CROP- AND LOCATION-SPECIFIC DROUGHT INDEX FOR AGRICULTURAL WATER MANAGEMENT:

DEVELOPMENT, EVALUATION, AND FORECASTING

A Dissertation

by

RACHEL MCDANIEL

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Chair of Committee,	Clyde Munster
Committee Members,	John Nielsen-Gammon
	Patricia Smith
	Wayne Smith
Head of Department,	Stephen Searcy

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ABSTRACT

Severe droughts have plagued the United States over the last few years. The 2011 Texas drought, the 2012 U.S. drought, and the current California drought have greatly impacted the nation's economy and agricultural production. Different crops vary in their response to water stress. Despite this, commonly used drought indices, such as the Palmer Drought Severity Index, do not consider crop specific factors. The goal of this project was to create a methodology to produce crop and location specific drought and yield trend forecasts to help agricultural producers make more informed water management decisions. To achieve this, a drought index was developed and analyzed, weather forecasts were used in a hydrology/crop model to predict hydrologic conditions and crop yields, and an example interactive map interface were created to convey this information to water stakeholders.

The drought index uses five parameters that affect or are affected by drought. These parameters include precipitation, temperature, cumulative biomass, soil moisture, and transpiration. Soil moisture and temperature are ranked against crop-specific threshold values, while precipitation and cumulative biomass are ranked against location-specific normal values. Transpiration is ranked against the location-specific potential transpiration. A case study was performed in the Upper Colorado River Basin located in West Texas using this drought index. Cotton is the primary crop grown in the watershed and was used in this study. The Soil and Water Assessment Tool (SWAT) was used to estimate the cumulative biomass, soil moisture, and transpiration. A multiple linear regression model was developed for each week of the growing season based on the significant parameters during that stage of the growing season. These models were used to predict yield trends and drought severity.

Two week forecasts for each drought parameter, yield trends, and the drought index were generated for 2010 through 2013 by using forecasted precipitation and temperature data as inputs for the hydrologic and crop model. This provided forecasted soil moisture, transpiration, and cumulative biomass production. Parameter rankings, yield trends, and the drought index were compared for those calculated with actual precipitation and temperature data as well as forecasted precipitation and temperature data. The precipitation ranking, temperature ranking, cumulative biomass ranking, transpiration ranking, estimated yield

trends, and drought index indicated satisfactory forecast results. The soil moisture forecast did not result in satisfactory forecast.

The final step in the project was to create an example interface for agricultural producers and water managers to view drought related stresses. ArcGIS online was used to create maps which show graphs of the weekly drought index and soil moisture ranking. Maps were created at the county scale. These maps provide agricultural producers readily accessible information that can be used for decision making related to water management.

DEDICATION

This dissertation is dedicated to my husband, Mitchell McDaniel, who has been so understanding and supportive throughout my education. I want to thank him for always encouraging me to pursue my dreams.

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CHAPTER I

INTRODUCTION

1.1 Water Scarcity

Water resources are an essential component to everyday life. People expect to be able to turn on the tap for what seems like an endless supply of water for agricultural, industrial and domestic purposes. There is, however, a limit to the amount of water that can be sustainably used. Many areas of the world are already experiencing water scarcity. Water scarcity generally occurs when the demand for water exceeds the supply. As of 2006, about 1.4 billion people lived in watersheds where water use exceeded supply (UNDP, 2006). Rijsberman (2005) concluded that there is a "physical water scarcity affecting food production and productive water use … in North Africa and the Middle East." Smakhtin et al. (2004) assessed water scarcity using the combined water requirements for environmental and human needs. They determined that a wider range of locations are experiencing water scarcity, including large areas of North America, North Africa, Asia, and the Middle East.

Issues with water scarcity are likely to increase due to factors such as climate change, increasing populations, and the overuse of water resources. In fact, the World Economic Forum's 2013 Global Risks report identifies water supply crises as one of the top risks for both impact and likelihood to occur at the global scale during the next decade (WEF, 2013).

The global average temperature has increased by 0.85°C since 1880 (IPCC, 2014). Higher temperatures have and will continue to increase evapotranspiration from surface waters, soil, and plants, thus affecting water availability. In addition to increasing temperatures, the number of drought occurrences has also increased in recent years. Stahle and Cleaveland (1988), for example, examined the drought record in North Texas from 1698 to 1980 and determined that five out of the six worst droughts in June have occurred since 1917. Trenberth et al. (2014) discuss how climate change will likely affect drought including quicker onset, more intense, and longer drought conditions.

The rapidly increasing global population is expected to place an ever increasing strain on water resources and increase water scarcity. By 2050, the United Nation predicts that the global population will reach nearly 9 billion people (UN, 2004), an increase in about 1.8 billion people. One of the major water scarcity concerns from the standpoint of rising populations is the need to increase agricultural production. It is estimated that 70-80% of the water currently used is for agricultural production (Premanandh, 2011; UNESCO, 2012). Rijsberman (2005) reviewed several water scarcity measures and concluded that water will be a major constraint for agriculture in the future. The United Nations World Water Development Report 4 states that "responsible agricultural water management will make a major contribution to future global water security" (UNESCO, 2012).

Lastly, many areas are withdrawing more water than is sustainable (UNESCO, 2012). The flows of several of the world's major rivers have been greatly reduced because of too much water being withdrawn including the Colorado, Indus, Rio Grande, Yellow, Teesta, and Murray rivers. Groundwater is also being rapidly depleted. For example, the High Plains Aquifer in the United States was reduced by an average of 14 feet across the aquifer, or 273 million acre-feet, from pre-development through 2009 (McGuire, 2011). McGuire found that the largest decline was 234 feet in the Texas Southern High Plains.

1.2 Crop Development and Stressors

As previously stated, an estimated 70-80% of water resources are currently used for agricultural purposes, making it the single largest user of water resources. Crop yields can be severely impacted by the amount and timing of moisture inputs. Crop development is generally divided into three broad phases: (1) germination and emergence, (2) the vegetative phase, and (3) the reproductive phase (Milthorpe and Moorby, 1974).

Two environmental factors, water and temperature, are particularly important for crop growth. They influence essential processes, including photosynthesis, as well as process rates (Milthorpe and Moorby, 1974). Pettigrew (2004) found a 35% reduction in cotton leaf area index under moisture stress conditions associated with drought. High temperatures have been associated with root senescence (Sánchez et al., 2014) and yield reductions (Asana and Williams, 1965). Stressors can affect yields more during critical crop growth stages. For example, Snowden et al. (2014) demonstrated that cotton yields were most affected by stress during the early flowering stage of growth. Spring wheat has been shown to have the highest drought-associated stress during or after heading (Robins and Domingo, 1962). Hane and

Pumphrey (1984) discuss the critical periods of several crops. They state that winter wheat yields are more strongly impacted by water shortages from emergence to flowering and peas are most affected by low moisture conditions during the flowering and pod filling stages.

1.3 Drought

The current and future stresses on water resources make many areas increasingly vulnerable to drought.

1.3.1 Drought Definitions

Drought is difficult to define, let alone measure, model or predict. There is not a single consensus on what defines drought. In fact, there are two types of drought definitions: conceptual and operational (Wilhite and Glantz, 1985). Operational definitions associate numbers with drought, where conceptual drought definitions are descriptive. Van Huijgevoort, et al. (2012) defined drought as being "characterized by a temporal, sustained, and spatially extensive occurrence of below average natural water availability." The American Meteorological Society (1997) stated that drought is "a temporary aberration, in contrast to aridity, which is a permanent feature of regional climate." The World Meteorological Organization (1986) described drought as "a sustained, regionally extensive, deficiency in precipitation." Palmer (1968) defined agricultural drought as "a transpiration deficit."

Dracup, et al. (1980) discuss the difficulties with settling on a single definition of drought. The first issue brought forth is the nature or primary interest of the drought changes with the interested person or group. The interest could be in precipitation, streamflow, soil moisture, economic value of water, or any combination thereof. Though the economic value of water is not discussed by Dracup, et al. (1980), socioeconomic drought has been identified as a drought type of interest by others (Wilhite and Glantz, 1985; American Meteorological Society, 1997). Secondly, Dracup, et al. (1980) discuss the issue of the period of interest. Depending on the interest in drought and the use of the drought definition, an individual or group may be interested in a monthly, seasonal, annual, or other time period. Agricultural producers, for instance, may be interested in short-term dry conditions to make the best use of their water resourced for crop irrigation. On the other hand, water resource planners may be more interested in long-term dry conditions which may affect municipal water supplies. The third issue when defining drought is the problem of truncation, or the value below which moisture conditions are considered lower than normal and thus drought is occurring. This truncation point can be determined by a variety of methods, but generally involves the median or mean of the parameter of interest. The final problem in defining drought posed by Dracup, et al. (1980), is that of the regionalization of drought. Regionalization requires drought to be grouped essentially in one of two ways: (1) by similar climate, similar geomorphology, and geographic proximity; or (2) by statistically similar hydrological or meteorological records. Difficulties such as these led Wilhite and Glantz (1985) to suggest that there should not be a single definition of drought.

1.3.2 Drought Classifications

The difficulties associated with creating one, universal drought definition has led to four commonly used drought categories which include meteorological, agricultural, hydrological, and socioeconomic drought (American Meteorological Society, 1997; Wilhite and Glantz, 1985). Meteorological drought is less than normal precipitation. The onset and end of meteorological drought can be rapid (Heim Jr., 2002); however, such drought can be persistent, lasting months or years at a time. Agricultural drought generally corresponds to low soil moisture conditions, especially during the growing season. Crop yields can be severely impacted by agricultural drought if these low moisture periods are persistent and/or occur during critical growing stages of the crop. For example, if low moisture conditions occur during the corn tasseling pollination stage, yield could be reduced up to 25% (Hane and Pumphrey, 1984). Soil can retain moisture conditions for long time periods, giving soil a 'memory' of recent moisture conditions (Orth and Senevirantne, 2012; Wu and Dickinson, 2004; Koster et al., 2000). Hydrologic drought is broadly thought of as a deficiency in water supply (Keyantash and Dracup, 2002). This deficiency can be in groundwater, streamflow, and/or lake or reservoir levels. These water supplies can be very dependent on recharge from high precipitation events; therefore, hydrological drought can be very persistent, even long after the end of meteorological drought (Heim Jr., 2002). Lastly, socioeconomic drought is associated with more demand for water or a product dependent on water sources than supply, thus having the potential to increase the monetary value of water or water dependent product (Wilhite and Glantz, 1985; American Meteorological Society, 1997). Drought typically begins with meteorological drought. Then, as it persists, it moves to agricultural and finally hydrological drought.

1.3.3 Drought Measurements and Indices

Several drought indices have been developed to quantify low moisture conditions in a region. Some of the most common drought indices are precipitation deciles (Gibbs and Maher, 1967); the Palmer Drought Severity Index (PDSI) (Palmer, 1965); the Standardized Precipitation Index (SPI) (McKee et al., 1993); the Vegetation Condition Index (VCI) (Kogan, 1990; Kogan, 1995); the Crop Moisture Index (CMI) (Palmer, 1968); and the Surface Water Supply Index (SWSI) (Shafer and Dezman., 1982).

1.3.3.1 Precipitation Deciles

Precipitation deciles were suggested as a measure of drought by Gibbs and Maher (1967) and divide precipitation records into groups based on every tenth percentile (deciles). Cumulative precipitation values falling in the 1st or 2nd decile (< 20% of the historical record) are considered extreme drought, while cumulative precipitation values falling within the 3rd and 4th deciles (20-40% of the historical record) are considered drought conditions (Kallis, 2008).

1.3.3.2 PDSI

Palmer (1965) developed PDSI as a method of evaluating drought severity with the goal of being able to compare the index across temporal and spatial distributions. The PDSI estimates the amount of moisture received by a region using precipitation and temperature data and compares it to the amount of moisture that ‘normally’ occurs in the region. Palmer (1968) describes the PDSI as an “estimate of the amount by which the actual weekly evapotranspiration deficit falls short of the ‘expected’ weekly evapotranspiration.” A calculated PDSI value of -4 would indicate extreme drought conditions while a value of +4 would indicate very wet conditions. As one of the most widely used drought indices (Mishra and Singh, 2010; Kallis, 2008), the PDSI has been used for a variety of studies. For example, Soulé (1992) examined the spatial pattern of droughts in the United States over 94 years using the PDSI. Liu and Hwang (2015) forecasted drought using the PDSI in Arkansas with the goal of improving the management of water resources. Long-term forecasts have been performed by to evaluate potential changes in drought conditions due to climate change (Cook et al., 2014; Rind et al., 1990).

1.3.3.3 SPI

McKee et al. (1993) developed the SPI, stating that "standardized precipitation is simply the difference of precipitation from the mean for a specified time period divided by the standard deviation where the mean and standard deviation are determined from past records." While they focused on using precipitation as the drought indicator, McKee et al. suggest that this method could be used with other water sources such as snowpack, streamflow, reservoir storage, soil moisture, or groundwater. An SPI value less than zero indicates drought and a value less than -2 indicates extreme drought. The SPI has been used to evaluate drought magnitude (Dashtpagerdi et al., 2015); spatial and temporal drought patterns (e.g. Raziei et al., 2015; Bonaccorso et al., 2003); climate change impacts on drought (e.g. Jenkins and Warren, 2015); among other topics.

1.3.3.4 VCI

The VCI (Kogan, 1990) is used to estimate drought stress associated with vegetative growth and is used for evaluating agricultural drought. It was developed to take advantage of satellite imagery which can be used to estimate vegetation conditions via the calculation of the Normalized Difference Vegetation Index (NDVI). At the time of development, the satellite had five spectral bands including the visible (Ch1) and near infrared (Ch2) bands which are used to calculate the NDVI (Equation 1).

$$NDVI = \frac{Ch2 - Ch1}{Ch2 + Ch1} \tag{1}$$

The NDVI essentially measures the amount of reflectance which is much less in healthy vegetation (Kogan, 1995). The VCI uses the weekly, smoothed NDVI and uses a linear ranking based on the weekly, long-term minimum ($NDVI_{min}$) and maximum ($NDVI_{max}$) (Equation 2).

$$VCI = 100 \times \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \tag{2}$$

The VCI ranges from zero to 100, with 100 indicating optimal vegetation conditions.

1.3.3.5 CMI

The CMI is used to evaluate agricultural moisture conditions and combines estimated evapotranspiration, as calculated by the PDSI, with a wetness index that takes into account excess moisture (Palmer, 1968). Negative CMI values indicate deficient evapotranspiration, or dry conditions, while positive values indicate wet conditions occurred through sufficient evapotranspiration or adequate rainfall. Palmer (1968) states that crop growth stages must be considered when interpreting moisture effects as calculated by the CMI on crops.

1.3.3.6 SWSI

Shafer and Dezman (1982) developed the SWSI for use in mountainous regions by accounting for melting snow which can be a major contributor to water supplies in these areas. This index uses both hydrological and climatological parameters including snowpack, precipitation, reservoir storage, and streamflow. Shafer and Dezman emphasize that the SWSI was created as a complement to the PDSI. As such, the scale of the SWSI is similar to that of the PDSI with a value of +4 indicating abundant water supplies and a value of -4 indicating extreme drought conditions.

1.3.4 Impact of Drought

The impact of drought is far reaching. First, drought has been identified as one of the costliest natural disasters. FEMA (1995) estimated that drought causes on average between $6 and $8 billion in damages annually in the United States. In 2000, Wilhite identified the 1988 drought as the costliest disaster in the history of the United States, with an estimated cost of about $39 billion from 1987 to 1989 (Riebsame et al., 1991). Other droughts have cost millions and billions of dollars in the agricultural sector. The Georgia drought from 1998 to 2000 resulted in an estimated $689 to $885 million in crop losses (Georgia DNR, 2001); crop losses of about $401 million were estimated for the 2002 South Dakota drought (Diersen and Taylor, 2003); the Texas drought of 2011 resulted in an estimated $7.6 billion in agricultural losses (Fannin, 2012); the California drought of 2014 resulted in an estimated $1.5 billion in direct agricultural losses.

Drought has led three Texas communities to run out of water in recent years, including Robert Lee, Spicewood Beach, and Barnhart (De Melker, 2012; Galbraith, 2013). Over 1,000 Public Water Systems (PWSs) had water restrictions as of December 2014 with 2/3 of the restrictions being mandatory (TCEQ, 2014). The water shortages in Texas have led to restrictions on water resource use for agricultural purposes such as rice farms on the Lower Colorado River (State Impact, 2014).

1.3.5 Forecasting Drought

Several methods have been used to forecast drought conditions. Kumar and Panu (1997) used a multiple linear regression model to predict agricultural drought. They used both the number of rainy days and the amount of rain in each month of the growing season to predict yield with the assumption that yield was a good drought indicator. Lohani and Loganathan (1997) used probabilistic weather data was used to compute a probabilistic range of PDSI values for Virginia. An agricultural drought forecasting method was suggested by Marj and Meijerink that uses climate signals in an artificial neural network to predict the NDVI. The NDVI is used as the drought indicator. Mishra and Desai (2005) used a combination of linear stochastic models and multiplicative Seasonal Autoregressive Integrated Moving Average (SARIMA) to forecast drought in a watershed located in India.

1.4 Decision Making

The decision making process is important when determining how to use limited water resources during periods of drought. The steps in the decision making process have been identified by many people in many ways (e.g. Gardiner and Edwards, 1975; Carroll and Johnson, 1990; Crozier and Ranyard, 1997; Tsoukias, 2009), but generally include some variation of the following eight steps: (1) identify the problem, (2) define the objectives, (3) collect data, (4) analyze the data, (5) develop alternatives, (6) select a solution, (7) implement a solution, and (8) follow-up (Figure 1). For example, an agricultural producer may begin by identifying crop water stress. The objective might be to reduce crop yield loss. Next, information or data would be collected and analyzed. This might include the amount of irrigation the crop needs, where the water can be obtained, how much the water costs, and an estimate of the potential yield gain from irrigation. Data collection and analysis may occur simultaneously and repeatedly. This means that data is collected and may immediately be analyzed; however, if there is not enough information after the data is analyzed to develop alternatives, more data may be collected and analyzed.

Several online tools have been developed to aid water resource users and managers collect and analyze data for the development of alternative solutions. For example, Modala (2014) developed a web application using a geographic information system (GIS) to convey potential impacts of climate change in the Texas Panhandle region.

1.5 SWAT Model

1.5.1 SWAT Overview

One way to aid the decision making process is to estimate system impacts through models such as the Soil and Water Assessment Tool (SWAT). SWAT is a widely used model for hydrologic assessments. It is a basin-scale, continuous time, process-based model that runs on a daily time scale (Gassman et al., 2007). It was developed for rural watersheds to assess "the impact of management on water supplies and nonpoint source pollution in watersheds" (Arnold et al., 1998). Components from several models were combined to form SWAT including Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS) which contributed the daily hydrology component, Groundwater Loading Effects on Agricultural Management Systems (GLEAMS) which contributed the pesticide fate component, Environmental Policy Integrated Climate (EPIC) which contributed the crop growth component, Routing Outputs To Outlet (ROTO) which contributed the streamflow routing component, and Enhanced Stream Water Quality Model (QUAL2E) which contributed the in-stream kintects component (Gassman et al., 2007).

SWAT is a semi-distributed model (Gassman et al., 2007). The basin is first distributed into subbasins. At the subbasin scale, SWAT uses lumped Hydrologic Response Units (HRUs) to calculate hydrology. HRUs consist of the all the area within a subbasin with the same landuse, soil type, and slope.

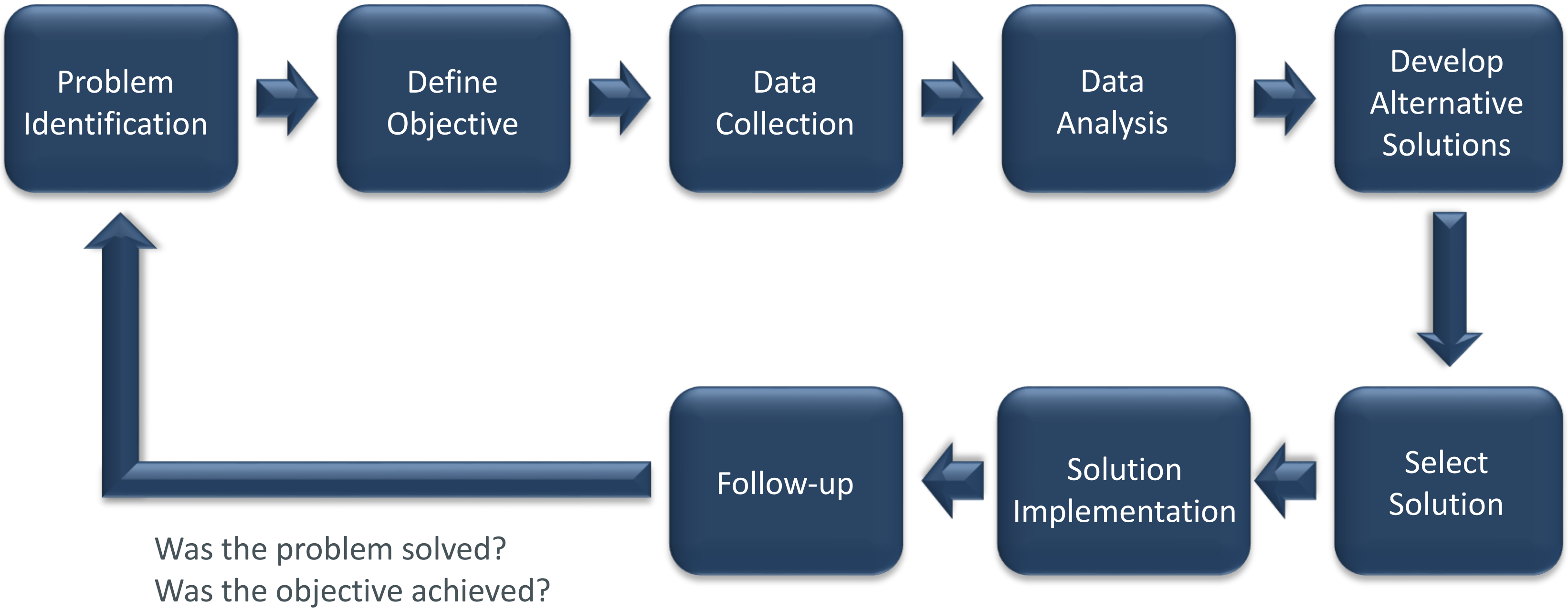

Figure 1: The decision making process generally consists of 8 steps including problem identification, objective definition, data collection, data analysis, alternative solutions development, solution selection, solution implementation, and finally follow-up. Decision making is an iterative process. If the problem was not solved, it may be necessary to repeat the process.

1.5.2 Modeling Hydrology

The SWAT model has been used by many researchers to evaluate a range of issues related to hydrology. A number of scientists have examined the effect of landuse change on various hydrologic processes (Guo et al., 2008; Fohrer et al., 2001; Vache et al., 2002; Li et al., 2009a). The effects of landuse change on hydrology was examined using SWAT by Fohrer et al. (2001) while the effects of landuse change on water quality was examined by Vache et al. (2002). Current and future groundwater recharge rates have been estimated using the SWAT model (Arnold et al., 2000; Eckhardt and Ulbrich, 2003). Point and nonpoint source pollution is a major problem in many watersheds and several studies have used SWAT to model the fate and transport of pollutants such as nutrients and sediments (Santhi et al., 2001; Vache et al., 2002). Seasonal soil moisture trends in Oklahoma were evaluated by Deliberty and Legates (2003). SWAT's ability to model potential evapotranspiration (PET) was evaluated by Earls and Dixon (2008) and they found that there was no significant difference between observed and modeled PET. Changes due to climate variability have also been examined (Jha et al., 2006; Eckhardt and Ulbrich, 2003; Li et al., 2009b; Bekele and Knapp, 2010). Jha et al. (2006) used SWAT to examine the potential changes in hydrology of the Upper Mississippi River basin under six climate change scenarios. The changes in groundwater recharge and streamflow due to climate change were assessed by Eckhardt and Ulbrich (2003).

1.5.3 Modeling Crop Yields

Several studies use SWAT to estimate crop yields in basins with substantial agricultural activity. Nair et al. (2011) demonstrates the importance of calibrating and validating crop yields as a part of model set-up. Srinivasan et al. (2010) modeled corn and soybeans in the Upper Mississippi River Basin and found that SWAT satisfactorily predicts yields even without calibration. Corn and soybeans were also modeled by Hu et al. (2007) to accompany their study on nitrate export. While they only evaluated crop model performance with the PBIAS, they found SWAT did not have a tendency to over- or under-predict yield values. In addition to typical row crops, SWAT has been used to model bioenergy crops such as miscanthus (Ng et al., 2010). The effects of different crop management practices on crop growth and water quality was examined by Bossa et al. (2012). Palazzoli et al. (2015)

examined different the effect of different climate change scenarios on wheat, corn, and rice yields.

1.5.4 Modeling Drought

SWAT has been used for several studies to evaluate drought. Trambauer et al. (2013) examined the ability of 16 hydrological models to be used for drought forecasting in Africa and stated that SWAT was one of five models that showed "higher potential and suitability for hydrological drought forecasting in Africa." Vu et al. (2015) examined both hydrological and meteorological drought by using ensemble climate projections in the SWAT model. Water availability was modeled using SWAT by Gies et al. (2014) for use in evaluating drought in East Africa.

In addition, researchers have used SWAT output as input to drought indices. SWAT output was used to calculate the PDSI in North China (Yan et al., 2013). Narasimhan and Srinivasan (2005) developed two drought indices, the Soil Moisture Deficit Index (SMDI) and Evapotranspiration Deficit Index (ETDI) to be used with the SWAT model for finer spatial resolution of drought conditions than the PDSI and SPI. Jain et al. (2015) developed the Integrated Drought Vulnerability Index (IDVI) and used it along with the SWAT model to examine drought vulnerability in the Ken River basin, India.

1.5.5 Model Evaluation

1.5.5.1 Overview of Model Evaluation Statistics

Many efficiency statistics and error indices exist to evaluate model results. For hydrologic models, the most widely used evaluation statistics are the coefficient of determination (R^2) and the Nash-Sutcliffe coefficient of efficiency (NS) (Arnold et al., 2012). However, it is also widely understood that these statistics are overly sensitive to high flows (Legates and McCabe, 1999; Krause et al., 2005; Arnold et al., 2012). Krause et al. (2005) also demonstrated that the R^2 and NS statistics are not sensitive to model biases, such as consistent under-prediction. For better model evaluation, several studies recommend using error indices in addition to typical model evaluation statistics (Legates and McCabe, 1999; Krause et al., 2005; Moriasi et al., 2007). Some suggested error indices include the Root Mean Square Error (RMSE), ratio of the RMSE to standard deviation of the observed data (RSR), and percent bias (PBIAS) (Legates and McCabe, 1999; Moriasi et al., 2007; Coffey et al., 2004).

1.5.5.2 Coefficient of Determination

R^2 (Equation 3) evaluates the amount of the observed variance that is explained by the model. The R^2 statistic ranges from zero to one. A value of zero indicates none of the observed variance is explained by the model while a value of one is optimal and indicates that all the observed variance is explained by the model. R^2 has been used to evaluate SWAT streamflow simulations in many studies (Arnold et al., 2000; Earls and Dixon, 2008; Vache et al., 2002; Vu et al., 2015, Yan et al., 2013; Santhi et al., 2001).

$$R^2 = \left\{ \frac{\sum_{i=1}^{N}(O_i - \bar{O})(P_i - \bar{P})}{\left[\sum_{i=1}^{N}(O_i - \bar{O})^2\right]^{0.5}\left[\sum_{i=1}^{N}(P_i - \bar{P})^2\right]^{0.5}} \right\}^2 \tag{3}$$

where O_i is the observed streamflow at time i, P_i is the predicted streamflow at time i, $\bar{O}$ is the average observed streamflow over the modeled period, and $\bar{P}$ is the average predicted streamflow over the modeled period.

1.5.5.3 Nash-Sutcliffe Coefficient of Efficiency

The NS (Equation 4) is an efficiency measure that evaluates how well the modeled data matches the observed along a line with a slope of 1 (Arnold et al., 2012). NS ranges from negative infinity to one with an optimal value of one. Negative values indicate that the model performed worse than using the observed mean, while a positive value indicates that the model performed better than using the observed mean. NS has been used to evaluate the calibration and validation of hydrologic parameters in many SWAT studies (Fohrer et al., 2001; Li et al., 2009a; Bekele and Knapp, 2010; Vu et al., 2015; Yan et al., 2013; Santhi et al., 2001).

$$NS = 1 - \frac{\sum_{i=1}^{N}(O_i - P_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2} \tag{4}$$

1.5.5.4 Percent Bias

The PBIAS (Equation 5) evaluates the model's tendency to over- or under-predict. A positive PBIAS indicates the model over-predicts, a negative value indicates the model under-predicts, while zero indicates the model does not have a tendency to over- or under-predict and is, therefore, optimal. PBIAS is used in a number of SWAT studies to evaluate model performance for both streamflow and crop yields (e.g. Li et al., 2009a).

$$PBIAS = \left(\frac{\sum_{i=1}^{N}(P_i - O_i)}{\sum_{i=1}^{N} O_i}\right) \times 100\% \tag{5}$$

1.5.5.5 Root Mean Square Error and RMSE to Observed Standard Deviation Ratio

The RMSE (Equation 6) measures the error of the model and weights errors with larger absolute values more weight, thus negatively emphasizing variance (Chai and Draxler, 2014). The RSR (Equation 7) is presented by Moriasi et al. (2007) as a method to standardize the RMSE. It normalizes the RMSE by dividing it by the standard deviation of the observed data (SD_O). The RSR error index is somewhat new, but has been adopted by some to evaluate SWAT model results (Li et al., 2009a; Bekele and Knapp, 2010; Earls and Dixon, 2008).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(O_i - P_i)^2} \tag{6}$$

$$RSR = \frac{RMSE}{SD_O} = \frac{\sqrt{\sum_{i=1}^{N}(O_i - P_i)^2}}{\sqrt{\sum_{i=1}^{N}(O_i - \bar{O})^2}} \tag{7}$$

1.5.5.6 Interpretation of Model Statistics

While there is no consensus about ranges for satisfactory model evaluation statistics, Moriasi et al. (2007) and Gassman (2008) provided recommended ranges. Gassman (2008) recommended R^2 values above 0.5 for monthly calibrations. Moriasi et al. (2007) recommended monthly calibration values for NS of greater than 0.5 and RSR values to be below 0.7. Three ranges were provided for satisfactory PBIAS of monthly calibrations based on typical parameter uncertainty. -25% to 25% was recommended for streamflow, -55% to 55% was recommended for sediment, and -70% to 70% for nutrients. Moriasi et al. (2007) state that appropriate relaxing and tightening of these values should be done for daily and annual calibrations.

1.6 Project Objectives

Drought is a costly hazard that impacts many people. Agricultural producers are being affected by both limited water resources and drought which impacts crop yields. The objective of this study is to create an early warning system/decision making (EWS/DM) system by forecasting meteorological, hydrological, crop yield, and drought trends with a two-week lead time to help agricultural producers better prepare for drought conditions and manage water resources. This will be achieved by:

1. Developing a crop- and location-specific drought index to provide crop specific information for irrigation water resource management decisions,
2. Verifying the drought index through a case study
3. Integrating two-week weather forecasts with a hydrologic model which will predict soil moisture, evapotranspiration, biomass production, and crop yield trends,
4. Comparing yield trends and drought conditions calculated with observed and forecasted weather data to determine forecast accuracy,
5. And generating a sample interactive map that will demonstrate an EWS/DM tool that could be used to disseminate forecasted hydrologic conditions and yield trends to agricultural producers.

CHAPTER II

CROP AND LOCATION SPECIFIC AGRICULTURAL DROUGHT QUANTIFICATION: PART I – METHOD DEVELOPMENT

2.1 Synopsis

Drought is generally understood as low moisture conditions over a period of time; however, no single definition exists for drought. The numerous drought definitions and classifications have led to many indices that attempt to quantify drought. Most of these indices rely on a single parameter such as precipitation or soil moisture and do not consider crop specific information such as threshold values, which cause crop stress when exceeded. An example of a crop threshold is the soil moisture depletion value below which causes moisture stress to the crop. The goal of this study is to provide a new methodology to quantify drought for a specific crop at a specific location, allowing for water management decisions on a crop-specific basis. This is achieved by ranking and combining five factors, including (1) precipitation, (2) temperature, (3) biomass production, (4) soil moisture, and (5) transpiration. The temperature and soil moisture rankings are calculated using crop specific stress thresholds, whereas precipitation and biomass production rankings are calculated by using location specific normal values. Transpiration stress is a crop and location specific value that is calculated by comparing the actual transpiration to the daily maximum transpiration. The parameters are combined via multiple linear regression models which estimate crop yields. A single model is created for each week of the growing season using the parameter or parameters that are significant for that week. The predicted yield deciles indicate the yield trend based on crop water stress and is therefore used as the crop specific drought index.

2.2 Introduction

Drought is a costly and wide spread natural disaster. It has been estimated that drought causes between \$6 and \$8 billion in damages per year on average in the United States (FEMA, 1995). As of 2000, the 1988 drought was identified as the costliest disaster in the United States (Wilhite, 2000). Recently, the Texas drought of 2011 cost the agricultural sector alone an estimated $7.6 billion in damages (Fannin, 2012). Drought also affects a large number of people worldwide. Wilhite (2000) stated that more droughts affected 1% or more of the world population from 1963 to 1992 than any other natural hazard.

Despite the widespread and costly impact of drought, drought has been difficult to define, measure, model, and predict. The World Meteorological Organization (WMO, 1986) stated that "drought means a sustained, extended deficiency in precipitation" while Palmer (1965) provides a broader definition by defining drought as a "prolonged and abnormal moisture deficiency". Kallis (2008) provides yet another definition by stating that drought is a "temporary lack of water, which is, necessarily but not exclusively, caused by abnormal climate and which is damaging to an activity, group, or the environment".

Though there are numerous definitions, drought has been generally grouped into four categories which include meteorological drought, hydrological drought, agricultural drought, and socioeconomic drought (Mishra and Singh, 2010). Meteorological drought occurs when there is a precipitation deficit over time; this can have far reaching impacts on everything from agricultural production to municipal water supplies. Hydrological drought occurs when there are reduced surface and subsurface flows; this impacts ecosystem dynamics and may affect downstream water supplies. Agricultural drought occurs when there is low soil moisture; this can cause crop stress and reduced yields. Lastly, socioeconomic drought occurs when there is more demand for water resources than the supply, which can lead to water restrictions. Each drought category is affected by differently by hydrologic and climatologic parameters, so they do not always begin, end, or even occur at the same time. Drought generally begins with meteorological drought or a lack of precipitation and, as it persists, leads to agricultural and hydrological drought. Socioeconomic drought can occur with or without other droughts because it refers to the supply to demand ratio of water which may or may not be affected by the current moisture conditions. For example, an area with a small supply of water may experience socioeconomic drought if there is not enough to go around, even when moisture conditions in the region are normal. Therefore, measuring, modeling, and predicting each drought type requires a unique approach for optimal results.

The variety in drought definitions and classifications has led to the creation of many different drought indices that attempt to quantify drought. Therefore, each classification of drought has several commonly used methods for quantifying drought. For instance, some of the commonly used meteorological drought indices include rainfall deciles, the Palmer Drought Severity Index (PDSI), and the Standardized Precipitation Index (SPI). Some of the commonly used hydrological drought indices include total water deficit, cumulative streamflow anomaly, and the Surface Water Supply Index (SWSI). Lastly, agricultural drought indices include the Crop Moisture Index (CMI), computed soil moisture, and the soil moisture anomaly index. Keyantash and Dracup (2002) provide a summary and evaluation of these and other commonly used drought indices. Socioeconomic drought is based on supply and demand and is therefore generally measured by the cost of water.

The focus of this study is on agricultural drought. Commonly used agricultural drought indices are limited because they are not crop specific and tend to solely rely on soil moisture. A crop specific index is important because crops respond to variations in moisture conditions differently. For example, cotton can withstand a 65% depletion in soil moisture before the onset of crop stress, but strawberries can only withstand an estimated 20% soil moisture depletion before causing crop stress (Allen et al., 1998). In addition, though soil moisture is an important indicator for drought, there are additional parameters that indicate crop stress or the potential for crop stress due to drought conditions. For instance, high temperatures can exacerbate drought conditions (e.g. Nicolas et al., 1984) and limited rainfall over time will lead to low soil moisture conditions, which will, in turn, limit crop transpiration.

Creating a crop specific drought index will help agricultural producers make improved water management decisions. Providing information about when crops are stressed will allow for irrigation scheduling based on this crop specific moisture stress information. This could reduce the amount of water used for irrigation over the growing season by optimizing the timing of irrigation applications.

The purpose of this study is to develop a drought quantification method that can be used to help agricultural producers better manage water resources by identifying the critical conditions for their crop. The objectives were to, (1) identify parameters important to drought and crop production to be used in quantifying drought, and (2) create a crop specific drought index that was adaptive to various crops grown in various locations. To accomplish this, a review of literature was performed to identify parameters that affect or can be affected by drought and are associated with crop yields. These parameters were then ranked against threshold and normal values to provide crop and location specific rankings. Finally, crop specific linear regression models were created for each week of the growing season to estimate yields and calculate the drought index.

2.3 Parameter Identification

Agricultural drought is largely dependent on conditions that occur within the growing season; therefore, this study focuses on short-term drought. Five parameters were chosen for use in quantifying crop and location specific drought, (1) precipitation, (2) temperature, (3) cumulative biomass production, (4) soil moisture stress, and (5) crop transpiration stress. These parameters are affected during different phases of drought. Drought generally begins with low precipitation and high temperatures followed by reduced soil moisture and transpiration. This ultimately results in lower biomass production.

2.3.1 Precipitation

Reduction of precipitation is generally the starting point for drought conditions. Low precipitation amounts can result in a number of surface and subsurface moisture problems including reduction of soil moisture, groundwater levels, streamflows, and reservoir levels. Though total amount of precipitation is possibly the most recognized precipitation variable associated with drought, it is not the only precipitation variable drought depends on. Precipitation intensity, frequency, timing, and distribution are also important (Kallis, 2008). A high intensity precipitation event will result in an increase in runoff volume and a decrease in the volume infiltrated into the soil when the soil infiltration rate is lower than the precipitation rate. Frequency is also important because smaller, more frequent precipitation events can help regulate soil moisture. On the other hand, larger, infrequent precipitation events will allow more time for the soil to dry out between events. In addition, the timing of precipitation events is very important for crop production because crops often have critical periods where low moisture conditions can be particularly damaging to yields. For example, the greatest drought stress in spring wheat occurs during or after heading (Robins and Domingo, 1962). Stegman and Lemert (1981) divided the sunflower growing season into three stages and determined that the crop exhibited the most stress during the middle stage. Cotton yields were most significantly affected by drought stress during the early flowering growth stage (Snowden et al., 2014). Lastly, the distribution of a precipitation event is important for moisture conditions because a localized storm with sufficient amounts of precipitation will only benefit a limited area, and the surrounding area will continue to dry.

2.3.2 Temperature

Temperature directly affects both surface and atmospheric water conditions, making it an important parameter in determining drought severity. Higher temperatures allow for more evaporation and transpiration, thus causing surface water to enter the atmosphere more rapidly. It also increases the atmosphere's water holding capacity, meaning a greater volume of water can be held in the atmosphere prior to atmospheric saturation.

Crop water stress can be exacerbated by high temperature conditions. High temperatures can result in higher transpiration rates from crops and higher evaporation rates from the soil surface, thus depleting the crop's water "reserves" more quickly. In addition, plants attempt to regulate canopy temperatures to maintain favorable growing conditions; however, there is a limit on their ability to regulate the canopy temperature. When this temperature limit is reached, the crop is stressed and its growth and development is altered. For example, high temperatures have been shown to cause accelerated root senescence and stop root elongation (Sánchez et al., 2014), thus limiting their ability to obtain water and nutrients. Asana and Williams (1965) exposed different wheat varieties to daily temperatures ranging from 25 to 31°C and found yields decreased with increasing temperatures.

2.3.3 Biomass Production

Low moisture conditions typically associated with drought often have negative impacts on biomass production. The relationship between soil moisture and biomass production has been extensively studied. Researchers have examined various plants grown in a variety of locations. Most have demonstrated a similar trend: reduced water availability caused a reduction in biomass production. For example, Delfine, et al. (2001) compared rainfed and irrigated conditions on the Leaf Area Index (LAI) of bell pepper plants in the Mediterranean and found a reduced LAI under the dryer, rainfed condition. Jamieson, et al. (1995) induced low soil moisture conditions on barley by withholding irrigation during the beginning, middle, and end of the growing season. They determined that all treatments reduced biomass production from the control plots, with the greatest reduction occurring when the low moisture conditions occurred during the beginning of the growing season. Pettigrew (2004) and Howell, et al. (2004) both demonstrated a reduction in LAI for cotton grown under dryland conditions compared to cotton grown under irrigated conditions.

This reduction in biomass production under low moisture or drought conditions is important in determining the effect of drought on crop yield. Biomass production has been associated with yield via the Harvest Index (HI), which is the fraction of crop yield to above-ground biomass (Hay, 1995). Several models estimate crop yield by multiplying the simulated biomass production by a pre-defined HI (e.g. Neitsch et al., 2011).

2.3.4 Soil Moisture

Soil moisture has been often been used to try to quantify agricultural drought. Many have referred to soil as having a "memory" because of its ability to retain moisture conditions for relatively long time periods (e.g. Orth and Senevirantne, 2012; Wu and Dickinson, 2004; Koster et al., 2000). This means that soil exposed to a soaking precipitation event followed by a long period of no precipitation will remain wet for some time. Conversely, it may take the soil profile a substantial amount of precipitation to become saturated after a long dry spell. Soil's persistent nature makes it a good indicator for short-term or seasonal moisture conditions.

Soil moisture is critical for crop biomass production and development. As previously mentioned, low soil moisture can result in limited root development, thus further impacting the plant's ability to obtain water and nutrients. Soil moisture can also cause reproductive stress; for example, soil moisture stress during cotton boll formation can cause boll abscission, thus reducing yields. Different crops are affected by soil moisture conditions differently. Allen et al. (1998) state that crops can withstand a soil moisture depletion fraction (p) ranging from roughly 0.2 to 0.8 before causing stress to a particular species. Therefore, though all crops are susceptible to low moisture conditions, their soil moisture threshold tolerances may vary significantly by crop.

2.3.5. Crop Transpiration

Below normal transpiration rates indicate that the plant is not receiving adequate moisture and may be experiencing moisture stress. Low transpiration rates not only affect the water content of the plant, but also reduce the amount of nutrients moving through the plant.

It can also limit the plant's ability to regulate its temperature, thus increasing the likelihood of temperature stress. Both moisture stress and temperature stress can reduce plant productivity.

2.4 Parameter Calculations and Rankings

To understand a particular drought parameter value, it needs to be compared against a value with meaning. This allows the parameter to be ranked with respect to effect on the crop or normal growing conditions in the area. Precipitation and biomass production are compared with historic normal conditions. The historic minimums and maximums are also found to provide limits to the rankings. The precipitation normals are calculated on a five week (35 day) basis, while the biomass production normals are calculated on a weekly basis. Precipitation normals are calculated for a longer time period because a week of no precipitation is not an uncommon occurrence and will not by itself cause water stress to a crop, whereas a month without precipitation can be detrimental to a crop. Cumulative biomass production normals were calculated on a weekly basis because the drought index is on a weekly basis.

High temperature values are compared against a given temperature stress value for a particular crop. Above this temperature value, the crop's growth begins to decline. The soil moisture stress is compared against the estimated root zone soil moisture depletion fraction (p) that a crop can withstand before becoming stressed. Lastly, the actual crop transpiration is compared against the potential transpiration. Table 1 summarizes the aforementioned parameters and how they were ranked. The five parameter rankings are then used to calculate the crop-specific drought index.

Table 1: Summary of parameter ranking method used in the crop-specific drought index.

Parameter	Ranked Against	Ranking Range
Precipitation	35 day normal	-10 to 10
Temperature	Number of days above threshold value over 35 day period	-10 to 0
Cumulative Biomass	Weekly normal biomass production	-10 to 10
Soil Moisture	Crop specific stress threshold	-10 to 10
Transpiration	Potential transpiration	-10 to 0

All five rankings used a basic linear ranking system. Two to three bounds were used, depending on the parameter. In the simple case of temperature and transpiration, the location-specific 30-year normal was used as the lower bound of the system, while zero was used as the upper bound. The ranking is linear from 0, indicating no crop stress, to -10, indicating the values are at or exceed the 30-year extreme for drought conditions. Precipitation, cumulative biomass production, and soil moisture have two linear ranking equations, depending on if it is above or below the threshold value. In the case of biomass production and precipitation this threshold value is the 30-year median whereas the soil moisture the middle value is the crop-specific soil moisture depletion stress threshold. Values above the threshold value are ranked linearly between the middle value and 30-year maximum. Values below the middle are ranked linearly between the threshold value and the 30-year minimum. Linear rankings were used because as moisture conditions increase, crop production generally improves, while decreasing moisture conditions generally cause reduced crop production. Two linear ranking equations were used because each ranking will then have the same meaning: above zero indicates a moist condition while below zero indicates dry conditions. The minimum and maximum 30-year normal were used as lower and upper bounds to provide location-specific ranks. For example, 5 inches of precipitation over a 35 day period may be extremely dry conditions in regions with high precipitation, but may be only moderately dry in regions with lower precipitation.

2.4.1 Precipitation Ranking (-10 to 10)

Ultimately drought is a lack of water; therefore lack of precipitation is the primary driving force behind drought. The precipitation amount is summed over a five week period including the current week of interest and the four previous weeks for a total of 35 days. Precipitation was ranked against the historic median value for the location of interest (Equations 8 – 11).

$$P_{Rank} = -10 \qquad for\ (P_{35} < P_{35min}) \tag{8}$$

$$P_{Rank} = \frac{P_{35med} - P_{35}}{P_{35med} - P_{35min}} \times (-10) \qquad for\ (P_{35min} < P_{35} \leq P_{35med}) \tag{9}$$

$$P_{Rank} = \frac{P_{35} - P_{35med}}{P_{35max} - P_{35med}} \times 10 \qquad for\ (P_{35med} < P_{35} < P_{35max}) \tag{10}$$

$$P_{Rank} = 10 \qquad for\ (P_{35} > P_{35max}) \qquad (11)$$

where P_{Rank} is the 35 day precipitation ranking, P_{35} is the amount of precipitation for the area of interest over the 35 day period, P_{35med} is the historic median precipitation amount over the 35 day period, P_{35min} is the historic absolute minimum precipitation amount over the 35 day period, and P_{35max} is the historic absolute maximum precipitation amount for the 35 day period. A value of ten indicates the precipitation amount over the 35 day period is at or more than the historic maximum precipitation amount for the same period. A value of zero indicates that the precipitation amount is equal to the historic median precipitation amount for the 35 day period. A value of negative ten indicates that the precipitation amount is at or less than the historic minimum precipitation amount for the 35 day period.

2.4.2 Temperature Ranking (-10 to 0)

Temperature was chosen as a parameter in this drought quantification method because of the aforementioned ancillary effects on drought and crop production. The temperature parameter is calculated by determining the number of days the crop is above a given temperature threshold value for a five week (35 day) period. The temperature threshold is the temperature above which causes heat stress to the crop of interest. This threshold is crop specific, resulting in a temperature ranking that better reflects temperature stress for each crop simulated. Historic data is used to calculate the typical and extreme temperature conditions for each simulated crop in the area of interest. The historic extreme maximum temperature parameter value is used to calculate the temperature stress ranking which is a ratio of the current temperature parameter and the long-term maximum (Equation 12).

$$T_{Rank} = \frac{T_P}{T_{max}} * (-10) \qquad for\ (T_P < T_{max}) \qquad (12)$$

$$T_{Rank} = -10 \qquad for\ (T_P > T_{max}) \qquad (13)$$

where T_{Rank} is the temperature ranking, T_P is the temperature parameter (number of days the crop is above the temperature threshold for a given length of time), and T_{max} is the historic maximum temperature parameter. A value of zero indicates there is no temperature stress during the specified time period, a value of -10 indicates the number of stress days over the specified time period is equal to or greater than the extreme historic maximum. The temperature ranking is only calculated for zero to -10 because lower temperatures than the stress threshold does not necessarily result in increased biomass production. Cotton, for instance, has a lower temperature threshold of 60°C, below which there is little cotton growth (National Cotton Council, accessed 2015).

2.4.3 Cumulative Biomass Ranking (-10 to 10)

Cumulative biomass production was chosen for this drought method because of its association with crop yield since a reduction in biomass production caused by drought conditions will likely also result in a reduction in the crop yield. The biomass parameter can be estimated by an appropriate model such as the Environmental Policy Integrated Climate (EPIC) used in the Soil and Water Assessment Tool (SWAT). It is ranked by calculating the fraction of cumulative biomass production for the week of interest to the historic median value (Equations 14 – 17). Both current and historic cumulative biomass production can be estimated by using a crop model such as SWAT.

$$B_{Rank} = -10 \qquad for\ (B_P < B_{min}) \tag{14}$$

$$B_{Rank} = \frac{B_{med} - B_P}{B_{med} - B_{min}} * (-10) \qquad for\ (B_{min} < B_P \leq B_{med}) \tag{15}$$

$$B_{Rank} = \frac{B_P - B_{med}}{B_{max} - B_{med}} * 10 \qquad for\ (B_{med} < B_P < B_{max}) \tag{16}$$

$$B_{Rank} = 10 \qquad for\ (B_P > B_{max}) \tag{17}$$

where B_{Rank} is the cumulative biomass production ranking for the week of interest, B_P is the estimated cumulative biomass production for the week of interest, B_{med} is the historic median cumulative biomass production during the week of interest, B_{min} is the historic absolute minimum cumulative biomass production for the week of interest, and B_{max} is the historic absolute cumulative maximum biomass production for the week of interest. A value of ten indicates the biomass production is at or greater than the historic maximum biomass production for the week of interest. A value of zero indicates that the biomass production is equal to the historic median biomass production for the week of interest. A value of negative ten indicates that the biomass production is at or less than the historic minimum biomass production for the week of interest.

2.4.4 Soil Moisture Stress Ranking (-10 to 10)

Soil moisture has a significant effect on crop growth and development. The soil moisture stress is calculated based on the methodology discussed in the FAO Drainage and Irrigation Paper No. 56 (Allen et al., 1998). Soil water stress (K_s) begins when the soil moisture deficit is below the Readily Available Water (RAW) in the root zone. To calculate both the K_s parameter and the RAW, the Total Available Water (TAW) must be determined first. Allen et al. (1998) defines TAW as "the amount of water that a crop can extract from its root zone." TAW is calculated using Equation 18.

$$TAW = 1000(\theta_{FC} - \theta_{WP})Z_r \tag{18}$$

where TAW is the total available soil water in the root zone in mm, Θ_{FC} is the water content at field capacity in m^3m^{-3}, Θ_{WP} is the water content at the wilting point in m^3m^{-3}, and Z_r is the rooting depth.

RAW can be calculated from the TAW using Equation 19.

$$RAW = p * TAW \tag{19}$$

where RAW is the readily available water in the root zone in mm and p is the average fraction of TAW that can be depleted from the root zone before moisture stress. Table 22 in Allen et al. (1998) provides p values for a variety of crops. The values range from 0.2 for crops such as spinach and celery to 0.8 for sisal or Mexican agave.

The K_s parameter is calculated using the calculated RAW and TAW values in conjunction with the soil water depletion as in Equation 20 below.

$$K_s = \frac{TAW - D_r}{TAW - RAW} \tag{20}$$

where D_r is the soil water depletion in the root zone in mm. Allen et al. (1998) only use this equation for D_r values less than the RAW; for D_r values greater than RAW, K_s is set equal one.

However, this method uses Equation 20 for all values of D_r. Therefore, K_s values above one indicate moisture conditions above the stress threshold, while K_s values below one indicate soil moisture conditions below the plant's soil moisture stress threshold.

The historic minimum and maximum at the location of interest for the week of interest are used to provide extreme upper and lower limits on the K_s parameter ranking which is calculated using Equations 21 – 24.

$$K_{Rank} = -10 \qquad for\ (K_s \leq K_{\min}) \tag{21}$$

$$K_{Rank} = \frac{1-K_s}{1-K_{min}} * (-10) \qquad for\ (K_{min} < K_s \leq 1) \tag{22}$$

$$K_{Rank} = \frac{K_s-1}{K_{max}-1} * 10 \qquad for\ (1 < K_s < K_{max}) \tag{23}$$

$$K_{Rank} = 10 \qquad for\ (K_s \geq K_{\max}) \tag{24}$$

where K_{Rank} is the crop soil moisture stress ranking for the week of interest, K_s is the estimated soil moisture ranking for the week of interest, K_{min} is the historic minimum soil moisture ranking for the week of interest, and K_{max} is the historic maximum soil moisture ranking for the week of interest. A value of ten indicates the soil moisture stress is at or greater than the historic maximum soil moisture stress for the week of interest. A value of zero indicates that the soil moisture stress is equal to the historic median soil moisture stress for the week of interest. A value of negative ten indicates that the soil moisture stress is at or less than the historic minimum soil moisture stress for the week of interest.

2.4.5 Transpiration Stress Ranking (-10 to 0)

The estimated transpiration is used as another means to determine the stress to the crop from the low moisture and high temperature conditions typically associated with drought. This is accomplished by estimating the actual transpiration and the potential crop transpiration and using these values to determine the crop water stress (Equation 25).

$$W = 1 - \frac{E_{t,act}}{E_t} \tag{25}$$

where W is the daily crop water stress due to transpiration, $E_{t,act}$ the estimated transpiration for a given day, and E_t is the estimated maximum plant transpiration for a given day. This information can be obtained from modeling daily conditions through a model such as SWAT.

The crop transpiration stress ranking is calculated using Equations 26 and 27.

$$W_{Rank} = \frac{W}{W_{max}} \times (-10) \qquad for(W \leq W_{max}) \tag{26}$$

$$W_{Rank} = -10 \qquad for(W > W_{max}) \tag{27}$$

where W_{Rank} is the ranking of transpirational water stress ranging from 0 to -10 and W_{max} is the historic maximum transpirational water stress. A value of zero indicates that the actual transpiration is equal to the maximum plant transpiration for the given day. In other words, there is no water stress limiting the amount of water passing through the plant. A value of negative ten indicates that the transpirational water stress value is at or greater than the historic maximum transpirational water stress.

2.5 Drought Index Calculation

Plant stress caused by drought ultimately results in reduced crop yields. Therefore, it is important to determine what the trend in the crop yield is for the growing season. The estimated crop yields are then used to provide the drought index. Crop specific yields were forecasted by performing a multiple linear regression with the five ranked parameters and historic observed yields. A linear regression model was created for each week of the growing season using the significant parameters for that week. Significant parameters were determined by performing a t-test ($\alpha = 0.1$) with the R statistical package. Predicted yields were then converted to yield deciles to indicate yield trends or, in other words, whether yields will be less than normal, normal, or greater than normal. Yield deciles were directly used as the drought index (Equation 28), but were converted from a range of 0 to 10 to a range of -10 to 10 with the following relationship:

$$D_{crop} = (2 \times Y_{crop}) - 10 \tag{28}$$

where D_{crop} is the crop specific drought index and Y_{crop} is the predicted yield decile. The method of using yield directly as an agricultural drought indicator has been used in previous studies (e.g. Kumar and Panu, 1997). In this study, a value of ten is obtained when yields are high and thus there is no drought occurring. Zero indicates that the current week's conditions forecast a normal yield. A value of negative ten indicates the moisture conditions for the week are very low, resulting in a low predicted yield and a low drought index value. A schematic of the overall drought index calculation process is provided in Figure 2.

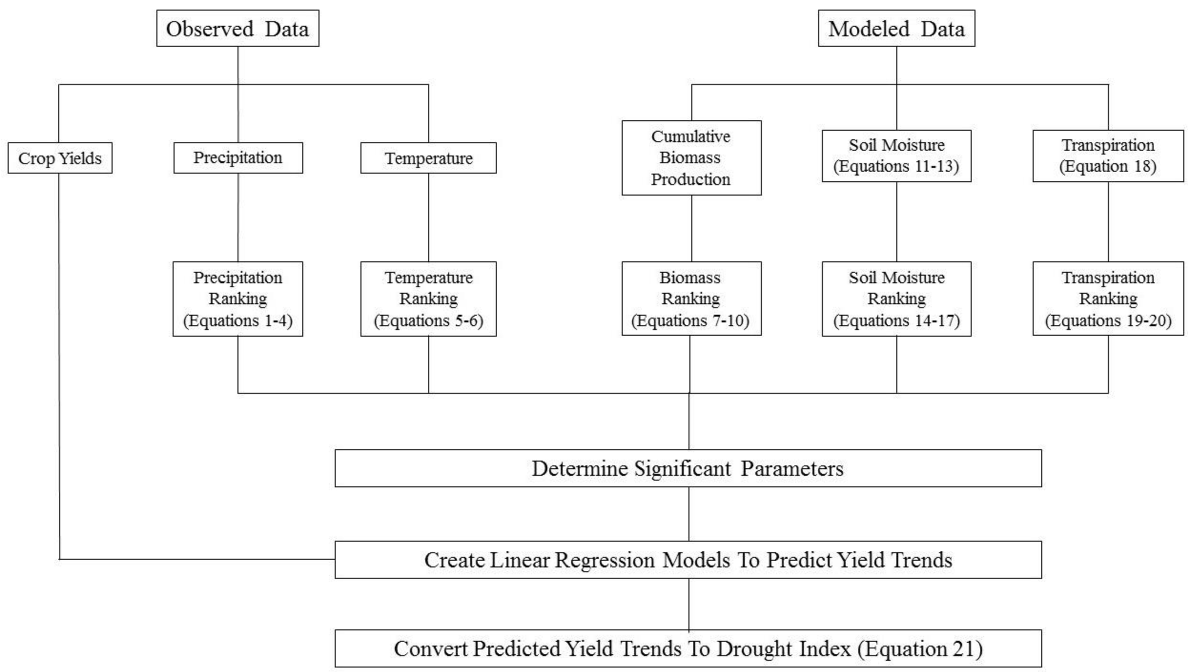

Figure 2: Schematic of drought index calculation.

2.5.1 Linear Regression Model

This drought index method uses linear models, which assume yields will increase with increasing moisture conditions. In an area experiencing drought conditions or has semi-arid or arid climates, this assumption holds. However, for areas not experiencing drought conditions, there may be reduced yields from an overabundance of water (flooding). In this case, other regression models, such as a polynomial regression, should be considered. This would allow the models to account for both high and low moisture conditions when forecasting yield trends, but it should be noted that this would require an alteration in the drought index as well. This is due to the fact that low yields resulting from the polynomial model may not indicate low moisture conditions associated with drought.

Linear regression models were created using the R statistical package. Significant parameters were used to generate linear equations for yield during each week of the growing season. The parameters were tested for significance via the t-test. Parameters with an alpha value above 0.1 was determined to be significant and included in the multiple linear regression model.

2.6 Summary and Conclusions

A crop-specific and location-specific drought index was created to communicate crop specific moisture conditions and forecasted yield trends to agricultural producers. Five parameters were ranked against crop- and location-specific values. Precipitation was ranked using the location-specific median value. Temperature was ranked using a crop-specific high temperature stress threshold value. Cumulative biomass production was ranked using the crop- and location-specific median cumulative biomass production of the crop for the week of interest. Soil moisture is ranked using a crop-specific soil moisture depletion stress threshold. Lastly, transpiration values are ranked using the crop- and location-specific estimated maximum transpiration. These five parameters along with observed yields were used to generate a linear model to predict yield trends for each week of the growing season. The forecasted yield trends were then converted to the crop- and location-specific drought index.

By utilizing this drought index, producers will be able to evaluate how their specific crop will respond to current meteorological/hydrologic conditions. This allows producers the ability to adjust irrigation timing and amounts for their crop to reflect the current hydrologic conditions. Therefore, producers will be able to manage limited water resources more efficiently and reduce the amount of water used for their crop.

Forecasted meteorological conditions could be used to estimate future hydrologic conditions, thus providing producers with advanced warning of low moisture conditions. Coupling this drought index with meteorological forecasts would provide producers the opportunity to preserve limited water resources for critical crop growth phases if below average moisture conditions are predicted. An online drought tool would provide producers with readily accessible information about moisture conditions for their crop and location. Information about yield trends and soil moisture conditions would provide producers with advanced warning of low moisture conditions and allow them to optimize their water resources.

CHAPTER III

CROP AND LOCATION SPECIFIC AGRICULTURAL DROUGHT QUANTIFICATION: PART II – CASE STUDY

3.1 Synopsis

An estimated 70 to 80 percent of water resources are used for agricultural production (UNESCO, 2012). The added moisture helps maintain adequate soil moisture for crops; however, drought can impact both the amount of water required for production and crop yields. Different crops are affected by moisture conditions in different ways; some crops can handle lower moisture conditions better than others. There are many drought indices that quantify low moisture conditions; however, they are not crop-specific and therefore, do not quantify moisture stress for a given crop. The goal of this study was to evaluate a crop-specific drought index by determining the index's ability to reflect yield trends due to moisture conditions. The drought index is a weekly index that uses five parameters, (1) precipitation, (2) temperature, (3) biomass production, (4) soil moisture, and (5) transpiration. This paper presents a case study which examines the effectiveness of the crop-specific drought index in determining moisture stress to crops by comparing the drought index with annual yield values. The site chosen for this study was the Upper Colorado River Basin (UCRB) located in West Texas because it is prone to drought. Cotton is one of the most widely grown row crops in this region and was, therefore, used in this study. A hydrologic and crop model, Soil Water Assessment Tool (SWAT), was set up to determine the biomass production, soil moisture, and transpiration. Observed precipitation and temperature data was also used. A multiple linear regression model was created for each week of the growing season because each parameter is important during different weeks of the growing season. For example, in the UCRB, soil moisture was found to be more important during the beginning of the growing season while biomass production was found to be more important during the end of the growing season. Ultimately the drought index was found to be a good indicator of moisture related yield conditions with an R^2 of 0.67, meaning that 67 percent of variation in yield is explained by the drought index. This index can be used to help make agricultural management decisions such as irrigation management.

3.2 Introduction

Droughts are costly natural disasters and have the potential to impact a large areal extent and number of people. FEMA (1995) estimated that drought causes an average of $6 to $8 billion in damages per year in the United States. Droughts can affect a large areal extent as indicated by the U.S. drought of 2012 which covered over 60% of the land area in the contiguous United States (NOAA, 2012). In terms of natural disasters, droughts also affect a large portion of the global population annually. From 1963 through 1992, there were more droughts that affected at least 1% of the global population than any other hazard (Wilhite, 2000).

In addition to drought, global climate change and population increases will place more strain on water resources in years to come. Climate change is expected to exacerbate the problem of water availability. Changes in both precipitation patterns (Li et al., 2009; Strzepek et al., 2010) and temperatures (IPCC, 2007) are likely to cause increased severity and extent of droughts (Burke et al., 2006; Li et al., 2009; Strzepek et al., 2010). Not only is the climate changing, but the global population is increasing. Therefore, water resource management and drought preparedness will become even more important.

Drought is a common occurrence in Texas and has placed a strain on water availability. Recent drought has led to three Texas communities; Robert Lee, Spicewood Beach, and Barnhart; to run out of water completely (De Melker, 2012; Galbraith, 2013). Robert Lee was forced to construct a 12-mile emergency pipeline while Spicewood Beach trucked in their water supply during the drought. As of December 2014, there were 1,175 Public Water Systems (PWSs) listed by the Texas Commission on Environmental Quality (TCEQ) as having water restrictions to avoid water uses (TCEQ, 2014) and 67 percent of those restrictions were mandatory. Due to these limitations on water resources, some areas in Texas have begun to restrict water resource use for irrigation purposes. In 2012, 2013, and 2014, rice farmers along the Lower Colorado River in Texas were prevented from withdrawing surface water for irrigation (State Impact, 2014).

There are many methods to evaluate drought. The Standard Precipitation Index, Palmer Drought Severity Index, and Vegetation Condition Index are three commonly used drought indices (Kallis, 2008; Mishra and Singh, 2010). While these are commonly used indices, they do not consider crop-specific drought impacts. Various crops are affected by weather and moisture conditions differently. For example, optimal growing temperatures and crop failure temperatures vary by crop. Luo (2011) summarized several studies and reported optimal crop yield temperatures of 23°C and 25°C for soybeans and cotton, respectively. Crop failure temperatures were reported as 32°C, 35°C, and 40°C for dry beans, cotton, and peanuts, respectively. Not only do crops respond to temperature conditions differently, they also can withstand differing amounts of soil moisture depletion. The FAO provide soil water depletion fractions for no stress by crop (Allen et al., 1998). For instance, strawberries can only withstand a 45% depletion, field corn can withstand soil moisture depletion of 55%, and cotton can withstand soil moisture depletion of 65%.

Regression analysis, time series analysis, probability models, and artificial neural networks are all used to model droughts (Mishra and Singh, 2011). Hydrologic models, such as the Soil and Water Assessment Tool (SWAT), have also been used to model drought and drought vulnerability (e.g. Jain et al., 2015; Vu et al., 2015). Kumar and Panu (1997) suggest using a linear regression drought model for a reference crop to estimate the effect on all regional crops; however, they do not consider a drought index specific to each crop.

The objective of this study was to examine a case study of the crop and location drought index developed by McDaniel et al. (2015a). This study uses the Soil and Water Assessment Tool (SWAT) to predict hydrologic conditions and crop growth in the Upper Colorado River Basin (UCRB) located in West Texas.

3.3 Methodology

3.3.1 Study Area

This study was done on the Upper Colorado River (UCR) watershed located in West Texas (Figure 3). Measured streamflow data was taken from a United States Geological Survey (USGS) gauge (8123850) located just above Silver, TX. The UCR is a low flowing river with an average streamflow at the Silver gauge of 1.2 cms (43 cfs) between 1990 and mid-2013. During this time period, the river had no flow nearly 10 percent of the time. This watershed has a semi-arid climate with annual precipitation typically ranges from 36 cm to 53 cm (14 to 21 inches) (LCRA et al., 2012). Four major reservoirs are located in the UCR watershed and include: (1) Natural Dam Lake, (2) Champion Creek Reservoir, (3) Lake Colorado City, and (4) Lake J.B. Thomas. The reservoirs do not release water into the UCR or its tributaries. In addition to the reservoirs, two dams are located in this watershed. The first is located on the main stem of the Colorado River near Colorado City. The second is on Beals Creek, downstream from Big Spring.

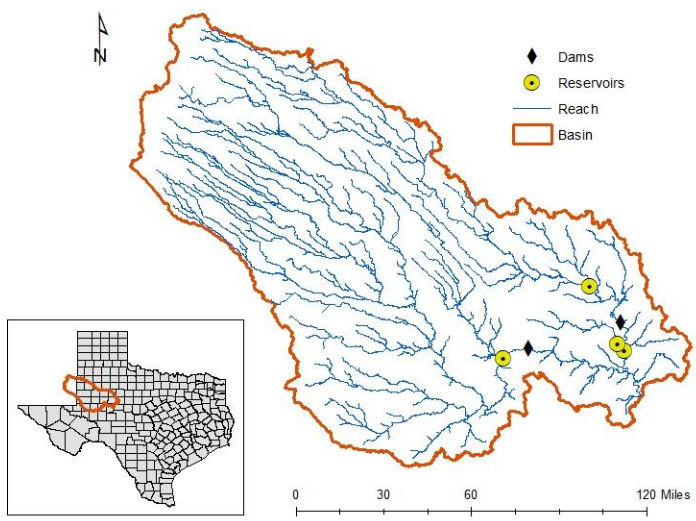

Figure 3: The Upper Colorado River Basin, located in West Texas, is highly managed with dams and reservoirs. The two diversion dams are shown as black diamonds and the four major reservoirs are shown as yellow circles.

The UCR watershed is a rural watershed with the major landuses being rangeland and agricultural row crops. The dominate crop grown in the area is cotton. Observed county cotton yields were obtained from the National Agricultural Statistics Service (NASS). Both dryland and irrigated cotton are grown with groundwater being the primary source for irrigation. The amount of cotton that is irrigated ranges from 2% to 60% depending on the county with the average amount of irrigated cotton land being 24%. Average county cotton yields between 1990 and 2010 range from about 390 to 730 kg ha^{-1} (350 to 650 lb ac^{-1}) (National Agricultural Statistics Service, 2014).

3.3.2 SWAT Model

3.3.2.1 Overview

SWAT is a basin-scale, physically based hydrologic model developed for use in rural watersheds. It is a continuous model that runs on a daily time step. The SWAT model divides the watershed into distributed subbasins. Each subbasin has a set of hydrologic response units (HRUs) which contain a unique combination of landuse, soil type, and slope. The SWAT model uses weather conditions, landuse, soil type, and topographic inputs to simulate hydrologic conditions including soil moisture, stream flow, and evapotranspiration as well as crop yields.

3.3.2.2 Model Setup

The SWAT model requires elevation, landuse, and soil Geographical Information System (GIS) data for model setup. The elevation dataset was obtained from the National Elevation Data (NED) provided by the USGS and has a 30 meter resolution. The National Land Cover Dataset (NLCD) 2006 was used to determine the landuse of the UCR basin. The NLCD has a 30 meter resolution and 16 different land cover types. Cotton is the most widely grown crop in the UCR, so landuse defined as agricultural crop land was simulated as cotton. The State Soil Geographic Database (STATSGO) soil data is provided with the SWAT model. This dataset has a 1 km resolution.

Weather data is also needed to for model simulations. Temperature data was obtained from the NOAA's National Climatic Data Center (NCDC) from 13 gauge stations throughout the watershed. The gauge precipitation data was from 16 gauge stations in the NCDC network. The radar precipitation data used in this study is from the National Weather Service.

3.3.2.3 Calibration and Validation

The SWAT model was calibrated and validated using gauge precipitation data and county cotton yields. The model was calibrated from 2005 to 2008 and validated from 2009 to 2012 on a weekly (7-day) average basis. The parameters used in hydrologic calibration can be found in Table 2 and included the routing method (IRTE), curve number calculation method (ICN) the surface runoff lag coefficient (SURLAG), curve number (CN2), maximum canopy storage (CANMX), soil available water content (Sol_AWC), groundwater delay time (GW_DELAY), baseflow alpha factor (ALPHA_BF), and deep aquifer percolation (RCHRG_DP). Parameters associated with stormwater, including the surface runoff lag, curve number, and canopy storage, needed to be changed to reduce streamflow as the original SWAT model set-up had a tendency to over-estimate the amount of runoff to the Upper Colorado River. The groundwater delay time and baseflow alpha factor were determined using the Baseflow Filter Program (Arnold et al., 1995; Arnold and Allen, 1999).

Table 2: Seven parameters were changed for the calibration of the SWAT model. The highly managed nature of watershed required use of the Muskingum method for water routing. Parameters associated with stormwater runoff (SURLAG, CN2, and CANMX) all needed to be changed to reduce streamflow as the model over-predicted. Both GW_DELAY and ALPHA_BF were calculated using the Baseflow Filter Program.

Calibration Parameter	Description	Original Value	Calibrated Value
IRTE	Routing method	Variable Storage	Muskingum
ICN	Curve number calculation method	Function of Soil Moisture	Function of ET
SURLAG	Surface runoff lag coefficient	4	1
CN2	Curve number		− 13%
CANMX	Canopy and surface storage (mm)	0	15
SOL_AWC	Available water capacity		+5%
GW_DELAY	Groundwater delay time (days)	31	20
ALPHA_BF	Baseflow alpha factor (1/days)	0.048	0.1148

Cotton yields were calibrated and validated over the same time period. A literature review was conducted to determine acceptable ranges for the parameters used to estimate cotton growth including the harvest index, radiation-use efficiency, and leaf area index among others (Table 3).

3.3.2.4 Model Evaluation

Three evaluation statistics were performed on the modeled streamflow and cotton yields including the Nash-Sutcliffe coefficient of efficiency (NS), the coefficient of determination (R^2), and the percent bias (PBIAS). NS was used to evaluate modeled streamflow conditions while R^2 and PBIAS were used to evaluate cotton yields.

Table 3: Eight crop growth parameters were changed during the calibration of cotton yields in the SWAT model. Literature was used to guide the changes made. Overall, the original SWAT set-up had a tendency to over-predict cotton yields.

Calibration Parameter	Description	Original Value	Calibrated Value	Source
BIO_E	Radiation-use efficiency	15	13	Rosenthal and Gerik (1991)
HVSTI	Harvest index ((kg/ha)/(kg/ha))	0.5	0.3	Pettigrew (2004)
BLAI	Maximum leaf area index	4	2	Howell et al. (2004)
FRGRW1	Fraction of the plant growing season to the 1st point on the leaf area curve	0.15	0.38	Howell et al. (2004)
LAIMX1	Fraction of the maximum leaf area index corresponding to the 1st point on the leaf area curve	0.01	0.25	Howell et al. (2004)
FRGRW2	Fraction of the plant growing season to the 2nd point on the leaf area curve	0.5	0.6	Howell et al. (2004)
WSYF	Lower limit of harvest index ((kg/ha)/(kg/ha))	0.4	0.29	Pettigrew (2004)
GSI	Stomatal conductance (m/s)	0.009	0.031	Rahman (2005)

The NS compares how the modeled streamflow compares to using the average streamflow (Equation 29). The NS ranges from negative infinity to one. A value of zero indicates that the model performs as well as using the average streamflow, a negative value indicates the model performs worse than using the average streamflow, and a positive value indicates that the model performs better than using the average streamflow. Typically, an acceptable value is greater than 0.5 (Moriasi et al., 2007).

$$NS = 1 - \frac{\sum_{i=1}^{N}(O_i - P_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2} \tag{29}$$

where O_i is the observed streamflow at time i, P_i is the predicted streamflow at time i, and $\bar{O}$ is the average observed streaflow over the modeled period.

The R^2 statistic ranges from zero to one and indicates how much of the variance in the observed data is explained by the model (Equation 30). A value of zero indicates that none of the variance is explained by the model, and a value of one indicates all variance in the data is explained by the model.

$$R^2 = \left\{\frac{\sum_{i=1}^{N}(O_i - \bar{O})(P_i - \bar{P})}{\left[\sum_{i=1}^{N}(O_i - \bar{O})^2\right]^{0.5}\left[\sum_{i=1}^{N}(P_i - \bar{P})^2\right]^{0.5}}\right\}^2 \tag{30}$$

where $\bar{P}$ is the average predicted streamflow over the modeled period.

The PBIAS statistic reveals if the model has a tendency to over- or under-predict values (Equation 31). Acceptable values are typically +/- 25%. A negative value indicates that the model typically under-predicts the parameter value while a positive value indicates that the model typically over-predicts the parameter value.

$$PBIAS = \left(\frac{\sum_{i=1}^{N}(P_i - O_i)}{\sum_{i=1}^{N} O_i}\right) \times 100\% \tag{31}$$

3.3.3 *Drought Index Overview*

This study uses a crop and location specific drought methodology developed by McDaniel et al. (2015a). The drought index calculation is discussed here, but for a complete description see McDaniel et al. (2015a).

The drought index uses five parameters to determine drought for a specific crop, (1) precipitation, (2) temperature, (3) cumulative biomass production, (4) soil moisture, and (5) transpiration. Each parameter was ranked using and crop and/or a location specific value. Precipitation was summed over a five week period and compared against the 30 year normal. Temperature was compared against a high temperature stress threshold. The number of days that exceeded the stress threshold were summed over a five week period and compared against the 30 year normal. The average weekly cumulative biomass production was compared against the 30 year normal for cotton in West Texas. Soil moisture was compared against a threshold value which was the fraction of soil moisture depletion beyond which causes stress to the crop. Cotton can withstand a depletion fraction of 0.65 prior to experiencing stress (Allen et al., 1998). Lastly, the weekly average cotton transpiration was compared against the average weekly potential transpiration. Cotton biomass production, soil moisture, transpiration, and potential transpiration were estimated using the SWAT model.

Cotton yields were estimated from multiple linear regression models for the first 20 weeks of the growing season. A different equation was used for each week due to varying parameter importance throughout the growing season. For example, cumulative biomass production is highly correlated (> 0.6) after week 10 of the growing season, whereas soil moisture has a high correlation during the middle of the growing season, around weeks 4 through 11. Model equations were determined using the R statistical package. The models were created using observed cotton yields and parameter rankings from ten counties over a ten year period (2000 to 2009). There are a total of 90 yield observation points which were used in generating each model. These models took the general form found in Equation 32.

$$Y_M = C_1 + C_2 P_{Rank} + C_3 T_{Rank} + C_4 B_{Rank} + C_5 K_{Rank} + C_6 W_{Rank} \tag{32}$$

Y_M is the modeled cotton yield. C_1, C_2, C_3, C_4, C_5, and C_6 are all constants generated by the multiple linear regression analysis.

Parameters that were not significant (α > 0.1) were not used in the linear models. Therefore, between one and five parameters were used to estimate yields for each of the first 20 weeks of the growing season.

3.4 Results and Discussion

3.4.1 SWAT Calibration and Validation

The SWAT model was calibrated and validated for streamflow and crop yields on a weekly basis. The streamflow calibration and validation used USGS streamflow measurements from the Colorado River gauge just above Silver, TX (08123850). The streamflow calibration resulted in a NS of 0.58 and a PBIAS of -0.18 while the validation resulted in a NS of 0.90 and a PBIAS of -0.14 (Figure 4). All values were within acceptable ranges, greater than 0.5 for NS and between -25 and 25 for PBIAS.

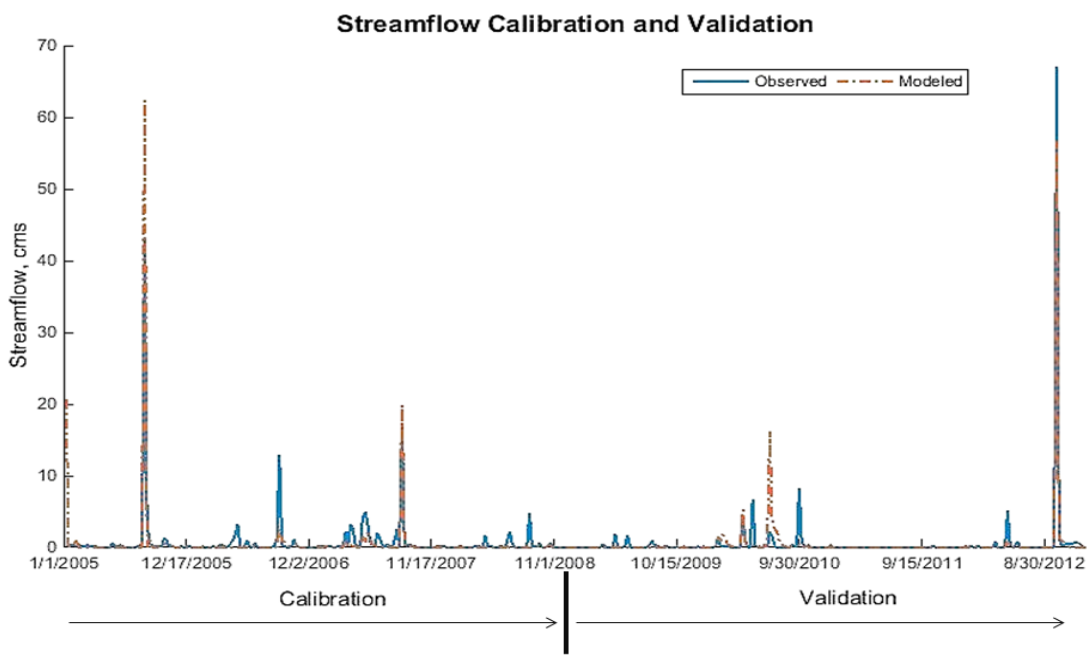

Figure 4: The streamflow calibration and validation of the SWAT model were acceptable with NS values of 0.58 and 0.9, respectively. The solid blue line is observed streamflow while the dashed red line is modeled streamflow. The calibration and validation was done at the location of the USGS stream gauge above Silver, TX (08123850).

Cotton yields were calibrated and validated using adjusted observed yields from the NASS (QuickStats 2.0, Retrieved 2012). Yields were adjusted because net yields were not available after 1990. Therefore, adjustments were made to take into account yield losses which can be substantial (> 25%) in the UCRB. Yields were adjusted by multiplying the observed yields by the fraction of harvested area compared to the planted area as shown in Equation 33,

$$Y_A = Y_O \times \frac{A_H}{A_P} \tag{33}$$

where, Y_A is the adjusted observed yield, Y_O is the gross observed yield, A_H is the harvested area, and A_P is the planted area. Using the adjusted observed yields, the calibration resulted in an R^2 of 0.59 and a PBIAS of 14.7 while the validation resulted in an R^2 of 0.64 and PBIAS of -6.7 (Figure 5). All statistical values were within acceptable limits.

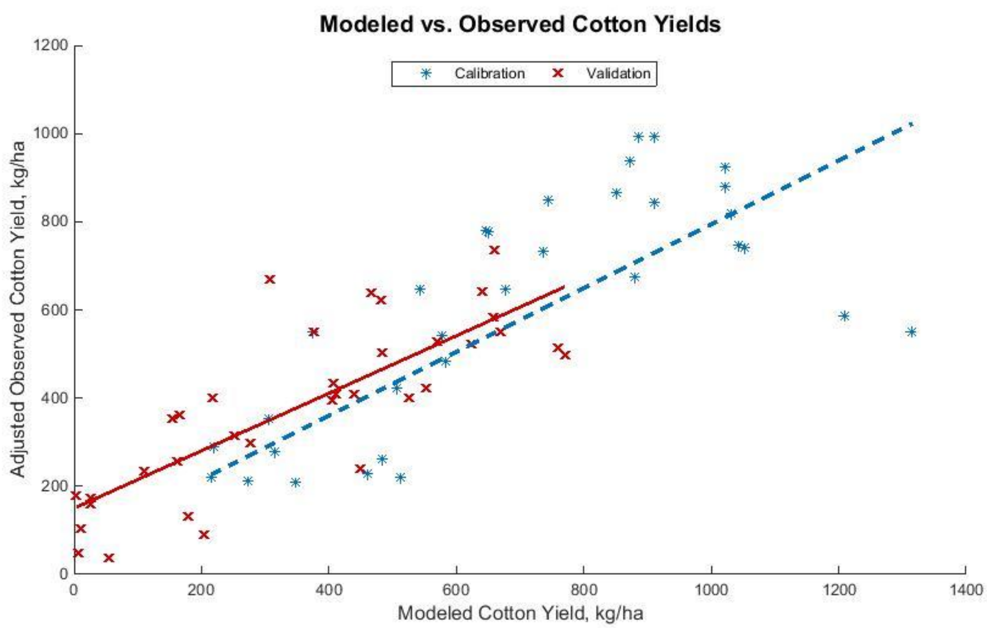

Figure 5: Cotton yield calibration and validation in the SWAT model were found to be acceptable with R2 values of 0.59 and 0.64, respectively. Crop yields were calibrated and validated for 10 counties for 2005 to 2008 and 2009 to 2012, respectively.

3.4.2 Multiple Linear Regression Models

Twenty linear regression models were created to predict yield trends, one for each of the first twenty weeks of the growing season. Different models were generated for each week of the growing season because each parameter is important at different times in the growing season. Figure 6 shows the Pearson's Correlation Coefficient (R) between each parameter and the observed yield. Pearson's R indicates the amount of linear dependence between two variables. A positive R value means there is a direct relationship between the variables while a negative R value means there is an inverse relationship between the variables. For cotton in the UCRB, the time when the precipitation and temperature rankings are correlated most strongly with yield is during the beginning (weeks 1 to 4) and middle (weeks 10 to 15) of the growing season. The time when the biomass ranking is most strongly correlated to yield is during the last half of the growing season (weeks 10 to 20). The time when the soil moisture ranking is most strongly correlated with yield is during the first half of the growing season (weeks 1 to 11). Lastly, the time when the transpiration ranking is most strongly correlated with yield is during the middle of the growing season (weeks 9 to 12). Therefore, only the significant parameters during each week were used to generate the linear regression models. Anywhere from one parameter to all five parameters were used depending on how many of the parameters were significant ($\alpha < 0.1$) to the multiple linear regression models when predicting cotton yields.

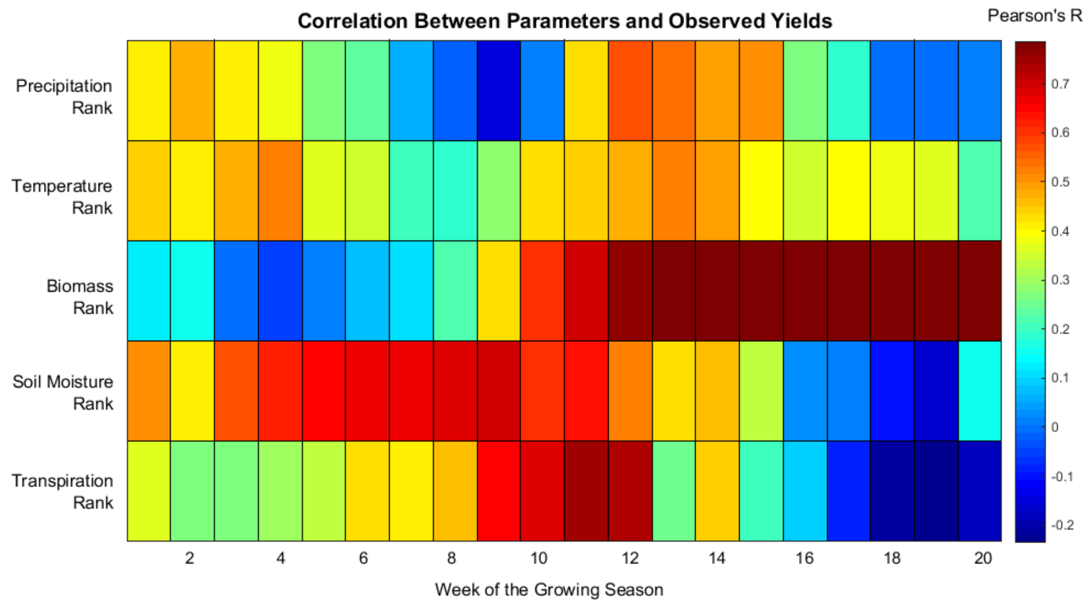

Figure 6: The correlation between parameters and observed yields show that the parameters are most strongly correlated with yield at different times in the growing season.

Yield trends were predicted from the multiple linear regression models which were used to generate the crop specific drought index. The predicted yield for each individual week reflects the conditions of the week and not the entire growing season. For example, a low moisture week will result in a low predicted yield whereas a high moisture week will results in a high predicted yield. Therefore, to determine the effectiveness of the methodology, the median yield for the first 20 weeks of the growing season was compared with observed cotton yields (Figure 7). The R^2 was 0.73, indicating a strong relationship between the median predicted yield and the observed yield. Additionally, the PBIAS was 0.7, indicating that the predicted cotton yields do not tend to over- or under-predict. There was one major outlier in the data which occurred in Mitchell County in 2000. The median predicted yield for the growing season suggests a relatively bountiful year, but the observed yield was very low. Other weather-related disasters such as hail or high winds may have contributed to the lower yields that year in Mitchell County.

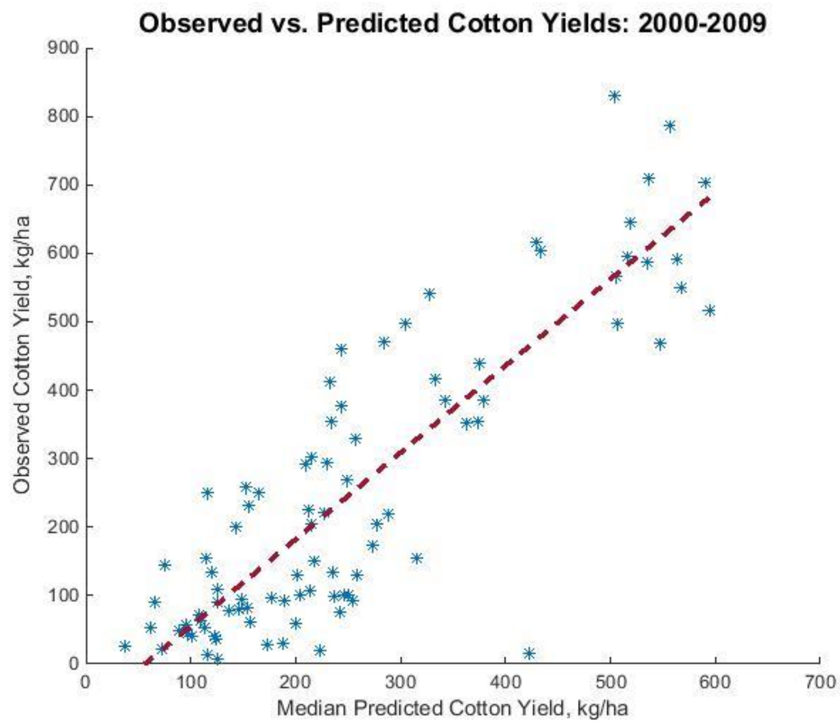

Figure 7: A comparison of observed and predicted cotton yields showed a strong relationship with an R^2 of 0.73. The red dashed line is the linear regression between the median predicted cotton yield for the growing season and the observed cotton yields. Predicted yields were determined by using the median value from a series a unique linear regression models for each week of the growing season.

The predicted yields were converted into yield percentiles ranging from zero to ten which were adjusted to the crop specific drought index range of negative ten to ten (Figure 8). Drought index values below zero indicate low moisture conditions which are predicted to result in below typical crop yields. Alternatively, drought index values above zero are high moisture conditions which are predicted to result in above typical crop yields. Not surprisingly, the drought index resulted in a similar relationship with the observed yields as the predicted crop yields; however, the linear R^2 was slightly lower (0.67 compared to the 0.73 discussed above) likely due to the discretization of the predicted cotton yields when converting to the drought index. Interestingly, the drought index demonstrated a stronger polynomial trend with the observed yield than linear trend and resulted in a polynomial regression R^2 of 0.71.

Minimal data was available for an independent validation period (2010 to 2013) due to limited yield data between 2011 and 2013 which were very dry years. During the period from 2010 through 2013, only 15 observed data points were available. Therefore, there is not enough data for adequate validation, but the preliminary data suggests the trend is maintained. The drought index was higher for all counties in 2010 than 2012 (Figures 9.a and 9.b). This indicates that 2010 had higher moisture conditions in the UCRB region than in 2012. Observed data supported this; of the ten counties, four had data for both 2010 and 2012 and these counties showed higher yields in 2010 than in 2012 (Figure 9.c). In 2010, Dawson and Martin counties had the highest of the four yields, followed by Terry county, and finally Yoakum county. The drought index also reflected this trend and 2012 was a universally low yield year which was also reflected in the drought index.

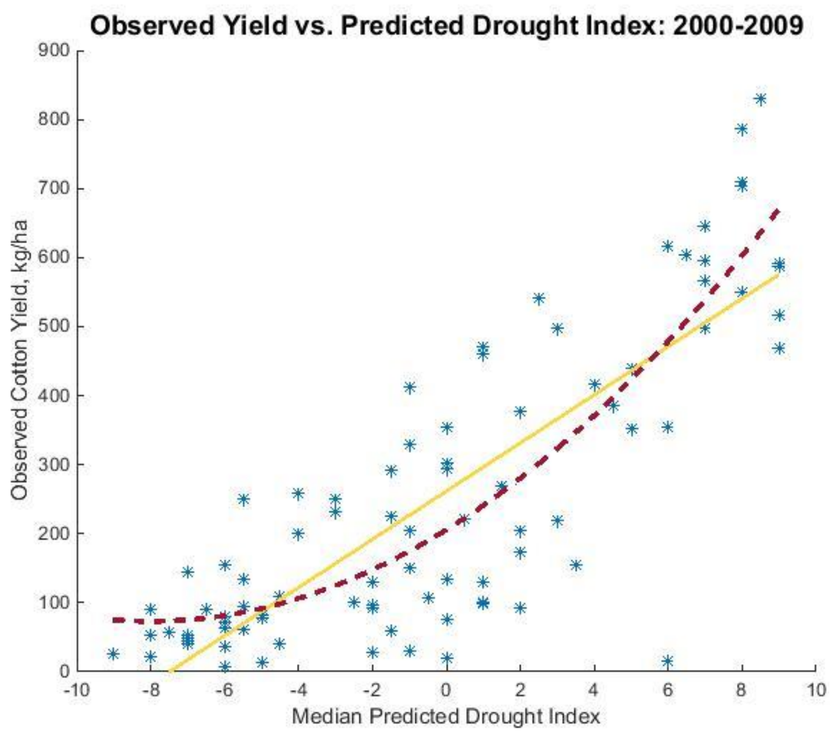

Figure 8: The drought index has a strong linear relationship with yield, but a stronger polynomial relationship. The yellow line is the linear regression for the predicted drought index and cotton yield, while the red line shows the polynomial regression.

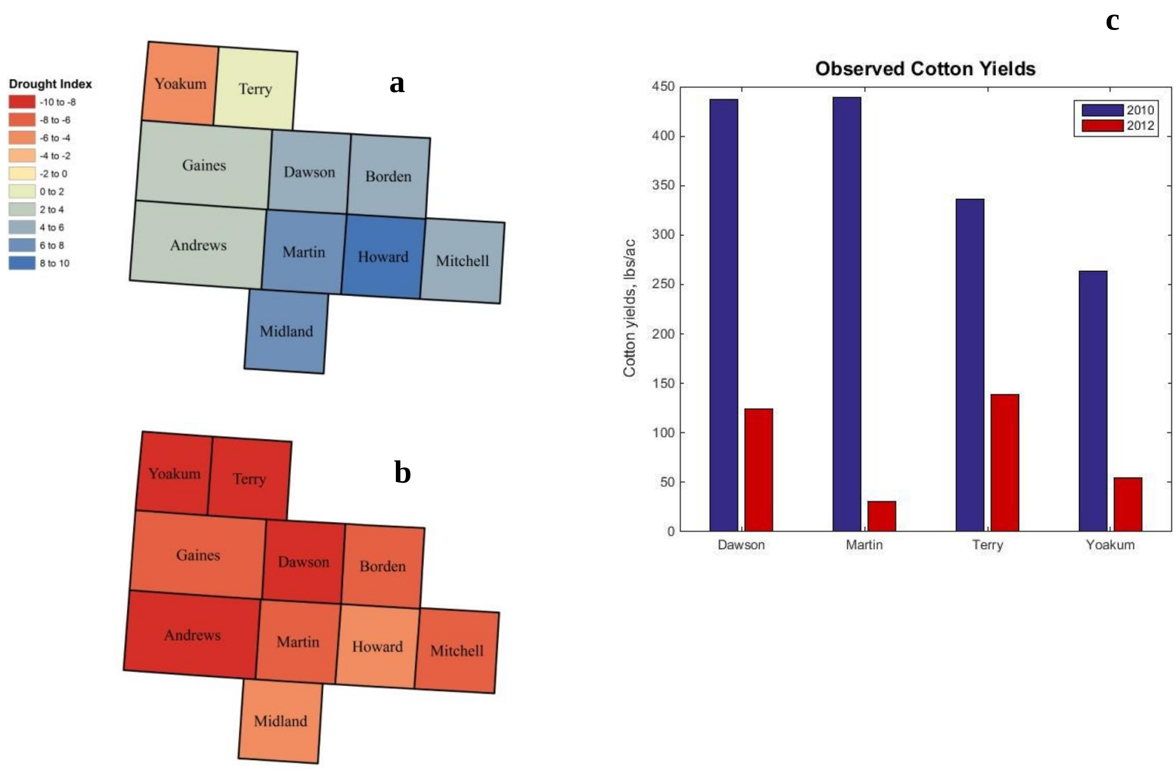

Figure 9: The county maps show the drought index for 2010 (a) and 2012 (b). They indicate that 2010 was a relatively moist year while 2012 was relatively dry. The graph (c) shows the adjusted observed cotton yields from four counties for the same time period. The observed yield supports the drought index results with high yields observed in 2010 and low yields in 2012.

Examples of the crop specific drought index and soil moisture ranking are provided for Mitchell County, TX, in Figure 10 and Figure 11. The critical period for cotton growth in the UCRB is shaded in red. Critical periods are those that are strongly affected by moisture and/or temperature conditions. Yields are particularly susceptible to stress conditions during this time. A drought index value of zero indicates that with the given moisture conditions, crop yields are predicted to be normal, or at the 50th percentile. Above zero indicates the crop yields are predicted to be above normal while below zero indicates the crop yields are predicted to be below normal. This crop specific drought index can be used as an aid for agricultural management decisions. For example, in Mitchell County, the drought index was predicted to be above normal throughout the 2010 growing season and below normal for the majority of the 2012 growing season. This indicates that there were greater water needs throughout the growing season in 2012 than in 2010.

The soil moisture ranking provides information about irrigation timing. A soil moisture ranking above zero indicates that the soil moisture is above the stress threshold for the crop. Alternatively, a soil moisture ranking below zero indicates that the soil moisture is below the stress threshold for the crop and will thus adversely affect growth. Consequently, the soil moisture ranking for each week provides information about when best to irrigate. In the UCRB it is typical for the soil moisture to go below the cotton stress threshold during the critical period due to high evapotranspiration rates. Based on the soil moisture ranking, in 2010 Mitchell County did not fall below the stress threshold prior to the critical period. It only fell below the stress threshold starting at week 11, during the critical period, indicating this may be the optimal time to irrigate. During 2012, on the other hand, the soil moisture ranking was below the stress threshold for the majority of the growing season indicating that irrigation was required throughout the growing season, even prior to the critical growth period.

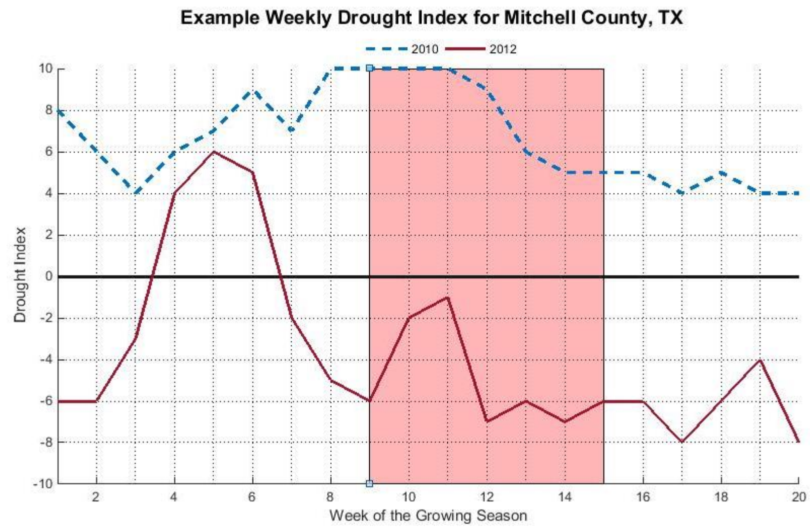

Figure 10: The drought index for Mitchell County, TX, indicates above typical yield conditions in 2010 and below typical yield conditions for 2012. The blue line is the drought index for 2010 while the red line is the drought index for 2012. The critical period is more susceptible to low moisture conditions and can greatly affect yields.

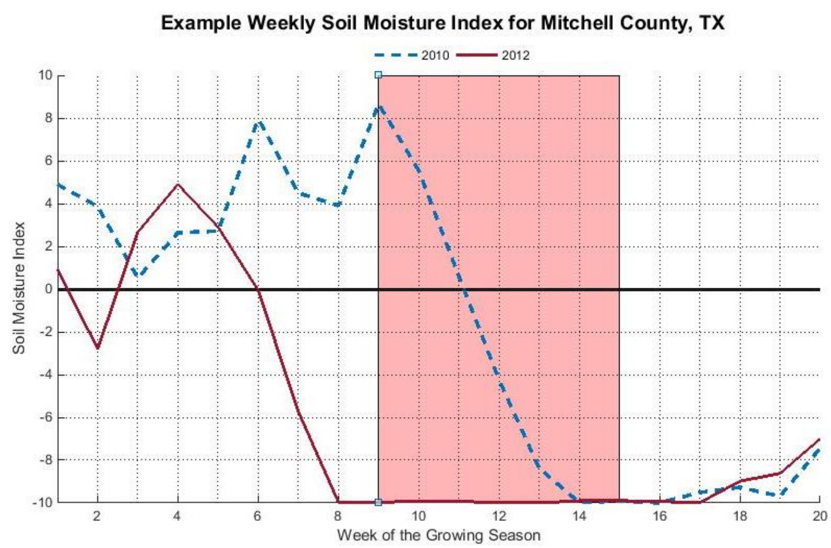

Figure 11: The soil moisture index for Mitchell County, TX, provides information about crop stress and can be used for irrigation timing. The blue line is the drought index for 2010 while the red line is the drought index for 2012. The critical period is more susceptible to low moisture conditions and can greatly affect yields.

3.5 Conclusion

The crop-specific drought index uses parameters that are linked to the crop itself (transpiration), location (precipitation), or both (biomass production). By doing this, the drought index is an indicator of moisture driven yield trends (low, normal, high yields). The case study demonstrates that different parameters are important during different times in the growing season. Therefore, different linear regression models were required for each week of the growing season. This case study in the UCRB demonstrated that this drought index can provide reasonable information for moisture conditions that can be used for agricultural management decisions. The weekly drought index provides information about the moisture driven yield trends and the weekly soil moisture ranking provides information that can be used for irrigation timing.

This crop-specific method could be used for decision making and advanced warning of low moisture conditions. Forecasting moisture conditions can be done by coupling weather forecasts with the SWAT hydrologic model. These forecasts could be used to make agricultural water management decisions including drought preparation decisions, irrigation timing, and irrigation amounts. An interactive tool could provide agricultural producers ready access to information about the moisture conditions and how it relates to their crop.

CHAPTER IV

CROP AND LOCATION SPECIFIC AGRICULTURAL DROUGHT QUANTIFICATION: FORECASTING WATER STRESS AND YIELD TRENDS

4.1 Synopsis

Agriculture is the largest water consumer, with 70% of global water withdrawals being used for irrigation. Water scarcity issues are being exacerbated by drought and population increases. Efficient water resource management in agricultural production will become more important as these issues increase. The objective of this paper is to evaluate the use of short-term weather forecasts for agricultural drought prediction. A crop-specific, linear regression drought analysis technique was used in this study. This study takes place in the Upper Colorado River Basin (UCRB) located in West Texas. Five parameters associated with agricultural drought (precipitation, temperature, biomass production, soil moisture depletion, and transpiration) were ranked and used to estimate cotton yields. The yield percentiles were used as a drought index. Precipitation and temperature were forecasted with a two-week lead time using probable scenarios based on historical data. The other three parameters were estimated using the SWAT model. Forecasts were generated for each week of the growing season from 2010 through 2013. Comparing the parameters using the forecasted weather data to those using the observed weather data revealed that four out of the five performed satisfactorily ($R^2 > 0.5$, NS > 0.5, -55% < PBIAS < 55%, RSR < 0.7). However, the soil moisture depletion forecasts were unsatisfactory. The forecasted cotton yields and drought index both performed satisfactorily, indicating this forecasting method may be used for decision making related to agricultural water management including irrigation timings.

4.2 Introduction

Water is a finite resource. Many areas in the world are already experiencing physical water scarcity, affecting 1.2 billion people. Physical water scarcity does not just occur in arid regions, but also where water sources are overcommitted (IWMI, 2007). In addition, the number of people living in water stressed regions is expected to increase, largely due to population growth and socio-economic development (Shen et. al, 2014). Agriculture plays a large role in global water resource use. 70% of global water withdrawals are used for irrigation. The rising demand for food and feed crops is projected to increase this amount by 70 to 90 percent by 2050 (IWMI, 2007).

Efficient management of water resources will become increasingly important as water stress grows and the amount of water available for irrigation is limited, especially in times of drought. Drought compounds water stress in existing regions with water scarcity. Drought can occur in several forms: (1) meteorological, (2) agricultural, (3) hydrological, and (4) socioeconomic (Wilhite and Glantz, 1985). Agricultural drought is caused by reduced precipitation, reduced soil moisture, increased temperature, and increased evapotranspiration, resulting in reduced biomass production. The economic impacts of agricultural drought can be substantial. The Georgia DNR (2001) reported estimated crop losses between $689 and $885 million in crop losses in the Georgia drought from 1998-2000; a 2002 drought in South Dakota resulted in $401 million in crop losses (Diersen and Taylor, 2003); the 2005 Illinois drought caused $1.3 billion in agricultural losses; an estimated $7.6 billion was lost in the agricultural sector during the 2011 Texas drought (Fannin, 2012); Howitt, et. al (2014) estimated the direct agricultural losses of the 2014 California drought at $1.5 billion.

Crop responses to drought vary and thus the effect of drought on yield can vary by crop. The FAO Drainage and Irrigation Paper No. 56 (Allen et al., 1998) provides information on the percent moisture depletion that crops can withstand before experiencing water stress. Total available water depletion can range from 20% to 80% before water stress occurs, depending on the crop. Therefore, agricultural water management should be crop specific.

To help agricultural producers make the most efficient use of their water resources, researchers have tried to predict and, therefore, provide early warnings of agricultural drought conditions. Shukla et al. (2014) discuss a method to generate seasonal soil moisture outlooks through a case study in East Africa. Marj and Meijerink (2011) used climatic data and an artificial neural network to predict the normalized difference vegetation index which served as the basis for predicting annual agricultural drought. Liu and Juárez (2001) also predicted NDVI using forecasted climatic data to assess agricultural drought onset. Kumar and Panu (1997) suggest using a multiple linear regression model and a reference crop to predict drought conditions for other crops in the area. These agricultural drought forecasting methods have limited utility for making crop water management decisions on a sub-seasonal time scale as they are either annual or are not crop-specific.

The objective of this study was to evaluate short-term weather forecast use in a crop-specific drought tool to identify the utility of this method for use in sub-seasonal water management decisions. A linear regression based crop-specific drought index developed by McDaniel et al. (2015a) was used in conjunction with two-week precipitation and temperature forecasts. The SWAT model was used to estimate additional parameters required for the drought index.

4.3 Methods

Forecasted weather conditions are used to forecast agricultural drought conditions for two weeks in advance. A crop specific method for determining agricultural drought developed by McDaniel et al. (2015a) was used in this study. This method also provides information about weekly moisture stress and seasonal yield trends. A brief overview of this method is provided in this section. For more information, see McDaniel et al. (2015b).

4.3.1 Study Area

A case study was completed on the Upper Colorado River Basin (UCRB) located in West Texas and into New Mexico. Ten counties in Texas are evaluated for drought conditions over the four year time period and include Andrews, Borden, Dawson, Gaines, Howard, Martin, Midland, Mitchell, Terry, and Yoakum counties. The landuse in this area is dominated by row crops and rangeland. Cotton is one of the dominant row crops in the area and thus was chosen as the crop examined in this study for crop-specific drought forecasting. Yields typically range from 390 to 730 kg ha^{-1} (350 to 650 lb ac^{-1}). Streamflows on the Upper Colorado River are very low with an average flow of 1.25 cms (44 cfs) from 1990 to 2010 calculated at the USGS gauge located just above Silver, TX (Site Number: 08156675). The UCRB was hard hit by the recent drought that has plagued Texas. The USDA designated all ten counties examined in this study as drought disaster areas from 2011 to 2014 (USDA, 2015).

4.3.2 Parameter Forecasting

Precipitation and temperature were forecasted using an ensemble forecasting method (Demargne, et al., 2013; Brown et al., 2014). In this method, probabilistic weather forecasts are produced and converted to a series of deterministic forecasts (ensembles) for use in a hydrologic model. For this study, two week forecast probabilities were created for each week of the growing season from 2010 through 2013. These forecasts were used to generate a set of 21 deterministic precipitation and temperature data sets that were input into the SWAT hydrologic model to estimate other moisture-related conditions including soil moisture, cumulative biomass production and transpiration. These forecasted values were ranked using the crop- and location-specific indicators prior to being used in the drought index calculation. This ultimately resulted in 21 scenarios for the drought conditions during the two week forecasted time period. A total of 1,680 scenarios were generated and analyzed for each of the ten counties (21 scenarios over the first 20 weeks of the growing season throughout four years).

4.3.3 Drought Index

Drought, moisture stress, and yield trends were determined using a crop- and location-specific drought methodology. Five parameters are used to calculate yield trends and drought: (1) precipitation, (2) temperature, (3) cumulative biomass production, (4) soil moisture, and (5) transpiration. Each parameter is ranked with regards to crop specific and/or location specific values. The accumulated 5-week precipitation is ranked against the 30-year normal precipitation. The number of days above a temperature stress threshold over a 5-week period is ranked against the 30-year normal. Cumulative biomass production is ranked against the 30-year normal. Soil moisture is ranked against the soil moisture stress threshold of the crop; in other words, the amount of soil moisture below which causes moisture stress to the crop. Lastly, transpiration is ranked against the potential transpiration. Precipitation, biomass production, and soil moisture depletion have rankings ranging from -10 to 10, where -10 is low moisture/biomass production conditions and 10 is high moisture/biomass production conditions. Temperature and transpiration have rankings ranging from -10 to 0, where -10 is a high number of days above the temperature stress threshold and low transpiration to potential transpiration ratio, respectively.

Soil moisture, cumulative biomass production, and transpiration are estimated by modeling the hydrologic conditions using the Soil and Water Assessment Tool (SWAT). SWAT is a basin scale hydrologic model that operates on a daily time step. It is a semi-distributed model (Gassman et al., 2007) that is distributed at the subbasin scale. Each subbasin is further divided into a series of Hydrologic Response Units (HRUs) made up of a unique landuse, soil type, and slope. The Environmental Policy Integrated Climate (EPIC) model was used as the basis for the crop growth portion of the SWAT model.

The SWAT model was calibrated and validated for weekly streamflow using the Nash-Sutcliffe coefficient of efficiency (NS) and the Percent Bias (PBIAS) as well as cotton yields using the Coefficient of Determination (R^2) and the PBIAS. All values were within acceptable ranges. The NS values were above 0.5, the R^2 values were above 0.5, and the PBIAS values were within 25%. Calibration was performed from 2005 through 2008 while validation was completed for 2009 through 2012. For more detail on the calibration and validation of the SWAT model, refer to McDaniel et al. (2015b).

SWAT outputs all parameters at the HRU level, including the precipitation and temperature. Parameter values are first ranked at the HRU level, and then an area weighted average is used to aggregate the rankings to the subbasin level and then ultimately to the county level.

These five, county-level parameter rankings are used to create a linear regression model for each week of the growing season to predict yield trends. A different linear regression model was used for each week because the parameters are important during different times in the growing season. For example, in the Upper Colorado River Basin (UCRB), the soil moisture ranking is strongly correlated with cotton yields during the first half of the growing season, whereas the cumulative biomass production ranking is strongly correlated with cotton yields during the second half of the growing season. Once yields are estimated using the linear regression model, they are converted into yield percentiles using historical data. The drought index is directly derived from the yield percentiles (Equation 34). This results in a drought index on the same terms as the parameter rankings, where below zero indicates dry conditions and above zero indicates moist conditions. In this work, the yield trends and drought indices were calculated for cotton as it is one of the most plentiful row crops in the study area.

$$D = 2 \times Y_P - 10 \tag{34}$$

where D is the drought index and Y_p is the yield percentile.

4.3.4 Forecast Evaluations

The cumulative distribution function (CDF) for precipitation, temperature, yield, and the drought index was calculated to determine if the forecasted distribution was significantly different than the observed data distribution. The difference between the forecasted and observed probability distribution function (PDF) was plotted to evaluate which areas of the distribution were over- and under-represented by the forecasts. The CDFs and PDFs were used as a visual comparison of the distributions between the forecasted and observed data. It provides insight into how the forecasted data distributions compare with the observed data distributions and where the data are concentrated at.

In addition to the overall distribution of the data, four model statistics were used to evaluate how the forecasts performed on a weekly basis at the county level. The forecasts were evaluated using several commonly used statistics for modeling studies; the R^2, NS, PBIAS, and the root mean square error to observed standard deviation ratio (RSR). These four statistics cover three groups of model evaluation statistics. R^2 is a regression statistic, the NS is a dimensionless statistic, and both PBIAS and RSR are error indices. The weekly values for the 21 forecast ensembles were averaged, resulting in a single value for each week of the forecast. These averages were used to calculate the R^2, NS, PBIAS, and RSR for the drought index input parameters (precipitation ranking, temperature ranking, biomass production ranking, soil moisture depletion ranking, and transpiration ranking) as well as the resulting yield trends and drought index.

4.3.4.1 Regression Model Evaluation

R^2 describes the amount of variance in the observed data that is explained by the model. The R^2 statistic is calculated using Equation 35,

$$R^2 = \left\{ \frac{\sum_{i=1}^{N}(O_i - \bar{O})(P_i - \bar{P})}{\left[\sum_{i=1}^{N}(O_i - \bar{O})^2\right]^{0.5}\left[\sum_{i=1}^{N}(P_i - \bar{P})^2\right]^{0.5}} \right\}^2 \tag{35}$$

where, $\bar{P}$ is the average predicted streamflow over the modeled period. The R^2 statistic ranges from 0 to 1. A value of 1 indicates that all the observed variance is explained by the model, or the model perfectly fits the observed data. On the other hand, a value of 0 indicates that none of the observed variance is explained by the model. Gassman (2008) compiled a number of

SWAT studies and reported that most had R^2 values above 0.5. Motovilov et al. (1999) suggested the common threshold R^2 values of greater than 0.75 for good model performance and between 0.36 and 0.75 for satisfactory model performance.

4.3.4.2 Dimensionless Model Evaluation

The NS statistic is used to evaluate how the model performance compares to using the average parameter value. The NS statistic is calculated using Equation 36.

$$NS = 1 - \frac{\sum_{i=1}^{N}(O_i - P_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2} \tag{36}$$

where, O_i is the observed value at time i, P_i is the predicted value at time i, and $\bar{O}$ is the average of the observed values over the modeled period. NS ranges from negative infinity to 1. A value less than zero indicates that the average observed value is a better predictor than the modeled value; a value of zero indicates that the model is performing as well as the average; a value above zero indicates that the model is a better predictor than the average. Moriasi et al. (2007) summarized statistical performances and provided recommended values for NS, PBIAS, and RSR. Their recommended minimum value for NS is reported to be 0.5 for monthly values. Based on the monthly recommendations by Moriasi et al. (2007), Nair et al. (2011) proposed minimum NS threshold values of 0.4 for daily, 0.5 for monthly, and 0.7 for annual time periods.

4.3.4.3 Error Indices

Both the R^2 and NS are sensitive to extreme values (Legates and McCabe, 1999) which can disproportionately affect the resulting statistical value. This sensitivity led Legates and McCabe (1999) to recommend using error indices when evaluating hydrologic and hydroclimatic models. Therefore, two additional model evaluation statistics were examined, the PBIAS and RSR, two error indices recommended by Moriasi et al. (2007).

The PBIAS describes whether the model has a tendency to over- or under- predict parameter values compared to the observed value. It also indicates how much the parameter is over- or under- predicted. The PBIAS is calculated using Equation 37.

$$PBIAS = \left(\frac{\sum_{i=1}^{N}(P_i - O_i)}{\sum_{i=1}^{N}|O_i|}\right) \times 100\% \tag{37}$$

The PBIAS can range from negative infinity to infinity. When the PBIAS is negative, it indicates that the model has a tendency to under-predict the parameter. When the PBIAS is positive, it indicates that model has a tendency to over-predict the parameter. Moriasi et al. (2008) recommends two ranges for PBIAS. The PBIAS for streamflow was recommended to be between -25% and 25% for satisfactory model performance; the PBIAS for sediment yield was recommended to be between -55% and 55% for satisfactory model; the PBIAS for modelling nitrogen and phosphorus loading rates had a recommended range of -70% to 70% for satisfactory model performance. The differences in recommended PBIAS ranges were based on typical uncertainty. Due to the increased uncertainty of using forecasted weather conditions instead of observed weather for the hydrological model, this study uses a moderate recommended range of -55% to 55%.

The root mean square error (RMSE) is often used as an error statistic; however, Singh et al. (2004) recommended considering the standard deviation when evaluating the RMSE. Based on this recommendation, Moriasi et al. (2007) suggested a normalized RMSE by dividing it by the standard deviation, resulting in the RMSE-observations standard deviation ratio, or RSR. The RSR is calculated using Equation 38.

$$RSR = \frac{\sqrt{\sum_{i=1}^{N}(O_i - P_i)^2}}{\sqrt{\sum_{i=1}^{N}(O_i - \bar{O})^2}} \tag{38}$$

The RSR statistic ranges from 0 to infinity. A value of 0 indicates that the model perfectly simulates observed conditions. Moriasi et al. (2007) recommended a range of 0 to 0.7 for a satisfactory model based on “typical uncertainty.”

4.4 Results and Discussion

4.4.1 Drought Index Input Parameter Forecasts

Observed parameter rankings (hereafter referred to as ‘observed’) were calculated using observed precipitation and temperature data. Forecasted parameter rankings (hereafter referred to as ‘forecasted’) were calculated from two-week weather forecasts. Each ensemble was used in the SWAT model and rankings were calculated from each ensemble as well. These forecasted rankings were evaluated to determine their individual accuracy.

4.4.1.1 Precipitation Ranking (-10 to 10)

A visual comparison between the forecasted and observed precipitation ranking CDFs (Figure 12.a) and PDFs (Figure 12.b) show a tendency for the forecasted rankings to be below the observed rankings. While there is an 8% larger proportion of observed rankings are concentrated at the extremely low end, a much higher proportion of the forecasted rankings (74%) are between -9 and 1 than the observed proportion (47%). Very little of the forecasted precipitation ranking distribution occurred at the high end of the rankings. Rankings from 7 to 10 only consisted of 2 % of the forecasted distribution, whereas this range made up 17% of the observed precipitation distribution.

The average weekly precipitation ranking was compared against the weekly observed precipitation. All four statistical tests performed were within range for satisfactory model performance (Table 4). Though within the acceptable range, the negative PBIAS (-34.2%) indicates that the forecasted rankings are much lower than the observed rankings. This is supports the visual comparison of the CDFs and PDFs that the forecasts have a tendency to under-predict precipitation. Though the forecasts generally under-predict precipitation, the NS (0.51) and R^2 (0.61) indicate that the forecasted rankings are following a similar trend as the observed rankings. The standard deviation of the forecasted rankings is 33% smaller than that of the observed rankings, which demonstrates that the forecasted rankings are not only under-predicted, but are also less dispersed.

4.4.1.2 Temperature Ranking (-10 to 0)

The temperature CDFs (Figure 12.c) and PDFs (Figure 12.d) show a similar trend between the distributions of the forecasted and observed temperature rankings. This is supported by the relatively low maximum difference between the CDFs (0.06). These graphs indicate there is a tendency for the distribution of the forecasted temperature rankings to be slightly higher than the observed temperature rankings. The forecasts had a lower proportion of values at the extreme low end of the distribution and a higher proportion of values at the extreme high end of the distribution.

The temperature ranking forecasts produced the best statistical results. The PBIAS supported the slight over-prediction of the forecasted temperature rankings with a value of 9.39%. However, this is well within the acceptable range. Both the NS (0.85) and R^2 (0.86) show a strong relationship between the forecasted and observed temperature rankings. The standard deviations of the forecasted and observed ranking have similar standard deviations as well at 3.24 and 3.02, respectively, indicating that the datasets have a similar dispersion.

4.4.1.3 Cumulative Biomass Ranking (-10 to 10)

Figures 13.e and 13.f depict the biomass production ranking CDFs and PDFs, respectively. These graphs show that the forecasted biomass production rankings have a higher proportion of lower values than the observed biomass production rankings. Nearly 75% of the forecasted biomass production rankings fall within the range of -10 to 1 whereas only about 54% of the observed biomass production rankings fall within the same range. The biomass production CDFs are very similar to the precipitation CDFs, likely because biomass production is strongly dependent upon precipitation. In fact, the observed biomass production ranking and precipitation ranking have a Pearson's correlation of 0.62.

The four model evaluation statistics for biomass production rankings all fell within the range for satisfactory model performance (Table 4). The moderately high NS (0.69), high R^2 (0.81), and low RSR (0.56) are promising. Though the PBIAS is within the satisfactory range for model performance, the forecasted biomass production ranking has a tendency to under-predict by a relatively large amount. The forecasted standard deviation is 22% lower than the standard deviation for the observed biomass production rankings. As with the precipitation rankings, this shows that the forecasted biomass production rankings are less dispersed in addition to being under-predicted.

4.4.1.4 Soil Moisture Stress Ranking (-10 to 10)

The soil moisture depletion ranking behaves differently than all other parameters. Comparing the CDFs (Figure 12.g) and PDFs (Figure 12.h) for the forecasted and observed soil moisture depletion rankings show that the forecast has a larger proportion in the mid-range and a smaller proportion at the extreme values. The forecasted soil moisture depletion rankings have 15% more values than the observed rankings between 0 to 2.

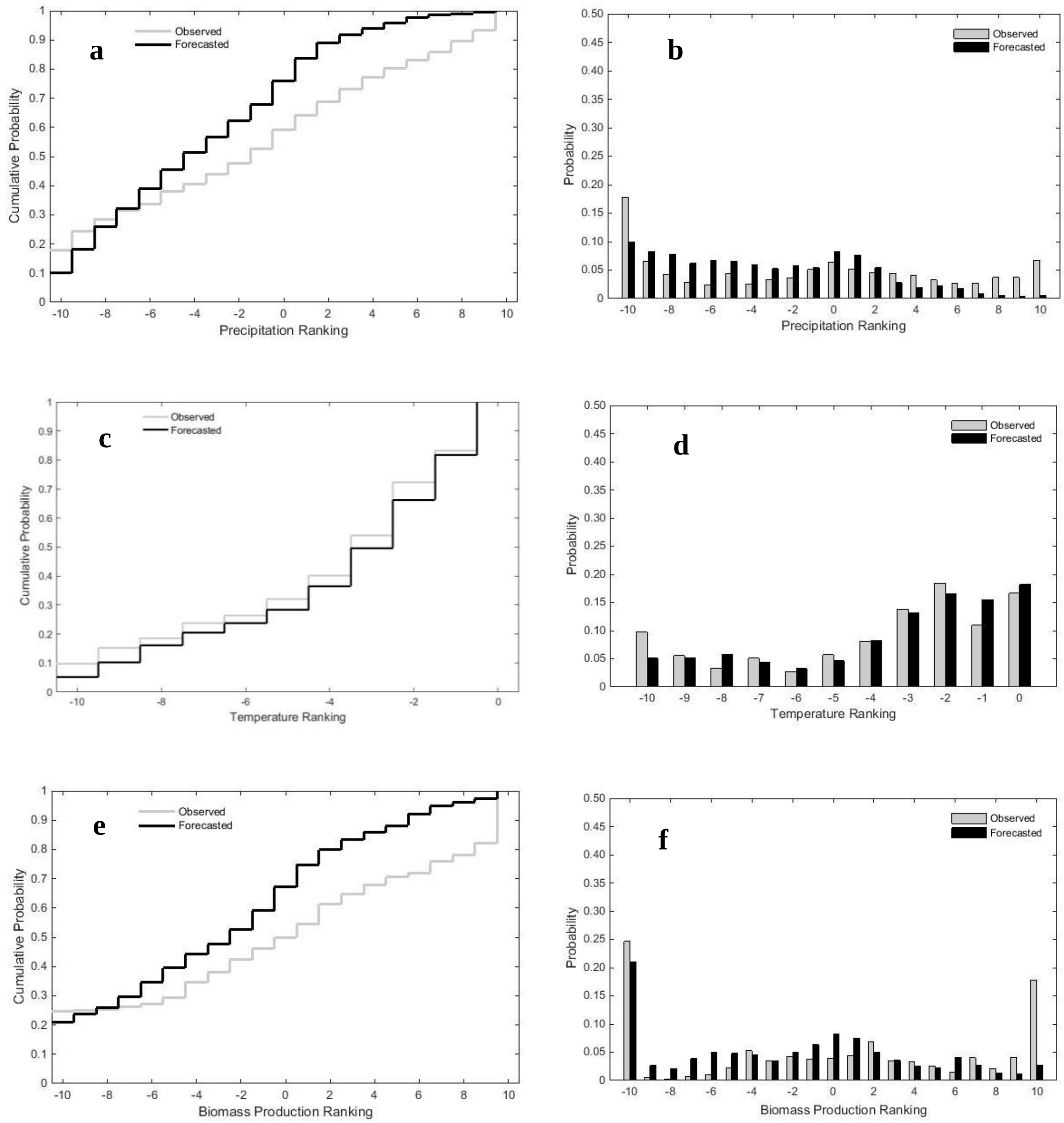

Figure 12: The CDFs and PDFs are provided for precipitation (a, b), temperature (c, d), biomass production (e, f), soil moisture depletion (g, h), and transpiration (i, j). Data in black represents the rankings calculated with forecasted weather data while gray represents rankings calculated with observed weather data. (Continued on next page)

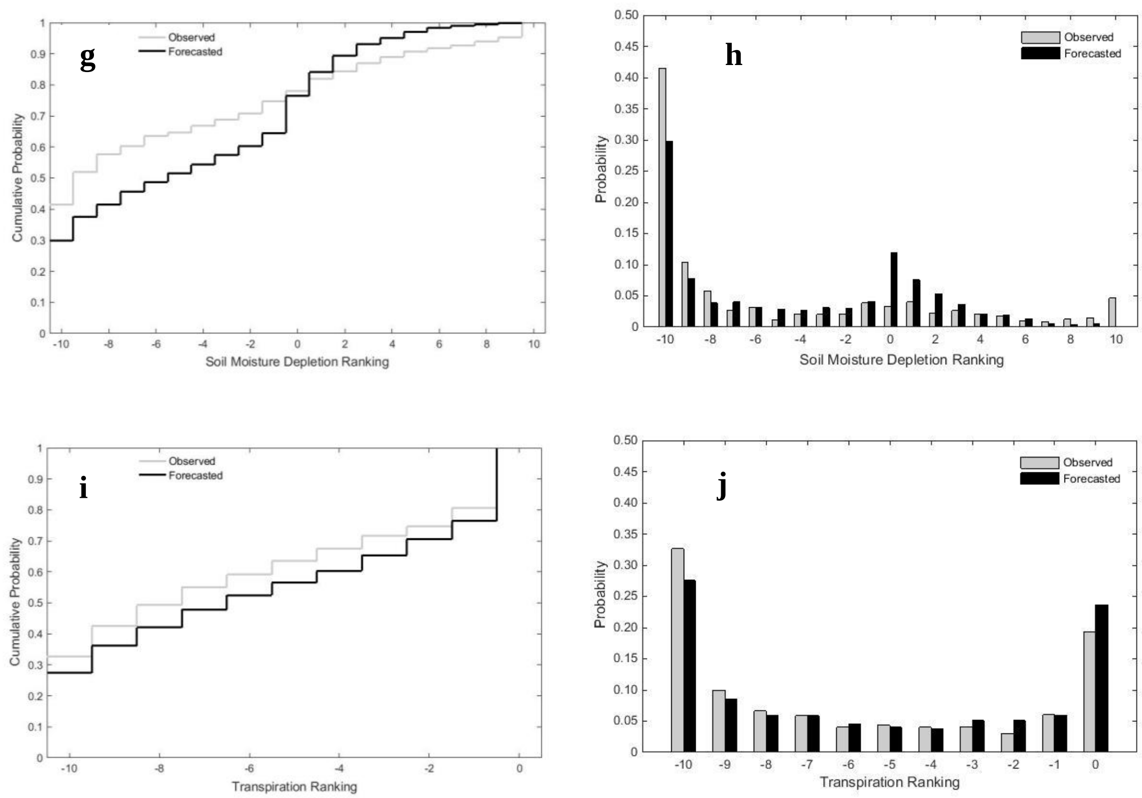

Figure 12 (continued)

Model evaluation statistics comparing the forecasted and observed soil moisture depletion rankings indicate that the forecasts poorly predict soil moisture trends. The NS (0.28), R^2 (0.33), and RSR (0.85) all need to be improved. Only the PBIAS (11.0%) falls within the range for satisfactory model performance. The PBIAS indicates that the forecasted soil moisture depletion rankings are generally higher than the observed rankings, suggesting that the soil moisture is slightly higher in the forecasts. Less dispersion of the forecasted soil moisture depletion rankings compared to the observed rankings as evidenced by the lower forecasted standard deviation.

Both the graphical comparison and model evaluation statistics provide unexpected results. The soil moisture depletion ranking is strongly correlated with precipitation ($R = 0.61$);

however, the CDFs and PDFs do not follow a similar pattern and the PBIAS for the soil moisture depletion ranking indicates that the forecasted values typically over-predict slightly whereas the forecasted precipitation rankings have a tendency to under-predict. This inconsistency is likely due to the fact that though, there are a higher proportion of forecasted precipitation rankings that are in the lower half of the range, there are also a much smaller proportion of forecasted precipitation events that result in no precipitation. Therefore, there is at least some precipitation more often in the forecasts than the observed precipitation data set. Even if the precipitation is minimal, it maintains the soil moisture, reduces soil moisture depletion, and thus, increases the ranking.

4.4.1.5 Transpiration Stress Ranking (-10 to 0)

The forecasted and observed transpiration ranking CDFs (Figure 12.i) and PDFs (Figure 12.j) show similar distributions. The largest difference between the two distributions occurred at the low and high end of the range. At -10, the proportion of forecasted transpiration rankings is 5% lower than the observed. At 10, the proportion of forecasted transpiration rankings is 4% higher. This indicates that the forecasted transpiration rankings have a tendency to be slightly higher than the observed transpiration rankings.

All four model evaluation statistics were within the range indicating satisfactory model performance. The PBIAS shows the forecasted transpiration ranks slightly over-predict as compared to the observed rankings, supporting the conclusions drawn from the CDFs and PDFs. This over-prediction is minimal and the standard deviation between the forecasted and observed transpiration are similar, suggesting the data have similar dispersion.

4.4.1.6 Summary

Overall, the forecasted soil moisture depletion rankings performed poorest out of the five parameters with only one model evaluation statistic in the satisfactory range (Table 4). The forecasted temperature ranking performed the best with all four model evaluation statistics out-performing all other parameters. Both the forecasted precipitation and cumulative biomass rankings tended to under-predict, though the PBIAS indicated they were within the acceptable range.

Table 4: The model evaluation statistics are provided in this table. Values with an asterisk indicate that the value falls within the satisfactory range for model performance. The model evaluation statistics for precipitation, temperature, biomass production, and transpiration are within the range for satisfactory model performance. The soil moisture depletion model statistics show the forecasted soil moisture depletion is unsatisfactory. 'Observed' indicates values calculated with observed weather data whereas 'forecasted' indicates values calculated with forecasted weather data.

Ranked Parameter	**Observed Average**	**Forecasted Average**	**Observed Standard Deviation**	**Forecasted Standard Deviation**	Dimensionless Evaluation	Regression Evaluation	Error Indices	
					NS	**R^2**	**PBIAS**	**RSR**
Satisfactory Range					**0.5 to 1.0**	**0.5 to 1.0**	**-55% to 55%**	**0 to 0.70**
Precipitation	-1.32	-3.32	6.69	4.50	**0.51***	**0.61***	**-34.2%***	**0.70***
Temperature	-3.76	-3.40	3.24	3.02	**0.85***	**0.86***	**9.39%***	**0.39***
Cumulative Biomass	0.07	-2.38	7.42	5.77	**0.69***	**0.81***	**-37.9%***	**0.56***
Soil Moisture Depletion	-5.02	-4.21	6.33	4.84	0.28	0.33	**11.0%***	0.85
Transpiration	-5.98	-5.35	3.98	3.69	**0.53***	**0.58***	**10.6%***	**0.69***

4.4.2 Yield Trend and Drought Forecasts

Cotton yields estimated with the forecasted weather data via the linear regression models resulted in a distribution similar to that calculated with the observed weather data. The largest difference between the forecasted and observed yield CDFs (Figure 13.c) was about 9.6%. The PDFs (Figure 13.d) show that a higher proportion of the forecasted yields occur below 500 kg ha^{-1} (450 lbs. ac^{-1}) and that a lower proportion between 530 to 730 kg ha^{-1} (475 to 650 lbs. ac^{-1}).

Table 5 provides the statistics for the forecasted average yield trends compared to observed yield trends. All the model evaluation statistics are within the range for satisfactory model performance. The NS (0.72) and R^2 (0.74) indicate that the estimated yields resulting from the forecasted weather data follow the same trend as those resulting from the observed weather data (Table 5). The data error is also within the appropriate range, though the PBIAS shows a slight tendency to under-predict.

The major difference between the drought index distribution calculated with the forecasted weather data and that calculated with the observed data occurs at the high end of the range, or a drought index greater than 6 (Figures 13.a and 13.b). The CDFs and PDFs for the drought index demonstrate that the forecasted drought index has a tendency to under-predict slightly as compared to the observed drought index.

The model evaluation statistics for the forecasted drought index are similar, but slightly better than the estimated forecasted yields. Like the forecasted yield, the drought index NS (0.76) and R^2 (0.79) demonstrated a strong relationship between the forecasted and observed values. The error indices were within the appropriate range and the PBIAS (-12.7%) indicated a slight tendency to under-predict.

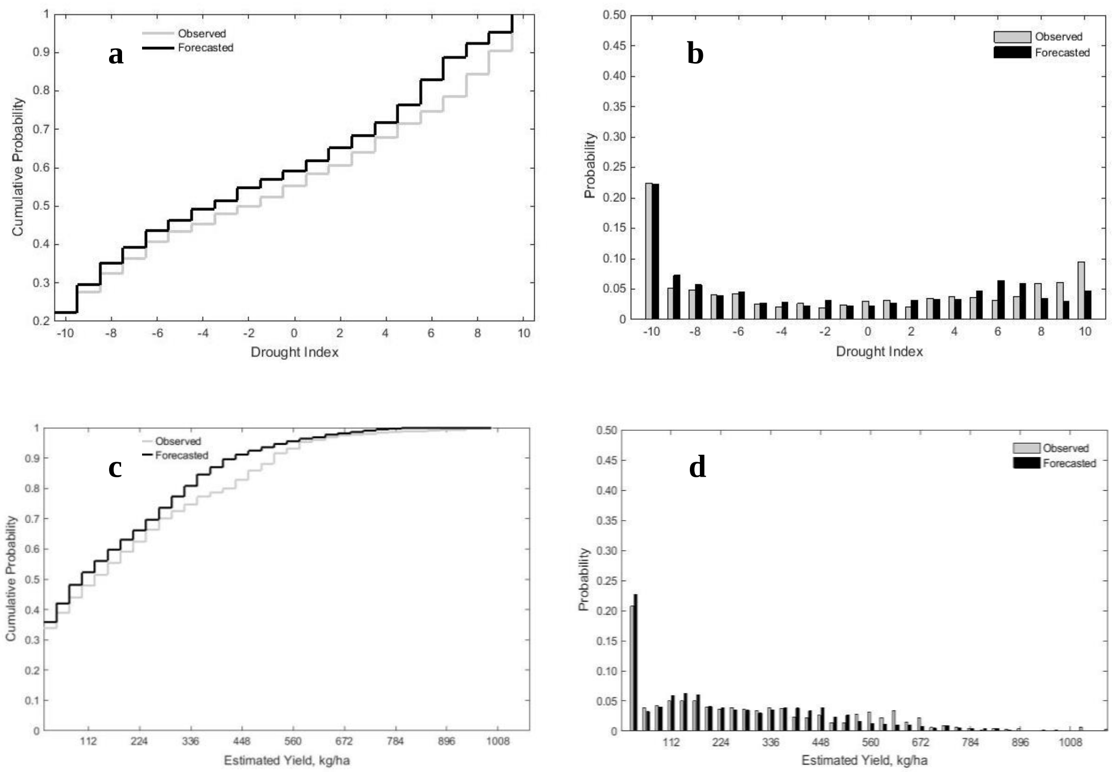

Figure 13: The CDFs and PDFs for the drought index (a, b) and cotton yields (c, d) are provided. Data in black represents the rankings calculated with forecasted weather data while gray represents rankings calculated with observed weather data.

The ability of the forecasted yields to match those calculated by observed weather conditions varies by week (Figure 14). Forecast rankings for one week and two weeks in advance were compared against observed rankings. In general, forecast rankings one week in advance were more closely matched to the observed rankings than forecast rankings two weeks in advance. All weeks had R^2 values greater than 0.5 for forecasts one week in advance or are within an acceptable range; however, forecasts two weeks in advance had R^2 values that fell below 0.5 four out of 20 weeks.

Table 5: The model evaluation statistics for forecasted cotton yields and drought index are provided in this table. Values with an asterisk indicate that the value falls within the satisfactory range for model performance. The model evaluation statistics for both cotton yields and the drought index are within the range for satisfactory model performance.

Statistic		Satisfactory Range	Yield Trends	Drought Index
Observed Average			235	-1.91
Forecasted Average			206	-1.03
Observed Standard Deviation			210	6.84
Forecasted Standard Deviation			181	7.53
Dimensionless Evaluation	**NS**	**0.5 to 1.0**	**0.72***	**0.76***
Regression Evaluation	**R^2**	**0.5 to 1.0**	**0.74***	**0.79***
Error Indices	**PBIAS**	**-55% to 55%**	**-12.3%***	**-12.7%***
	RSR	**0 to 0.70**	**0.53***	**0.49***

4.4.3 Decision Making Tool

Data obtained using this forecasting method can be used in association with a tool to aid water resource management decisions by agricultural producers. With forecasted yield trends and the drought index, agricultural producers would have an early warning of low moisture conditions that may lead to a reduction in yields and could adjust their water management practices accordingly. Figure 15 provides an example of information that can be conveyed to the tool user. The observed data is depicted as a line, while the two-week forecast is depicted as a shaded area. This figure shows the drought index for Borden County, TX, in 2013 for the first 12 weeks of the growing season. The forecasted drought index reveals that it is likely there will be moderately wet conditions in week 11 and typical moisture conditions in week 12 of the cotton growing season in Borden County. Therefore, producers could plan to save water in week 11 for later in the growing season when moisture conditions may become less favorable.

Though the current analysis has been performed on the county scale, by using the SWAT model, the forecasts can be achieved on a smaller, subbasin scale. This would provide agricultural producers with conditions at a more local scale.

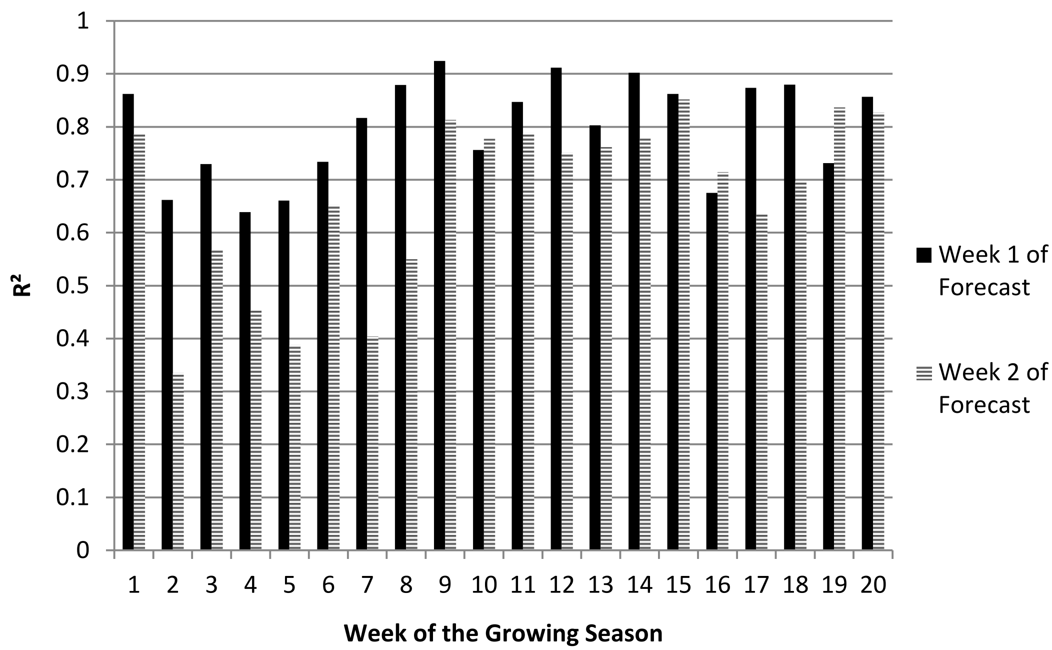

Figure 14: Comparison of yields calculated with the regression equation using observed weather data with week 1 of the forecast (solid bar) and week 2 of the forecast (striped bar) by week of the growing season. In general, week 1 forecast yields better match the observed yields than forecasts that are two weeks out.

4.5 Conclusions

The majority of the forecasts fall within the satisfactory range of the model evaluation statistics, indicating this forecasting method is satisfactory overall. It is important to note, however, that the forecasted precipitation and biomass rankings have a moderate tendency to under-predict. This should be taken into consideration when using the forecasts for decision making purposes. In addition, the model evaluation statistics for the soil moisture depletion ranking do not fall within the range associated with satisfactory model performance. Therefore, it is not recommended to use the forecasted soil moisture conditions as a basis for decision making. Rather, the soil moisture depletion ranking calculated with the observed weather conditions should be used.

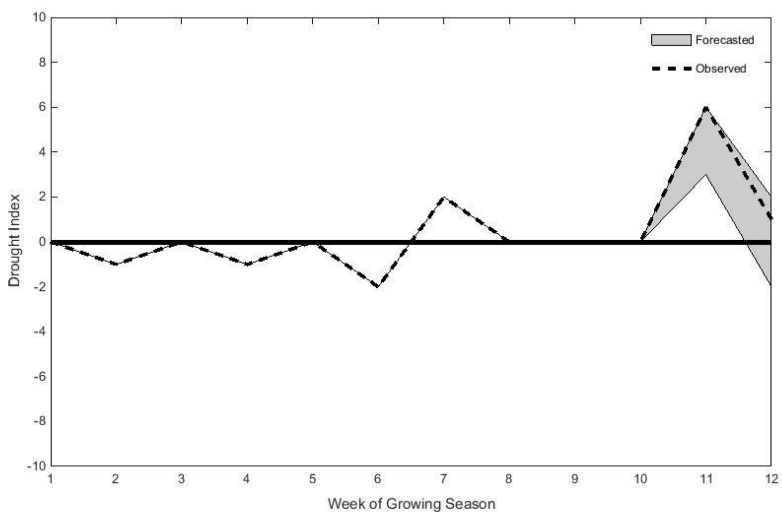

Figure 15: Example forecasted drought index for Borden County, TX in 2013. The first 10 weeks use the observed weather conditions to calculate the drought index while the last two weeks use weather forecasts. These forecasts provide a probable range of drought indices indicated by the gray area. The dashed black line is the drought index calculated using the observed weather data.

All four model evaluation statistics support that both the estimated yield and drought index can be predicted using forecasted weather data. These forecasts can be used to provide agricultural producers with information about near future moisture conditions, allowing them to make more informed decisions about water resource management. Creating an interactive tool on a county or subbasin scale would aid in the dissemination of the moisture trend information and help increase the efficiency of water resource use for agricultural purposes.

CHAPTER V

SUMMARY AND CONCLUSION

A weekly crop and location drought index was developed to help agricultural producers make informed water management decisions based on their crop's response to stress conditions associated with drought. To accomplish this, five parameters were identified as indicators of drought including precipitation, temperature, cumulative biomass, soil moisture depletion, and transpiration. Each parameter had a crop- or location- specific threshold value which was used to differentiate between wet and dry conditions and calculate parameter rankings. The amount of precipitation was summed over a five week period to provide a cumulative, five week precipitation value and with the 30-year normal indicating the threshold. The temperature parameter was defined as the number of days over the temperature stress threshold for the crop of interest during a five week period. Any period above the temperature stress threshold was considered to contribute to dry conditions. Cumulative biomass was calculated for the week of interest and used the 30-year normal for threshold value. Soil moisture depletion was evaluated against a crop-specific threshold value below which causes stress to the crop. Transpiration was evaluated against potential transpiration and the threshold value was transpiration less than the potential transpiration. A linear ranking system was used to standardize each parameter with bounds provided by the 30-year minimum and maximum value. A positive value indicates moist conditions while negative values indicate dry conditions that may lead to a reduction in yield.

Observed data was used to determine the precipitation and temperature rankings; however, limited information on weekly cumulative biomass, soil moisture, and transpiration made observed values impossible. Therefore, the Soil and Water Assessment Tool (SWAT) was used to estimate these parameters and calculate the 30-year normal values.

A multiple linear regression model was created for each week of the growing season to predict yields using the five parameter rankings. Observed county-level yields were used to develop the models, so all parameters were aggregated from the HRU level to the subbasin and finally, county levels using an area weighted average. Yields from the multiple linear regression models were used to calculate yield percentiles according to each model. These percentiles were used as the basis for the drought index. Yields at or below the 5th percentile correspond to very dry conditions and was given a drought index ranking of -10. Yields in the 50th percentile indicate typical conditions and were given a drought index ranking of zero. Lastly, yields at or above the 95th percentile were very wet and corresponded to a drought index ranking of 10.

The effectiveness of this drought index was evaluated through a case study in the Upper Colorado River Basin (UCRB) located in West Texas. The primary landuses of this region are rangeland and agricultural row crops. One of the most dominant crops in this area is cotton and was used in this study to evaluate the drought index.

Multiple linear regression models were created for the first 20 weeks of the growing season. Different parameters were found to be important during different times in the growing season. Soil moisture was most important in the beginning, transpiration in the middle, and cumulative biomass production at the end of the growing season. County level observed cotton yields were compared against the median predicted cotton yields from the 20 multiple linear regression models for 2000 through 2009. The two demonstrated a strong relationship with an R^2 of 0.73 and a PBIAS of 0.7. Additionally, the drought index demonstrated a strong linear relationship with the observed yields (R^2 = 0.67) and a slightly stronger polynomial relationship (R^2 = 0.71).

A secondary time period was examined to determine if the relationships hold. While there was limited observed data to make the comparison, 2010, a wet year, did predict higher yields (and thus drought index values) than 2012 which was a relatively dry year. Therefore, the drought index is a promising method for evaluating moisture related yield trends.

Once the drought index was evaluated for observed weather conditions, ensemble forecasted weather data was used to forecast yield trends and drought conditions. 21, 2-week forecasts were created for each week of the growing season. Rankings calculated using the observed precipitation and temperature data were compared against rankings calculated using the forecasted precipitation and temperature data. The average of the 21 forecasts was used to evaluate the forecast performance using typical statistical methods including R^2, NS, PBIAS, and RSR. The temperature rankings forecast performed the best, while the soil moisture depletion ranking performed the worst. Precipitation, temperature, cumulative biomass, and transpiration all demonstrated satisfactory performances. However, the soil moisture ranking did result in satisfactory performance. Overall, the drought index calculated using the forecasted parameter rankings compared well with the drought index calculated using the observed parameter rankings with all statistical tests well within the acceptable ranges.

This drought index has the potential to be used by agricultural producers to make crop-specific water management decisions. However, to do this, this information needs to be conveyed to producers in an accessible, understandable format. Generating an interactive mapping tool via GIS would be one method to accomplish this. With that in mind, a sample map (Figure 16) was created to demonstrate the functionality of this dissemination method.

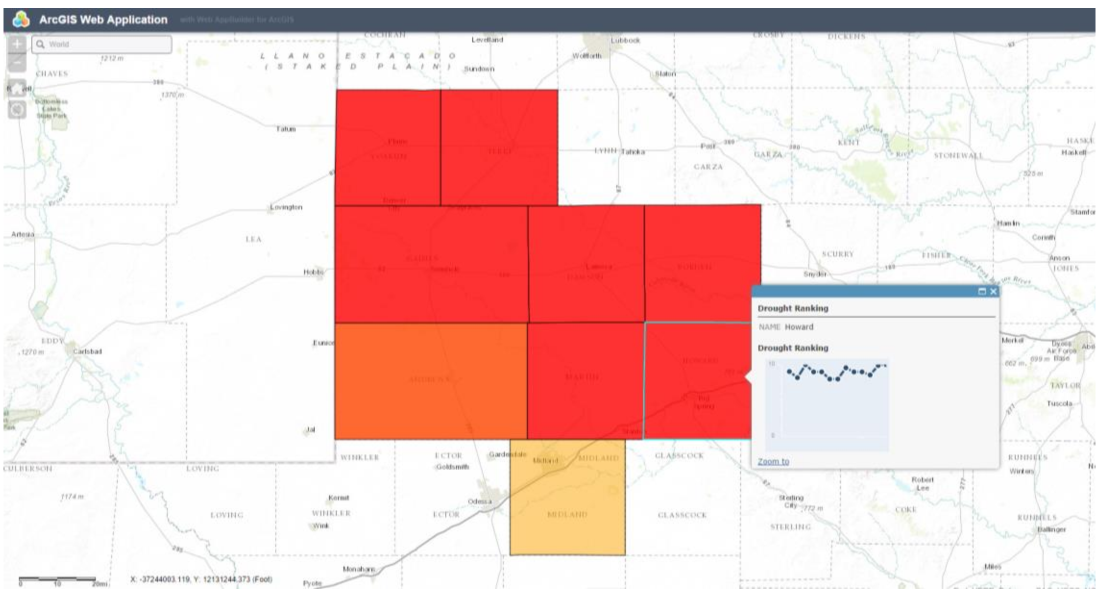

Figure 16: An interactive mapping tool created using ArcGIS online. Red indicates dry conditions while blue indicates wet conditions. When a county is selected, a graph depicting the seasonal drought ranking is provided.

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