological factors (Lu et al. 2017). Crop yield anomalies derived from this approach indicate the percentage of crop yield lower or
higher than normal (Lu et al. 2017). We performed Pearson correlation analyses between corn/soybean yield anomalies and ISDI during growing seasons (March through October) at the state level to evaluate the performance of this new drought index. Corn has five major phonological stages: emerged, silking, dough, dent, and mature and soybean has four major phonological stages: emerged, blooming, setting pods, and dropping leaves (USDA 2009). Yield sensitivity to drought varies with stage. ISDI values were extracted from pixels of land cover types: grassland/herbaceous, pasture/hay, and cultivated crops, from NLCD 2001 and were then spatially averaged for each state.

4.4.4 Empirical validation with maps of USDM, VegDRI, and Gridded SPI from PRISM

ISDI with optimum weights were visually compared with United States Drought Monitor (USDM) maps and Vegetation Response Index (VegDRI) maps for empirical validation and assessment. The archives of USDM maps from 2000 to present are available from the National Drought Mitigation Center (http://droughtmonitor.unl.edu/). The USDM map is based on climate indices, numerical models, and the inputs of regional and local experts, which is not a strictly quantitative product, but a blend of science and subjectivity (Svoboda et al. 2002). The archives of VegDRI maps from 2009 to present are also available from the National Drought Mitigation Center (http://vegdri.unl.edu/). VegDRI integrates traditional drought indicators (e.g., PDSI and SPI) and NDVI with other biophysical information to monitor vegetation responses to drought conditions using a data mining technique (Brown et al. 2008). Since the USDM and VegDRI maps are created weekly, we used the end of month maps for comparison. Further, ISDI maps were also visually compared with gridded monthly SPI3 maps for empirical validation. We calculated SPI values across CONUS using 4-km gridded PRISM (Parameter-elevation
Relationships on Independent Slopes Model) precipitation dataset (Daly et al. 2008) from 1895 to 2014 as an in-situ reference of spatial variability of drought severity. We computed SPI values following the method of McKee et al. (1993), modeling precipitation accumulations of different time scales with a gamma distribution.

4.5 RESULTS AND DISCUSSION

4.5.1 Correlation with in-situ drought indices

Table 4.3 Averaged Pearson correlation coefficients between in-situ drought indices and scaled LST, scaled PCP, scaled SM, and scaled NDVI over 342 climate divisions (The highest averaged correlation coefficient for each in-situ drought index in each column is shown in bold)

<table>
<thead>
<tr>
<th>Correlation coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Z-index</td>
</tr>
<tr>
<td>Scaled NDVI</td>
</tr>
<tr>
<td>Scaled LST</td>
</tr>
<tr>
<td>Scaled PCP</td>
</tr>
<tr>
<td>Scaled SM</td>
</tr>
</tbody>
</table>
Averaged correlation coefficients between in-situ drought indices and scaled LST, scaled PCP, scaled SM, and scaled NDVI over 342 climate divisions (The highest averaged correlation coefficient for each in-situ drought index in each column is shown in bold)

Table 4.3 shows the averaged correlation coefficients between in-situ drought indices and scaled LST, scaled PCP, scaled SM, and scaled NDVI for 342 climate divisions.

Scaled PCP shows higher correlation with the Palmer Z-index and shorter-duration SPI values (i.e., 1-month, 2-month, and 3-month) than with other scaled drought indices. Thus, scaled PCP is especially appropriate for monitoring short-term drought.

Scaled LST has higher correlation with PDSI, PMDI, and Z-index than SPIs because PDSI, PMDI, and Z-index are based on the supply-and-demand concept, which are calculated from precipitation, temperature and available water content (AWC) of the soil (Palmer 1965b), while SPIs are calculated only from precipitation data (McKee et al. 1993).

Among all scaled variables, scaled SM shows the highest correlation with PDSI, PMDI, 6-month SPI, 9-month SPI, and 12-month SPI (Table 4.3). As the time scale of SPI increases from 1 to 9 months, the correlation coefficient increases, which indicates that soil moisture responds slowly to precipitation variations. The high correlation between scaled SM and PDSI/PMDI suggests that scaled SM is especially appropriate for agricultural drought monitoring, since PDSI and its variation, PMDI, were considered to be useful primarily for agricultural drought and other water uses that are sensitive to soil moisture (Guttman 1998).

Generally, scaled NDVI (VCI) is not closely correlated with in-situ drought indices as other scaled variables (Table 4.3), because in-situ drought indices are mainly calculated
from precipitation and temperature data and less directly convey vegetation information, while scaled NDVI reveals more information about drought influences on photosynthetic capacity of vegetation canopy, greenness level, leaf area index, and biomass. Among all in-situ drought indices, scaled NDVI shows higher correlation with PMDI, PDSI, and SPI of longer time scale (i.e., 3-month, 6-month, 9-month, and 12-month). The correlation coefficient increases as the time scale of SPI increases from 1-month to 12-month, an expected finding because of the lag of vegetation response to precipitation deficit.

Figure 4.1 Spatial variation of Pearson correlation coefficients between PDSI and scaled land surface temperature (LST), scaled precipitation (PCP), scaled soil moisture (SM), and scaled NDVI

We used PDSI to demonstrate the spatial variation of the correlations between scaled variables and in-situ drought indices (Figure 4.1) because PDSI is very suitable for agricultural drought monitoring. The correlation coefficients between PDSI and scaled SM are higher than other scaled variables. With respect to the spatial variation, the scaled PCP,
scaled LST, and scaled SM do not show any significant spatial patterns with PDSI over precipitation gradients. By contrast, an obvious spatial pattern exists for scaled NDVI (VCI) – correlation values with PDSI are higher in drier areas and lower in wetter areas (Figure 4.1) because vegetation is more susceptible to drought variability in drier areas.

Overall, scaled SM provides valuable information for drought monitoring in addition to SDCI (combination of scaled NDVI, scaled LST, and scaled PCP) proposed by Rhee et al. (2010).

4.5.2 Optimal Integrated Scaled Drought Index (ISDI)

We tested 15 systematic sets of weights to find and derive an optimal Integrated Scaled Drought Index (ISDI) (Table 4.4). Correlation analyses were performed between in-situ drought indices and ISDI with different sets of weights. The highest three Pearson correlation coefficients for each in-situ drought index (each column) were highlighted (Table 4.4). The correlation coefficients are all statistically significant over 342 climate divisions between different in-situ drought indices and ISDIs (p-value < 0.01). Weight set 3 shows a particularly high correlation with the Z-index and 1-, 2-, and 3-month SPI values. Weight set 4 shows especially higher correlation with PDSI, PMDI and 6-, 9-, and 12-month SPI values. Weight set 9 shows higher correlation with PDSI, PMDI, and both shorter and longer time scale SPI (i.e., 2-month, 3-month, 6-month, 9-month, and 12-month). It shows the highest correlation with PDSI and 3-month SPI among all weights. PDSI and 3- and 6-month SPI are especially suitable for monitoring agricultural drought (Rouault and Richard 2003). Thus, the linear combination of scaled LST, scaled PCP, scaled SM, and scaled NDVI with the weight set 9 (LST=1/6, PCP=1/3, SM=1/3, and
NDVI=1/6) is selected as the optimal Integrated Scaled Drought Index (ISDI). We compared the performance of ISDI with VHI (Table 4.4). ISDI shows much higher correlation with in-situ drought indices than VHI. We also compare the performance of ISDI with SDCI. Originally, SDCI uses MODIS and TRMM data, and here we alternatively used AVHRR and NARR data. Except for Z-index and 1-month SPI, ISDI shows higher correlation with in-situ drought indices (e.g., PDSI, PMDI, 2-month SPI, 3-month SPI, 6-month SPI, 9-month SPI, and 12-month SPI) than SDCI. Thus, ISDI generally performs better than both VHI and SDCI.

4.5.3 Validation using crop yield data

Corn is most sensitive to drought during the early reproductive stage (tasseling, silking, and pollination) (Kranz et al. 2008). Droughts that occur during silking period can cause poor pollination and result in the greatest yields reduction (Kranz et al. 2008, Berglund et al. 2010). Soybeans are most sensitive to drought during the mid- to late-reproductive stages: pod development and seed fill stages (Kranz and Specht 2012, Doss, Pearson and Rogers 1974). Droughts that occur during those periods can have the greatest impact on soybean yields potential, resulting in reduced number of seeds per pod and reduced seed size (Kranz and Specht 2012).
Table 4.4 Averaged Pearson correlation coefficients between ISDI with 15 sets of weights and in-situ drought indices over 342 climate divisions (the highest three correlation coefficients for each in-situ drought index and the highest three sets of weights are shown in bold)

<table>
<thead>
<tr>
<th>Weights</th>
<th>Correlation coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scaled LST</td>
<td>Scaled PCP</td>
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We performed Pearson correlation analyses between ISDI values during growing seasons (March to October) and corn/soybean yield anomalies from 1981 to 2013 for validation of the potential use of ISDI. Corn yield anomalies are higher correlated with ISDI in June, July and August than other months, with the highest correlation in July. This period corresponds most closely with the early reproductive stage (tasseling/silking) for corn in most states, which is the most critical month for corn growth. Soybean yield anomalies are closely correlated with ISDI in July, August and September than other months, with the highest correlation in August. This period corresponds to the critical mid-to late-reproductive stages of soybean: pod development and seed fill stages. Drought can significantly influence corn and soybeans during these critical growing periods as shown by the strong linear correlation between ISDI and corn (Figure 4.2) and soybean (Figure 4.3) yield anomalies.

In addition, we selected four representative drought years: 1983, 1988, 2002, and 2012 to compare the spatial pattern of July/August ISDI and county-level corn/soybean yield anomalies, respectively. The county-level corn/soybean anomalies are calculated following the method of Lu et al. (2017). We find a very strong correspondence between July/August low ISDI values and lower-than-normal corn/soybean yield during those representative drought years (Figure 4.4). These results partially illustrate the effectiveness and robustness of this new agriculturally-based drought index.
Figure 4.2 Scatterplots and Pearson correlations between corn yield anomalies and the Integrated Scaled Drought Index (ISDI) in July for (a) Alabama, (b) Delaware, (c) Illinois, (d) Indiana, (e) Kentucky, (f) Maryland, (g) New Jersey, (h) Pennsylvania, (i) South Carolina, (j) Texas, (k) Virginia, and (l) West Virginia in the US.
Figure 4.3 Scatterplots and Pearson correlations between soybean yield anomalies and the Integrated Scaled Drought Index (ISDI) in August for (a) Alabama, (b) Delaware, (c) Florida, (d) Georgia, (e) Illinois, (f) Kansas, (g) Kentucky, (h) Maryland, (i) Mississippi, (j) New Jersey, (k) Oklahoma, and (l) Pennsylvania in the US
Figure 4.4 Spatial pattern of July/August Integrated Scaled Drought Index (ISDI) and corn/soybean yield anomalies in 1983, 1988, 2002, and 2012 in the US (the first column: July ISDI; the second column: corn yield anomalies; the third column: August ISDI; the fourth column: soybean yield anomalies).

4.5.4 Empirical comparison with USDM maps and VegDRI maps

ISDI shows the highest correlation with corn and soybean yield anomalies in July and August, respectively, the two months most critical for corn and soybean growth. USDM maps are available from 2000 to present and VegDRI maps are available from 2009 to present. So, we choose to do a year-to-year comparison between ISDI and USDM maps in July from 2000 to 2013 and a year-to-year comparison between ISDI and VegDRI maps in August from 2009 to 2013 for empirical validation of ISDI. Also, we used gridded 3-month SPI maps calculated from PRISM data as an in-situ drought reference, since time scale of 3-month is considered very appropriate for agricultural drought monitoring (Rouault and Richard 2003).
Figure 4.5 Comparisons between Integrated Scaled Drought Index (ISDI), gridded 3-month SPI from prism data, and the United States Drought Monitor (USDM) maps in July from 2000 to 2013.

Generally, the annual changes and spatial distribution of ISDI agree well with USDM maps in July from 2000 to 2013. The ISDI could provide much more detailed information when compared with USDM (Figure 4.5). USDM is not a strictly quantitative product but the state-of-the-art blend of science and subjectivity including experts input (Svoboda et al. 2002), while ISDI is a completely quantitative product without any expert inputs. The ISDI does not agree with USDM in earlier years (i.e., 2000 and 2001), but agrees very well in later years (Figure 4.5). In 2000, ISDI detected a more severe drought...
west of the 100° W meridian and in the south of Texas than USDM did. In 2001, ISDI also detected a more severe drought in the south of Texas than the USDM did. Generally, ISDI shows better agreement with 3-month SPI calculated from PRISM than USDM in most years (Figure 4.5).

Figure 4.6 Comparisons between Integrated Scaled Drought Index (ISDI) and the Vegetation Drought Response Index (VegDRI) maps in August from 2009 to 2013.

Overall, ISDI agrees quite well with VegDRI maps to show US drought conditions in August from 2009 to 2013 (Figure 4.6). In 2009, ISDI and VegDRI both detected extreme and severe droughts in the coastal Northwest, the West and the Southwest, and extreme drought in south Texas. In 2010, they both detected scattered drought conditions. In 2011, they both detected severe and extreme drought conditions in the South. In 2012,
they both showed severe and extreme droughts covering the entire United States. In 2013, they both detected drought condition in the Northwest, West, Southwest and South. However, ISDI detected severe drought in Upper Midwest and Ohio Valley, but VegDRI did not. The severe drought conditions shown in those areas from the 3-month SPI indicates the better performance of ISDI in 2013 (Figure 4.6). These comparisons with USDM maps, VegDRI maps, and gridded 3-month SPI maps illustrate the effectiveness and robustness of ISDI.

4.6 CONCLUSION

This study successfully develops a new agriculturally-based drought index, the Integrated Scaled Drought Index (ISDI) which integrates four components (scaled NDVI, scaled land surface temperature (LST), scaled precipitation (PCP), and scaled soil moisture (SM)) to accounts for interannual variability of drought during the longest possible time-frame of the satellite era. We used long-term satellite-based observations of vegetation conditions from GIMMS AVHRR NDVI (available from 1981 to present) and NECP North American Regional Reanalysis (NARR) data (available 1979 to present) to make the long-term agricultural drought quantification and measurements from 1981 to present possible. Our results provide a long-term climatology of continuous drought monitoring over the US which is beneficial for historical drought impacts assessment and future drought monitoring.

This new drought index incorporates a range of important variables controlling agricultural drought process, especially as it integrates soil moisture, an important but infrequently observed in-situ variable affecting drought measurement. Among all scaled variables, scaled soil moisture shows the highest correlation with PDSI, PMDI, and SPI at
longer time scales (i.e., 6-month, 9-month, and 12-month), which suggests that scaled soil moisture can provide valuable information to monitor agricultural drought in addition to SDCI. Among those components in this new drought index, we highlight the significance of the soil moisture component in agricultural drought monitoring. The ISDI with optimum weights shows much higher correlations with in-situ drought indices than VHI. Except for the Z-index and 1-month SPI, ISDI shows higher correlation with in-situ drought indices (i.e., PDSI, PMDI, 2-month SPI, 3-month SPI, 6-month SPI, 9-month SPI, and 12-month SPI) than SDCI. The ISDI performs better than VHI and SDCI to correlate with in-situ drought indices.

This new drought index measures agricultural drought in the long-term and over large regions in a consistent and quantitative fashion. The results indicate that the ISDI can identify historical major drought events and show potential for future operational implementation in drought monitoring and assessment. ISDI shows highest correlations with corn yield anomalies in July, which corresponds to the early reproductive stage (tasseling/silking) of corn, and shows highest correlation with soybean yield anomalies in August, which corresponds to the pod development and seed fill stages of soybean, periods when corn and soybean are most sensitive to water stress. Consequently, there are strong linear correlations between ISDI and state-level corn and soybean yield anomalies. Additionally, a very strong spatial correspondence can be found between July/August low ISDI values and lower-than-normal corn/soybean yield during four representative drought years (i.e., 1983, 1988, 2002, and 2012). Further, ISDI agrees well with the two nationwide drought monitoring systems: USDM and VegDRI maps, and can detect year-to-year changes of drought conditions in the US. Through scaling NDVI and climate variables
from 0 to 1 by historical minimum and maximum values for each pixel and for each month, ISDI could be spatially invariant and comparable. ISDI is a strictly quantitative drought monitoring product without any expert inputs that shows more detailed and precise spatial drought information than USDM maps. When referred against 3-month SPI calculated from PRISM data, ISDI agrees better with 3-month SPI than USDM maps in earlier years (i.e., 2000 and 2001) and agrees better with 3-month SPI maps than VegDRI in 2013. These results all indicate a good performance of ISDI to monitor agricultural drought.

4.7 ACKNOWLEDGEMENT

This research has been conducted through the Carolinas Integrated Sciences & Assessments (CISA) program and supported by the National Oceanic and Atmospheric Administration (NOAA) Office (grant no. NA160AR4310163).
CHAPTER 5 UNCERTAINTY AND HOTSPOTS IN 21ST CENTURY PROJECTIONS OF AGRICULTURAL DROUGHT FROM CMIP5 MODELS

3 Lu, J., G. J. Carbone, and J. M. Grego. To be submitted to *Climate Dynamics*. 
5.1 ABSTRACT

Future climate changes could alter hydrometeorological patterns and change the nature of droughts at global to regional scales. However, there are still considerable uncertainties in drought projections. Here, we focus on agricultural drought by analyzing surface soil moisture outputs from CMIP5 multi-model ensembles (MMEs) under RCP2.6, RCP4.5, RCP6.0, and RCP8.5 scenarios. First, we investigate the MME annual and seasonal percentage change of surface soil moisture and evaluate the statistical significance of change using paired student t-tests for each grid by controlling the false discovery rate (FDR) at a significance level of 0.05. The annual mean soil moisture by the end of the 21st century shows statistically significant large-scale drying and limited areas of wetting for all scenarios, with stronger drying as the strength of radiative forcing increases. Second, we calculate the duration, frequency, severity, and spatial extent of severe agricultural drought. The MME median frequency of both short-term and long-term drought increases in most regions and most scenarios. Individual months are more likely to cluster into consecutive dry months to produce longer-term drought for RCP8.5 than RCP2.6. The MME mean projections of the spatial extent of severe drought increase for all regions and all future RCP scenarios, and most notably in Central America (CAM), Europe and Mediterranean (EUM), Tropical South America (TSA), and South Africa (SAF). Third, we quantify and partition three sources of uncertainty associated with these drought projections: internal variability, model uncertainty, and emission scenario uncertainty. Variability between models presents the largest source of uncertainty (over 80%) across the entire 21st century owing to the wide range of precipitation projections, simplified hydrological models in many CMIP5 climate models, and complicated processes
controlling soil moisture. The inter-model uncertainty of drought projections is larger for higher emission scenario than the lower emission scenario. Finally, we examine the spatiotemporal variability of annual and seasonal signal to noise (S/N) change in soil moisture anomalies across the globe and for different lead times. The spatial pattern and magnitude of S/N do not change significantly by lead time, indicating that the spreads of uncertainties become larger as the signals become stronger.

Keywords: Agricultural drought; Climate projection uncertainty; Signal to noise (S/N) ratio; CMIP5 multi-model ensembles

5.2 INTRODUCTION

Future drought risks could be exacerbated by spatiotemporal changes in hydro-meteorological variables due to climate change (Mishra and Singh 2011, AMS 2013). It is generally agreed that, with increased water vapor in the atmosphere, associated with rising global temperature especially at lower latitudes, the global hydrological cycle intensifies and the occurrences of both droughts and floods increase in some regions (IPCC 2007). Warming associated with climate change accelerates land surface drying, enhances evapotranspiration, and increases the potential incidence and severity of droughts (IPCC 2007). Changes in the frequency, intensity, and duration of droughts would have significant impacts on water management, natural resources, agriculture, and aquatic ecosystems. In the context of climate change, it is important for decision makers to understand how drought conditions might change on the regional scale in order to plan adequate adaptation and mitigation strategies (Heinrich and Gobiet 2012).
Drought is a complex multivariate phenomenon caused by interaction of atmospheric, hydrological, and biogeophysical processes. Compared with other natural hazards (e.g. earthquake and hurricane) occurring within finite periods, drought develops slowly, often without visually obvious damaging impacts (Ding et al. 2011). The gradual accumulation of precipitation deficits prolong drought and cause a trail of impacts on natural habitats, ecosystems, and economic and social sectors (AMS 2013). The magnitude of impacts depends on the timing, duration, frequency, severity, and intensity. Also, drought involves a wide range of related variables of drought. Different types of drought highlight different variables of interest; for example, meteorological droughts highlight precipitation, agricultural droughts highlight soil moisture, and hydrological droughts highlight streamflow/runoff (AMS 1997, Heim 2002).

There are considerable uncertainties in evaluating drought trends even in the instrumental record. For example, the IPCC Fourth Assessment Report (IPCC 2007) concluded that, since the 1970s, more intense and longer droughts have been observed over wider areas, particularly in the tropics and subtropics, which are linked with higher temperatures and decreased precipitation. However, the IPCC Fifth Assessment Report (AR5) (IPCC 2013) indicated that the global increasing trends in drought since 1970 were no longer supported. Recent evidence has yielded conflicting results on drought changes (Sheffield, Wood and Roderick 2012, Dai 2013). There is low confidence in a global-scale observed drought trends, possibly due to lack of direct observations, inconsistencies associated with drought index choice, geographical variability, and difficulties in distinguishing decadal-scale variability in drought from long-term climate change (IPCC
Such phenomena demonstrate the challenges and uncertainties in quantitatively detecting long-term changes of this complex phenomenon.

In addition to uncertainties with respect to past observations, there are even more considerable uncertainties associated with future drought projection centering on a different set of factors including, inherent climate variability, model errors, and uncertainty in future radiative forcing. Under RCP8.5, AR5 projections by the end of the century indicate that an increased risk of drought is likely (medium confidence) in present dry regions linked to regional to global scale projected decreases in soil moisture as global temperatures increase, particularly in the Mediterranean, Southwest USA, and southern Africa (IPCC 2013). The AR5 also stated that a comprehensive evaluation of CMIP5 models for drought is still currently unavailable (IPCC 2013).

Prior work investigating potential changes in drought has revealed that different drought indices can produce different results. The standardized precipitation index (SPI; McKee et al. 1993) has been used frequently with general circulation model (GCM) or regional climate model (RCM) output to estimate future drought risks as it directly considers changes in spatial and temporal precipitation patterns (Loukas et al. 2008, Vidal and Wade 2009, Mishra and Singh 2009). Dubrovsky et al. (2009), however, discovered different risk levels between a relative SPI and relative Palmer Drought Severity Index (PDSI). SPI values indicated a decreased drought risk in summer and an increased risk in both winter and spring, while the PDSI indicated an increased drought risk at all stations and all seasons. The difference, of course, is that PDSI incorporates components of the water budget in addition to precipitation. Similarly, Touma et al. (2015) found that future changes in Standardized Precipitation Evapotranspiration Index (SPEI) and Supply-
Demand Drought Index (SDDI) are much stronger than the changes in SPI and Standard Runoff Index (SRI) due to the greater influence of temperature changes in the SPEI and SDDI indices.

In this study, we focus on agricultural drought. Agricultural droughts reduce soil-water availability, affect crop production and yield, and pose threats to livestock industries that rely on non-irrigated pastures. Soil moisture is an important indicator for agricultural drought, since it can reflect the total effects from all hydrological process, represent the status of agriculture, and determine the available water supply for healthy plant growth (AMS 1997, WMO 1975, Keyantash and Dracup 2002).

Modelling soil moisture change is much more complicated than precipitation and temperature, because soil moisture is not only influenced by precipitation and temperature, but also vegetation state, land use/cover change, soil texture and properties, atmospheric CO₂ (influence plant stomatal conductance, and hence plant transpiration). Future soil moisture changes depend on the total interaction of temperature and precipitation, the complex surface hydrological process, as well as other factors, such as wind speed, vegetation, land use/cover change. Increased precipitation tends to increase the soil moisture. However, the changes of soil moisture not only depend on the change in mean precipitation, but also the changes in frequency and intensity of precipitation and seasonality of changes (Sheffield and Wood 2008). Moreover, increased temperature tends to increase the indirect transpiration and direct evaporation from the soil. The actual evaporation could be enhanced by precipitation increase or diminished by precipitation decrease (Sheffield and Wood 2008). Thus, due to the complex process, we use soil
moisture from GCM outputs as an integrative variable to reflect the change in agricultural drought risks.

Past studies mainly used two methodologies to explore uncertainties associated with climate models: Multi-Model Ensembles (MMEs) and Perturbed Parameter Ensembles (PPEs). The MMEs are constructed from existing model simulations from multiple climate modeling groups, such as World Climate Research Programme’s CMIP3 and CMIP5 MMEs. The PPEs are created by systematically sampling on perturbing uncertain physical parameters (e.g. climate sensitivity and carbon cycle feedback) from a single standard model (Murphy et al. 2007, Collins et al. 2006). PPEs allow determination of which parameters contribute most to uncertainty, however, PPEs fails to take into account different choices of model structure (e.g. spatial-temporal resolution, numerical scheme, and parameterization schemes) and the estimates of uncertainty from PPEs depends on the underlying parameters (Rowell 2012, Collins et al. 2006). In this study, we use a Multi-Model Ensembles (MMEs) approach to consider different model structures, instead of a single model.

Prior studies have assessed and quantified model uncertainty associated with primary climate variables like surface air temperature (Hawkins and Sutton 2009, Morice et al. 2012) and precipitation (Hawkins and Sutton 2011, Rowell 2012). However, fewer studies have assessed and quantified uncertainties in projecting agricultural drought conditions. AR5 stated that the regional to global-scale projections of drought conditions remain relatively uncertain compared to other aspects of the water cycle (IPCC 2013). Understanding and modeling uncertainties and hotspots in drought projection are of great importance in natural resource and water resources planning management. Quantifying and
partitioning uncertainty associated with drought are also very important for decision makers to understand the scope and direction for narrowing the uncertainty through investment in climate science (Hawkins and Sutton 2009).

Here, we use all available GCMs under the framework CMIP5, which enable us to capture model uncertainty in the representation of climate sensitivity and climate process. We use all available RCP scenarios: RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5, which enable us to understand the uncertainty derived from unknown future greenhouse gas emissions and radiative forcing. We focus on agricultural drought and use soil moisture as an important indicator for agricultural drought. We analyze raw GCM model output for surface soil moisture, instead of the computing drought indices from related variables. First, we investigate the seasonal and annual percentage change of surface soil moisture in the 21st century and evaluate the statistical significance of change using paired student t-tests for each grid. Second, we analyze the spatial-temporal change of the frequency, duration, and spatial extent of the severe agricultural drought. Third, we partition and quantify the three sources of uncertainty in the projection of agricultural drought trends: internal variability, model uncertainty, and scenario uncertainty. Finally, through a signal-to-noise (S/N) ratio analysis for each grid and for different lead times, we measure the magnitude of the expected change of the soil moisture anomalies compared with the uncertainty in the projection and examine the spatiotemporal variability S/N change.

5.3 DATA SOURCE AND METHODOLOGY

5.3.1 Climate models

We used climate model simulations under the fifth phase of the Coupled Model Intercomparison Project (CMIP5) (IPCC 2013). Four emissions scenarios, called
representative concentration pathways (RCPs) were used. Each is identified by its approximate total radiative forcing W/m$^2$ in year 2100 relative to preindustrial conditions (1750): RCP2.6, RCP4.5, RCP6.0 RCP8.5 (IPCC 2013). The radiative forcing of RCP2.6 peaks first and then declines, representing the lowest scenario; the radiative forcing of RCP4.5 stabilizes at 4.5 W/m$^2$ by 2100, representing the medium-low scenario; the radiative forcing of RCP6.0 and RCP8.5 does not stabilize by 2100, representing the medium-high and highest scenario respectively. The CMIP5 multi-model ensembles are accessed via portals to the Earth System Grid Federation (ESGF) archive (http://cmip-pcmdi.llnl.gov/cmip5/).

We used the monthly surface (upper 10 cm) soil moisture (variable: mrsos) output from the CMIP5 multi-model ensembles (MMEs) for historical simulations (1900-2005) and future projections (2006-2100). We used all available models providing surface soil moisture values during the simulation periods (listed in Table 5.1). To enable comparison across the four RCP scenarios, Figure 5.4, Figure 5.5, and Figure 5.7 only contain models that are available across all RCP scenarios and historical forcing (those models are annotated with star symbols in Table 5.1). All model outputs were interpolated onto a common 2°×2° latitude-longitude grid by bilinear interpolation method to allow for computing multi-model mean and uncertainty. Multi-ensemble mean was calculated for each GCM model and each scenario.

Table 5.1 List of GCMs and number of ensembles for each GCM and each scenario (the blanks indicate no simulation available and the numbers indicate the number of ensembles used and the model name with a star symbol indicate this model has all four RCP scenario runs, totally 17)

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5.3.2 Soil moisture anomalies

Near-surface soil moisture is a fraction of precipitation, evapotranspiration, soil texture and infiltration, drainage, slope, vegetation cover, etc. which are heterogeneous and difficult to characterize (IPCC 2013). The global annual mean surface soil moisture (upper 10 cm) for different models are quantitatively more comparable than the total soil moisture due to the substantial differences between climate models in the soil depth and soil layers (Berg, Sheffield and Milly 2017, IPCC 2013). We use the upper 10 cm surface soil moisture, instead of the total soil moisture which should have more uncertainty because of difference in soil depth and layers. Very few studies have evaluated simulated soil moisture from global-scale models (IPCC 2013).

The surface soil moisture provided by CMIP5 MMEs differs greatly model by model. For example, the global (excluding Antarctica and Greenland) annual mean surface soil moisture for the period of 1976-2005 varies from 8.381 kg/m² in model IPSL-CM5A-MR to 33.598 kg/m² in model FGOALS-s2, while the standard deviation for the period of 1976-2005 is only 0.058 kg/m² in model IPSL-CM5A-MR and 0.089 kg/m² in model FGOALS-s2. Differences between models are far greater than interannual variability for a single model. Thus, comparing the raw surface soil moisture between models is not robust. Here, we compute the soil moisture anomalies using future projections (or historical
simulation) minus the mean of historical simulation (1900 – 2005). In addition, since the interannual variability of soil moisture differs by model, we also compute the standardized soil moisture anomalies to investigate how future long-term changes compare to historical interannual variability (Koster et al. 2009). The standardized soil moisture anomalies are computed using future projections (or historical simulation) minus the mean of historical simulation (1900 – 2005) and normalized by interannual standard deviation of historical simulation (1900 – 2005). The anomalies are calculated for each month and each pixel separately due to varying soil moisture conditions each month, and because of spatial heterogeneity.

5.3.3 Drought quantification

We estimate future wetting and drying of surface soil moisture with respect to an historical empirical probability distribution (Sheffield and Wood 2008). Our approach considers United States Drought Monitor (USDM) drought classification categories: D0 abnormally dry (21st to 30th percentile), D1 moderate drought (11st to 20th), D2 severe drought (6th to 10th), D3 extreme drought (3rd to 5th), and D4 exceptional drought (0 to 2nd) (http://droughtmonitor.unl.edu/). Here, we focus on severe drought and worse (0 to 10th percentile), i.e., D2, D3, and D4. A threshold value of 10% is chosen reflecting drought for a specific month could be expected once every ten years on average. Hence, following the method of Sheffield and Wood (2008), for each grid point, each month, and each GCM model, a 1-month drought occurrence either in the historical period or future period is defined as one month with a surface soil moisture value lower than the 10% quantile threshold based on the empirical cumulative distribution function from the
historical simulation, 1900 – 2005. We selected a long enough historical period (106-year) to account for the historical variability in soil moisture anomalies sufficiently.

Based on the theory of runs and the method of Sheffield and Wood (2008), a drought event is characterized in terms of duration, severity, intensity, and spatial extent. A consecutive sequence of 1-month drought occurrence results in a drought event of different durations in months. We define two types of drought duration based on the USDM: short-term drought (less than 6 months) and long-term drought (longer than or equal to 6 months). We define severity as the sum of deficit below the 10% threshold. For example, the cumulative probability of the surface soil moisture in the 1st, 2nd, and 3rd month during a 3-month drought event are respectively 6%, 2%, and 3%, and hence the deficit below the 10% threshold of those three months is 4%, 8%, and 7% respectively. Consequently, the sum of deficit below the threshold is 19%, i.e., the severity of this drought event is 19%. We define intensity as the mean deficit below the threshold for the duration of a drought event, i.e., severity divided by duration. For example, the intensity of this 3-month duration drought mentioned above is 19%/3 (6.33%). We define spatial extent of drought as the percentage of grid points in which the surface soil moisture falls below the threshold for each month in the region of interest. The area of each grid points is weighted by the cosine of the latitudes to account for the actual grid size. We also estimate drought characteristics for the 15 regions used by the IPCC (2013) (Figure 5.4) and calculate the regional mean for each drought statistic using an area-weighted mean by the cosine of the latitudes.

5.3.4 Uncertainty quantification and partition

Future climate change projections are subject to considerable uncertainties. Here, we consider three sources of uncertainty in drought projection (Hawkins and Sutton 2009):
1) internal variability of climate system, i.e., natural fluctuation, which arises in the absence of any radiative forcing; 2) model uncertainty (known as response uncertainty), which occurs because different GCM models project different climate changes in response to the same radiative forcing; and 3) scenario uncertainty, which arises from uncertainty in future anthropogenic greenhouse gas emissions, leading to uncertainty in future radiative forcing due to imperfect knowledge of future radiative forcing.

We follow the methods in Hawkins and Sutton (2009) and Hawkins and Sutton (2011) to partition and quantify uncertainties for drought projection. Here, we describe the method in brief. 1) For each individual projection, we apply a smooth fourth-order polynomial model fit to the decadal mean projection during the period, 1900-2100, to account for the non-linearity and to separate out the trend and internal variability. Each model is assumed independent and weighed equally. The internal variability for each projection is defined as the variance of the residuals from the smooth fit. We assume that the internal variability is constant over lead time and that changes of internal variability are negligible. We take the multi-model mean of the variances of the residuals as the internal variability component. 2) For one particular scenario, the spread of different models is considered as the model uncertainty. We estimate the model uncertainty for each scenario as the variance of the smooth fits for different models. The multi-scenario mean of the variance is considered as an estimate of model uncertainty. 3) The spread of multi-model mean for each scenario is considered as the scenario uncertainty. We estimate the scenario uncertainty as the variance of the multi-model means for the four scenarios. The model uncertainty and scenario uncertainty varies by lead time. Those three uncertainties are assumed independent from one another (Hawkins and Sutton 2009). The total uncertainty
can be estimated as the sum of internal uncertainty, model uncertainty, and scenario uncertainty.

5.4 RESULTS

5.4.1 Global multi-model mean surface soil moisture change

We investigate future agricultural drought change by calculating multi-model mean percentage change of the surface soil moisture for the period of 2071-2100 (RCP forcing) relative to 1976-2005 (historical forcing) for each emission scenario (Figure 5.1). Percentage change is calculated since the magnitude of surface soil moisture varies by model; a 30-year period is chosen to sufficiently filter out interannual variability, but maintain multi-decadal variability. We evaluate the statistical significance of change using paired two-sample student two-tailed t-tests for each grid by testing the null hypothesis that the population means for the annual/seasonal mean soil moisture from the CMIP5 multi-model ensembles for historical period and RCP period are the same. A paired two-sample t-test is used to control sources of variability in which the annual/seasonal mean soil moisture for the two 30-year periods from the same GCM model is a matched-pair sample. An independent two-sample t-test is not appropriate in such cases. Moreover, since we perform multiple comparisons using paired two-sample t-test and calculate the p-values for more than 3000 of grids for each emission scenario, we control for the false discovery rate (FDR) (i.e., the expected proportion of false discoveries among the total number of discoveries) at a significance level of 0.05 and adjust the p-values for each grid cell following the method of Benjamini and Hochberg (1995) (Figure 5.1).

The annual mean surface soil moisture by the end of 21st century shows statistically significant large scale drying over most of Australia, South America, North America,
southern Africa, Europe and Mediterranean, and east Asia, and statistically significant wetting in limited areas of east Africa, south Asia, and central Asia (Figure 5.1). The overall spatial patterns of drying and wetting are generally consistent across the four RCP scenarios, with stronger drying as forcing increases (Figure 5.1). The soil moisture drying in Mediterranean, southwestern USA, northeast South America, and southern Africa is associated with projected widening of the Hadley Circulation that shifts downwelling and inhibits precipitation in these regions, and globally increased temperature and evapotranspiration (IPCC 2013).

Figure 5.1 Global multi-model mean annual percentage change in the surface soil moisture for the period of 2071-2100 (RCP forcing) relative to 1976-2005 (historical forcing) based on CMIP5 multi-model ensembles under four scenarios: RCP2.6, RCP4.5, RCP6.0, and RCP8.5. The grids with stippling indicate statistical significance using paired two-sample student t-tests by controlling the false discovery rate (FDR) at significance level of 0.05, i.e., there is strong evidence that the long run mean of annual soil moisture for period of 2071-2100 is not equal to that of 1976-2005 for those grid cells. The results are based on all available models for each RCP scenario and the corresponding models in the historical forcing.
The changing signal is more pronounced in winter or summer than annually because of compensating effects during the whole year (Figure 5.1, Figure 5.2, and Figure 5.3). We have also detected a strong seasonality in many regions in the mid- and high-latitudes of the North Hemisphere, with wetting in the winter and drying in the summer (Figure 5.2 and Figure 5.3) which is most likely due to increased temperature and evapotranspiration, increased precipitation throughout whole year, and earlier melting of ice and snow.

Figure 5.2 Same as Figure 5.1 with summer (JJA in North hemisphere and DJF in South hemisphere)
5.4.2 Global multi-model drought characteristics change

We calculate the drought characteristics: frequency of short-term drought (longer than or equal to 2 months and less than 6 months) and frequency of long-term drought (longer than or equal to 6 months) for the 30-year period of 1976-2005 (historical forcing) and 2071-2100 (RCP forcing) for each region (Figure 5.4). The multi-model median (shown in the boxplots) frequency of short-term drought is projected to increase by the end of 21st century for most regions and for most RCP scenarios (Figure 5.4). In most cases, the increase in frequency of short-term drought is higher for RCP2.6 than RCP8.5. There are several cases that the frequency of short-term drought is projected to decrease for the highest radiative forcing RCP8.5 compared to historical period, such as ENA, EUM, SAF, TSA, and the global. This is because, in the RCP8.5 scenario, sequences of consecutive
dry months are more likely, thus increasing the frequency of long-term drought and decreasing the frequency of short-term drought. Figure 5.4 shows that the median frequency of long-term drought is projected to increase in most regions, with the greatest increase in EUM, TSA, CAM, ENA, and SAF, and the smallest increase in NAS, SAS, CAF and NAF. The highest radiative forcing shows the greatest increase in the long-term drought in most regions. However, as the boxplot show, the multi-model ensembles have a range that is much larger than the change (Figure 5.4).

Figure 5.4 Boxplots of global mean frequency of short-term drought (longer than or equal to 2 months and less than 6 months, defined in USDM), frequency of long-term drought (longer than or equal to 6 months, defined in USDM) for the period of 1976-2005 (historical forcing) and 2071-2100 (RCP forcing) under four emission scenarios: RCP2.6, RCP4.5, RCP6.0, and RCP8.5. The range of the variation for each period is based on CMIP5 multi-model ensembles. The 15 regions are defined in (IPCC 2013): Western North America (WNA), Eastern North America (ENA), Central America (CAM), Tropical South America (TSA), Southern South America (SSA), Europe and Mediterranean (EUM), North Africa (NAF), Central Africa (CAF), South Africa (SAF), North Asia (NAS), Central Asia.
(CAS), East Asia (EAS), South Asia (SAS), Southeast Asia (SEA) and Australia (AUS). The GLB stands for Global.

The global multi-model ensemble mean in the spatial extent of severe drought is projected to increase from approximately 11% for the period of 1976-2005 to 27% under RCP2.6, 29% under RCP4.5, 32% under RCP6.0, and 33% under RCP 8.5 for the period of 2071-2100. Figure 5.5 shows the regional seasonal patterns of future drought projections in the RCP forcing compared with the historical forcing. The multi-model mean spatial extents of severe drought are projected to increase for all regions and all future RCP scenarios, with progressively larger spatial extent of severe drought as the strength of radiative forcing increases (RCP8.5 > RCP6.0 > RCP4.5 > RCP2.6) in most cases. The seasonal curve tends to be skewed towards warmer months. The increase in spatial extent of drought tend to be larger in warmer seasons than cooler seasons in most regions. In southern hemisphere (TSA, SSA, AUS, and SAF), the largest increase in spatial extent occurs predominantly in the Austral Spring. The increase in spatial extent of soil moisture deficit in high latitude regions (e.g. NAS) tends to be concentrated in the warm season and diminished in the cool season. The seasonal disproportionate change of soil moisture deficit is mainly because of changes in snow and ice. During the cooler season, the temperature increase tends to reduce the snow cover, increase the ratio of rainfall to snowfall, and drive earlier spring melting which limits soil moisture deficit, while during the warmer season, earlier spring melting coupled with higher evapotranspiration strengthen the soil moisture deficit (Sheffield and Wood 2008). This mechanism leads to the seasonal disproportionate change in the spatial extent of drought in warmer months compared with the cooler months.
Figure 5.5 Global and regional multi-model ensemble mean, 30-year mean of monthly spatial extent of severe drought for the period of 1976-2005 in historical forcing and 2071-2100 in RCP forcing under four emission scenarios: RCP2.6, RCP4.5, RCP6.0, and RCP8.5.

CAM and EUM shows the largest spread across emission scenarios, i.e., these regions respond very differently to different radiative forcing compared with other regions (Figure 5.5). For those regions, the highest radiative forcing (RCP8.5) creates a much greater spatial extent of drought than the lowest radiative forcing (RCP2.6). By contrast, NAF, SAS, SEA, and CAF show the smallest spread resulting from different emission
scenarios (Figure 5.5), i.e., the spatial extent of drought in these regions is relatively insensitive to the differences in radiative forcing compared with other regions.

Figure 5.6 Empirical cumulative distribution functions (CDFs) of global monthly spatial extent of severe drought for the period of 1976-2005 (360 months) in historical forcing and 2071-2100 (360 months) in RCP forcing under four emission scenarios: RCP2.6, RCP4.5, RCP6.0, and RCP8.5. The thin lines indicate the CDFs for individual GCM models and the thick lines indicate the CDFs for multi-model ensembles for each scenario.

We fit empirical CDFs of the global monthly spatial extent of drought for each individual model for the 360-month in the period of 1976-2005 (historical forcing) and the 360-month in the period of 2071-2100 (RCP forcing) to investigate both the mean projection change and temporal variability (inter-month variability) change (Figure 5.6). Most of the GCM models project increases in the spatial extent of severe drought, in which the MME mean of RCP8.5 shows the largest increase. The multi-model ensembles under RCP forcing show very large inter-model uncertainty, in which RCP8.5 shows the widest range of projections, while RCP2.6 shows the narrowest range of projections, indicating that the projection uncertainty increases as the radiative forcing increases. This is true when
the four RCP scenarios contain the same GCM models (not shown here). Furthermore, for each individual GCM projection under RCP forcing, in most cases, the CDFs, especially under RCP8.5, are flatter when compared with the CDFs using historical forcing, indicating greater temporal (inter-month) variability in spatial extent of severe drought, i.e., more widespread drought and more extreme drought events.

![Image of spatial extent of severe drought](image)

Figure 5.7 Mean spatial extent of severe drought for the period of 1976-2005 in historical forcing and for the period of 2071-2100 in RCP forcing under four emission scenarios: RCP2.6, RCP4.5, RCP6.0, and RCP8.5. H, 2, 4, and 8 in the x-axis represent historical, RCP2.6, RCP4.5, RCP6.0, and RCP8.5 scenario respectively. The columns are globe (GLB) and 15 regions.

We calculate 30-year mean of the spatial extent of severe drought for the globe and for 15 regions using historical (1976-2005) and RCP forcing (2071-2100) (Figure 5.7). Visually, the variations across models are much larger than the variations across RCP scenarios, i.e., the model spread is much larger than the scenario spread. The model results from the same institution are similar and highly correlated (e.g. GISS-E2-R and GISS-E2-H, IPSL-CM5A-MR and IPSL-CM5A-LR, GFDL-ESM2M and GFDL-ESM2G) and those
climate models developed by the same institution and sharing model components might have shared biases. The multi-model and multi-scenario mean spatial extent of CAM, EUM, TSA, and SAF are projected to increase the most, while the mean spatial extent of SAS, SEA, NAS, and CAF are projected to increase the least. Also, Figure 5.7 shows that the variations between models are also larger than the variations across those 15 regions. The model difference is a significant contribution to the variation of the future drought projections.

5.4.3 Uncertainties in projection of global mean severe drought

Figure 5.8 Global a) decadal mean standardized soil moisture anomalies; b) decadal sum of 1-month drought occurrence; c) decadal sum of severity; d) decadal mean spatial extent of drought from CMIP5 multi-model ensembles under four RCP scenarios: RCP2.6, RCP4.5, RCP6.0, and RCP8.5 from 1900 to 2100 (the thin lines represents individual GCM model and the thick lines represent multi-model mean for each scenario). The fluctuations (“wiggles”) superimposed on the long-term trends in each projection approximate the internal variability in climate; the spread of the thin lines in the same color represents the model uncertainty for a particular scenario (e.g. red color for RCP8.5); the spread of the four thick colored lines represents the scenario uncertainty.
Figure 5.8(a) shows time series of global decadal mean standardized soil moisture anomalies. Soil moisture is projected to decrease in the twenty-first century, with the strongest drying associated with the highest emissions scenario. Figure 5.8(b) shows time series of global decadal sum of 1-month drought occurrence, representing the month counts in a 10-year moving window when soil moisture values fall below the 10th percentile of the historical simulation (1900-2005). Figure 5.8(c) shows time series of global decadal sum of severity, representing the sum of severity for all drought events in a 10-year moving window. The time series of decadal sum of 1-month drought occurrence and sum of severity show similar results, both are projected to increase over 21st century with the highest increase for RCP8.5, and the lowest increase for RCP6.0 before mid-century and for RCP2.6 after mid-century. Figure 5.8(d) shows time series of the global decadal mean spatial extent of severe drought, representing the global decadal mean percentage of areas experiencing severe drought conditions. The multi-model mean is projected to increase from approximately 10% during the 20th century to 26.5% (RCP2.6) and 35.2% (RCP8.5) by the end of the 21st century. Collectively, Figure 5.8 shows that the spread of different models in response to the same radiative forcing (the spread of thin lines of the same color) is much larger than the spread of the different responses depending on the radiative forcing (RCP) (the spread of four thick lines) for the 21st century.

In addition to visually presenting the uncertainty of future agricultural drought change, we partition and quantify the three dominant sources of uncertainty in those projections following the methods of Hawkins and Sutton (2009) and Hawkins and Sutton (2011). The projection of soil moisture shows large model uncertainties (Figure 5.9(a)) during the entire 21st century owing to the simplified hydrological models of many CMIP5
climate models (Kirtman et al. 2013), even if soil moisture is expressed in standardized anomaly format that already reduces the differences in soil moisture among models. The differences in the model response is the largest source of uncertainty (over 80%) over the entire 21st century. In the period before 2030, internal variability is the second largest source of uncertainty. After 2030, the scenario uncertainty exceeds internal variability and becomes the second largest source of uncertainty.

The contributions to total uncertainty for the three drought statistics: 1-month drought occurrence, sum of severity, and spatial extent, all show similar patterns (Figure 5.9(b-d)). The model uncertainty is always the dominant source of uncertainty during the entire 21st century. In the early period, the internal variability typically is the second largest source of uncertainty in the early half of the 21st century. By the latter half of the century, it is often exceeded by scenario uncertainty. Our finding that uncertainty in soil moisture projections is dominated by model differences contrasts with the uncertainty partition for global decadal annual mean temperature changes found by Hawkins and Sutton (2009). In the case of global temperature, model uncertainty is relatively high in the early part of the century, but steadily falls and is exceeded by scenario uncertainty by the middle of 21st century. By the end, the scenario uncertainty accounts for approximately 82% of the total uncertainty and the model uncertainty accounts for 18%. Our results for soil moisture more closely approach the uncertainty in precipitation projections observed by Hawkins and Sutton (2011) wherein model uncertainty is the largest source of uncertainty over the entire 21st century. Of course, differences in modelled precipitation contribute greatly to simulated soil moisture differences. Yet, it is revealing that scenario uncertainty is so diminished despite the important role of temperature on evapotranspiration rates.
Undoubtedly, uncertainty in simulated soil moisture values also results from the complexity of the water balance system and the model treatment of important factors, such as land use/cover, soil characteristics, landforms, vegetation, and evapotranspiration.

Figure 5.9 Fraction of total variance in a) Global decadal mean standardized soil moisture anomaly, b) Global decadal sum of 1-month drought occurrence, c) Global decadal sum of severity, and d) Global decadal mean spatial extent of drought, explained by three components of total uncertainty: internal variability (orange), scenario uncertainty (green), and model uncertainty (blue). The four uncertainty partitions correspond to the four sets of time series in Figure 5.8.
Regional patterns of uncertainty partition in decadal mean spatial extent of severe drought are similar and model uncertainty dominant uncertainty (approximately 80%) for all regions in the 21st century. The difference across regions results mainly from the slight differences in the magnitude of scenario uncertainty shown in Figure 5.5.

5.4.4 Signal to noise ratio analysis in the soil moisture anomaly

How large is the expected change of drought compared to uncertainty in the projections? We now use the signal-to-noise ratio to measure the robustness of soil moisture projections. Understanding and modeling signal-to-noise ratio (S/N) for different regions could aid water resource planning. We quantify the signal as the change of soil moisture anomalies relative to the mean of the baseline period 1976-2005 and the noise as the square root of the total uncertainty (sum of internal variability, model uncertainty, and scenario uncertainty) in the projection (Hawkins and Sutton 2011, Giorgi and Bi 2009). We calculate the S/N ratio for each pixel. We also examine the spatiotemporal variability of annual and seasonal S/N change across the global and at different lead times (3rd decade, 6th decade, and 9th decade) (Figure 5.10). An absolute value of S/N greater than 1 means that the magnitude of soil moisture anomaly change signal exceed uncertainty.

At the end of 21st century, the annual negative S/N occurs across the Mediterranean and Europe, in many parts in United States, Mexico, southern Africa, many parts of northern South America, Southeast China, and West Australia. However, the S/N is less than -1 in a very limited region of the Mediterranean and Europe, Southwest United states, and southern Africa. The S/N ratio for drying is stronger in the summer than the winter. The annual positive S/N are found in limited regions including mid- to high-latitude Asia, high-latitude North America, India, east Argentina, and Sahara, but no regions show S/N
values greater than 1. Positive S/N are more commonly found in the winter than the summer, especially in mid- to high-latitude Asia, and high-latitude North America. The spatial patterns of S/N do not change too much through time; while the magnitude of S/N become slightly greater, it does not change significantly. This indicates that the spread of uncertainty becomes larger as the signal becomes stronger.

Figure 5.10 The annual and seasonal signal to noise ratio of surface soil moisture anomalies for the 3rd decade, 6th decade, and 9th decade relative to mean of 1976-2005 based on CMIP5 multi-model ensembles (summer: JJA in North hemisphere and DJF in South hemisphere; winter: DJF in North hemisphere and JJA in South hemisphere). The negative values indicate drying and the positive values indicate wetting. The grids with stippling indicate an absolute value of S/N greater than 1, which means that the magnitude of soil moisture anomaly change signal exceed uncertainty.

We compare S/N of soil moisture anomaly with the temperature and precipitation projections (Hawkins and Sutton 2011). Signal to noise ratio are far higher for temperature than for soil moisture anomalies over all regions and all three lead times and the S/N peaks at the middle of 21st century which is greater than 3 in the lower- to mid- latitude and even
4 in the tropics. For precipitation, the highest wetting S/N is mainly shown in the high-latitude region. Over lead time, the high-latitude S/N is increasing approximately from 1 to 2 and even more. The drying S/N is mainly shown in Mediterranean and Central America and the absolute value of S/N is increasing slightly from below 1 to above 1 over lead time. Thus, the S/N of both temperature and precipitation are stronger than that of the soil moisture anomalies, with the S/N of temperature far stronger.

5.5 DISCUSSION AND CONCLUSION

We have analyzed the raw surface soil moisture output from all available GCMs for four RCP scenarios: RCP2.6, RCP4.5, RCP6.0, and RCP8.5 under the CMIP5 framework. We evaluate the statistical significance of change in surface soil moisture using paired two-sample student t-tests for each grid and control for false discovery rate (FDR) at a significance level of 0.05. We have found statistically significant annual drying over most of Australia, South America, North America, south Africa, Europe and Mediterranean, and east Asia, with stronger drying as the strength of forcing change increases, but statistically significant wetting in limited areas of east Africa, south Asia, central Asia by the end of 21st century. The soil moisture drying in Mediterranean, southwestern USA, northeast South America and southern African is mainly associated with the projected widening of the Hadley Circulation and increased temperature and evapotranspiration (IPCC 2013). The drying or wetting signal is more pronounced for seasonal than annual because of compensating effects for the whole year. We also have detected a strong seasonality in many regions in the mid- and high-latitude of North Hemisphere, with wetting in winter and drying in summer.
We used soil moisture to calculate the duration, frequency, severity, and spatial extent of severe drought (i.e., that which occurs approximately once every ten years for specific month). The multi-model median frequency of short-term drought is projected to increase by the end of 21st century in most regions and most scenarios. In most cases, the increase in frequency of short-term drought is higher for the RCP2.6 than the RCP8.5. In the latter scenario, individual months are more likely to cluster into consecutive dry months to form a long-term drought. The median frequency of long-term drought is also projected to increase in most regions, with the strongest increase in EUM, TSA, CAM, ENA, and SAF. The multi-model mean projects increasing spatial extent of severe drought for all regions and all emission scenarios, with progressively larger spatial extent of severe drought as the strength of radiative forcing increases by the end of 21st century. The multi-model and multi-scenario mean spatial extent of severe drought in CAM, EUM, TSA, and SAF are projected to increase the most. The increases in spatial extent of drought tend to be larger in warmer seasons than cooler seasons in most regions because of increasing temperature and evapotranspiration. Among all regions, CAM and EUM are most sensitive to different radiative forcing and the highest radiative forcing (RCP8.5) tends to expand the spatial extent and worsen the severe drought impacts more than the lowest radiative forcing (RCP2.6). Inter-model variability is high and contributes the most to uncertainty in future projections. This source of uncertainty increases with radiative forcing, i.e., the model uncertainty is higher for RCP8.5 than for RCP2.6. Compared with the historical (control) period (1976-2005), each individual GCM projection in the future (2071-2100) shows greater temporal (inter-month) variability in spatial extent of severe drought, resulting more widespread and extreme drought events. Furthermore, the variation in the
spatial extent of drought across models are much larger than the variations across the RCP scenarios, i.e., the model spread is much larger than the scenario spread. The variation across models are also much larger than the variations across different regions, i.e., the model spread is much larger than the spatial heterogeneity.

We have partitioned and quantified the three dominant sources of uncertainty with respect to decadal mean standardized soil moisture anomalies, decadal sum of 1-month drought occurrence, decadal sum of severity, and decadal mean spatial extent of drought from the CMIP5 MMEs. We have found that more than 80% of the uncertainty associated with future drought projection in the 21st century comes from differences between GCMs. This dominance results because of different treatment of clouds and precipitation in the models, as well as various local factors considered in soil moisture modelling. Regional patterns of uncertainty partition in spatial extent of drought for those 15 regions are similar to that for global and model uncertainty contributes approximately 80% to all the uncertainty. The difference across regions results mainly from the slight differences in the magnitude of scenario uncertainty.

When measured by simulated soil moisture conditions, drying occurs in large parts of the Mediterranean and Europe, many parts of the United States, Mexico, Southern Africa, many parts in Northern South America, Southeast China, West Australia. However, since the inter-model variability is so high, the signal to noise ratio of drying in soil moisture is less than -1 in only limited regions including the Mediterranean and Europe, the southwestern United states, and southern Africa. Model output for wetting occurs in mid-to high-latitude Asia, high-latitude North America, India, east Argentina, and Sahara, but none of these regions have a S/N ratio greater than 1. The spread of uncertainty becomes
larger as the signal becomes stronger and thus the spatial pattern and magnitude of S/N does not change significantly.

Improving future projection of agricultural drought depends on improved model performance in simulating soil moisture, e.g., improved representation of surface hydrological process. The GCM models might have limited abilities to simulate the water cycle and all relevant interactions between the atmosphere and land surface and the situation is further complicated by the fact of error propagation that model biases in one variable affect other variables through the causal chain (e.g. the simulation of soil moisture depends on the simulation of precipitation and evapotranspiration, representation of the soil layers and soil characteristics, etc.). The model uncertainty could be attributed to imperfect representation of the processes, or limited understanding of the very complex process, or inherent challenges in mathematically representing the processes (IPCC, 2013).

5.6 ACKNOWLEDGMENT

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CHAPTER 6 CONCLUSION

The three phases of research in my dissertation represent three consecutive and consequent themes in agricultural drought research. The first phase of research uses long-term nonlinear and nonstationary state- and county-level corn yield data from 1895 to 2014 to visualize the historical drought impacts on agriculture with examples of six major drought events in the US. Despite recent improvements in technology and in crop yield potential, food production and food security remain highly dependent on weather and climate variation (Rosenzweig et al. 2001). We have shown that in the regions where severe droughts occur, the corn yields were reduced by 50% and more in 1936, 40% to 50% in 1954 and 1980, 30% to 40% in 1988 and 2002, 30% to 50% in 2012. The condition is better for areas west of 100° W because of agricultural irrigation, while the agriculture productivity east of 100° W are highly dependent on the drought severity. The impact of an extreme drought event on agriculture depends not only on the severity of the event itself, but also on the vulnerability and resilience of the agricultural system that experience it. Thus, drought monitoring is critical for agricultural production and risk adaptation as effective drought quantification can mitigate losses. The second phase of research has developed a new agriculturally-based drought index, the Integrated Scaled Drought Index (ISDI) which integrates four components (scaled NDVI, scaled land surface temperature (LST), scaled precipitation (PCP), and scaled soil moisture (SM)). This new drought index incorporates a range of important variables controlling agricultural drought process, especially as it integrates soil moisture, an important but infrequently observed in-situ
variable affecting drought measurement. Further, not only should we build a
comprehensive agricultural drought monitoring and early warning system, but also should
understand how drought conditions might change in the future in the context of climate
change. It is important for decision makers to map out adequate adaptation and mitigation
strategies, since future drought risks could be exacerbated by spatio-temporal variabilities
in hydro-meteorological variables due to climate change. Thus, the third phase of research
focuses on the change in future agricultural drought risk. We have found a large scale of
statistically significant drying over most of Australia, South America, North America,
south Africa, Europe and Mediterranean, and east Asia, but statistically significant wetting
in limited areas of east Africa, south Asia, central Asia by the end of 21st century. The
MMEs median frequency of long-term drought is projected to increase in most regions,
with the strongest increase in EUM, TSA, CAM, ENA, and SAF. Also, the multi-model
and multi-scenario mean spatial extent of severe drought in CAM, EUM, TSA, and SAF
are projected to increase the most. Thus, for those regions where are in the hotspots and
highest risks, it is necessary for decision-makers to provide appropriate adaptation
strategies and plans to mitigate risks.

This dissertation has produced methodologies that can be used or generalized by
future researchers. The first phase of research has developed a methodology that can aid
analysis of agricultural yield for both empirical and modeling studies connecting
environmental and climate conditions to crop productivity. This approach is data self-
adaptive, which can simulate the underlying pattern of the non-linear time series and
detrend a large amount of time series automatically. It can separate out the high-frequency
fluctuation caused by the weather and climate variations from the long-term increasing
trend caused by the science and technological advances. This study has derived a term called “crop yield anomaly”, representing the percentage of yield lower or higher than normal yield conditions. This “crop yield anomalies” can be also used in the analysis of climate change impacts on agriculture. This approach not only can be applied to agricultural and climate studies, but also can be used in other environmental and ecological studies. The second phase of research has developed a new agriculturally-based drought index called the Integrated Scaled Drought Index (ISDI). This index includes a range of important component in controlling agricultural drought, such as vegetation, precipitation, temperature, and soil moisture. This index can be generalized to incorporate other satellite data or in-situ observation, such as soil moisture data from SMAP (Soil Moisture Active Passive), precipitation data from TRMM (Tropical Rainfall Measuring Mission), temperature data from AVHRR and MODIS, NDVI data from MODIS, etc. However, more researches and works are needed for ISDI. The ISDI has the potential for real-time operational agricultural drought monitoring and assessment if provided with in real-time satellite data or in-situ observations. The ISDI could also take the land use and land cover change in agricultural land into consideration in the future.

This dissertation has also pointed out that more research and analyses are warranted for investigating climate change impacts on future agricultural drought risks. The third phase of research has partitioned and quantified the three dominant sources of uncertainty (internal variability, model uncertainty, and scenario uncertainty) with respect to decadal mean standardized soil moisture anomalies, decadal sum of 1-month drought occurrence, decadal sum of severity, and decadal mean spatial extent of drought from the CMIP5 multi-model ensembles (MMEs). We find that more than 80% of the uncertainty associated with
future drought projection in the 21st century comes from differences between GCMs, i.e. model uncertainty. This dominance results because of different treatment of clouds and precipitation in the models, as well as various local factors considered in soil moisture modelling, such as slope, vegetation cover, land use, soil characteristic and texture, and soil depth and layers. Improving future projection of agricultural drought depends on improved model performance in simulating soil moisture, e.g., improved representation of surface hydrological process. The GCM models might have limited abilities to simulate the water cycle and all relevant interactions between the atmosphere and land surface. The situation is further complicated by the fact of error propagation that model biases in one variable affect other variables through a causal chain (e.g. the simulation of soil moisture depends on the simulation of precipitation and evapotranspiration, representation of the soil layers and soil characteristics, etc.). The model uncertainty could be attributed to imperfect representation of the processes, limited understanding of very complex processes, or inherent challenges in mathematically representing the processes (IPCC, 2013).
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