Fall 12-1-2015

An Integrated Drought Index (IDI) Incorporating Physical and Social Aspects

Rebecca L. Lanier
University of Southern Mississippi

AN INTEGRATED DROUGHT INDEX (IDI) INCORPORATING

PHYSICAL AND SOCIAL ASPECTS

by

Rebecca Lanier

A Thesis
Submitted to the Graduate School
and the Department of Geography and Geology
at The University of Southern Mississippi
in Partial Fulfillment of the Requirements
for the Degree of Master of Science

Approved:

____
Dr. Bandana Kar, Committee Chair
Assistant Professor, Geography and Geology

____
Dr. Grant L. Harley, Committee Member
Assistant Professor, Geography and Geology

____
Dr. Carl A. Reese, Committee Member
Professor, Geography and Geology

____
Dr. Karen S. Coats
Dean of the Graduate School

December 2015

ABSTRACT

AN INTEGRATED DROUGHT INDEX (IDI) INCORPORATING

PHYSICAL AND SOCIAL VARIABLES

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The purpose of this research was to determine significant bio-physical (physical and environmental) and social variables that can be integrated into a drought index to predict areas susceptible to drought. Severe drought events are capable of causing millions of dollars in damage. The 1988 drought caused the United States approximately $40 billion in damage. Drought forecasting, modeling, and detection have, therefore, become imperative to understand the social, economic, and environmental impacts of droughts, and also to explore how these impacts play a role in the occurrence of a drought. A number of drought indices widely used in the U.S. rely on physical and meteorological factors to describe and predict drought conditions. Though social factors, especially, urbanization seem to contribute to the occurrence and severity of a drought they are rarely used in drought prediction and monitoring. In this research, the following research questions were answered to aid with drought prediction by incorporating physical and social variables: (1) Which physical parameters are significant in drought forecasting? (2) Can a social variable be used as a predictor for drought? If so, what impact does it have on drought severity?

ACKNOWLEDGMENTS

Firstly, I would like to express my sincere gratitude to my advisor, Dr. Bandana Kar, for her continuous support of my thesis, patience, and motivation. Her guidance and knowledge helped me through the research and writing of this thesis.

In addition to my advisor, I would like to thank the rest of my thesis committee, Dr. Andy Reese and Dr. Grant Harley, for their encouragement and critiques during the writing process which lead me to widen my research.

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CHAPTER I

INTRODUCTION

Overview

Severe drought events are capable of causing billions of dollars in damage worldwide and in the United States (U.S.) (Kogan 1997). Drought forecasting, modeling, and detection have, therefore, become imperative to understand the social, economic, and environmental impacts of droughts, and also to explore their role in drought occurrence. A number of drought indices have been developed for drought forecasting which rely on physical and meteorological factors. Though social factors seem to contribute to the occurrence and severity of a drought, rarely these factors are used in drought monitoring or forecasting. The purpose of this research was to determine significant bio-physical (physical and environmental) and social variables that contribute to drought occurrence, and to integrate these variables in an index following the Multi-Criteria Evaluation (MCE) technique to predict locations susceptible to drought based on their bio-physical risk and social vulnerability.

In this chapter, a definition of drought is provided followed by a discussion of potential drought impacts and mitigation techniques used to reduce drought impacts in the U.S. Finally, a discussion of the goals, objectives and main research questions examined, and the significance and potential outcomes of this research is presented.

Drought and Drought Types

Though a drought can be defined in a variety of ways, there are four main types of droughts: meteorological, hydrological, agricultural and economical. A meteorological drought refers to a lower amount of rainfall compared to the “normal” amount over a certain time-period (University of Nebraska-Lincoln 2013). Because there is no universal precipitation level that can be used to classify all regions as having a deficiency of rain due to varying climates, defining a meteorological drought is done on a regional basis (University of Nebraska-Lincoln 2013). A hydrological drought is dependent on the actual amount of precipitation, including rainfall, snowfall and the subsurface water supply. It tends to occur later than a meteorological drought because the hydrologic systems, such as stream flow or change in reservoir levels, take a longer time to be affected (University of Nebraska-Lincoln 2013). Though a limited amount of literature focuses specifically on hydrological droughts, the common understanding is that there will typically be a time lag between a meteorological drought and a hydrological drought, often lasting a number of months (Tallaksen and Van Lanen 2004). An agricultural drought refers to the effects of both meteorological and hydrological droughts on agriculture and is impacted by a shortage in precipitation and reduction in groundwater levels (University of Nebraska-Lincoln 2013). Given that some crops are more dependent on water than other crops and certain crops rely on top soil moisture versus subsoil moisture during different stages of their growing cycles, an agricultural drought is defined by the reduction in crop production due to water deficiency (University of Nebraska-Lincoln 2013). An economical drought is a result of the other three types of droughts and their impacts on the supply and demand of economic goods.

The key components used to classify a drought and measure its severity are a drought’s duration, spatial extent and the availability of precipitation (Tallaksen and Van

Lanen 2004). The duration of a drought refers to the length of time in which a drought condition persists, and the spatial extent refers to the area impacted by the drought.

Drought Impacts

A drought can have a number of impacts that can be classified into the following three categories: economic, environmental, and social (Knutson et al. 1998). Economic impacts often result from a drought's direct damage to agriculture. This can lead to an increase in prices of crops that were affected by a drought, thereby directly impacting consumers' expenses. Similar to crops, a drought can impact the availability of food for livestock and lead to the loss of livestock and a subsequent economic burden on consumers and the consumer-market driven economy. This impact is especially concerning due to the persistence of drought over an extended period of time. For instance, the U.S. is a hub for certain food products, such as corn. A drought impacting this crop will likely cause a shortage in food products associated with corn, thereby influencing the consumer market of countries around the world, many of which depend on U.S. food production, causing a price increase for these food products (Knowledge@Wharton 2012).

Environmental impacts can include impacts to animal or plant life, wetlands, and even air quality. The social impacts, on the other hand, cover a much wider variety of subjects. These can encompass adverse health conditions resulting from lack of proper food and/or availability of nutritional food. A very good example of the societal impacts of drought is the situation in Ethiopia where a lack of nutritional food due to lingering drought conditions caused health-related issues and the deaths of thousands of people (UNICEF 2013). Since the early 1970s, Ethiopia has been experiencing long-term droughts every few years. The drought of 2011 caused the deaths of approximately 250,000 of the country's livestock, creating a shortage of food for Ethiopians (Kronsteiner 2011). Due to a lack of available water, people were forced to walk 26 km to find drinking water, and this was a nearly impossible task for the elderly population (Kronsteiner 2011). The drought impacts in Ethiopia are diverse and have long-term effects on society and the environment.

The social impacts of droughts can also encompass recreational and public safety aspects (Knutson et al. 1998). For instance, in 2012, Austin, Texas had to implement its Stage 2 Watering Restrictions (Austin Water Utility 2014), according to which residents could water lawns and gardens during certain designated certain hours in a particular day. The restriction also prohibited restaurants from serving water unless a customer requested it (Austin Water Utility 2014). In April 2015, the State Water Resources Control Board of California mandated a reduction in water usage by 25 percent for all urban water users due to the continuous drought conditions experienced in the state (Kostyrko 2015).

Given its current rank as the country with highest economic damage due to droughts, the United States is one of the many countries in need of continuous drought research (Table 1). Since 2000, the U.S. has been impacted by three major droughts according to the *Centre for Research on the Epidemiology of Disasters* (CRED) (EM-DAT 2014). The drought of 2002 caused an estimated damage of $3.3 billion followed by the 2011 and 2012 droughts that caused approximately $8 billion and $20 billion damage respectively (EM-DAT 2014). The regions most affected by these later droughts were the Midwest and Southeastern United States. The frequency of drought occurrence within the

U.S. since 1900 indicates an increasing trend in drought in recent years (Table 2), which could be due to the earth's changing climate (National Wildlife Federation 2014).

Table 1

Top 10 Most Important Drought Disasters for the Period 1900 to 2014 (EM-DAT 2014)

Country	Date	Damage (000US$)
United States, Drought	Jun-2012	20,000,000
China P Rep, Drought	Jan-1994	13,755,200
China P Rep, Drought	Jan-2013	10,000,000
United States, Drought	Jan-2011	8,000,000
Australia, Drought	1981	6,000,000
Spain, Drought	Sep-1990	4,500,000
China P Rep, Drought	Oct-2009	3,600,000
Iran Islam Rep, Drought	Apr-1999	3,300,000
United States, Drought	Jul-2002	3,300,000
Spain, Drought	Apr-1999	3,200,000

Table 2

Drought Occurrences in the United States Since 1933 (EM-DAT 2014)

Start Date	End Date	Location	Est. Damage (US$ Million)	DisNo
00/06/2012	00/12/2012	South-West regions, Mid-West regions	20000	2012-9489
00/06/2012	00/00/2012	Midwest	n/a	2012-9235
00/01/2011	00/11/2011	Texas, Oklahoma, New Mexico…	8000	2011-9363
00/10/2007	00/06/2009	California, Georgia, Maryland…	300	2007-9548
00/07/2002	00/08/2002	Midwest	3300	2002-9853
00/11/2000	00/00/2000	Wyoming	n/a	2000-9712
00/06/2000	00/00/2002	South Carolina, Georgia	1100	2000-9339
00/07/1999	00/00/1999	Kentucky, Maryland, Ohio…	1100	1999-9358
00/07/1991	00/07/1991	Pennsylvania, Maryland	335	1991-9523
00/01/1991	00/07/1991	California	1000	1991-9476
00/04/1988	00/06/1988	n/a	n/a	1988-9707
00/00/1933	00/00/1937	Great Plains	n/a	1933-9003

Currently, the U.S. ranks third in terms of the highest number of people directly exposed to or living in drought-prone areas (PreventionWeb 2009). Because drought impacts tend to be severe, it is pertinent for people residing within drought-prone regions to understand the risks involved in living within those regions so that they can implement appropriate steps to reduce severity of drought impacts. In light of the growing severity and frequency of droughts along with rising population in the drought impacted areas in the U.S., this research is a step towards understanding how physical as well as social factors contribute to drought occurrence and subsequent impacts.

Mitigation Solutions

Despite their frequent occurrence, understanding all the risks associated with a drought is still a research topic (Knutson et al. 1998). The National Drought Mitigation Center (NDMC) in the U.S. has worked with drought planners worldwide to develop a checklist of the possible impacts of a drought. The checklist developed by the NDMC in 1998 includes questions pertaining to economic, environmental, and social impacts with regard to current, historical or potential future droughts (NDMC 2014). Typically, this list is used by agencies at local and national level and water utility companies to aid in mitigating potential drought conditions.

Based on the ranking of drought impacts, the NDMC guide has identified six basic steps of preparatory actions to reduce drought risk (Knutson et al. 1998). First, an individual (typically a policy maker) must identify a mitigation strategy to follow and use with the NDMC guide as the guide was designed to be used in conjunction with other mitigation strategies (Knutson et al. 1998). The next step requires assessing the risk of a drought and its direct impacts - environmental, social and economic. The drought risk refers to the amount of exposure or potential exposure of a region to a drought event. The third step requires ranking the impacts based on cost, areal extent, public opinion and other items identified in the NDMC guide (Knutson et al. 1998) in order to identify the most significant and severe impacts for a selected region. The final step is to determine underlying causes for a region's susceptibility to droughts so that specific mitigation actions can be undertaken.

The Federal Emergency Management Agency (FEMA) (2013) also developed a guide to reduce drought risk in the U.S. The major difference between the FEMA and the NDMC identified steps is that the FEMA (2013) guide includes steps that specifically take into account available water supply and a plan of action for drought events. FEMA's mitigation steps also begin by assessing the risk of a region to drought at a chosen local level, such as a county. The first step in this process includes gathering climate data to determine local climatic conditions and drought history, and identifying all available water supply sources. The second step requires monitoring drought conditions by determining local factors to aid in early warning. For instance, the drought condition of a region receiving snowfall will be impacted by the amount of snowpack available in a specific year. The guide, however, does not explicitly state using a drought index for monitoring though using an index, especially a local drought index, could be very helpful in predicting drought impact areas. The next step requires monitoring water supply amount to plan for a drought with the help of policy makers (FEMA 2013). The final step requires water conservation during a drought which may include prevention of overgrazing or excess water usage and is aimed at residents/businesses with livestock

(FEMA 2013). An advantage of using FEMA's mitigation guidelines is that they are more recent than the NDMC guidelines from 1998.

Determining drought impacts is pertinent to mitigate these impacts and prepare for future drought events. One useful resource for determining drought impacts is the Drought Impact Reporter (DIR) developed by the NDMC. The DIR provides users and drought planners the ability to visualize where the greatest impacts have occurred from droughts during a selected time period (NDMC 2014). It also breaks down the impacts into different categories for a specific location (i.e. a state or a county). For instance, from Figure 1 that depicts drought impacts for the conterminous U.S. during February 1, 2004 to February 1, 2014, it is evident that Texas experienced the highest economic, social and environmental impacts during this ten year period. Because the DIR also provides information about specific impacts a region experiences, it can also be used to mitigate and prepare for droughts by policy makers and local stakeholders.

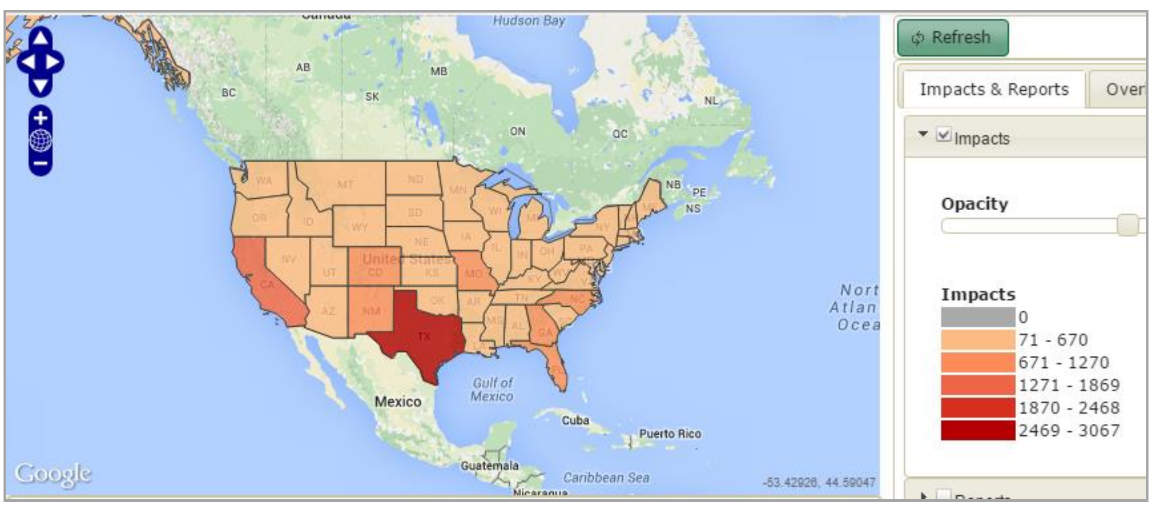

Figure 1. Drought Impact Reporter U.S. Drought Impacts: 02/01/2004 to 02/01/2014 (NDMC, Drought Impact Reporter 2014).

Numerous mitigation techniques, tools and indices are available to reduce drought impacts. The PREVIEW Global Risk Data Platform utilizes the Standardized Precipitation Index (SPI) to determine drought-related risks (UNEP/UNISDR 2013). Because this organization is comprised of numerous other agencies, it integrates data and information from a variety of sources to analyze risk and develop risk reduction measures. Unlike this platform, rarely drought indices are used in conjunction with the dynamic nature of the physical and social environments to help stakeholders (e.g., planners and policy makers) prepare for future droughts.

Research Questions

Undoubtedly, numerous physical and social factors influence drought occurrence. Naturally occurring events, such as tropical storms, have also been found to alleviate drought conditions in the southeast U.S. (Maxwell et al. 2013). The purpose of this research was to determine physical, meteorological, and social factors that play a significant role in drought occurrence, and develop a drought index by combining these factors that can be used to predict locations at-risk to experience a drought. The scope of this study does not include events that can alleviate drought conditions, but rather focuses on identifying physical and meteorological factors from literature, and examining the impact of specific social factors (e.g., population density), which can be integrated with the physical and meteorological variables to help determine areas at-risk to future droughts. This index can be used to explore how population growth can impact future drought conditions. This study builds on the Self-Calibrating Palmer Drought Severity Index (SC-PDSI). The main research questions investigated in this study were: (1) Which physical parameters are significant in drought forecasting? (2) Can a social variable be used as a predictor for drought? If so, what impact does it have on drought severity?

Research Significance

It is evident that numerous possible input parameters can be used in drought prediction and forecasting (listed in Table 1 in Chapter 2), and including all these parameters to determine a drought's severity or to forecast its occurrence is nearly impossible. An alternative to addressing this issue is to review previous studies and indices already in place to narrow down the list of parameters that are frequently used and are of import in drought prediction. For instance, the Palmer Drought Index (PDI) has been the most commonly used index in the U.S. since its development in 1965 (National 2013). The PDI and other such indices use meteorological and bio-physical variables that are significant in predicting drought and, therefore, should be used in a drought index. However, none of the indices available and used include any social parameters in predicting drought occurrence. The first research question focuses on determining pertinent and appropriate physical parameters contributing to drought risk.

A hydrological drought is influenced by a number of social variables, such as population density, water usage, household size, etc. The second question emphasizes identifying the appropriate social variable(s) that affect a drought's severity and/or its occurrence and therefore should be used in future drought forecasting models.

Summary

A drought has the potential to cause billions of dollars in damage. Research on Earth's changing climate shows the possibility of increased drought occurrences due to climate change (National Wildlife Federation 2014). While a drought can affect people during and after its occurrence, population size/density likely has an effect on the severity of drought conditions. It is, therefore, crucial to examine the impact of growing population on possible drought occurrence for the development of improved mitigation strategies for planners and other stakeholders.

This manuscript is organized into the following chapters. The next chapter provides a comprehensive literature review of drought indices established within the United States and the variables used in these indices followed by a discussion of the advantages and limitations of using remote sensing in drought studies. The methodology chapter introduces to the study site and discusses the research methodology used in this study (i.e. the scale of analysis, data sets, data processing steps and analytical techniques). This section is followed by the presentation and discussion of results, and then by the conclusion sections in which conclusions drawn from results and recommendations for future work are presented.

CHAPTER II

LITERATURE REVIEW

Overview

This chapter discusses the role of teleconnections in drought occurrence and provides an overview of physical risk and social vulnerability. A comprehensive table (Table 3) of drought indices used in and across the U.S. is presented along with a discussion of the variables and formulas used (if any), and other criteria required for developing and deploying each index. Because remote sensing data is used to derive different variables, such as biomass and soil moisture, that are used as proxies for drought prediction, it has steadily become an important component in drought research. A discussion of the merits and disadvantages of using remote sensing data is presented in this chapter. A discussion of physical risk and social vulnerability is also presented to lay the foundation for determining the locations physically and socially susceptible to future droughts.

Drought Introduction

A drought is a hydro-meteorological hazard that influences countries worldwide, including the United States. The United States experienced the most expensive drought during 1987-89 that caused approximately $40 billion in financial loss (Kogan 1997; NCDC 2013). At its peak, this drought covered about 36% of the U.S. (NCDC 2013), as opposed to the 70% of the U.S. that was impacted by the Dust Bowl drought of the 1930s that persisted for about six years, but came in three distinct waves: 1934, 1936 and 1939-1940 (NCDC 2013). The drought of 1980s began on the west coast in 1987, but intensified by 1988 by spreading to the eastern U.S. including parts of the Mississippi

River Basin (NCDC 2013). This drought affected society in multiple ways with record-setting temperatures in the Midwest and problem with crop growth and barge navigation along the Mississippi River (NCDC 2013). The U. S. experienced another severe drought in 2000, which lasted until 2004. The 2000 drought covered 35% of the contiguous U.S., but by 2001, the drought coverage shrank to about 15% of the entire U.S. Between 2002 and 2004 the spatial extent of the drought increased that covered approximately 50% of the contiguous U.S. (NCDC 2012). The most recent drought that affected the U.S. was during 2011-2012, which is considered to be the worst drought in the past 25 years (Knowledge@Wharton 2012). As of January 2013, the estimated financial loss from this drought due to impacts to agricultural and food industries was about $35 billion (Rice 2013).

Drought Teleconnections

In the U.S.,the occurrence of droughts can be related to the oscillations resulting from the shifting of wind speed and ocean currents. These oscillations affect the intensity and duration of a drought. The El Niño Southern Oscillation (ENSO) is the warm phase of the Southern Oscillation during which the waters off the western coast of South America experience unusually warm temperature and any nutrient-rich cold water is stopped from upwelling from the deep ocean (USDM 2014). The ENSO occurs from an unusual shift in winds which leads to the Peru Current weakening and/or reversing. The high pressure develops farther west than its typical location in the South Pacific Ocean, which leads to low pressure development along the western coast (California Department of Fish and Wildlife 2014). The change in pressure causes the winds to blow from the opposite direction than what is typically observed. Typical winds observed are the easterly trade-winds, but ENSO weakens these or reverses the direction to a westerly wind (California Department of Fish and Wildlife 2014). The ENSO - colloquially known as the El Niño - has been linked with global shifts in weather patterns (USDM 2014). During an El Niño event, weather conditions are typically affected during the winter months, causing the Southeastern U.S. to experience above normal precipitation and cooler than normal temperatures, which lessens the likelihood of a drought (Ropelewski and Halpert 1986). In contrast, the northwest coast could receive extreme heat waves during this time if the event is strong enough to cause a displacement in the jet stream (USDM 2014). The La Niña event describes the opposite effect of the Southern Oscillation, during which the sea surface temperatures across the west coast of South America are cooler than normal, and the winter temperatures across the Southeastern U.S. tend to be warmer than normal with drier conditions (NOAA 2014). Thus, there is the increased possibility for drought conditions to persist during winter in the Southeast. While each phase cycles every 3 to 7 years, a phase may persist for approximately 6 to 18 months (USDM 2014).

There are also other ocean oscillations that impact the weather of the U.S., such as the Pacific Decadal Oscillation (PDO). The PDO has similar effects as ENSO, but a different behavior with its ocean patterns and timing (Climate Impacts Group 2014). The PDO is located in the North Pacific Ocean and its warm phase occurs when the eastern Pacific Ocean receives higher than normal temperatures, while the central and western Pacific receives cooler than normal temperatures (Climate Impacts Group 2014). During the cool phase of the PDO, the Pacific regions of the U.S. experiences the exact opposite ocean temperature pattern than the warm phase (Climate Impacts Group 2014). Each phase of the PDO can persist for 20-30 years, which is much longer than that of the ENSO (Climate Impacts Group 2014). The warm phase of the PDO and the El Niño, and the cold phase of the PDO and La Niña have similar impacts in the Southeastern U.S..

The Atlantic Multidecadal Oscillation (AMO) also influences the weather conditions across the U.S.. The warm/positive phase of this corresponds to warmer sea surface temperatures across the tropical Atlantic Ocean and the cold/negative phase corresponds to colder than normal temperatures (McCabe et al. 2004). Each phase persists for about 40 to 50 years with the warm phase of the AMO bringing below-average amounts of precipitation to the central U.S. (McCabe et al. 2004), thereby increasing the possibility for drought conditions.

The timing of these oscilliations is critical to forecasting drought conditions. If all the oscillations were in a phase during which precipition is inhibited in the Southeastern U.S., then this would enhance the intensity and duration of a drought. However, if a lesser amount of rainfall occurs during one oscillation, while increased rainfall occurrs during the other two oscillations, a balance in precipitation could occur. Likewise, depending upon an oscillation, peristent drier conditions could be eliminated due to greater than normal rainfall, thereby either obliterateing or moderating a drought and/or drought conditions.

Evidently, there is a relationship between ocean oscillations and climate change. According to Climate Communication (2014), the current warming trend of the Earth is intensifying the phases of the oscillations and increasing their durations. Therefore, the ENSO has become a much more intense and frequent event in recent years (Climate Change 2014). Because climate change impacts the intensity, duration and severity of oscillations which subsequently influence the spatial and temporal extents, severity and magnitude of a drought, it is critical to forecast drought occurrence to better manage its social and financial impacts.

Drought Indices

Drought was originally defined by Alfred Judson Henry in the early 1900s as “a period of twenty-one days or more was 30 percent, or less of the normal for the season” (Henry 1906, 54). Using this definition, researchers developed a number of drought indices to predict and/or monitor drought severity in and across the U.S.. Although drought severity is determined by the average amount of precipitation a location receives, some indices define severity based on the duration of a drought. A discussion of these indices, the variables and techniques used to create them, and their pros and cons is presented in the following section.

The Munger’s Index is the first drought index that was developed in 1916 to explore forest fire risk (Heim 2002). This index uses amount of precipitation coinciding with the timing of a drought to determine drought severity by using Equation (1) - a technique similar to calculating the area of a right angle triangle:

$$\text{Equation (1): severity of drought} = \tfrac{1}{2} * L^2$$

where *L* is the length of drought in days, and drought, in this instance, is defined by a location experiencing less than 1.27 mm of rainfall within 24 hours (Heim 2002). In 1919, Kincer’s Index was developed in which drought was defined as “30 or more consecutive days with less than 6.35 mm (0.25 in) of precipitation in 24 h” (Heim 2002). This new index was successful in depicting precipitation distribution with regard to seasonal changes and subsequently frequency of droughts east of the Rocky Mountains.

Markovitch's Index, developed in 1930, uses both temperature and precipitation to measure drought severity (Equation 2):

$$\text{Equation (2): drought index} = \tfrac{1}{2}\,(N/R)^2$$

Where *N* is the number of two or more consecutive days above 90^0 F (32.2 C) and *R* is the total amount of summer rainfall for those same months (Heim 2002). In 1942, the Blumenstock's Index was developed using the duration of a drought. According to this index, a drought is terminated when the accumulated precipitation level reaches 2.54 mm (0.10 in.) within 48 hours (Heim 2002). The Antecedent Precipitation Index (API) was developed in 1954 to aid with soil moisture estimation for flood forecasting (Heim 2002). The API is calculated daily by multiplying the previous day's precipitation with a factor, which changes for snowfall (Heim 2002). McGuire and Palmer developed the Moisture Adequacy Index in 1957,which is simply a ratio of the actual amount of soil moisture and the percentage of moisture needed for plant growth (Heim 2002). This index gave rise to the idea of using potential evapotranspiration (the amount of evaporation that would occur is a sufficient water source was available) for drought monitoring.

The most widely used index in the U.S. is the Palmer Drought Severiy Index (PDSI) which was developed in 1965 by Wayne Palmer and incorporates the following variables: precipitation, temperature, moisture supply and moisture demand (Heim 2002). This index was heavily influenced by Thornthwaite's pioneering work on evapotranspiration (Heim 2002). The PDSI is useful for meteorological droughts, but because it incorporates precipitation, evapotranspiration and soil moisture conditions, it can also be used to determine hydrological droughts (Alley 1984). Palmer also created a number of other indices which were adapted from the original PDSI. For instance, the

Palmer Hydrological Drought Index (PDHI) is used to determine long term hydrologic moisture conditions and the *Z* Index which is used to determine moisture anomalies, i.e. when the moisture conditions depart from the normal (the average or mean value) moisture conditions typically observed (Heim 2002). It can either be expressed in terms of drought conditions or wetness. In 1968, Palmer introduced the Crop Moisture Index (CMI) as an agricultural index, which is dependent on drought conditions at the beginning of a week and calculates the amount of soil recharge occurring by the end of the week (Heim 2002).

Despite the PDSI's attention and popularity in the U.S., it has received criticisms for its inability to compare its values among regions with different climatic conditions, and it suffers from numerous limitations and assumptions (Wells et al. 2004). The most serious problems are: the arbitrary classification of drought severity and the arbitrary rules used to quantify the beginning and ending of droughts (Alley 1984). To address the local variability of drought conditions, Wells et al. (2004) developed a new index known as the Self-Calibrating Palmer Drought Severity Index (SC-PDSI) (discussed in detail in the Methodology chapter). The SC-PDSI allows for the empirical constants, originally calculated when the PDSI was developed, to become variables that can be recalculated automatically for any location by using the climatic data for that location (Wells et al. 2004). Because a drought can be explained based on the variation in moisture content from the average climatic conditions of a particular area, it is important to know the area's history of precipitation and temperature.

The Keetch-Byram Index (1968) was developed to control fire and for wildfire monitoring, and is based on a fixed soil moisture storage capacity of 203 mm (8 inches)

(Heim 2002). The index values range from 0 (no moisture defecit) to 800 (absolute drought). In 1981, the Surface Water Supply Index (SWSI) was developed for Colorado, which is an enhancement of the PDSI as it accounts for snowpack and other variables (NDMC 2013) as listed in Table 3 influencing drought conditions. The Standardized Precipitation Index (SPI), also developed for Colorado, is based on the probability of precipitation (NDMC 2013). The Vegetation Condition Index, developed in 1995, compares the current Normalized Difference Vegetation Index (NDVI) to the previously calculated NDVI (Copernicus 2013) and utilizes the visible and near infrared bands of the Advanced Very High Resolution Radiometer (AVHRR) for the NDVI calculations (Heim 2002). Because of its dependency on vegetation, it is most useful during the summer growing seasons.

In 1999, the federal and state agencies collaborated to develop a new drought monitoring tool - the U.S. Drought Monitor which is maintained by the National Drought Mitigation Center. The tool uses climatic data and values from other indices such as the PDSI, CPC Moisture Model, USGS Weekly Streamflow, and SPI to determine spatial distribution of drought on a weekly basis in the coterminous U.S. (USDM 2013). The tool produces a map of drought severity for the contiguous U.S. and the drought severity classifications range from D0 (abnormally dry) to D4 (exceptional drought) (Heim 2002). The Percent of Normal Index (PNI) is a simple mathematical equation that divides the actual precipitation by the normal precipitaiton and multiplies the division results with 100 to get a percentage output. Because the PNI calculates percent precipitation, it can be calculated for any time scale, but it uses the normal precipitation for a 30-year mean for calculations (Indiana Department of Natural Resources 2013). The Reclamation Drought

Index (RCI), a product of the Reclamation States Drought Assistance Act of 1988, is very similar to the SWSI, and the index incorporates temperature, precipitation, snowpack, reservoir levels and streamflow at the river basin level (NDMC 2013). The RCI is typically used as an indicator for determining when the drought emergency relief funds need to be released. The Deciles Index, developed in 1967, simply uses the deciles statistic on monthly precipitation data (NDMC 2013). The deciles method splits up any set of ranked data into 10 equal parts. The deciles process has 5 categories all 20% apart and each category represents precipitation occurrences (NDMC 2013). For instance, below normal precipitation occurs in the 1-2 deciles category representing the lowest 20% of precipitation amount recorded (NDMC). The most recently developed drought index is known as the Standardized Precipitation Evapotranspiration Index (SPEI). This index encompasses precipiation and climatic temperature and has some similarities to the SPI and SC-PDSI (Vicente-Serrano et al. 2010). Table 3 provides a comprehensive list of currently available drought indices, and the variables used and the time scale of each index.

Table 3

U.S. Drought Indices

Index Name	Year	Variables	Time Scale
Munger's Index	1916	Precipitation, Drought Length	Daily
Kincer's Index	1919	Precipitation	Seasonal
Marcovitch's Index	1930	Precipitation, Temperature	Seasonal
Precipitation Effectiveness Index	1931	Precipitation, Evapotranspiration	Monthly/Yearly
Blumenstock's Index	1942	Precipitation	Daily
Antecedent Precipitation Index	1954	Precipitation	Daily
Moisture Adequacy Index	1957	Precipitation, Soil Moisture	Daily
Palmer's Index (PDSI and PHDI)	1965	Precipitation, Temperature, Hydrologic Cycle	Weekly, Biweekly, Monthly
Deciles	1967	Precipitation	Monthly
Crop Moisture Index	1968	Precipitation, Temperature, Evapotranspiration, Soil Moisture, Runoff	Weekly
Keetch-Byram Drought Index	1968	Precipitation, Soil Moisture Capacity	Daily
Surface Water Supply Index	1981	Precipitation, Snowpack, Reservoir Storage, Stream flow, Runoff	Monthly

Table 3 (continued).

Index Name	Year	Variables	Time Scale
Standardized Precipitation Index	1993	<u>Precipitation</u>	Monthly/Seasonal
Vegetation Condition Index	1995	VIS an NIR from AVHRR	Daily
Drought Monitor	1999	<u>Precipitation</u>, Soil Moisture, Stream flow, PDSI, SPI, CMI, VHI, other climatic variables	Weekly
Percent of Normal	n/a	<u>Precipitation</u>	Monthly
Reclamation Drought Index (RDI)	1988	<u>Precipitation</u>, Temperature, Snowpack, Reservoir Levels, Stream flow	Monthly
SC-PDSI	2004	<u>Precipitation</u>, Temperature, AWHC	Weekly, Biweekly, Monthly
Standardized Precipitation-Evapotranspiration Index (SPEI)	2010	<u>Precipitation,</u> Potential Evapotranspiration	Weekly, Monthly

Note. Sources: Heim 2002; NDMC 2013; IDNR 2013; Niemeyer 2008; Wells et al. 2004; Vicente-Serrano et al. 2010

Drought Variables and Data

It is apparent from Table 3 that the most commonly used variables in drought indices are precipitation and temperature. The data for these two variables can be obtained from weather stations around the country (i.e. United States) and interpolated to determine values for data-void regions. Due to the limited availability of weather station data, data about other variables, such as soil moisture and NDVI are generally obtained from remote sensing data. With the availability of numerous satellite sensors with multiple bands, obtaining these data sets is not impossible. Though field work can be conducted to collect data about soil moisture and vegetation condition, it can only be conducted for smaller sites, and can become time consuming and expensive. In contrast, remote sensing provides easy access and a wider coverage to many data sets that can be/are used in drought prediction and monitoring, especially, while dealing with large sites (Kogan 1997; Schubert et al. 2007). The most useful indicators of drought conditions derived strictly from remotely sensed data are the NDVI and Vegetation Condition Index (VCI) as they are highly sensitive to drought conditions. Remote sensing data is also used to estimate soil moisture content for drought research (Alley 1984). Therefore, remotely sensed data is used to monitor and assess drought efficiently.

Kogan (1997) used NDVI, VCI (Vegetation Condition Index), and Temperature Condition Index (TCI) derived from the AVHRR satellite sensor imagery to determine drought severity. The author generated VCI and TCI from the NDVI layers to compare with ground data, such as rainfall, temperature, vegetation density, biomass, and yield, the PDSI and the Crop Moisture Index (CPI) in order to validate the drought severity determined by the remotely sensed data. The methodology developed by Kogan (1997) has been successful in detecting drought based on vegetation stress in other countries such as Asia, Africa, the Americas, and Europe.

Using remote sensing data, a number of tools have also been developed for public and government use. These tools provide information about drought severity of a location and help implement mitigation techniques to reduce drought impacts. One such tool is the

National Integrated Drought Information System (NIDIS). The online web application - NIDIS - is run by the U.S. Drought Portal and promotes interaction among various government agencies including NASA, which provides access to remote sensing data to improve drought monitoring and forecasting techniques.

Wang et al. (2008) used the Normalized Difference Water Index (NDWI) in the near-infrared and shortwave infrared bands of the Landsat TM and ETM+ remotely sensed images to observe the oak crown die-back, a characteristic that indicates decline of oak trees and their subsequent mortality due to a drought. To monitor and assess drought in Southwest Asia, Thenkabail et al. (2004) used the monthly highest NDVI and the unique spectral signatures of tree canopies. They concluded that the satellite data is the most reliable way to receive data most consistently which can be used in predicting the onset of drought.

Kogan (1997) and Thenkabail et al. (2004) used the AVHRR satellite, but the satellite has a spatial resolution of 1.1 km x 1.1 km that is coarser than many other sensors. Despite having a daily temporal resolution, the authors concluded that AVHRR satellite is not suitable for smaller scale drought cases because of its coarser spatial resolution. Another satellite option for drought research is the Landsat 7 which has a higher spatial resolution (30m x 30m), but a lesser temporal resolution of sixteen days. The spatial resolution of satellite data is a major constraint seen by these researchers, especially if the area being monitored is relatively small. There are a wide variety of spatial resolutions available when using remotely sensed data, but the finest resolution data available (30m) was chosen for analysis for the study.

Physical Risk and Social Vulnerability

A drought has very diverse impacts on the physical and social environments. With the growing concern about a drought and other meteorological hazards' potential financial and societal impacts, the United Nation (UN) has undertaken the Disaster Risk Reduction (DRR) initiative (UNISDR 2007). Risk assessment is one of the major requirements of the DRR initiative, which focuses on identifying the physical risk zones (UNISDR 2007; Peduzzi et al. 2009). Risk assessment, the main component of DRR, is based on assessing hazards (their type, location, intensity, frequency, and probability of occurrence), vulnerability and exposure. In other words, it is a function of hazard, vulnerability and exposure (Peduzzi et al. 2009; Bründl et al. 2009).

The hazard analysis component of risk assessment focuses on determining the expected physical impacts a region will experience for a defined period by a hazard event (Bründl, et al. 2009). It takes into account the topographic features and meteorologic conditions of the region to determine the intensity of the hazard and its probability of occurrence primarily through modelling techniques (Bründl, et al. 2009). Exposure refers to population, structures, infrastructures, and physical environment subjected to harm from hazards (Lavell et al. 2012; Peduzzi et al. 2009). The exposure analysis focuses on identifying the people and assets at risk based on certain factors such as how many people and structures are in a region, their values and the probability the people and structures will be exposed to such a hazard (Bründl, et al. 2009). Finally, the outcomes of the hazard occurrence and exposure analyses are combined to determine the expected damage and loss (physical and financial) (Bründl, et al. 2009).

Vulnerability, in general, refers to the potential and degree of susceptibility of an individual, a group, or a community to experience adverse impacts of hazards due to socio-cultural, physical, economic, and environmental conditions (Burton et al. 1993; Cutter 1996). Social vulnerability refers to the factors that affect the outcomes of a specific hazard to a social group (Cutter et al. 2003). Some of the predominant factors contributing to social vulnerability include the social capital of a community (i.e. social networks), the socio-economic conditions, cultural beliefs and customs, limited or no access to resources, the physical conditions of individuals (i.e. limited physical ability due to health conditions or due to old age) (Cutter et al. 2003). In addition to these factors, population growth of a region can also increase vulnerability (Cutter et al. 2003). An understanding of the physical and meteorological conditions contributing to a drought's occerrence combined with the socio-economic conditions that may increase the drought's potential impacts will help develop an index integrating both physical and social conditions of the region.

Summary

Conclusions

A drought is a phenomenon that is dependent on multiple factors. The drought severity is typically analyzed through drought indices by using the most commonly used factor - precipitation. However, all the existing drought indices lack a social component. Because the population density of a location appears to impact drought condition of that location, it is an important factor to be considered as part of any drought study. Although the PDSI is the accepted drought index within the U.S., the SC-PDSI is an improvement upon the PDSI because it accounts for local climatic characteristics (Wells et al. 2004).

However, this new index does not incorporate social factors that contribute to drought conditions. Therefore, the proposed new index was built on the SC-PDSI by integrating social factors. Knowing how a changing population will impact drought conditions can help formulate and improve mitigation techniques to address the impact of population growth on drought events.

Limitations of these studies

As with any research, this research has some limitations. The main limitation being the use of data sets at varying spatial scales of analysis and spatial resolutions. These varying scales and resolutions will result in the Modifiable Area Unit Problem (MAUP) – a common fallacy associated with geo-spatial studies due to changing and varying scales of analysis. To reduce the influence of MAUP, a raster data model and a standardized spatial resolution were used. Another limitation results from the use of interpolation techniques to create a continuous surface of meteorological variables (i.e. precipitation, temperature) from point data. Measures were taken to standardize the spatial resolution of these surfaces and assess the cumulative error and spatial distribution of error in these surfaces. The final limitation of this study is the use of specific social variables, especially, population growth and economic conditions instead of other social variables that may influence a drought (e.g. water draw down by each household, water table condition in each study site, etc.). Because this study was the first study to incorporate social variables, the scope of this study included only population of a region to determine its drought risk potential instead of other social variables. By limiting the social variables, this study achieved the goal of obtaining more accuracy while integrating social variables with physical and meteorological variables.

CHAPTER III

METHODOLOGY

Overview

This chapter discusses the methodology implemented to answer the following research questions: (1) Which physical parameters are significant in drought forecasting? (2) Can a social variable be used as a predictor for drought? If so, what impact does it have on drought severity?

In the first section of this chapter, the justification for selecting particular Texas counties is presented. The next section outlines the study's scope and data sets in which a discussion of the final set of variables used for analysis and their data sources is presented. With these established, the research designs and analytical techniques used to answer the research questions are discussed. The final section of this chapter discusses the steps implemented to validate the index and asses its accuracy in comparison to other existing indices (SC-PDSI and PDSI).

Study Site

For this research, the state of Texas was selected due to the frequent occurrence of drought in this state. As evident from Figure 1, Texas has the highest reported drought impacts. Among the 254 counties in Texas, the counties with the highest population density were Dallas, Harris, Tarrant and Bexar Counties (Figure 2) as per the 2010 U.S. census. Because the SC-PDSI accounts for the subsurface water supply, it was crucial to choose counties for this study that draw their water supply from the subsurface as well as surface water sources for comparative analysis purpose. Given the purpose of this study was to incorporate social factors in predicting drought occurrence potential, these counties - Harris and Bexar (drawing water from subsurface sources) and Dallas and Tarrant (drawing water from surface water supplies) (Figure 5) were used in this study because of their higher population density in comparison to other counties in Texas (Table 4). Table 4 lists the decadal population increase experienced by these counties during 1990 – 2010 as well as their varying water supply sources.

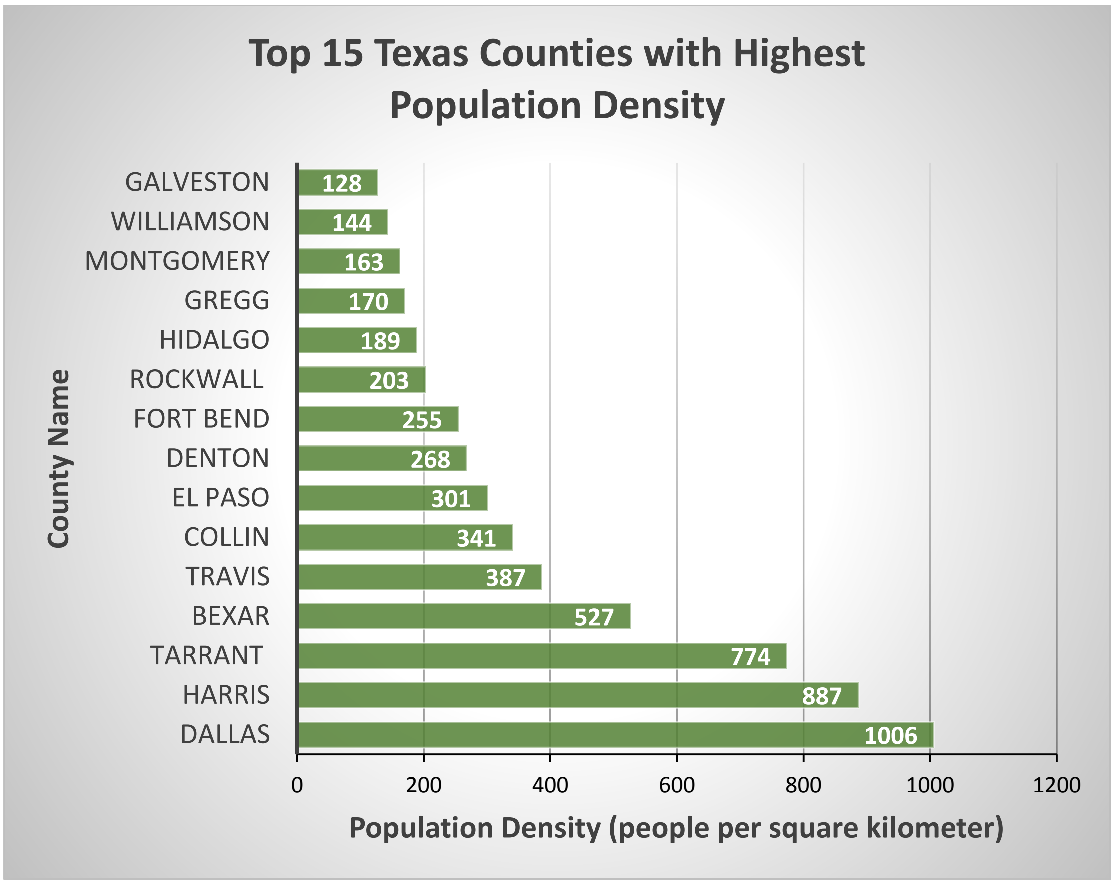

Figure 2. Texas Counties' Population Densities from the 2010 Census

Harris County, which is located in the southeastern part of Texas, draws 29% of its water supply from the Evangeline and Chicot underground aquifers (City of Houston 2014). Bexar County also pumps the majority of its water from underground water sources which include: the Edwards Aquifer, Trinity Aquifer and Carrizo Aquifer (San

Antonio Water System 2014). Dallas County strictly uses surface water resources from nearby lakes, such as Lake Ray Hubbard and Lake Lewisville (City of Dallas 2014). Tarrant County also draws water from surface supply consisting of the following lakes: Eagle Mountain Lake and Lake Worth (City of Fort Worth 2014).

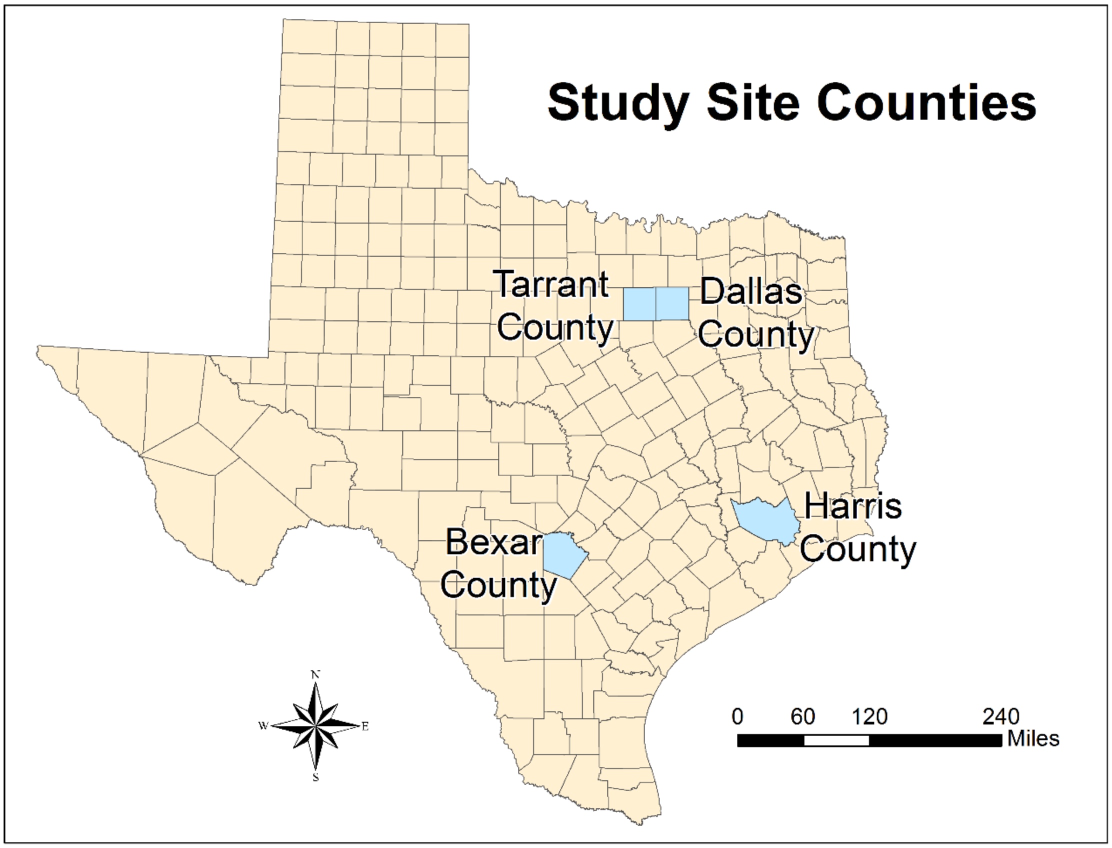

Figure 3. Study Site Locations

Table 4

Percentage Decadal County Population Growth From 1990 - 2010

Variable	Bexar County	Dallas County	Harris County	Tarrant County
1990 Total Population	1185394	1852810	2818199	324877
2000 Total Population	1392931	2218899	3400578	1446219
2010 Total Population	1714773	2368139	4092459	1809034
Population Increase (%) 1990 - 2000	17.5%	19.8%	20.7%	23.6%
Population Increase (%) 2000-2010	22.6%	6.8%	20.3%	24.8%
Major Cities	San Antonio	Dallas	Houston	Fort Worth

The two counties – Dallas and Tarrant - with a strictly surface-based water supply are under the direct influence of fracking (hydraulic fracturing), which is used in places where the soil has very low permeability and is located above a large reservoir of oil or gas. The process of fracking breaks up the soils with low permeability to allow drilling into the oil or gas wells by injecting a fluid through a perforated casing (Earthworks 2014). The increased pressure from the fluid buildup causes the ground to crack. This can impact a county's decision to use a subsurface water supply versus a surface supply because the fracking fluid can be toxic and could contaminate groundwater supplies within the region (Earthworks 2014). Dallas and Tarrant (two neighboring counties), contain numerous fracking (Figure 4, WorldMap 2011; SkyTruth 2013). This can explain the use of surface water supplies in these counties. Bexar and Harris Counties currently have little to no fracking sites (WorldMap 2011) (SkyTruth 2013). Bexar County is unique because of its location in a karst region. Karst is a type of terrain typically characterized by caves and sinkholes, which help steer water underground creating underground aquifers (Elliott 2014). Bexar County pumps water from the Edwards Aquifer which is a karst aquifer. This variation in the geological makeup of the soil may explain variation in results when Bexar County is compared to other counties.

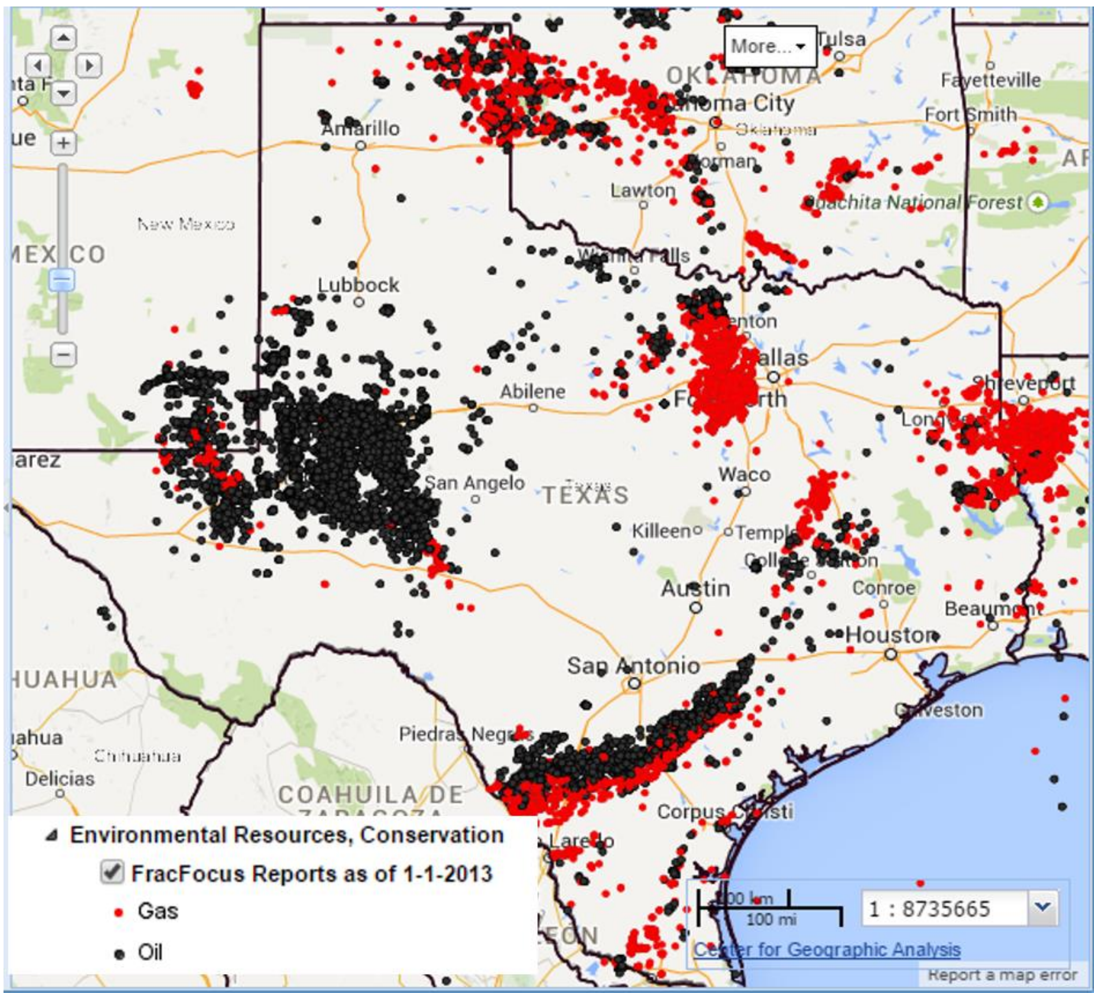

Figure 4. FrackMap Showing Disclosed Location of Oil and Gas Fracking Sites (SkyTruth 2013) (WorldMap 2011)

Data Sources and Processing

Both physical and social variables required for drought prediction are available at multiple spatial and temporal scales of analysis and from different data sources. For instance, meteorological data, such as temperature and precipitation, are often available as point data from meteorological stations, which can be interpolated to estimate precipitation level and temperature for locations where no such data is available. Likewise, population data can be obtained from the U.S. Census Bureau at the county, tract, block group and block levels. For instance, meteorological data, such as temperature and precipitation, are often available as point data from meteorological stations, which can be interpolated to estimate precipitation level and temperature for locations where no such data is available. Likewise, population data can be obtained from the U.S. Census Bureau at the county, tract, block group and block levels.

The proposed new index incorporates population, temperature, precipitation and soil moisture data with the SC-PDSI (Table 5). For this study, meteorological data (precipitation and temperature) were collected from the United States Historical Climatology Network (USHCN) as excel spreadsheets for 1902 to 2013 for the fifty-five stations spread across the Texas region (Figure 5). The temperature data indicates monthly average temperatures in Fahrenheit, and the precipitation data represents the total monthly rainfall in inches.

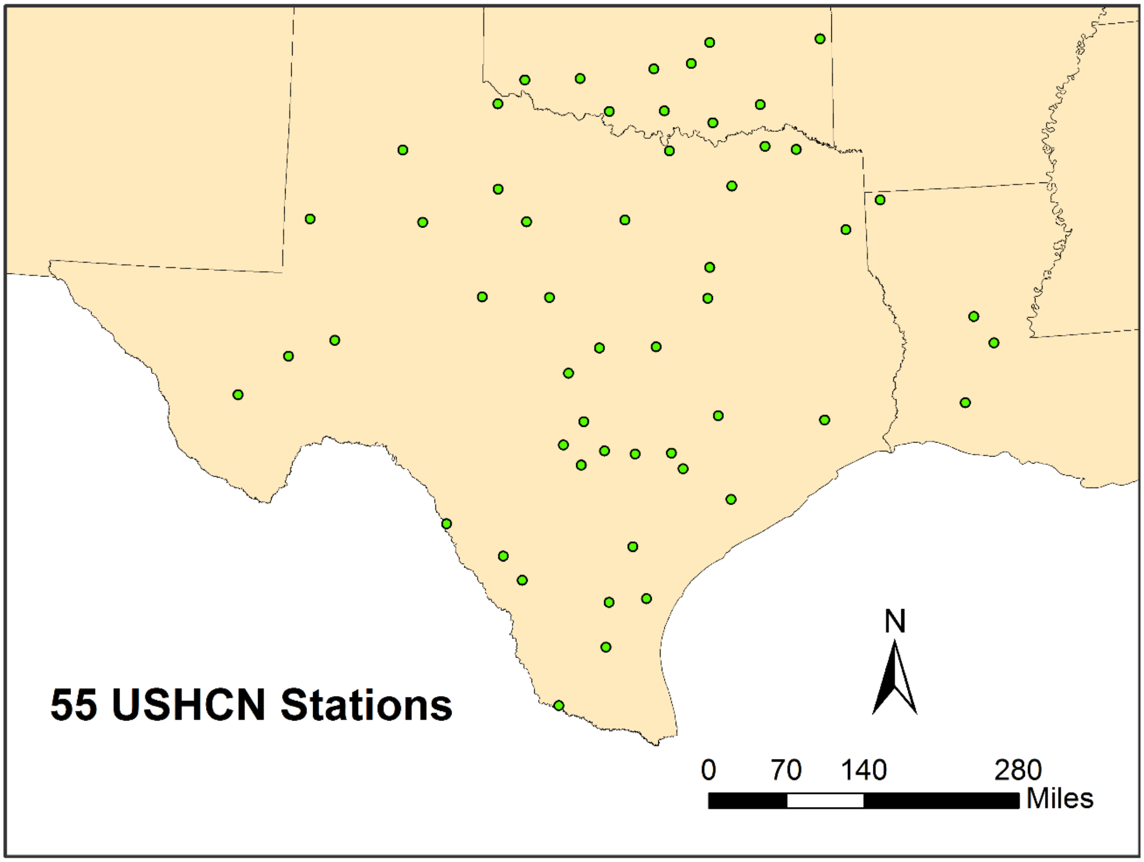

Figure 5. Untied States Historical Climatology Network Data Points

The Available Water Holding Capacity (AWC) data were collected through the Web Soil Survey at every station's location. The AWC values depict the average holding capacity of the soil from 0 to 150 cm in depth. The 2010 census data were obtained from the United States Census Bureau at the block group level. The 2000 block group census data were downloaded from the American Fact Finder (2015) and the 1990 census data were obtained from the Texas State Data Center (2015) as Summary Level Files. Both the 1990 and 2000 census data were joined with the U.S. Census block group boundaries obtained from the National Historical Geographic Information System. The soil moisture data was obtained for the year 2011 because the soil moisture data was available for the entire study area for this year. This data was gathered through TAMU North American

Soil Moisture Database (2013). Depending on the sensor used for data collection, the selected soil moisture measurement of 20cm – 25cm was used in this study.

Before processing, all datasets were projected to North American Datum 1983 Universal Transverse Mercator (UTM) Projection, Zone 14. Next, the area of each block group was computed in square kilometers which was used to compute population density (number of people per square kilometer) at the block group level.

Table 5

Data Sets and Sources

Data Set	Source	File Format	Web URL
Precipitation	USHCN	Excel	http://cdiac.ornl.gov/epubs/ndp/ushcn/ushcn.html
Temperature	USHCN	Excel	http://cdiac.ornl.gov/epubs/ndp/ushcn/ushcn.html
2010 Population	U.S. Census Bureau	Polygon shapefile	https://www.census.gov/geo/maps-data/data/tiger-data.html
2000 Population	American Fact Finder	Summary File 1	http://factfinder2.census.gov
2000 Block Group Boundary	U.S. Census Bureau	Polygon Shapefile	https://www.census.gov/geo/maps-data/data/tiger-data.html
1990 Population	Texas State Data Center	Summary Tape Level 1B	http://txsdc.utsa.edu/Data/Decennial/1990/Index.aspx
1990 Block Group Boundary	NHGIS	Polygon shapefile	https://www.nhgis.org/research

Table 5 (continued).

Data Set	Source	File Format	Web URL
AWC	Web Soil Survey	N/A	http://websoilsurvey.nrcs.usda.gov/app/websoilsurvey.aspx
Soil Moisture	TAMU	Text File	http://soilmoisture.tamu.edu/

Research Methods and Techniques

An exploratory research design was implemented to answer the research questions. Integrating a social component into a drought index is a novel approach in drought research, and determining how this variable will impact drought intensities will benefit other researchers within this field. The NDMC (2013) concluded that because too many meteorological parameters are responsible for a drought event, it is a challenge to depict drought severity and forecast a drought accurately. Therefore, through the exploratory design, the impact of certain social and meteorological variables (i.e. population density, temperature, precipitation and soil moisture) on drought severity were determined. A descriptive research design was also used to answer the second research question, which provides insight into the impacts of population density on drought occurrences and how the new index results compare to SC-PDSI and PDSI.

The ability to determine the occurrence of a drought accurately is critical for mitigation, and made easier through the use of indices. PDSI is the most commonly used and accepted index in the U.S., but in recent years a modified version of the PDSI, known as the SC-PDSI, was developed. The SC-PDSI was modified to include a social parameter along with precipitation, temperature and soil moisture for drought severity classification through the use of a Weighted Linear Combination (WLC) technique. A discussion of SC-PDSI and WLC is presented in the following sections. Figure 6 depicts the steps implemented in this research.

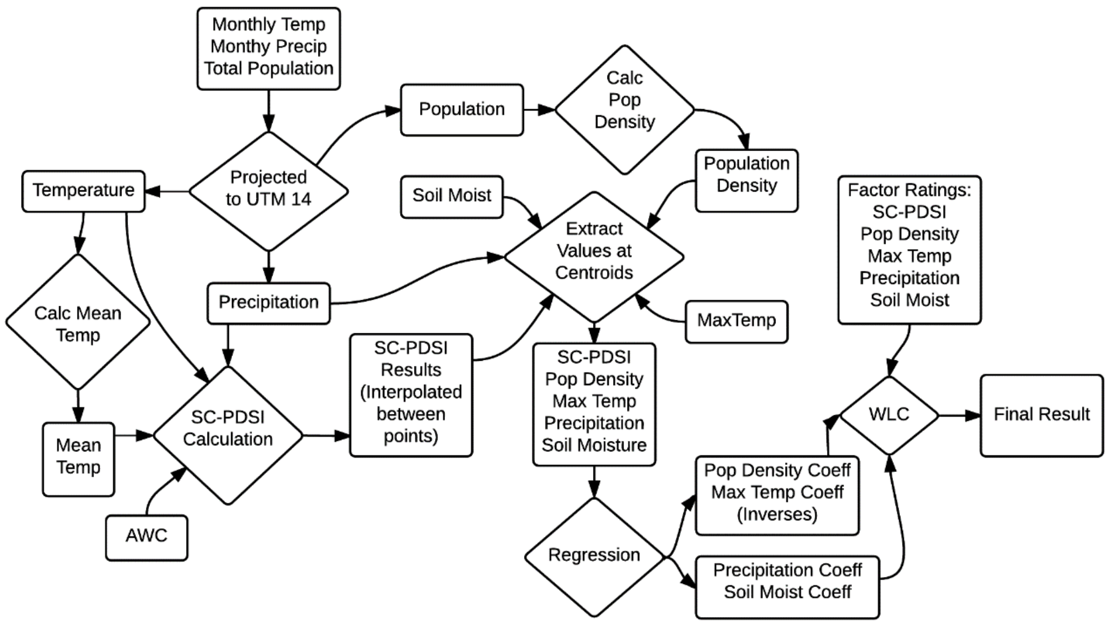

Figure 6. Flow Chart of Entire Work Process

SC-PDSI Index Calculations

The variables required for the implementation of the SC-PDSI are the mean monthly temperatures, total monthly precipitation, at least a 25-year mean temperature for each month, and the Available Water Content (AWC). As discussed in Wells et al. (2004), the input variables listed here are used to calculate the following variables used in the SC-PDSI: evapo-transpiration (ET), recharge (*R*), runoff (RO), loss (*L*), potential ET (PE) (calculated using Thornthwaite's method), potential recharge (PR), potential runoff (PRO), and potential loss (PL). The Climatically Appropriate for Existing Conditions

(CAFEC) value represents how much precipitation is needed for the soil moisture level to remain normal which is calculated by combining all the potential values (PE, PR, PRO and PL) and associated weights for each potential value. The weighting factors (α, β, γ, or δ) for each potential value are calculated by the following equations:

$$\text{Equation (3): } \alpha_i = \frac{\overline{ET_i}}{\overline{PE_i}} \qquad \beta_i = \frac{\overline{R_i}}{\overline{PR_i}} \qquad \gamma_i = \frac{\overline{RO_i}}{\overline{PRO_i}} \qquad \delta_i = \frac{\overline{L_i}}{\overline{PL_i}}$$

The equation for the CAFEC precipitation, $\hat{P}$, is denoted by Equation (4):

$$\text{Equation (4): } \hat{P} = \alpha_i PE + \beta_i PR + \gamma_i PRO - \delta_i PL$$

The moisture departure (*d*) is then calculated from the difference in CAFEC precipitation and the actual precipitation, P, recorded for the month using Equation (5).

$$\text{Equation (5): } d = P - \hat{P}$$

K, which is described as the climate characteristic, is next calculated using the following equations where *K'* represents the moisture anomalies.

$$\text{Equation (6): } K'_i = 1.5 \log_{10}\left(\frac{\frac{\overline{PE_i} + \overline{R_i} + \overline{RO_i}}{\overline{P_i} + \overline{L_i}} + 2.8}{\overline{D_i}}\right) + 0.5$$

Following the calculation of K', the PDSI approximation is calculated using Equation (7).

$$\text{Equation (7): } Z_{PDSI} = dK'$$

Wells et al. (2004) defines *K* by using percentiles of the PDSI (Z_{PDSI}), and uses the PDSI non-extreme values ranging from 4 to -4, where negative numbers indicate dryer conditions and positive numbers indicate wetter conditions. *K* is calculated by using Equation (8).

$$\text{Equation (8): } K = \begin{Bmatrix} K'\{-4.00/(2nd\ Percentile)\}, & if\ d < 0 \\ K'\{4.00/(98th\ Percentile)\}, & if\ d \geq 0 \end{Bmatrix}$$

The moisture anomaly index, Z, represents wetness or dryness of an area in a single month and does not account for the current precipitation trends. Z is calculated using Equation (9).

Equation (9): $Z = dK$

The SC-PDSI (X) calculation is performed with the following equation:

Equation (10): $X_i = pX_{i-1} + qZ_i$

Where p, q, and Z_i are:

Equation (11): $p = (1 - \frac{m}{m+b})$

Equation (12): $q = \frac{C}{m+b}$

Equation (13): $\sum_{i-1}^{i} Z_i = mt + b$

The variables *p* and *q*, known as the duration factors, are derived from the linear relationship between the summation of the *Z* index and the recorded PDSI, where *C* is the calibration index (*C* = -*4*). The line of best fit is determined giving the slope and intercept values *m* and *b*, and the duration factors are computed using the least squares method with those parameters. Equation (13) is calculated for both extremely wet spells and extremely dry spells. The threshold values for the extreme spells of the PDSI range from -4.0 and below for an extreme drought and from 4.0 and above for extremely wet conditions. Once the thresholds of -4.0 and 4.0 have been reached, a “spell” has been established (either dry or wet for the respective value).

All SC-PDSI calculations were performed with a tool written in C++ and provided by The GreenLeaf Project (2014). This tool also calculates the PDSI which is used for the final comparison among all the indices.

Final Index Calculations

The SC-PDSI value at each meteorological station was calculated using the tool, and then the values were used and interpolated to create a continuous surface of the SC-PDSI values. The two interpolation techniques, Kriging and IDW, were implemented on the SC-PDSI dataset at a 30m resolution. The results were then compared by using cross-validation graphs and the Root Mean Square Error (RMSE) values. The interpolation technique producing the lowest RMSE was used for the creation of surfaces for temperature and precipitation. The soil moisture data was also interpolated across the study site at a 30m resolution. Because soil moisture data points were sparsely distributed across the study site than the meteorological data, the nearest neighbor interpolation technique was used.

After all the surfaces were created using interpolation, the values for each variable were extracted within each block group using the block group centroid in the study counties. The block group population shape file layer was converted to a raster layer at a 30m resolution to get the population density data for the proposed index.

Multi-Criteria Evaluation (MCE) and Weighted Linear Combination (WLC)

Multi-Criteria Evaluation (MCE) is a tool used to simplify decision-making tasks that may involve a number of stakeholders, have a diverse set of possible outcomes, and be influenced by numerous qualitative and quantitative criteria (Proctor and Drechsler 2003; Drobne and Lisec 2009). As the goal of this research is to develop an index combining social and meteorological factors for the purpose of predicting future locations susceptible to droughts, a GIS-based Weighted Linear Combination (WLC) technique was employed to accomplish this goal which is one of the most commonly used MCE approaches (Voogd, 1983; Carver, 1991). The WLC allows stakeholders to weigh a set of factors based on certain criteria (Kar and Hodgson 2008; Drobne and Lisec 2009). The ratings of each factor are then multiplied with corresponding weights and all layers are then added to determine a ranked spatial distribution of final weights (Malczewski 2000; Kar and Hodgson 2008; Drobne and Lisec 2009).This approach allows the results to show varying degrees of suitability for the chosen factors.

In this study, population density, precipitation, temperature and soil moisture (for 2011 only) were included with the SC-PDSI to determine the intensity rating of droughts. The results depict the influence of certain variables on the variance of the SC-PDSI. Each factor was assigned an associated factor rating (FR) value and multiplied with a respective weight (*w*). Finally, all the weighted layers were added to create a layer depicting spatial distribution of drought severity for the region. Equation 15 depicts the implementation of WLC (Kar and Hodgson 2008):

$$\text{Equation (15): } Score = (\sum_{j}^{n} FR_j * w_j)$$

Where *Score* = drought severity rating, FR_j = factor rating for factor j, n = number of factors included in the model and w_j = weight assigned to factor j such that each weight is the factor's coefficient from the regression analysis.

Tables 6 through 10 indicate the factor ratings for each variable ranging from 0 to 10, where 10 indicates the strongest drought conditions and 0 indicates no drought. These classes were used because it is easier to implement the WLC on a standardized scale of 0 to 10. The SC-PDSI factor ratings (Table 6) are based off of the U.S. Drought Monitor's (2013) defined PDSI severity classes. The U.S. Drought Monitor (2013) uses 5 severity classes on a single unit interval to classify the PDSI, but for this research each class is based off of a half-unit interval instead creating factor rating classes ranging from 0 to 10, where 10 depicts the most intense droughts (Table 6). The population density factor ratings were determined using the Jenks Natural Breaks Classification method on the 2010 U.S. Census block group data (Table 7). This method was chosen over the equal interval classification because the equal interval classification showed very little distinction between the highly populated and less populated areas. The maximum temperature (Table 8), precipitation (Table 9) and soil moisture (Table 10) factor ratings were determined using the equal interval classification. Because temperature and precipitation vary from month to month, each case study month has its own set of factor ratings per variable.

Table 6

SC-PDSI Factor Ratings

SC-PDSI	Factor Rating	Drought Description
> -1.0	0	No Drought
-1.0 – -1.5	1	Abnormally Dry
-1.5 – -2.0	2	Abnormally Dry
-2.0 – -2.5	3	Moderate Drought
-2.5 – -3.0	4	Moderate Drought
-3.0 – -3.5	5	Severe Drought
-3.5 – -4.0	6	Severe Drought
-4.0 – -4.5	7	Extreme Drought
-4.5 – -5.0	8	Extreme Drought
-5.0 – -5.5	9	Exceptional Drought
<-5.5	10	Exceptional Drought

Table 7

Population Density Factor Ratings

Population Density	Factor Rating
0 – 239	0
240 – 599	1
600 – 1000	2
1001 – 1426	3
1427 – 1903	4
1904 – 2483	5
2484 – 3271	6
3272 – 4635	7
4636 – 7219	8
7220 – 11792	9
>= 11793	10

Table 8

Maximum Temperature Factor Ratings (Fahrenheit)

June 1990	September 2000	October 2011	Factor Rating
< 85.28	< 83.67	< 77.96	0
85.28 – 86.81	83.67 – 85.06	77.96 – 79.42	1
86.81 – 88.34	85.06 – 86.44	79.42 – 80.88	2
88.34 – 89.86	86.44 – 87.83	80.88 – 82.34	3
89.86 – 91.39	87.83 – 89.22	82.34 – 83.80	4
91.39 – 92.91	89.22 – 90.61	83.80 – 85.26	5
92.91 – 94.44	90.61 – 92.00	85.26 – 86.72	6
94.44 – 95.96	92.00 – 93.38	86.72 – 88.18	7
95.96 – 97.49	93.38 – 94.77	88.18 – 89.64	8
97.49 – 99.02	94.77 – 96.16	89.64 – 91.10	9
> 99.02	> 96.16	> 91.10	10

Table 9

Precipitation Factor Ratings (Inches)

June 1990	September 2000	October 2011	Factor Rating
> 3.25	> 3.01	> 4.97	0
2.93 – 3.25	2.74 – 3.01	4.57 – 4.97	1
2.61 – 2.93	2.46 – 2.74	4.16 – 4.57	2
2.29 – 2.61	2.19 – 2.46	3.76 – 4.16	3
1.97 – 2.29	1.91 – 2.19	3.36 – 3.76	4
1.65 – 1.97	1.63 – 1.91	2.95 – 3.36	5
1.33 – 1.65	1.36 – 1.63	2.55 – 2.95	6
1.01 – 1.33	1.08 – 1.36	2.15 – 2.55	7
0.69 – 1.01	0.80 – 1.08	1.74 – 2.15	8
0.37 – 0.69	0.53 – 0.80	1.34 – 1.74	9
< 0.37	< 0.53	< 1.34	10

Table 10

Soil Moisture Factor Ratings (m3 water/m3 soil)

Soil Moisture	Factor Rating
> 0.4120	0
0.3723 – 0.4120	1
0.3325 – 0.3723	2
0.2928 – 0.3325	3
0.2531 – 0.2928	4
0.2133 – 0.2531	5
0.1736 – 0.2133	6
0.1338 – 0.1736	7
0.0941 – 0.1338	8
0.0543 – 0.0941	9
< 0.0543	10

To determine the factors' weights, a multi-variate regression analysis was conducted using the regular values for SC-PDSI as dependent variable and population density, precipitation, maximum temperature, and soil moisture as independent vairables. The resulting beta coefficients that indicate the impact of each independent variable on the dependent variable and its statistical significance was used as the factor weighting for each independent variable. Because the study counties are not geographically neighboring a regression was implemented for each county separately to examine the impact of each independent variable including population density on SC-PDSI (i.e. drought severity) based on the county's water supply source.

After implementing the regression analysis, each input variable was reclassified to the defined factor ratings (discussed above), and then multiplied with its respective weight (coefficient) determined in the regression. The weighting factor (regression coefficients) for population and temperature were inverted before implementing WLC. While population and temperature appear to influence drought severity, the original regression coefficients indicate that an increase in temperature and population density relates to a stronger drought that is represented by lower SC-PDSI. Just based on the sign of the drought severity factor ratings, this appears to be an inverse relationship. However, once the factor ratings were applied, the directionality changed. Now, an increase in population density or temperature gave a higher factor rating, but to keep its relationship the same with the SC-PDSI factor ratings as observed in the original coefficients, the newly converted SC-PDSI factor rating value should also increase to indicate a stronger drought. The conversion resulted in these variables having a positive relationship with one another. For the WLC computation, the sign of the coefficients found for these two variables during the regression analyses had to be inversed to maintain the correct relationship between the SC-PDSI and temperature and population density.

The precipitation and soil moisture weighting factors directly equal the coefficients found in the regression. Both of these variables were expected to have positive relationships with the SC-PDSI found in the regression results, indicating that an increased value also increased the SC-PDSI value (showing weaker drought conditions). After the factor ratings were applied, the higher precipitation and soil moisture values got the lowest factor ratings because they indicate weaker droughts while the SC-PDSI higher values which also indicated weaker drought conditions were also assigned the lower factor ratings. As the precipitation/soil moisture reading would increase, there would be a decrease in the factor rating value. To show the weakening drought conditions due to this, the SC-PDSI also needed to show weaker drought conditions. Therefore, these variables' factor ratings still maintain the same positive relationship that was seen in the regression analysis before the variables were converted to factor ratings without having to invert the coefficients. Finally, all three variables were multiplied by their respective weights, and summed with the SC-PDSI for the final index output. The results then show how these variables influenced the SC-PDSI with an increase, decrease or no change in drought severity. All variables that were not statistically significant were omitted from the WLC computation.

Case Study

The drought of 2011 was used as the main case study for this research. During this year, Texas experienced its worst 12-month drought in history (NPR 2011). On October 4th in 2011, Texas experienced exceptional drought in 88% of the state, extreme drought in 9%, severe drought in 2%, and moderate drought in 1% (NPR 2011). This day in particular had the highest coverage of extreme drought conditions seen in Texas since 2000 (NPR 2011). The other two drought events that occurred on September 2000 and June 1990 were also used as case studies using 2000 and 1990 census and meteorological data. The month of June in 1990 and September in 2000 were the months when the drought condition was most severe in Texas according to the NIDIS Map and Data Viewer (2015).

Validation

Statistical analyses were conducted to explore if any variables had significant relationships with one another. A regression analysis was performed using the variables (population density, precipitation, temperature and soil moisture) against the SC-PDSI. The *R Square* value, produced during the regression, showed the extent to which independent variables account for the variance of the dependent variable (drought severity), and the coefficients, which became the weighting factors, indicated the amount of impact each variable had on the final drought intensity. Finally, the new index was compared against the PDSI and the SC-PDSI. A Paired Samples T-Test was run using the PDSI and SC-PDSI separately against the new index to test the significance and correlation. The results of the three indices were also visually compared to identify general trends in maximums, minimums, and overall drought patterns in the study site.

CHAPTER IV

RESULTS AND DISCUSSIONS

Overview

This chapter is divided into two sections. The first section describes the results and discussions found prior to the final index calculation. The second section outlines the results and discussions pertaining to the final index calculations.

Interpolation and Regression

Results and Discussions

After the SC-PDSI calculations were completed at the specified points, the data were then interpolated to provide a continuous surface of drought severity values. The interpolation was initially performed using both Kriging and IDW techniques. Kriging had the lower RMSE of 1.296962 while IDW had a RMSE of 1.389249. The Kriging technique was chosen because of the lower RMSE. The SC-PDSI, population density, precipitation, temperature and soil moisture (for 2011 only) values were then extracted for each county at each block group centroid.

The regression analysis for the SC-PDSI provided the *R Square* values and the standardized coefficients for the predictors (population density, precipitation, temperature and soil moisture). These *R Square* values depict the percentage of the dependent variable (SC-PDSI) that the predicting factors as a whole could account for. Each independent variable was also run individually against the dependent variables to determine the individual *R Square* values and the extent to which each independent variable influences the dependent variable. Tables 11-13 show the pertinent results from the regression analysis for the selected three years. It is important to note that the stronger a drought is, the lower (more negative) the SC-PDSI value is. When analyzing the coefficients and their signs, if the value is positive, an increase in the predictor variable indicates an increase in SC-PDSI (i.e. weaker drought conditions) or vice versa. A negative coefficient value means that an increase in the predictor variable leading to a decrease in SC-PDSI (i.e. stronger drought) or vice versa.

Table 11

October 2011 Regression Results

Year County	Variable	R Square	Standardized Coefficient	Coefficient Significance
2011 Bexar	Total	19.6%		
	Population*	10.7%	-0.349	0
	Max Temperature*	5.6%	-0.327	0
	Precipitation*	0.2%	-0.108	0.003
	Soil Moisture*	0%	-0.030	0.439
Regression Equation:	SCPDSI = – 0.349*(Pop) – 0.327*(Temp) – 0.108*(Precip) – 0.030*(SoilMois)			
2011 Harris	Total	25.1%		
	Population*	5.7%	-0.158	0
	Max Temperature*	5.2%	0.372	0
	Precipitation*	6.9%	0.482	0
	Soil Moisture*	0%	-0.140	0

Table 11 (continued).

Year County	Variable	R Square	Standardized Coefficient	Coefficient Significance
Regression Equation:	SCPDSI = – 0.158*(Pop) + 0.372*(Temp) + 0.482*(Precip) – 0.140*(SoilMois)			
2011 Dallas	Total	59.0%		
	Population*	0%	0.077	0
	Max Temperature*	56.0%	-1.069	0
	Precipitation*	11.9%	0.117	0
	Soil Moisture*	49.5%	0.357	0
Regression Equation:	SCPDSI = – 0.077*(Pop) – 1.069*(Temp) + 0.117*(Precip) + 0.357*(SoilMois)			
2011 Tarrant	Total	89.7%		
	Population*	2.8%	-0.051	0
	Max Temperature*	16.1%	-0.543	0
	Precipitation*	69.5%	0.582	0
	Soil Moisture*	7.7%	0.667	0
Regression Equation:	SCPDSI = – 0.051*(Pop) – 0.543*(Temp) + 0.582*(Precip) + 0.667*(SoilMois)			

Note. All independent variable *R Square* values were determined by analyzing each variable separately with the SC-PDSI.

In 2011, there were severe drought conditions in the study site. Dallas and Tarrant Counties had the highest total *R Square* values compared to Bexar and Harris Counties due to the temperature, precipitation and soil moisture variables (Table 11). There is a pattern to when and where population density impacted drought. Bexar and Harris

Counties draw from the subsurface water sources, which the SC-PDSI accounts for, explaining the higher *R Square* values for population density. Bexar County had a higher *R Square* than Harris County which could be explained by Bexar County's strict use of subsurface water, while Harris County only acquires 29% of its water from the subsurface. Dallas and Tarrant Counties draw their water from lakes (surface water supplies) due to fracking in the region and therefore, the population density showed little influence (lower *R Square*) on the SC-PDSI. The population density was a statistically significant factor for all counties except Dallas. Soil moisture had no influence in Bexar County and was not statistically significant in this county, which could be attributed to the karst geology of the county. Temperature and precipitation had less influence on drought severity in Bexar and Harris Counties. Bexar County's precipitation variables showed a negative coefficient which is opposite than expected, and Harris County's temperature coefficient also had a sign opposite than what was expected. The expected signs should show a positive coefficient for precipitation (an increase in precipitation increases the SC-PDSI value indicating a weaker drought), and a negative coefficient for temperature (an increase in temperature decreases the SC-PDSI value indicating a stronger drought).

Table 12

September 2000 Regression Results

Year County	Variable	R Square	Standardized Coefficient	Coefficient Significance
2000 Bexar	Total	24.4%		
	Population*	0.5%	0.019	0.503
	Max Temperature*	16.8%	-0.563	0
	Precipitation*	0.2%	-0.315	0
Regression Equation:	SCPDSI = 0.019*(Pop) – 0.563*(Temp) – 0.315*(Precip)			
2000 Harris	Total	69.1%		
	Population*	0.2%	-0.069	0
	Max Temperature*	51.2%	0.376	0
	Precipitation*	60.3%	-0.547	0
Regression Equation:	SCPDSI = – 0.069*(Pop) + 0.376*(Temp) – 0.547*(Precip)			
2000 Dallas	Total	56.4%		
	Population*	3.0%	-0.137	0
	Max Temperature*	0.3%	-0.245	0
	Precipitation*	49.4%	0.747	0
Regression Equation:	SCPDSI = – 0.137*(Pop) – 0.245*(Temp) + 0.747*(Precip)			

Table 12 (continued).

Year County	Variable	R Square	Standardized Coefficient	Coefficient Significance
2000 Tarrant	Total	26.6%		
	Population*	1.6%	0.127	0
	Max Temperature*	9.7%	-0.235	0
	Precipitation*	20.3%	0.394	0
Regression Equation:	SCPDSI = 0.127*(Pop) – 0.235*(Temp) + 0.394*(Precip)			

Note. All independent variable *R Square* values were determined by analyzing each variable separately with the SC-PDSI.

Although Texas experiences a drought in September of 2000, this drought was overall weaker than the 2011 drought, and the results indicate that population seemingly had very little influence on this drought's severity in the study counties. Population density was not even a significant factor for Bexar County in 2000. Soil moisture was not used for this year, or 1990, because there was an insufficient amount of data available for the study counties. Bexar County results showed the expected directionality of the coefficient for temperature, but the opposite for precipitation with a very low *R Square* value. The results for Harris County showed that temperature and precipitation contributed to the majority of the total *R Square* but both variables had the opposite coefficient sign than the typical relationships seen between those variables and drought conditions. Temperature should have seen a negative coefficient indicating that higher the temperature, the stronger the drought (i.e. the lower the SC-PDSI value). Precipitation should have had a positive coefficient indicating a relationship in which higher amounts of rainfall lead to a lesser drought (higher SC-PDSI values). Temperature and precipitation coefficient patterns were consistent for Dallas and Tarrant Counties, and precipitation was found to be most influential for these two counties in 2000.

Table 13

June 1990 Regression Results

Year County	Variable	R Square	Standardized Coefficient	Coefficient Significance
1990 Bexar	Total	41.1%		
	Population*	13.2%	0.269	0
	MaxTemperature*	22.7%	0.621	0
	Precipitation*	0.2%	0.373	0
Regression Equation:	SCPDSI = 0.269*(Pop) + 0.621*(Temp) + 0.373*(Precip)			
1990 Harris	Total	38.5%		
	Population*	1.2%	-0.083	0
	Max Temperature*	34.9.%	-0.490	0
	Precipitation*	20.3%	0.192	0
Regression Equation:	SCPDSI = – 0.083*(Pop) – 0.490*(Temp) + 0.192*(Precip)			
1990 Dallas	Total	65.6%		
	Population*	2.0%	0.035	0.012

Table 13 (continued).

Year County	Variable	R Square	Standardized Coefficient	Coefficient Significance
	Max Temperature*	39.4%	-0.406	0
	Precipitation*	51.5%	0.552	0
Regression Equation:	SCPDSI = 0.035*(Pop) – 0.406*(Temp) +0.552*(Precip)			
1990 Tarrant	Total	73.1%		
	Population*	0%	0.049	0.002
	Max Temperature*	72.7%	-0.860	0
	Precipitation*	0.8%	-0.032	0.046
Regression Equation:	SCPDSI = 0.049*(Pop) – 0.860*(Temp) – 0.032*(Precip)			

Note. All independent variable *R Square* values were determined by analyzing each variable separately with the SC-PDSI.

June 1990 experienced weaker drought conditions than that of 2011 as well, which resulted in a weak influence from population density. While Bexar County had a relatively high *R Square* value for population and temperature, the coefficients had the opposite directionality than what was expected. Tarrant County experienced an atypical coefficient sign for precipitation, but the variable was almost not significant and showed a very low *R Square* value. Temperature had the highest *R Square* for every county, except Dallas where the highest *R Square* came from precipitation. The standardized coefficients listed in the above tables were used as the weighting factors in the WLC, as previously discussed.

Final Index

Results and Discussions

For this study, population density was chosen as the only social variable that will have an impact on drought severity, and hence, was analyzed at the block group level to see the distribution within each county. The regression analysis was performed using the interpolated values of each variable: SC-PDSI, maximum temperature, precipitation and soil moisture. Based on the significance value of the standardized coefficients of each variable, the variables that were not significant were omitted from being used in the index. Next, all variables were reclassified to their assigned factor ratings. Once this was completed, the identified coefficient became the weighting factor for each variable. Two variables, population density and maximum temperature, required the sign of their corresponding coefficients to be inversed to determine the associated weighting factor. As previously discussed, this was done to keep the same relationship between the two variables, that was seen prior to converting them to factor ratings. The coefficients were then multiplied by the factor ratings determined for each variable then summed using the WLC equation (Equation 15). The process was repeated for September 2000 and June 1990 to determine how well this index depicts drought conditions over time and during varying drought conditions.

The final index was compared to the PDSI and SC-PDSI in the Paired Samples T-Test. To most accurately compare these indices, the SC-PDSI and PDSI values were converted to the same factor rating values used for the SC-PDSI in the WLC since these values were used to create the final index. Table 14 lists the results of the Paired Samples T-Test between all the indices. 2011 and 2000 show weak negative correlations between the new index and the existing two. The SC-PDSI and PDSI display strong positive correlations, which is to be expected since the only difference between them is that one accounts for the region's historical climatological data (SC-PDSI) and the other uses derived constants (PDSI). There is also a statistically significant correlation between them. The correlation significance for the new index and the SC-PDSI for 2011 is not significant, indicating they are independent and not similar. The data for 1990 was unable to produce a result for the correlation with two of the pairs. This is due to the SC-PDSI values all being zero for that month/year, and a "0" factor rating indicates no drought being present. For the new index and PDSI in 1990, there was a strong positive correlation between those two indices. The correlation was likely stronger due to the weaker drought conditions present. When stronger droughts are present, there should be more variation in the indices because of the added parameters. The Paired Samples T-Test resulted in a statistically significant difference among each index for every year.

Table 14

Paired Samples T-Test Results

Year	Variables	Paired Samples Correlation	Correlation Significance	Paired Samples Test Significance
2011	New Index – PDSI	-0.420	0	0
2011	New Index - SC-PDSI	-0.018	0.150	0
2011	SC-PDSI - PDSI	0.801	0	0
2000	New Index - PDSI	0.081	0	0
2000	New Index - SC-PDSI	-0.178	0	0
2000	SC-PDSI - PDSI	0.795	0	0
1990	New Index - PDSI	0.812	0	0
1990	New Index - SC-PDSI	n/a	0	0
1990	SC-PDSI - PDSI	n/a	0	0

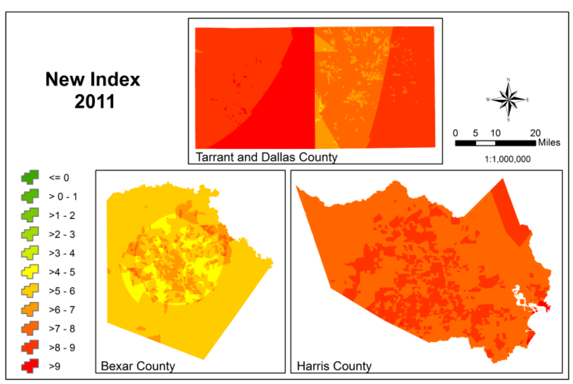

Figure 7. New Index for 2011

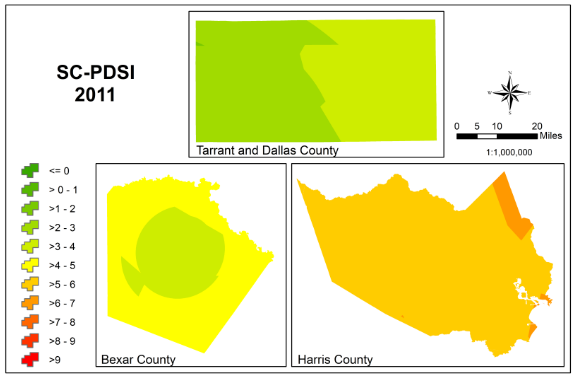

Figure 8. *SC-PDSI for 2011*

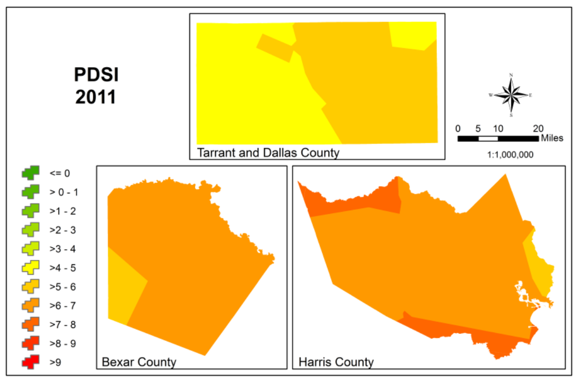

Figure 9. *PDSI for 2011*

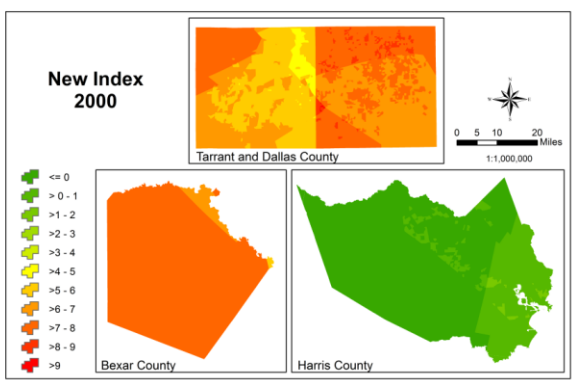

Figure 10. *New Index for 2000*

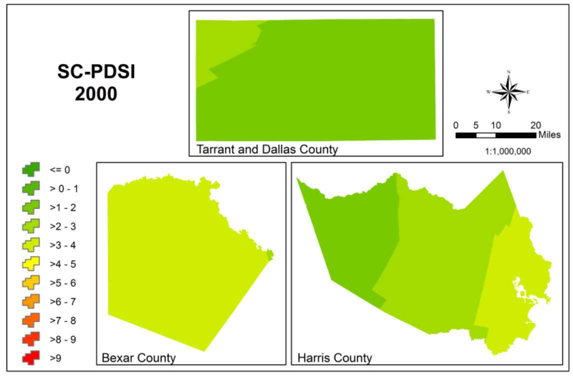

Figure 11. SC-PDSI for 2000

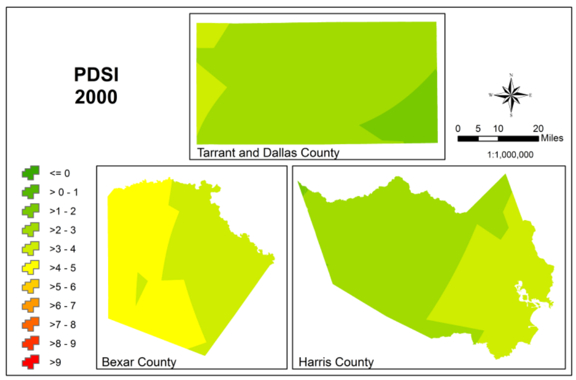

Figure 12. PDSI for 2000

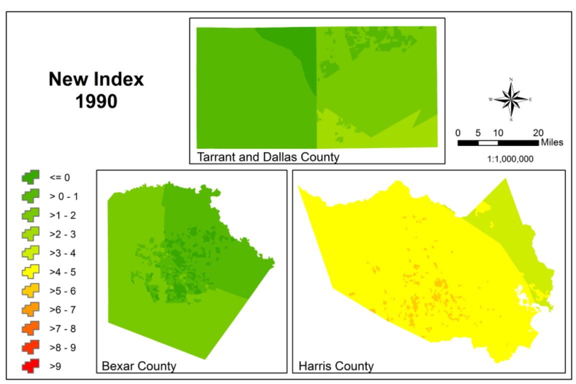

Figure 13. New Index for 1990

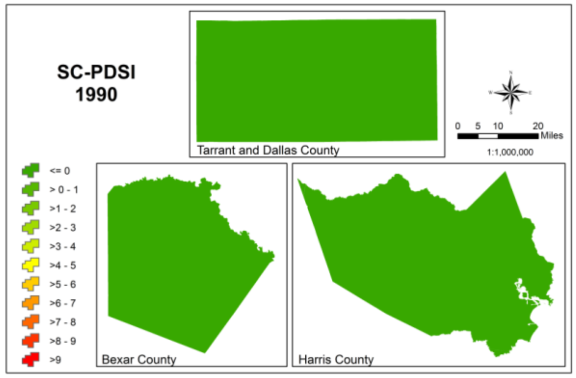

Figure 14. SC-PDSI for 1990

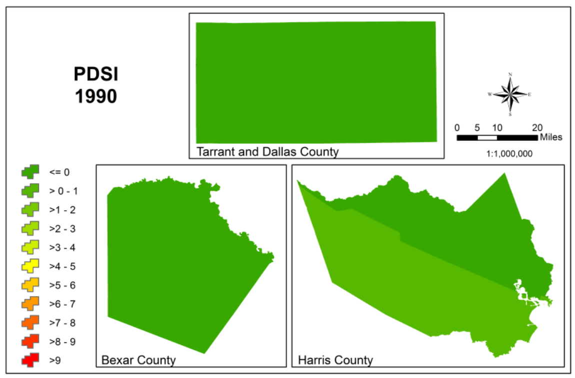

Figure 15. PDSI for 1990

The new index was also compared to the SC-PDSI and PDSI visually. Visual interpretations of drought severity are important because that is how many people interpret drought severity. The SC-PDSI and PDSI were first converted to their factor ratings. Then, all three indices were symbolized on the same scale for easier visual comparisons. Figures 7-15 depict the final results of the new drought index, SC-PDSI and PDSI for 2011, 2000, and 1990. For 2011 (Figures 7-9), the new index produced overall stronger drought values compared to the other two indices. It is important to note that the population density variable stood out in the new index because there was more variation in the index severity within each county. This was the strongest drought year selected for this study and was depicted well by the new index among all the years.

For 2000 (Figures 10-12), the new index still showed overall stronger drought values, except in Harris County, where the values appeared much lower in comparison. This can be attributed to the weak influence from population and the opposite signs of the coefficients for maximum temperature and precipitation for this year/county. Overall the patterns among the three indices were similar in Bexar County that had the strongest drought conditions.

In 1990, the drought condition was the weakest, and based on SC_PDSI value of “0”, there was no drought in the study counties. The visual depiction of indices (Figures 13-15) agreed with there being no correlation as per the Paired Samples T-Test results (Table 14). Once again, the new index produced slightly stronger drought severity than the other two indices, and it was especially noticeable for Harris County.

Across the years, the new index displayed more variation due to population density though the influence of population was much more prominent in Bexar and Harris Counties. As previously mentioned this was due to their use of an underground water supply while Dallas and Tarrant Counties use surface water. It is expected that the counties using the subsurface water supplies show more of an impact from population density. The population impact appeared to be more influential in 2011 compared to the other years as well. This indicated that the stronger drought years experienced more impact from population.

Limitations

Drought is a complex phenomenon with many impacting factors, and it is important to note that this research only includes a select number of those factors, which were analyzed for a small number of study counties. Further research is needed to incorporate more study sites and more case study droughts to further validate the research findings and prove that population is an impacting factor on a large scale. Another limitation is the scale at which this study was performed on. While examining drought severity at the block group level produced results at a finer resolution within each county, it is also a limitation because the census data at a block group level is only gathered every ten years. So, predicting a drought occurrence in between censuses will not produce accurate results as compared to this study in which drought severity was examined for the years when census data was available. The availability of meteorological data can also be considered a limitation. The SC-PDSI values are calculated at specific stations located throughout Texas, where the temperature and precipitation data are collected. These data were then interpolated for this study at a 30m resolution, thereby introducing error.

CHAPTER V

CONCLUSIONS

Overall Conclusions

Incorporating social factors into a drought severity measurement is an innovative concept. While temperature and precipitation are the most commonly used factors for drought prediction, there are many others that should be considered as well, especially for regions with large and increasing populations because increasing population density is a cause for concern. This research indicated that population density in fact influences drought severity, and this impact is noticeable in areas relying on underground water supplies. There is no clear answer as to whether an index is classified as correct or not, and science is continually evolving to enhance previous research. Anytime new variables are added into an equation results are going to vary when compared to prior research.

The *R Square* values calculated from the regression for only population density was on the lower side ranging from 0% to 10.7%, indicating that this variable can only account for up to 10.7% of the variability of SC-PDSI. The highest *R Square* values were seen in Bexar County in 2011 during a very intense drought, and it is important to remember that Bexar County uses the subsurface water source. These overall values of *R Square* for population density were seemingly low compared to the other variables, but that was to be expected because many variables impact and contribute to drought intensity. The three meteorological and physical variables – temperature, precipitation and soil moisture were found to have higher impact on drought severity based on their *R Square* values. However, population density did appear to have contributed to drought to some extent, and also found to be more influential in counties drawing from the subsurface water sources during the worst drought years.

From these findings, it can be concluded that population density and SC-PDSI are more strongly related during more intense droughts. Furthermore, though population density appears to be a weaker predictive variable, it is still a cause for concern, especially, for counties experiencing an increase in population density and relying on sub-surface water sources. One major threat to the Edwards Aquifer, which supplies water for Bexar County, is pollution and extraction (The University of Texas at Austin 2015). The increasing population creates a higher demand for water usage which could potentially affect the water levels of the aquifer. This could have been the reason for watering restrictions put in place in Bexar County. If people did not impact drought and enhance drought severity, these water restrictions would not be in place. Another current example of population density's impact on drought can be seen in California. The state has been experiencing extreme drought conditions so far in 2015, which led to the state government to place a mandatory water usage reduction (James 2015).

As discussed previously, the signs of the coefficients were important because they indicated the directionality of the variables and how they influence the SC-PDSI value. The sign for most of the coefficients was "typical" - what the expected relationship would be between the particular variable and the SC-PDSI. However, some variables did not display an expected relationship, for instance, the results for Harris County for the 2000 drought condition. The absence of an expected relationship between drought severity and temperature and precipitation could have been due to the very high resolution. Drought is typically analyzed on a larger scale (i.e. state or climate division) and rarely analyzed at this fine resolution, i.e., at the block group level. Another possible explanation could be the use of interpolation technique. Insitu meteorological data was not gathered every 30m, which would be ideal for this study but impossible to find. Interpolation itself is not perfect and the values are derived, which always introduces some error. Another issue was including all variables in one multi-variate regression analysis. According to Siminoff (2009), two collinear variables should be excluded from the regression analysis as a general rule of thumb, but there are instances in which collinear predictors are needed. In this case, temperature and precipitation are very important predictors of drought. Although these two variables are collinear, they did not display a strong collinear relationship. This could be an explanation to the opposite signs of the coefficients and the significant differences seen among all the indices in the Paired Samples T-Test results.

The findings of this study reveal that population density does influence drought severity and hence should be included in drought prediction research. However, the extent to which population influences drought is a matter that needs further investigation. In counties where majority of the water supply depends on subsurface water sources, population appears to be a major factor in drought occurrence. Therefore, for these locations and locations experiencing significant population growth, drought related mitigation measures should account for population growth and subsequent water usage.

This study is probably the first study to have included social variable to examine drought severity and its occurrence. Therefore, future research should focus on incorporating more study sites and a larger quantity of case studies to increase validity of the research findings. Although the methodology is easily replicable, one component that should be paid more attention in future research is the identification of study sites drawing from subsurface water supplies. Another area where further research should be conducted is the impact of spatial scale of analysis on index computation. Many drought studies are performed on a larger scale, generally at the state or the climatic division level, but rarely at the block or block group level where most of the population growth analysis are conducted. Therefore, it would be crucial to examine how the spatial scale at which data are available and collected influence index computation and subsequently drought severity determination so that appropriate mitigation measures can be taken.

APPENDIX

LIST OF COMMON ABBREVIATIONS

Palmer Drought Severity Index (PDSI)

Self-Calibrating Palmer Drought Severity Index (SC-PDSI)

National Drought Mitigation Center (NDMC)

Normalized Difference Vegetation Index (NDVI)

Weighted Linear Combination (WLC)

Drought Impact Reporter (DIR)

Federal Emergency Management Agency (FEMA)

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