SPATIAL SCALE DEPENDENCE OF DROUGHT CHARACTERISTICS AND IMPACT OF DROUGHT ON AGRICULTURE AND GROUNDWATER

A Dissertation
Submitted to the Graduate Faculty
of the
North Dakota State University
of Agriculture and Applied Science

By

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In Partial Fulfillment of the Requirements
for the Degree of
DOCTOR OF PHILOSOPHY

Major Department:
Civil and Environmental Engineering

November 2016

Fargo, North Dakota

North Dakota State University
Graduate School

Title

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DOCTOR OF PHILOSOPHY

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ABSTRACT

Drought is a water related natural hazard. It is difficult to characterize drought because of its diffused nature and spatiotemporal variability. However, understanding the variability of drought characteristics such as severity, frequency, duration, and spatial extent is critical in drought mitigation and planning. Impact of drought on agriculture, water supply, and energy sectors has been long-recognized. The current understanding of drought and its impact is limited due to its complex characteristics and ways in which it impacts various sectors. This study focuses on two important aspects of drought: variability of drought characteristics across different spatial scales, and impact of droughts on crop yield and groundwater. Two drought indices, one integrating severity and spatial coverage, and also taking into account the type of specific crops, were investigated for county level use. The developed indices were used in studying drought at the county level, and its impact on crop yields. These indices can be used for resource allocation at the county level for drought management. Drought is reported in the United States (U.S.) for different administrative units at different spatial scales. The variation of drought characteristics across different spatial scales and scale dependence was investigated, demonstrating the importance of considering spatial scales in drought management. A methodology is proposed to quantify the uncertainty in reported values of drought indices using geostatistical tools. The uncertainty was found to increase with increasing spatial scale size. Artificial Neural Network and regression methods were used to model the impact of drought on crop yield and groundwater resources. Relationships of crop yields and groundwater levels with drought indices were obtained. Overall, this study contributes towards understanding of the spatial variation of drought characteristics across different spatial scales, and the impact of drought on crop yields and groundwater levels.

ACKNOWLEDGEMENTS

At the outset, I would like to thank my advisor Dr. G. Padmanabhan, for his constant support and excellent guidance, without whom this work would not have been possible. I am also grateful for the exemplary mentorship that he has provided. He has a very positive influence on my life and career. My deep appreciation is extended to my co-adviser Dr. Adnan Akyüz for his valuable inputs and encouragement. I would also like to acknowledge my committee member Dr. Peter Oduor for taking time to shape my work in terms of language and ideas. I profusely thank my committee members Dr. Saleem Shaik and Dr. Chu for being integral parts of my committee and providing me with valuable suggestions, support, guidance, and good will.

I am proud to acknowledge North Dakota Water Resources Research Institute (NDWRRI) Fellowship program and NDSU Graduate School Doctoral Dissertation Fellowship for providing financial support to carry out my research.

I would also like to thank the Department of Civil and Environmental Engineering for providing me with a platform to showcase my skills and also for providing financial support, Milka Singha and Jan Lofberg for taking care of all the little things and all the paper work, and all my friends and fellow graduate students who made my journey with lots of pleasant memories.

I would like to thank my wife Vishnuveni and son Aathiran for their love and affection throughout my Ph.D. work. Their presence with me during my study gave me the strength to overcome many hurdles that I encountered during my pursuit to attain scholastic competence. My special appreciations go out to my mother, brothers, sisters and family members for their love and unconditional support. Last but not least, I would like to thank the Almighty Lord for providing me with the physical and mental strength to emerge successful despite all odds.

DEDICATION

I dedicate this dissertation to my mother Navaratnam Satgunawathy who taught me patience and persistence.

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CHAPTER 1. INTRODUCTION

Drought is water related natural hazard and is generally associated with scarcity of freshwater. The main reasons for drought are shortage in precipitation compared to demand for water and poor water management. Therefore, drought is influenced by nature as well as human beings. Unlike other natural hazards such as flood, earthquake, and hurricanes the occurrence and impact of drought are not realized immediately. However, the socio economic impact due to drought is huge. Drought essentially impacts all the water dependent sectors directly including agriculture, water supply, recreation, energy, and social. Even though losses and threat of droughts to society are recognized, the current understanding of drought and the way it impacts the different sectors are limited. Several studies have been conducted on droughts in the past and commendable progress has been made in some areas. Specifically, several drought indices have been developed to define and monitor drought. Those indices are also used extensively to study (a) drought characteristics in both time and space domain (Karl, 1983; Vicente-Serrano, 2006; Logan et al., 2010; Gocic and Trajkovic, 2014), (b) relating the indices with other large scale climate indices (Piechota and Dracup, 1996; Chiew et al., 1998; Shabbar and Skinner, 2004) (c) evaluating impact (Elagib, 2014; Li et al., 2009; Mendicino et al., 2008; Mishra and Cherkauer, 2010; Peters et al., 2005), and (d) assessing and comparing performances of different indices (Dai, 2011; Guttman, 1998; Heim, 2002; Keyantash and Dracup, 2002; Mishra and Singh, 2010; Narasimhan and Srinivasan, 2005; Qin et al., 2015). Severity, duration, frequency, and spatial coverages are four major characteristics necessary to define drought. These characteristics either individually or collectively have been studied for several regions of interest using station data or for defined spatial units. In the United States (U.S.), drought indices are mostly reported as a single severity value for a spatial unit (e.g., climate division). Only the relatively recently developed drought monitoring tool, U.S. drought Monitor (USDM) reports the spatial coverages of drought at different intensity levels. An index integrating intensity and spatial coverage for administrative unit will be useful for drought management. In this study, USDM spatial coverages of different intensity droughts were integrated for use at the county level. The spatial variations of characteristics of drought from a spatial scale perspective have not received adequate attention in the past. Also, the uncertainty associated with reporting drought at different spatial scales has not been explored adequately. A clear understanding of drought across different spatial scale is essential since drought is monitored and managed at different spatial units. This study demonstrates a distinct methodology to address these problems. Studies on drought impact on various sectors based on past data will be helpful in tackling future impact of drought. Numerous studies have been conducted in the past to quantify the impact of drought. Recent modeling tools and data, such as, Artificial Neural Network (ANN); intensity-areal coverage data from USDM, and groundwater levels data from the U.S. Geological Survey Ground-Water Climate Response Network (USGS CRN) wells can be effectively used now to study drought impact. In this study, drought impact on crop yields and groundwater resources were analyzed using such tools and data.

1.1. Background

Drought is a complex natural phenomenon difficult to accurately describe because of its spatially and temporally varying nature and context-dependency (Quiring, 2009). Drought stands apart from other natural hazards in many ways, particularly in that it is difficult to identify and predict its onset and termination (Dracup et al., 1980a; Hisdal and Tallaksen, 2000; McKee et al., 1993; Tallaksen et al., 1997). It is characterized by diffused spatial and temporal bounds.

Creeping behavior of droughts makes it difficult to define and understand, and also to quantify its impact (Gillette, 1950; Wilhite et al., 2014).

Drought indices are used to identify and monitor drought conditions, and to decide the timing and level of mitigating actions that need to be taken in response to droughts (Steinemann et al., 2005). Historically, losses from droughts across the world have significantly increased due to an increase in number of droughts; and/or drought severity (Wilhite, 2000). In the past, U.S. had experienced many severe droughts including droughts during 1930-1936 and 1970. Cook et al., (2015) predicted that there is a high risk for severe extended drought in the Southwest and Central Plains of Western North America in coming years due to climate change and warns that it may lead to a "mega drought." Impact of drought on agriculture, water resources, and social sectors has been long-recognized. The following section (section 1.2) reviews the definition, indices, and impacts of droughts. Additional background information is provided in each chapter relevant to the specific subtopic.

1.2. Literature Review

1.2.1. Drought Definition

There are more than 150 published definitions of drought (Wilhite and Glantz, 1985). Mishra and Singh (2010) lists several organizations/researchers who use different definitions of drought, for example, the World Meteorological Organization (WMO), the United Nations (UN) Convention to Combat Drought and Desertification, the Food and Agriculture Organization (FAO) of the UN, the Encyclopedia of Climate and Weather, Gumbel, 1963, and Palmer, 1965. Although many definitions of drought exist, the central theme in documented literature on drought lies behind the context of water deficiency (Sonmez et al., 2005). The four types of drought commonly recognized are meteorological, agricultural, hydrological, and socioeconomic droughts (Wilhite and Glantz, 1985; American Meteorological Society, 2013). Meteorological drought is usually defined on the basis of the degree of dryness (in comparison to some "normal" or average amount) and the duration of the dry period over a region for a period of time. Generally, meteorological drought is analyzed based on precipitation (Pinkayan, 1966; Santos, 1983). Agricultural drought links various characteristics of meteorological (or hydrological) drought to agricultural impacts, focusing on precipitation shortages, differences between actual and potential evapotranspiration, soil water deficits, reduced groundwater or reservoir levels, and so forth. Hydrological drought is associated with the effects of periods of precipitation (including snowfall) shortfalls on surface or subsurface water supply (i.e., stream flow, reservoir and lake levels, groundwater). Hydrological drought has been widely analyzed using stream flow data (Dracup et al., 1980b; Sen, 1980). Socioeconomic definitions of drought associate the supply and demand of some economic good with elements of meteorological, hydrological, and agricultural drought (American Meteorological Society, 2013).

1.2.2. Drought Indices

Drought index is typically a single number representing the drought condition. The drought indices are derived from meteorological variables (e.g. precipitation, temperature) and/or hydrological variables (e.g. stream flows, reservoir storage, soil moisture, groundwater levels) (Steinemann et al., 2005). The indices are used for drought monitoring and decision making purposes. These indices are used also for categorizing drought based on their threshold values. Numerous drought indices have been developed. The most commonly used indices include: (i) Palmer Drought Severity Index (PDSI) (Palmer, 1965); (ii) Standardized Precipitation Index (SPI) (McKee et al., 1993; 1995); (iii) Crop Moisture Index (CMI) (Palmer, 1968); and (iv) Surface Water Supply Index (SWSI) (Shafer and Dezman, 1982). Several authors have discussed the usability and/or applicability of the indices (Dai, 2011; Guttman, 1998; Heim, 2002; Keyantash and Dracup, 2002; Mishra and Singh, 2010; Narasimhan and Srinivasan, 2005; Qin et al., 2015). A comparison study of Palmer Drought Index and Standardized Precipitation Index based on their spectral characteristics can be found in (Guttman, 1998). Heim (2002) did a comprehensive review of past drought indices used in the U.S. Keyantash and Dracup (2002) evaluated some selected hydrological, agricultural, and meteorological drought indices for their usefulness based on a weighted score of six criteria: robustness, tractability, transparency, sophistication, extendibility, and dimensionality. They found overall rainfall deciles are superior to SPI, cumulative precipitation anomaly, Rainfall Anomaly Index (RAI), Drought Area Index (DAI), and PDSI for representing the meteorological drought; total water deficit is better than cumulative stream flow anomaly, SWSI, and PHDI for representing the hydrological drought; and computed soil moisture better represents the agricultural drought compared to soil moisture anomaly index, Palmer’s Z-index, and CMI. Narasimhan and Srinivasan (2005) discussed the PDSI, CMI, SPI, and SWSI. They also have developed and evaluated Soil Moisture Deficit Index (SMDI) and Evapotranspiration Deficit Index (ETDI) using a hydrologic model, Soil and Water Assessment Tool (SWAT). Mishra and Singh (2010) listed and discussed several commonly used drought indices in their review paper on drought concepts. Dai (2011) compared the calculation method, classification scheme, strength, and weakness of commonly used drought indices. Qin et al. (2015) evaluated the performance of drought indices derived from precipitation and soil moisture. Although there are several drought indices, each index has its own advantages and disadvantages from the users’ perspectives. In a 2009 workshop held at Lincoln, Nebraska, on “Indices and Early Warning Systems for Drought” the importance of having a general agreement on standard index for each type of drought (i.e., meteorological, agricultural, and hydrological) was recognized. Although SPI was recommended as a standard index to monitor the meteorological drought universally, the group did not recommend any particular index for agricultural and hydrological droughts. The workshop participants, on the other hand, did not want to diminish the importance of local indices that are currently used (Hayes et al., 2011).

Kallis (2008) discussed the drought in detail from an interdisciplinary perspective, and emphasized the usage of multiple indices and qualitative judgments in drought monitoring. Drought monitoring products using multiple indices include USDM data (Svoboda et al., 2002), Joint Deficit Index (JDI) (Kao et al., 2009), and Multivariate Standardized Drought Index (MSDI) (Hao and AghaKouchak, 2013). JDI and MSDI were developed using multiple drought indices based on probabilistic concepts. USDM drought indicator is a combination of agricultural, meteorological, and hydrological severity indicators plus a subjective assessment of the impact of drought conditions by the community of drought observers (Svoboda et al., 2002).

There are several other notable sources also available for drought indices data. For example, (i) NOAA's National Centers for Environmental Information (NCEI) has in its database monthly climate indices including the suite of PDSI and SPI on a climate division scale. (ii) the University of Washington Surface Water Monitor (SWM) publishes hydrologic and drought condition data (soil moisture (SM), snow water equivalent (SWE), runoff, SPI, Standardized Runoff Index (SRI)) for contiguous U.S. and Mexico at half degree resolution on a daily basis (Wood, 2008). (iii) US-Mexico Drought Prediction Tool uses probabilistic prediction of SPI and publishes the data (Lyon et al., 2012; Quan et al., 2012). (iv) Global Integrated Drought Monitoring and Prediction System (GIDMaPS) is another data source for drought indices at different spatial and temporal scales (Hao et al., 2014). (v) Western Regional Climate

Center's WestWide Drought Tracker (WWDT) provides monthly drought conditions at county scale (Abatzoglou, 2013).

1.2.3. Impact of Drought

Drought has been one of the costliest natural disasters to strike the U.S. (Cook et al., 2007; Lott and Ross, 2006; Smith and Katz, 2013). Mishra and Singh (2010) discussed the recent droughts around the world and their impact. It is estimated that drought costs the U.S. $6–8 billion annually (FEMA, 1995). Drought creates stress on water resources (i.e., surface water, groundwater), and on soil moisture which in turn impact water-dependent industries including agriculture, water supply, energy, and recreation (Kumar and Panu, 1997). There have been numerous studies on impact of droughts (Elagib, 2014; Leelaruban et al., 2012; Li et al., 2009; Lott and Ross, 2006; Mendicino et al., 2008; Mishra and Cherkauer, 2010; Peters et al., 2005). Drought impact quantification is not an easy task because of the difficulty of precisely defining droughts and the complex dynamics of impact sectors.

1.3. Motivations for this Study

Globally, drought research is on the increase (Mishra and Singh, 2010; Wilhite, 2000). Most of the past and recent researches on droughts include studies on drought characteristics, drought processes, drought prediction, drought comparisons, and drought impacts. The current understanding of the dynamics of droughts is relatively limited due to their complex nature compared to floods, another well-studied water related hazard, especially, the drought's spatial behavior, and its impact on various sectors corresponding to its characteristics: severity, duration, frequency, and aerial coverage. The challenges in drought study include dealing with varying definitions, representative indices, impact sectors, appropriate analytical techniques etc.

Also, droughts vary significantly in their characteristics from one region to another (Bordi and Sutera, 2007).

As discussed in section 1.2.1, there are numerous drought indices. However, an index which could reflect spatial extent of droughts of different severity will be advantageous for administrative purposes of allocating resources to drought mitigation. Also, impact assessment of droughts on various sectors is essential for resource allocation to prepare and manage future droughts. Researchers have used many analytical techniques to study droughts and their impact in the past. However, analytical techniques such as Artificial Neural Network (ANN) and geostatistics used in other fields successfully have not been used effectively in drought studies. These techniques were used in this study.

This study will contribute to understanding the characteristics of droughts better especially the spatial aspects of droughts across spatial scales, and the impact of drought on agriculture and groundwater. Although there have been many studies on these topics, this study can be distinguished from previous studies based on the use of novel approaches and on the use of recent computational tools such as ANN and geostatistics to address the problem. The detailed information about how this study differs from past work is explained in each chapter relevant to the specific work. Though the major portion of this study mainly focuses on the state of North Dakota (ND), U.S., the methodologies used in this study are not specific to ND, and can be adapted to other study sites.

1.4. Objectives

Main objectives of this study were to:

1. Integrate drought indices which could incorporate severity and spatial extent (coverage) of droughts and also crop-specific information.

2. Discern drought occurrences and their characteristics across of county, climate division, state, region and contiguous U.S. scales.
3. Analyze uncertainty in drought reporting across spatial scales
4. Evaluate groundwater level responses to drought, and;
5. Study the impact of drought on crop yield.

1.5. Dissertation Organization

This dissertation is organized in seven chapters. Chapter 1 includes the introduction of the research problem, literature review, motivation, and objectives of the research. Chapters 2-6 address each specific objective listed in section 1.4. Chapter 2 contains materials from Navaratnam Leelaruban's Master thesis (2011), and paper titled "Leveraging a Spatio-Temporal Drought Severity and Coverage Index with Crop Yield Modelled as a Stochastic Process" published in the International Journal of Hydrology Science and Technology (Leelaruban et al., 2012). This study was a continuation of the master's degree research work. Chapters 3 and 4 describe the drought occurrences and their characteristics in the contiguous U.S. across selected spatial scales and uncertainty in drought reporting across spatial scales respectively. Research on the relationship between drought indices and groundwater levels is presented in Chapter 5. A part of the material in Chapter 5 has been published in the Proceedings of the World Environmental and Water Resources Congress (Leelaruban and Padmanabhan, 2015). Chapter 6 describes the results of the investigation on the impact of droughts on crop yields in North Dakota; U.S. Chapter 6 study has been published in the Neural Network World (Odabas et al., 2014). The overall conclusions of the dissertation research and recommendation for future directions are summarized in Chapter 7. The references are listed following Chapter 7.

CHAPTER 2. DEVELOPMENT OF COUNTY-LEVEL DROUGHT INDICES[1]

2.1. Introduction

A county-level approach to addressing drought severity, duration, frequency, and impact is ideal since most drought management is best administered on a county basis. A drought indicator could be beneficial only if it could be associated with drought management and impact reduction objectives (Steinemann et al., 2005). Dow et al. (2009) emphasize issues that need to be addressed in greater detail in decision-making such as understanding what units are useful to local drought information and awareness and acceptance of the uncertainty, and tradeoffs involved in mapping climate information to a 'local' scale. Their web-based survey revealed that a majority of water managers identified county level was indeed the most viable local areal scale to display drought compared to climate division boundaries, 8-digit Hydrologic Unit Code (HUC) or areas allied to National Weather Services (NWS) stations.

In this study, two county-level indices were developed: Drought Severity and Coverage Index (I_{SC}), and Crop Specific Drought Severity-Coverage Index ($I_{SC,AG}$) for selected crops. The spatial and temporal variations of drought was analysed for the state of North Dakota (ND) using I_{SC}. Geographic Information Systems (GIS) platform was utilized to address and display spatiotemporal variations. GIS provides effective tools necessary to analyse parametric variation

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This chapter was extracted from a published article in IJHST (Leelaruban, N., Oduor, P.G., Akyuz, A., Shaik, S., Padmanabhan, G., 2012. Leveraging a spatio–temporal drought severity and coverage index with crop yield modelled as a stochastic process. International Journal of Hydrology Science and Technology, 2(3): 219-236. DOI: 10.1504/IJHST.2012.049184).

[1]The material in this chapter was co-authored by Navaratnam Leelaruban, Dr. Peter Oduor, Dr. Adnan Akyuz, Dr. Saleem Shaik, and Dr. G Padmanabhan. Navaratnam Leelaruban had primary responsibility for constructing data base and conducting analysis. Navaratnam Leelaruban was the primary developer of the conclusions that are advanced here. Navaratnam Leelaruban also drafted and revised all versions of this chapter. Other co-authors assisted in discussion; and served as proofreader and checked the analysis conducted by Navaratnam Leelaruban.

in datasets from different federal and local authorities. Drought data from the U.S. Drought Monitor (USDM) and crop yield data from the National Agriculture Statistics Service (NASS) were used in this study. Identifying spatial drought vulnerabilities could help the decision making process regarding: adjustment in practices in water-dependent sectors, natural resource planning, and addressing drought from a hazard-mitigation perspective (Sonmez et al., 2005). The usefulness of the indices I_{SC} and $I_{SC,AG}$ to assess the impact of drought on crop yields was also investigated.

2.2. Study Area and Data

2.2.1. Study Area

North Dakota, the study area, is one of the north-central states of U.S. comprising of 53 counties and spanning 9 climate divisions. Figure 2.1 shows the counties and climate divisions of North Dakota. The state has a north-south temperature gradient, an east-west precipitation gradient and is a leading agricultural producer of many crops, including durum wheat, barley, other spring wheat, sunflower, and dry edible beans. Drought is a normal part of North Dakota's climate variability and has significantly impacted North Dakota in the past (Karetinkov et al., 2008).

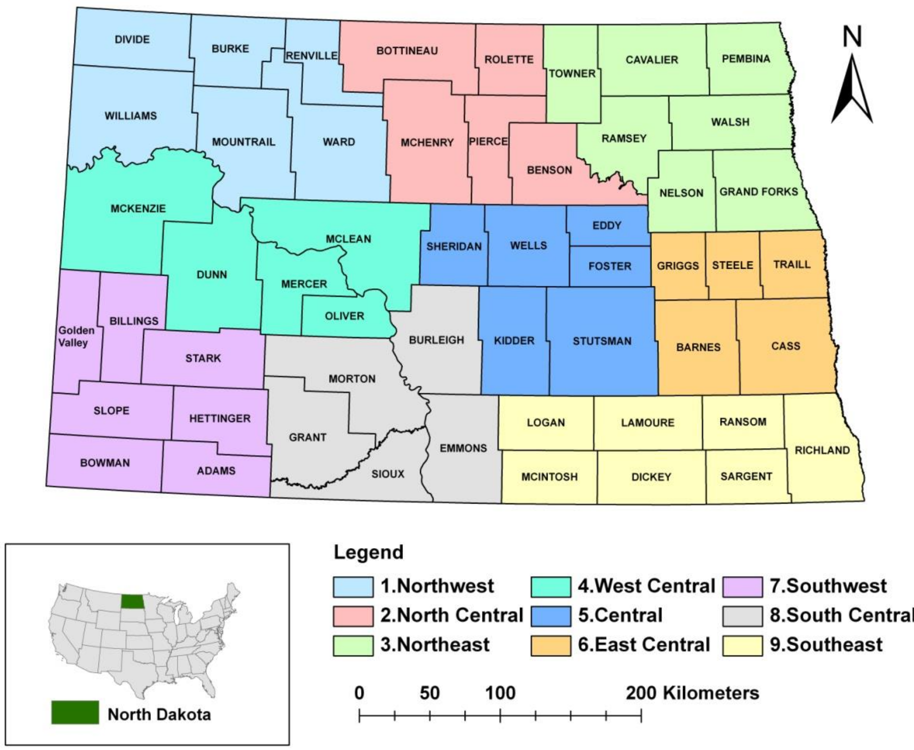


Figure 2.1: North Dakota counties and climate divisions.

2.2.2. U.S. Drought Monitor Data

The United States Drought Monitor (USDM) is a major source of drought data in the U.S available to the public from the National Drought Mitigation Center (NDMC) at the University of Nebraska, Lincoln (Svoboda et al., 2002). NDMC provides various climate and drought information to the public which includes easy to use U.S. Drought Monitor. The purpose of the USDM is not forecasting drought rather it was developed as a comprehensive tool to capture and depict the drought conditions as they exist across the U.S. (Hayes et al., 2005).

The USDM data products (map/table) can be accessed at NDMC's web site (http://www.drought.unl.edu/dm/monitor.html). Several federal agencies including U.S. Department of Agriculture (USDA), and National Oceanic and Atmospheric Administration (NOAA) also contribute to produce USDM data products. USDM data on areal coverage under different drought intensity categories: D0 (abnormally dry), D1 (moderate drought), D2 (severe drought), D3 (extreme drought), and D4 (exceptional drought) (Svoboda et al., 2002) were utilized in this study. USDM employs key drought indicators such as Palmer Drought Index, CPC Soil Moisture Model (Percentiles), USGS Weekly Stream flow (Percentiles), Standardized Precipitation Index (SPI), and Objective Short and Long-term Drought Indicator Blends (Percentiles) and numerous supplementary indicators to define the intensity categories. For example, drought category will be designated as D0, if Palmer Drought Index is in the range -1.0 to 1.9, CPC Soil Moisture Model Percentile 21 to 30, U.S. Geological Survey (USGS) weekly Stream Flow Percentile 21 to 30, Standardized Precipitation Index -0.5 to -0.7, and Objective Short and Long-term Drought Indicator Blends Percentiles 21 to 30. The ranges of the indicators used in the USDM classification scheme often may not point to the same USDM classification. Therefore, the final USDM category will be defined based on majority of the indicators. In addition, USDM will weigh the indices based on their performances over the time and space and incorporate information from many local experts around the country, and use additional indicators if necessary.

2.2.3. Crop Data

Major agricultural crops grown in North Dakota such as barley, corn, hay alfalfa, hay (all), oats, spring wheat, and durum wheat were selected for this study to investigate the capability of proposed indices to capture the yield variation. Crop yield county-by-county data from National Agricultural Statistics Service (NASS) web portal was used. Planting and harvesting times data was derived from prescribed metadata files that accompany NASS datasets (Figure 2.2).

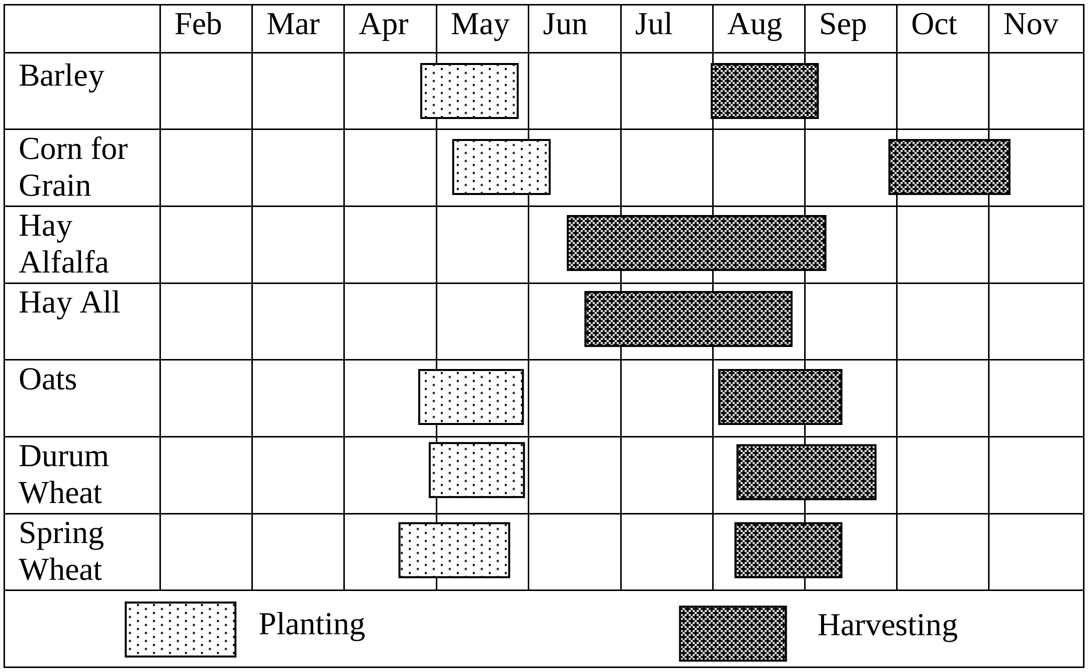


Figure 2.2: Usual planting and harvesting dates for North Dakota (derived from USDA/NASS, December 1997 Metadata).

2.3. Approach

2.3.1. Drought Severity-Coverage Index (I_{SC})

This weekly county-level drought impact index was developed based on an approach used by Akyuz (2009) in which area covered by higher drought severity is magnified by using an arbitrarily chosen increasing higher multiplying factor as shown in Equation 2.1.

$$I_{SC} = 1 \times (A_{D0}) + 2 \times (A_{D1}) + 3 \times (A_{D2}) + 4 \times (A_{D3}) + 5 \times (A_{D4}) \qquad (2.1)$$

where A_{D0}, A_{D1}, A_{D2}, A_{D3}, and A_{D4} are percentage area coverage for D0, D1, D2, D3, and D4 respectively. In Eq. (2.1), a numeric value of 500 indicates the worst possible dry scenario implying that 100% of the county would be deemed under exceptional drought. A value of zero would therefore imply that 0% of the county is facing dry conditions. This refined index could account for the intensity and spatial extents of droughts with reasonable spatial (county-level) and temporal (weekly) resolution.

2.3.2. Crop Specific County-Level Index ($I_{SC,AG}$)

Based on the statistical relationship between drought intensity categories and yield values a unique county-level Crop Specific Drought Severity-Coverage Index ($I_{SC, AG}$) was developed for selected crops: barley, corn, durum wheat, hay-alfalfa, hay, oats, and spring wheat. USDA NASS county-level yield data, and areal coverages of drought intensity categories from USDM were utilized for this part of the study.

Equation (2.2) was used to determine the relationship between drought intensity categories and crop yield. Average values of A_{D0}, A_{D1}, A_{D2}, A_{D3}, and A_{D4} were calculated for the weeks between planting and harvesting where A_{D0}, A_{D1}, A_{D2}, A_{D3}, and A_{D4} are percentage area coverage of D0, D1, D2, D3, and D4 respectively. Then panel data set was constructed representing 53 counties by 9 years using Yield, Avg(A_{D0}), Avg(A_{D1}), Avg(A_{D2}), Avg(A_{D3}) and Avg(A_{D4}) for i = 1,2,……..53 counties and t = 1,2,…….9 (2000 -2008) years of observation. A regression model as in equation Eq. 2.2 was developed. This study used two-way random effects model. Random effects models are used in the analysis of hierarchical or panel data. Random effect model takes into account spatial and temporal variation; and removes bias or trends.

$$\begin{aligned} Yield_{it} = {} & \alpha_0 + \alpha_1 \times Avg(A_{D0})_{it} + \alpha_2 \times Avg(A_{D1})_{it} + \alpha_3 \times Avg(A_{D2})_{it} + \alpha_4 \times Avg(A_{D3})_{it} \\ & + \alpha_5 \times Avg(A_{D4})_{it} + \varepsilon \end{aligned} \tag{2.2}$$

The coefficients α_1, α_2, α_3, α_4, α_5 were tested for statistical significance at the 5% level. These were then used in to improve estimates of Drought Severity-Coverage Index using the relation (Eq 2.3):

$$I_{SC,AG} = \alpha_1 \times (A_{D0}) + \alpha_2 \times (A_{D1}) + \alpha_3 \times (A_{D2}) + \alpha_4 \times (A_{D3}) + \alpha_5 \times (A_{D4}) \tag{2.3}$$

where ($I_{SC,AG}$) can be defined as a unique county-level drought index for each crop based on impact of drought intensity categories. $I_{SC,AG}$ is suitable for implementing best agriculture practice based on drought scenarios because the coefficients (i.e., $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$) accounted for the impact of each intensity category on yield.

2.4. Methods of Analysis

2.4.1. Spatial variability of drought severity and frequency in North Dakota

Annual spatial variations of drought based on the average value of Drought Severity-Coverage Index (I_{SC}) were evaluated for the period between 2000 and 2008. Weekly I_{SC} values were calculated for each county, and then annual average values were calculated for all counties (2000-2008). New attribute columns representing annual average values of I_{SC} were created in the North Dakota county polygon ArcGIS-ArcINFO® GIS shapefile for year 2000 to year 2008. Then, annual average I_{SC} values were mapped using ArcGIS-ArcINFO® to display the spatial variation of drought for each year. Each county had an assigned color and aptly labeled based on annual average value of I_{SC}. This offers a lucid picture of drought variation within North Dakota for years 2000 to 2008. In addition, a drought spatial variation map was developed based on overall average values of I_{SC} for sampling period (485 weeks, Jan. 2000 – Apr. 2009), these values were displayed in a county spatial scale using ArcGIS-ArcINFO®.

To analyze the drought frequency, the sum total of drought occurrence, n, within each county under each drought severity category was determined for the sampling period and classified as shown below (Table 2.1).

A graduated symbol map for the classes was generated for each category using ArcGIS-ArcINFO® to display the spatial trend of drought occurrences. Occurrence patterns of drought based on climate divisions were analyzed. It shows the local (county) drought occurrence variation within climate divisions.

Table 2.1: Classified categories with I_{SC} ranges (n is number of occurrence associated with I_{SC}).

Category	$\boldsymbol{n}$
A ($I_{sc} \leq 100$)	$n_{(I_{sc} \leq 100)}$
B ($100 < I_{sc} \leq 200$)	$n_{(100 < I_{sc} \leq 200)}$
C ($200 < I_{sc} \leq 300$)	$n_{(200 < I_{sc} \leq 300)}$
D ($300 < I_{sc} \leq 400$)	$n_{(300 < I_{sc} \leq 400)}$
E ($400 < I_{sc} \leq 500$)	$n_{(400 < I_{sc} \leq 500)}$

2.4.2. Relationship between Yield and Severity-Coverage Index (I_{SC})

Impact of drought on crop yield was studied using derived Drought Severity-Coverage indices (I_{SC}) and county-level crop yield data. Average value of I_{SC} were calculated for period between planting and harvesting (Figure 2.2) for years 2000-2008. Based on Average I_{SC} ($AvgI_{SC}$) and agriculture yield data, a panel data set representing 53 counties by 9 years was constructed. This is an unbalanced panel data, because there were some missing yield data in some cases. A random effects model was applied to examine the relationships between I_{SC} and crop yield. The dependency of crop yield on growing conditions which are climate driven can be analysed using linear regression. In this study, crop yield is hypothesized as a function of drought. Randomizing removes bias or trends that may be inadvertently introduced by presence of null values thereby enhancing inference. The relationship between I_{SC} and yield is expressed by the following equation (Eq. 2.4) for i = 1, 2,……..53 counties and t = 1,2,…….9 years of observation:

$$Yield_{it} = \beta_0 + \beta_1 \times (AvgI_{SC})_{it} + \varepsilon_{it} \tag{2.4}$$

where β_0, β_1 are the coefficients and ε_{it} is the error term (which accounts for all other factors which would influence *Yield* other than I_{SC}). The unit used for yield is bushels/acres for barley, corn, durum wheat, oats, and spring wheat and tons/acre for hay-alfalfa and hay. The relationship between yield and drought intensity categories (i.e., D0, D1, D2, D3, and D4) were also studied (see section 2.3.2).

2.4.3. Markov Chain modeling

Markov chain modeling was used to derive the transition probability matrix of crop yield classes from less severe drought condition to more severe drought conditions for barley, corn, durum wheat, hay alfalfa, hay, oats, and spring wheat. Crop yield classes (8 classes) were derived using an equal interval classification based on the yield range within the sampled period (2000 – 2008) with Class 1 as the lowest crop yield range. $I_{SC,AG}$ was used to determine less severe and more severe drought years for each crop. The transition probabilities were derived using the software SemGrid. This study demonstrates how $I_{SC, AG}$ can be used in conjunction with Markov Chain modeling to study the risk of crop yield loss due to drought.

A first order Markovian process $\{X_t\}$ can be defined as a stochastic process where for any set of *n* successive times, for which, $t_n \in T$ and $n = \{0,1,2,\ldots\}$ with an index set T = {0, ∞} there exists a conditional probability not affected by earlier states given by (Kokkinos and Maras, 1997; Wu et al., 2006; McCauley, 2007). The basic equation is:

$$P_{X(1|n-1)}\left(X_n, t_n \middle| X_1, t_1; X_2, t_2; \ldots; X_{n-1}, t_{n-1}\right) = P_{X(1|1)}\left(X_n, t_n \middle| X_{n-1}, t_{n-1}\right) \tag{2.5}$$

The time-stationary transition probability matrix can be expressed as:

$$p_{ij}(t) = P\{X_t = j \mid X_{t-1} = i\} = p_{ij}$$

where p_{ij} are the elements in the matrix of transition probabilities and $\sum p_{ij} = 1$

$P_{ij} \geq 0; i, j \geq 0.$

In this study; i, j are crop yield classes.

2.5. Results and Discussion

2.5.1. Drought Severity

Figure 2.3 shows each county with an assigned color schema and labeled based on overall average values of I_{SC} for the sampling period (485 weeks, Jan. 2000 – Apr. 2009). The spatial variation of the drought impact within North Dakota is depicted using a red to green hue with a transitional yellow color gradation (Figure 2.3). Spatial variation results indicated that the following counties located on the south-western part of the state; Bowman, Slope, Adams, Hettinger, Stark, Golden Valley, Billings, Grant, Sioux and Dunn Counties had a higher than average value of I_{SC} for the sampled period.

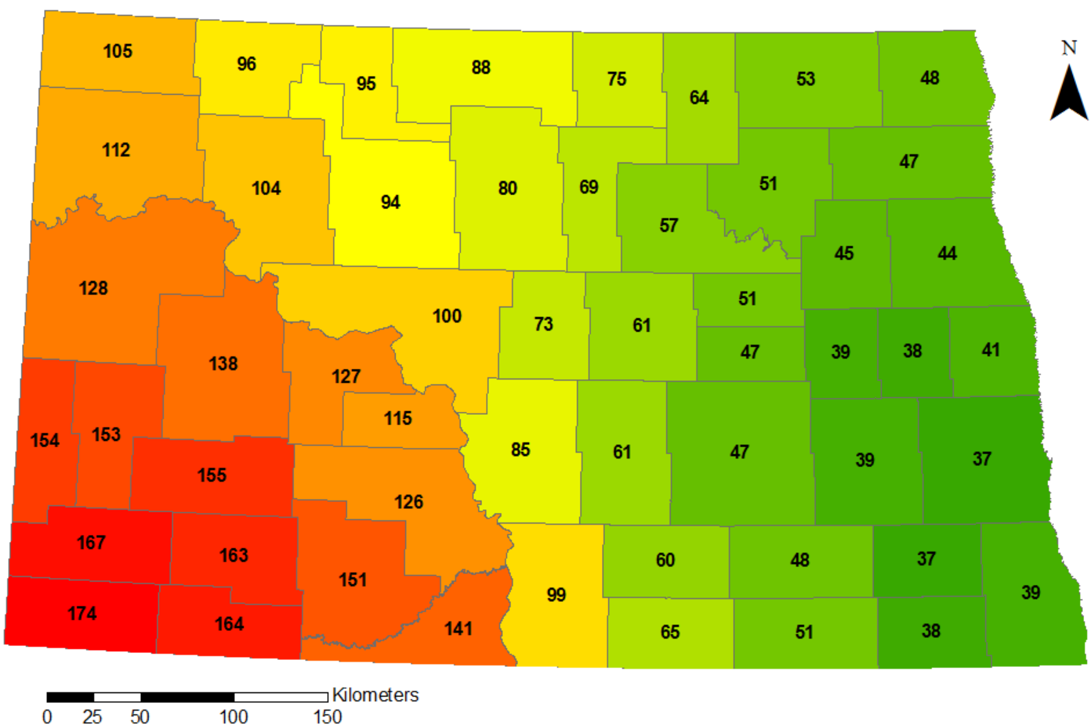


Figure 2.3: Average drought intensity variation within North Dakota (Jan. 2000 – Apr. 2009).

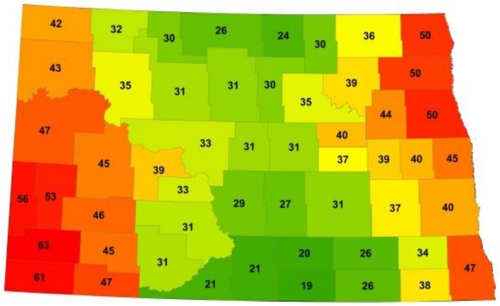
The maximum average value of I_{SC} was 174 for Bowman county and minimum value was 37 for Cass County. I_{SC} distribution depicts West-East gradient across the state. The index ranges from zero (no drought) to 500 (indicating 100% of the county is under D4 category drought for the period used). Combination of lesser amounts of precipitation and greater daytime heating during growing season make southwestern parts of the state the most drought-prone area of the State.

Figure 2.4 shows the annual drought variations within North Dakota for year 2000 to 2008. The maps county labels show the annual average values of Drought Severity-Coverage Index (I_{SC}). The color red to green with a transitional yellow hue color gradation shows the drought intensity level, the color gradation was in such a way that red was assigned to higher drought and green to low drought. The results (Figures 2.4) show that for all the year (2000-2008) south west part of the state had higher impact of drought, and eastern part of the state has lower impact. In 2000, eastern and western North Dakota areas were equally affected while central part of the state experienced a low drought index value even though drought intensity level for the entire state was very low (that is I_{SC} <75). In years 2000 and 2001 the drought intensity indices were lower compared to subsequent years with relative higher intensities experienced in the south-western part of the state.

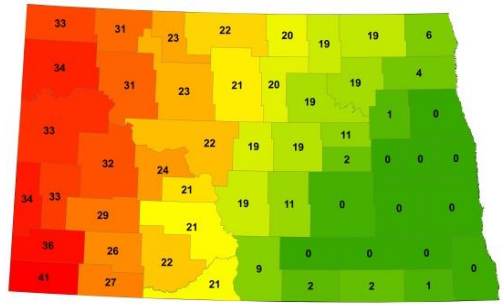
Figure 2.5 depicts spatial distribution of the drought frequency variation within North Dakota using graduated symbols and it shows that the counties that had high number of occurrences of lower Category A drought incidences ($n_{I_{sc} \leq 100}$) were Steele ($n_{I_{sc} \leq 100} = 454$), Walsh ($n_{I_{sc} \leq 100} = 432$), Nelson ($n_{I_{sc} \leq 100} = 432$), Ransom ($n_{I_{sc} \leq 100} = 432$), and Griggs ($n_{I_{sc} \leq 100} = 431$). It can be seen from the figures that the eastern counties were less vulnerable to drought. McKenzie ($n_{100 < I_{sc} \leq 200} = 176$), Burleigh ($n_{100 < I_{sc} \leq 200} = 173$), Billings ($n_{100 < I_{sc} \leq 200} = 167$), Oliver ($n_{100 < I_{sc} \leq 200} = 149$), and Mercer ($n_{100 < I_{sc} \leq 200} = 148$) counties had high numbers of category B ($n_{100 < I_{sc} \leq 200}$). High numbers of intermediate drought category C ($n_{200 < I_{sc} \leq 300}$) droughts occurred in Grant ($n_{200 < I_{sc} \leq 300} = 158$), Sioux

($n_{200 < I_{sc} \leq 300} = 156$), Morton ($n_{200 < I_{sc} \leq 300} = 148$), Slope ($n_{200 < I_{sc} \leq 300} = 133$), Hettinger ($n_{200 < I_{sc} \leq 300} = 133$) and Adams ($n_{200 < I_{sc} \leq 300} = 130$). Although the number of occurrences in category B and C are relatively the same, area under C should be of more serious consequence because of higher severity. Considering a higher drought severity index corresponding to Category D ($n_{300 < I_{sc} \leq 400}$), counties like Bowman ($n_{300 < I_{sc} \leq 400} = 72$), Adams ($n_{300 < I_{sc} \leq 400} = 54$), Slope ($n_{300 < I_{sc} \leq 400} = 40$), Hettinger ($n_{300 < I_{sc} \leq 400} = 29$), and Golden Valley ($n_{300 < I_{sc} \leq 400} = 27$) displayed higher n values. In the highest category E ($n_{400 < I_{sc} \leq 500}$), counties like Sioux ($n_{400 < I_{sc} \leq 500} = 5$), Emmons ($n_{400 < I_{sc} \leq 500} = 3$), Morton ($n_{400 < I_{sc} \leq 500} = 2$), and Grant ($n_{400 < I_{sc} \leq 500} = 2$) were counties that exposed to severe drought frequently.

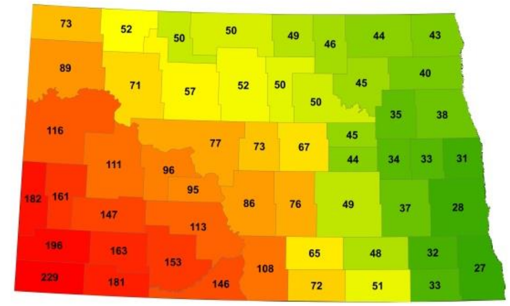
Histograms of drought categories corresponding to derived *n* values for each defined climate division (Figure 2.1) within the state are depicted in Figure 2.6. All the counties experienced higher *n* values for category A (least severe) drought especially for Northwest, North Central, Northeast, Central, East Central and Southeast climate zones. Climate divisions Northeast, Central, South Central, and Southeast experienced higher *n* values for A and B drought categories and these divisions few times experienced C and D drought categories. Climate divisions; West Central, Southwest and South Central were affected most frequently and had a higher severity drought. Climate division South Central is the only division affected by E drought category which is the very severe drought category.



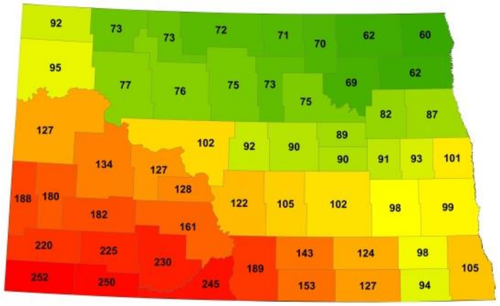
(a) Year 2000



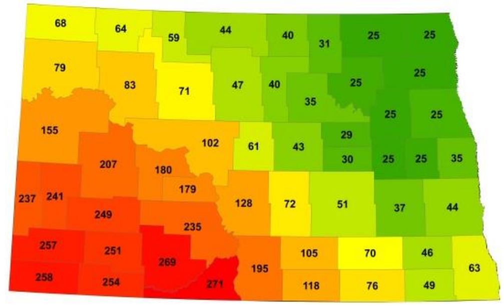
(b) Year 2001



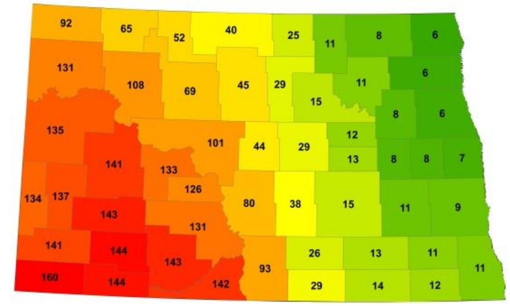
(c) Year 2002



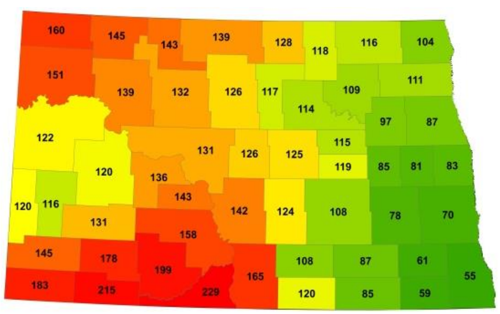
(d) Year 2003



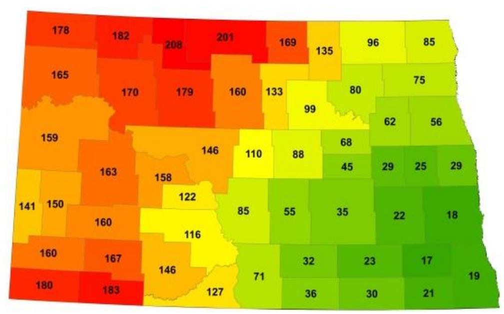
(e) Year 2004



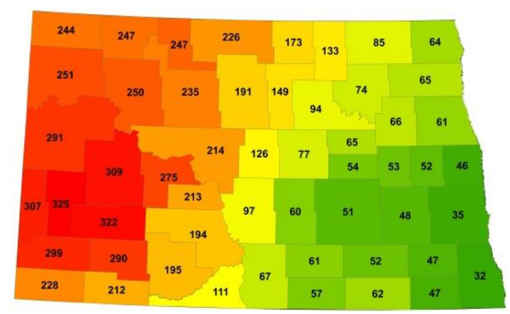
(f) Year 2005



(g) Year 2006



(h) Year 2007



(i) Year 2008

Figure 2.4: Annual drought variation map for North Dakota State (2000-2008).

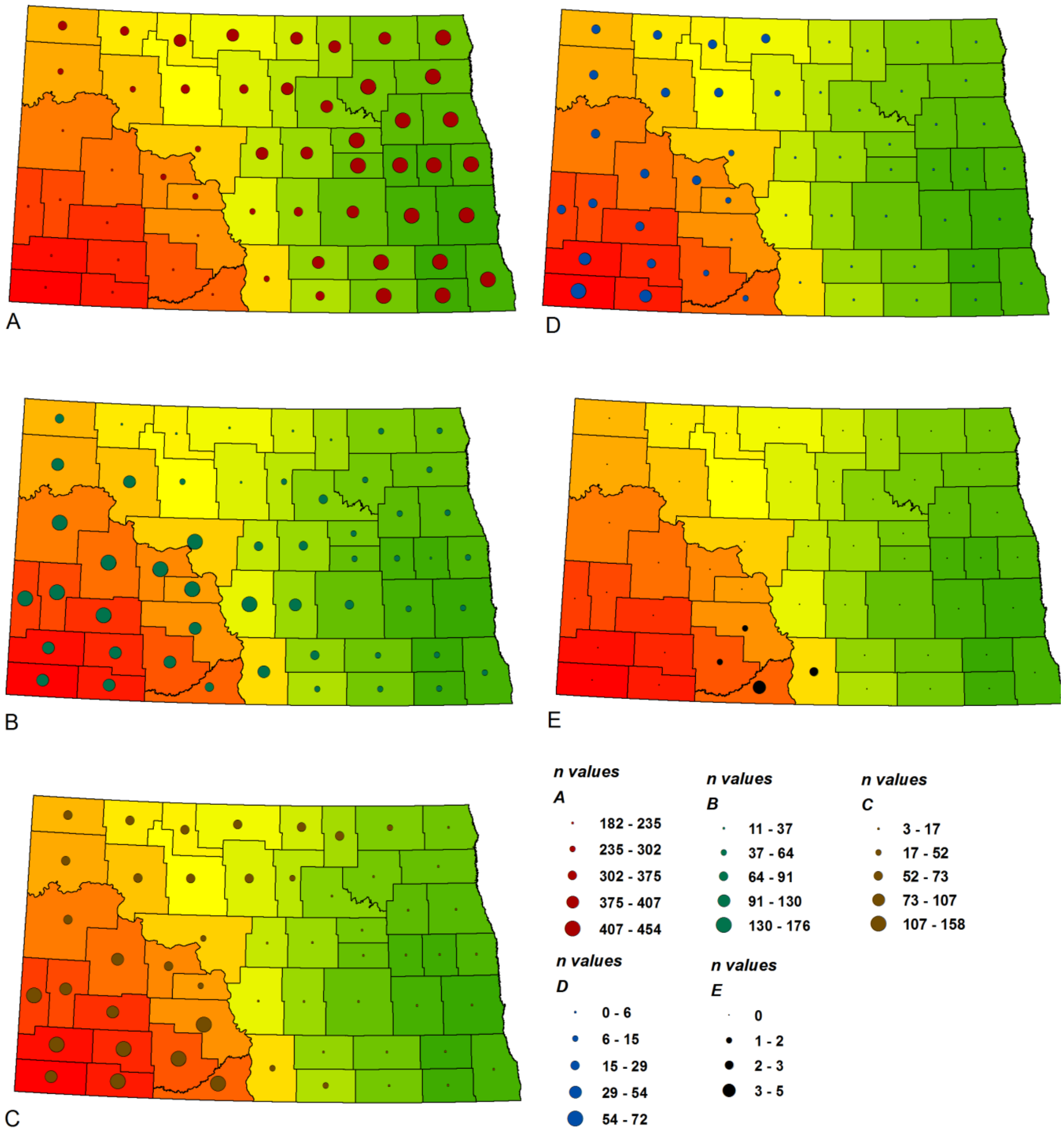
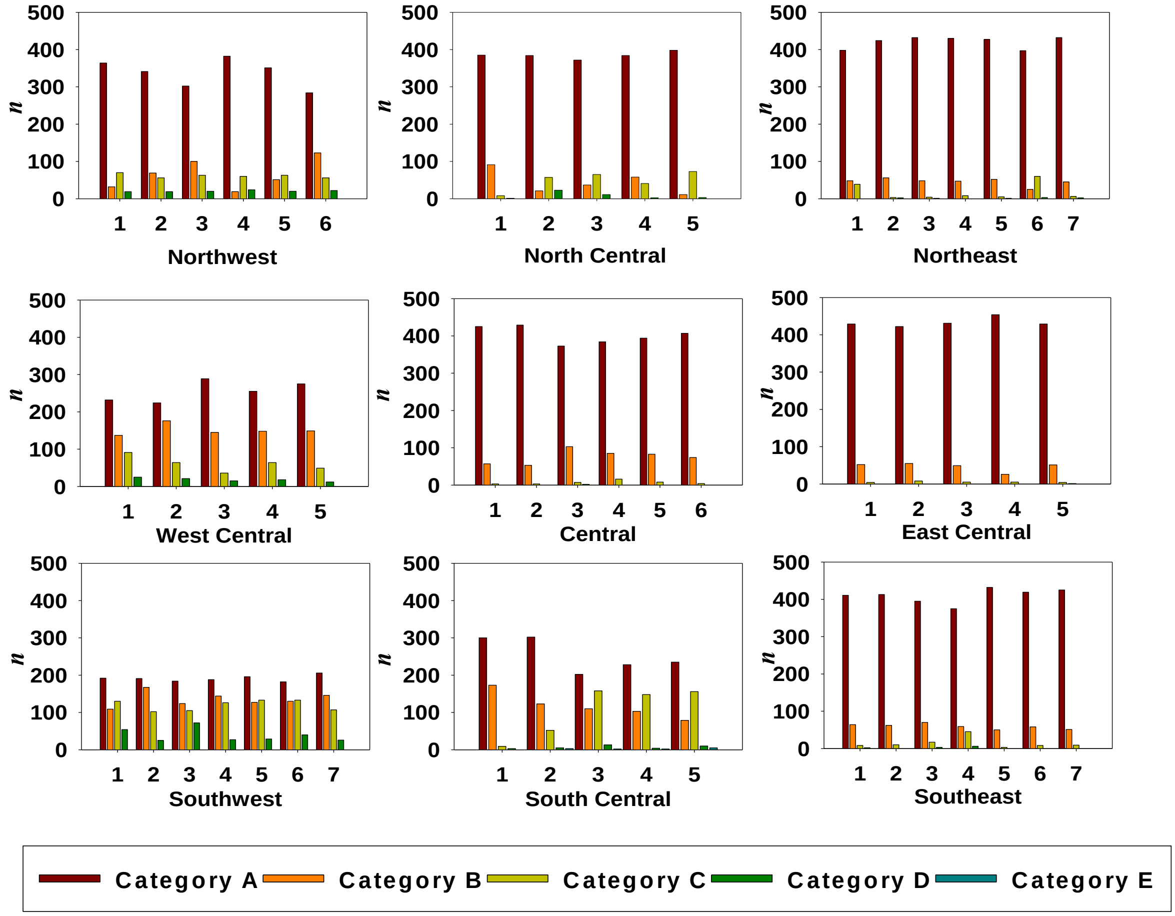


Figure 2.5: A, B, C, D and E depict class categories of $n_{(Isc \leq 100)}$, $n_{(100 < Isc \leq 200)}$, $n_{(200 < Isc \leq 300)}$, $n_{(300 < Isc \leq 400)}$, and $n_{(400 < Isc \leq 500)}$ respectively.



Northwest: 1-Burke,2-Divide,3-Mountrail,4-Renville,5-Ward,6-Williams **North Central:**1-Benson,2-Bottineau,3-McHenry,4-Pierce,5-Rolette **Northeast:**1-Cavalier,2-Grand Forks,3-Nelson,4-Pembina,5-Ramsey,6-Towner,7-Walsh **West Central:**1-Dunn,2-McKenzie,3-McLean,4-Mercer, 5-Oliver **Central:**1-Eddy,2-Foster,3-Kidder,4-Sheridan,5-Stutsman,6-Wells **East Central:**1-Barnes,2-Cass,3-Griggs,4-Steele,5-Traill **Southwest:** 1-Adams,2-Billings,3-Bowman,4-Golden Valley,5-Hettinger,6-Slope,7-Stark **South Central:**1-Burleigh,2-Emmons,3-Grant,4-Morton,5-Sioux **Southeast:**1-Dickey,2-LaMoure,3-Logan,4-McIntosh,5-Ransom,6-Richland,7-Sargent

Figure 2.6: Drought occurrences of each category for nine climate divisions of North Dakota.

2.5.2. Drought Index – Crop Yield Relationship

2.5.2.1. Statistical Relationship between Yield and Drought

From table 2.2, randomized two way block statistical results show that drought (I_{SC}) values had significant impact on yield for all crop types. The P-values from Eq. (2.4), for barley, corn (for grain), hay (alfalfa), hay (all), oats, durum wheat and spring wheat approach zero. Estimated parameters (β_1) explain the impact of drought for each crop, for example there will be an estimated 0.0848 bushel/acre loss in yield if there is one unit increment in $AvgI_{SC}$. Estimated parameters (β_0) present the estimated yield if there is no drought ($AvgI_{SC} = 0$). The R^2 values indicate the percentage of variation in yield explained by I_{SC}. For example, 24.35 % of variation in barley yield can be explained by I_{SC}. The developed regression model only estimates the influence of drought on crop yield. However, the crop yield also depends on other variables such as soil characteristics, and management practices. A comprehensive model should account for all the variables that influence the yield. In this study, the average values (first moment) of drought indices between planting and harvesting were used to represent the drought condition. Though it is not done in this study, variance (second moment) of drought indices between planting and harvesting also could have been used as a variable in the model.

Table 2.2: Estimated parameters, P-values and R-square.

Commodity	Estimated parameter (β_0)	Estimated parameter (β_1)	P-Value	R-Square (%)
Barley	59.276	-0.0848	0.000	24.35
Corn for Grain	95.265	-0.0867	0.000	7.16
Hay Alfalfa (Dry)	2.258	-0.0031	0.000	10.00
Hay All (Dry)	1.938	-0.0023	0.000	10.32
Oats	63.831	-0.1035	0.000	21.24
Durum Wheat	35.259	-0.0669	0.000	23.33
Spring Wheat	38.73	-0.0672	0.000	25.73

2.5.2.2. Crop Specific Drought Severity-Coverage Index ($I_{SC,AG}$)

Table 2.3 lists necessary possible coefficient combinations derived from Eq. (2.2). Negative values suggest that yield reduces with increasing drought severity as expected. Even though estimated parameters display P-values less 5% level, for some crops drought intensity categories are not key drivers for estimating yield. For example, P-value for corn at D0 (abnormally dry) is 0.579 which implies that for D0, drought does not have significant impact on yield of corn. To improve (I_{SC}) it is possible to adopt ($I_{SC,AG}$) (Eq. 2.3) with derived coefficients from table 2.3.

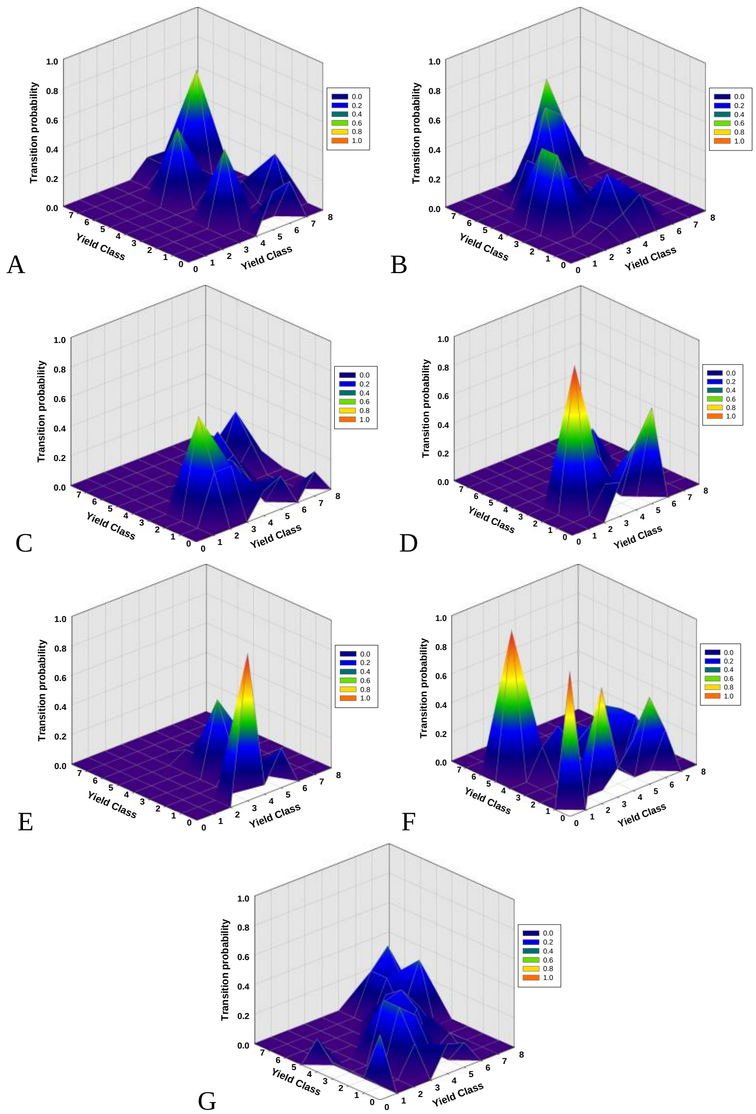
2.5.2.3. Transition Probabilities

Figure 2.7 shows transition probabilities for derived sub-periods from ($I_{SC,AG}$) (Eq. 2.3) and crop yield values: (i) 2001 (wet year) and 2008 (dry year) for (A) barley, (B) spring wheat, (C) hay (alfalfa), (D) hay (all); and (ii) 2001 (wet year) and 2006 (dry year) for (E) oats, (F) durum wheat, and (G) corn. Listed class ranges for each crop is also displayed. Two dry seasons were ascertained for crops analysed, that is, 2006 and 2008; and 2001 was the wet year. From Figure 2.7 (A) the probability of barley yield transiting from 64.4 - 72.9 bushels/acre to 55.8 - 64.3 bushels/acre is null, and from 64.4 - 72.9 bushels/acre to 22.3 - 29.8 bushels/acre is 0.33. It is interesting to note that the probability of spring wheat transiting from higher yield to lower yields is relatively low (Figure 2.7 (B)). Probability of hay (Alfalfa) transiting from a range of 3.47 - 3.96 (tons/acre) to 2.47 - 2.96 (tons/acre) is 0.33; for all other decreased yields variation the probability ranged from 0.07 to 0.28 (Figure 2.7 (C)).

The highest likelihood of hay (All) transiting to a lower value is 0.67 for transiting from a range of 2.17 - 2.57 (tons/acre) to no yield at all (Figure 2.7 (D)). From Figure 2.7 (E), the likelihood of oats transiting from a yield range of 35.2 - 47.0 bushels/acre to no yield is 1.00. From Figure 2.7 (F), there exists an equal probability of durum wheat transiting from yield class range of 39.8 - 46.0 bushels/acre to no yield, 14.8 - 21.0 bushels/acre, and 21.1 - 27.2 bushels/acre. Corn on the other hand during the sampled period is more likely to move from higher yields to lower yields during severe drought (Figure 2.7 (G)). In this study it is prudent to leverage drought severity as pertaining to specific crops in order to forecast what yield values can be expected from data extremes from a sample set.

Table 2.3: Estimated coefficients and P-values.

Commodity	Intercept		AvgD0		AvgD1		AvgD2		AvgD3		AvgD4		R^2
	α_0	P-Value	α_1	P-Value	α_2	P-Value	α_3	P-Value	α_4	P-Value	α_5	P-Value	
Barley All	58.630	0.000	-0.074	0.009	-0.104	0.000	-0.309	0.000	-0.321	0.000	-4.914	0.005	25.3
Corn	93.934	0.000	-0.027	0.579	-0.235	0.000	-0.100	0.201	-0.483	0.000	-7.788	0.036	9.5
Hay Alfalfa (Dry)	2.474	0.000	-0.008	0.000	-0.009	0.000	-0.011	0.000	-0.019	0.000	-0.040	0.600	13.0
Hay All (Dry)	2.069	0.000	-0.006	0.000	-0.007	0.000	-0.007	0.000	-0.014	0.000	-0.074	0.164	13.3
Oats	62.886	0.000	-0.072	0.057	-0.204	0.000	-0.251	0.000	-0.487	0.000	-346.800	0.088	21.9
Durum Wheat	35.741	0.000	-0.088	0.000	-0.129	0.000	-0.208	0.000	-0.259	0.000	-174.681	0.113	24.3
Wheat Spring	37.432	0.000	-0.029	0.147	-0.099	0.000	-0.176	0.000	-0.311	0.000	-0.497	0.220	27.6



Yield Class	barley (bushels / acre)	Corn (bushels / acre)	Durum wheat (bushels / acre)	hay Alfalfa (tons / acre)	hay (tons / acre)	oats (bushels / acre)	Spring wheat (bushels / acre)
1	12.6 - 21.2	22.5 - 39.3	8.5 - 14.7	0.47 - 0.96	0.51 - 0.92	11.3 - 23.2	7.0 - 14.5
2	22.3 - 29.8	39.4 - 56.2	14.8 - 21.0	0.97 - 1.46	0.93 - 1.33	23.3 - 35.1	14.6 - 22.0
3	29.9 - 38.4	56.3 - 73.0	21.1 - 27.2	1.47 - 1.96	1.34 - 1.74	35.2 - 47.0	22.1 - 29.5
4	38.5 - 47.1	73.1 - 89.9	27.3 - 33.5	1.97 - 2.46	1.75 - 2.16	47.1 - 59.0	29.6 - 37.0
5	47.2 - 55.7	90.0 - 106.8	33.6 - 39.7	2.47 - 2.96	2.17 - 2.57	59.1 - 70.9	37.1 - 44.5
6	55.8 - 64.3	106.9 - 123.6	39.8 - 46.0	2.97 - 3.46	2.58 - 2.98	80.0 - 82.8	44.6 - 52.0
7	64.4 - 72.9	123.7 - 140.5	46.1 - 52.2	3.47 - 3.96	2.99 - 3.39	82.9 - 94.7	52.1 - 59.5
8	80.0 - 81.6	140.6 - 157.4	52.3 - 58.5	3.97 - 4.46	3.40 - 3.81	94.8 - 106.7	59.6 - 67

Figure 2.7: Transition probability variation for the sub-periods.

2.6. Conclusions

In this study, two county-level weekly indices - Drought Severity and Coverage Index (I_{SC}) based on USDM data, and $I_{SC,AG}$ a unique county-level drought index for each crop based on impact of drought intensity categories - were proposed and investigated for their applicability. The results demonstrated that the southwestern counties of North Dakota, U.S., may be more prone to drought and require Best Management Practices (BMPs) to address future drought impacts. Agricultural productivity of the eastern counties within North Dakota may be further increased since these counties do not display higher drought severity indices or frequency of drought occurrences.

Input from $I_{SC,AG}$ were used to model transition probabilities of various crop yield response from a period of wetness to dry for a pulsed-time interval. Crops like corn, durum wheat and hay (all) display greater tendency to transit to lower yields in response to severe drought whereas probability of spring wheat transitioning from higher yield to lower yields is relatively low. This study modeled crop yield as a first order Markovian process with spatial and temporal variation where temporal extremes were used to detect yield response to periodic dryness. The proposed indices I_{SC} and $I_{SC,AG}$ can be used to study drought occurrences at a county level, and to assess the crop yields and their susceptibility to drought respectively as this study demonstrated. These proposed indices will be very helpful also for drought administration purposes because drought response authorities struggle to declare county specific drought mitigation measures.

CHAPTER 3. DROUGHT OCCURRENCES AND THEIR CHARACTERISTICS ACROSS SELECTED SPATIAL SCALES IN THE CONTIGUOUS UNITED STATES

3.1. Introduction

A study of variation in severity, duration, frequency, areal coverage, and impact of drought events at different spatial scales will be helpful in understanding the mechanism of drought propagation and to plan for future drought events. There are many studies in the literature that address drought characteristics from different study areas. For example, spatiotemporal characteristics of drought for the U.S. using PDSI (Karl, 1983); spatiotemporal properties of droughts and their impacts in North Dakota, U.S. using a refined county-level drought index from USDM data (Leelaruban et al., 2012); spatial pattern of drought in Iberian Peninsula based on SPI using Principal Component Analysis (Vicente-Serrano, 2006); spatiotemporal variability of drought using SPI for central plains region of the U.S. (Logan et al., 2010); and drought characteristics in Serbia (Gocic and Trajkovic, 2014). However, none of these studies investigated the effect of spatial scale on drought characteristics. Only recently, some studies have been reported on this aspect. Russo et al. (2015) studied the effect of Circulation Weather Types (CWT) on variability of drought at different spatial scales in the Iberian Peninsula. Mishra and Singh (2011) summarized some of the studies on spatiotemporal drought analysis. Wang et al. (2014) listed selected drought studies on global, continental, and regional scales. They also studied the area and frequency of severe droughts on a global and continental scale using Standardized Precipitation Evaporation Index (SPEI). Panu and Sharma (2002) emphasized the need to study spatial behaviour of droughts at different spatial scales. It is possible that drought characteristics and mechanics of propagation may be different not only across different spatial scales in one region, but also across multiple scales in different geographic regions.

Focus of this part of the study was the pattern and frequency of occurrences of droughts, their spatiotemporal characteristics, and their variation over different spatial scales in the contiguous U.S. The USDM data form years 2000 to 2014 was used. The occurrences of droughts of different intensity categories, spatiotemporal propagation of drought at different spatial scales, and the characteristics of droughts under different spatial scales were analysed. The results could help identify the areas in contiguous U.S. that have been exposed to frequent and intense droughts in recent years, and potentially in the future; and also, identify the characteristics of different intensity categories from different spatial scales perspective.

3.2. Study Area and Data

USDM data on droughts is available to the public from the NDMC since the year 2000. This part of the study used USDM weekly percentage area coverage of different drought intensity categories (D0, D1, D2, D3, and D4) for the years 2000 to 2014. This study does not involve time series analyses in the strict sense except for comparison of yearly values in one of the components of the study. Spatial scales chosen for the study were national, regional, state, climatic division, and county. Contiguous U.S., High Plains Region (HPR), North Dakota (ND) State, South Central Climate Division (SCCD) in ND, and Grant County in ND were the areas selected to gauge drought characteristics variation under the selected spatial scales (Figure 3.1). Percentage area coverage values for different USDM drought intensity categories were derived for years 2000 – 2014 (15 years) from the USDM web portal for the areas representing the selected spatial scales.

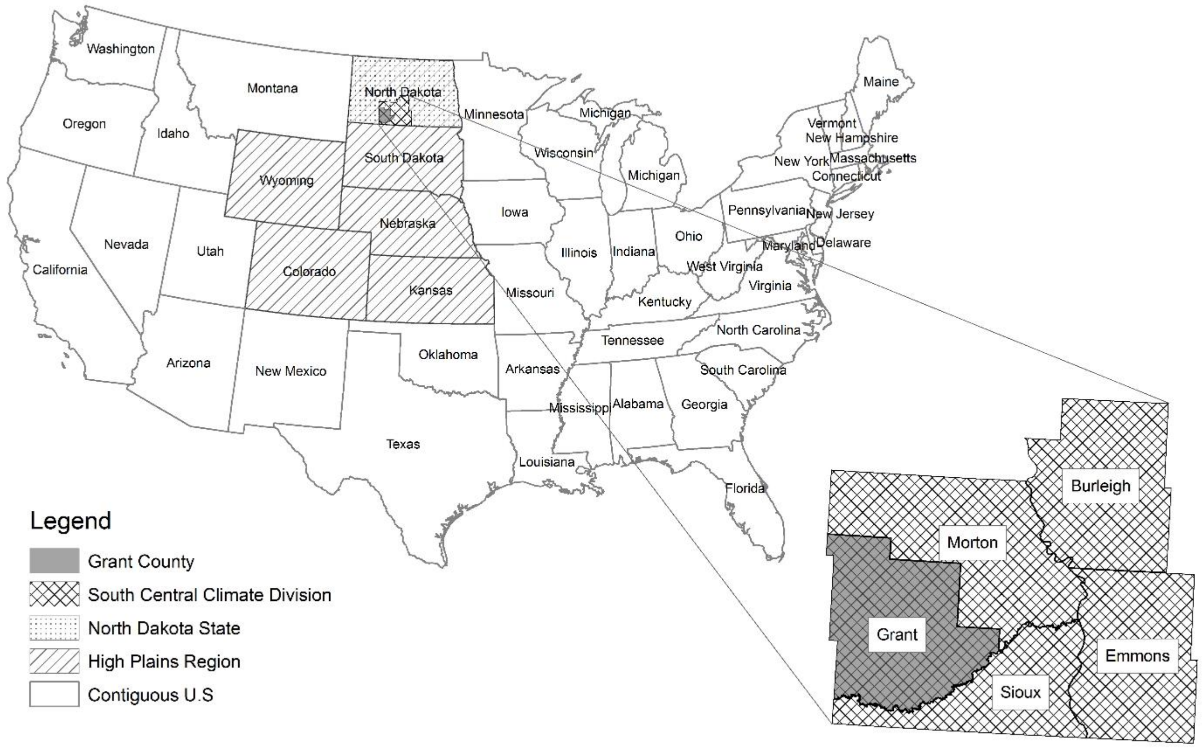


Figure 3.1: Spatial scales considered in this study.

3.3. Methods

3.3.1. Occurrences of drought in the contiguous U.S.

The contiguous U.S. has experienced several drought episodes during the study period (2000 – 2014). In this part of the study, the goal was to analyse the occurrences of different drought intensity categories. The weekly USDM GIS shapefiles were obtained from USDM web portal for years 2000 to 2014 and were used in ArcGIS10.3®. A series of batch commands were executed to clip the shapefiles into contiguous U.S., and extract areal extents pertinent to different USDM drought intensity categories (i.e., D0, D1, D2, D3, and D4).

The number of weeks that an area has been hit by D1, D2, D3, and D4 drought intensity category during years 2000 to 2014 was extracted first. It was decided not to include D0 because of two reasons: (i) due to the difficulty in processing a large number of multiple intersections (as subsequently described), and (ii) also D0 is an “abnormally dry” condition not significant enough in terms of its intensity to qualify for a “drought” condition. The following steps were implemented in ArcGIS 10.3® to count the number of weeks that an area has been hit by D1, D2, D3, and D4: (a) The “Union” tool was used to combine all 783 weekly shapefiles of selected intensity drought. (b) Weekly USDM shapefiles had several attributes including drought intensity category (DM). The final shapefile, after combining all 783 weekly data, contained all the attributes from 783 weekly files in different columns. Except for the attributes that indicated the drought category (DM) all the other fields were deleted. (c) The attribute table was exported to Microsoft EXCEL sheet and the *“countif”* function was used to count the number of drought occurrences within each feature. Each weekly shapefile for particular intensity had several polygonal features. The union of 783 weekly shapefile inputs created numerous features in the output as a result of multiple intersections (output of union for 783 weeks of D4, D3, D2, and D1 category droughts had 63453, 683381, 2115430, 38994466 polygon features respectively). Each feature had attributes from 783 input shapefiles which included the occurrences of drought categories. The attribute from output of union were exported to Microsoft Excel and number of occurrences were counted.

The drought coverage areas were also extracted for all intensity categories (D0, D1, D2, D3, and D4) on a yearly basis for the period 2000 to 2014. The D0 was included for this and following part of the analysis because an understanding of variation in areal coverages of D0 will help to understand the drought, and can be related to other intensity categories. The extracted drought intensity categories from the weekly data for each year were grouped, and spatially combined to get the yearly intensity coverage. The intensity coverages were mapped for each year from 2000 to 2014. The total area coverage queried was one that experienced a particular intensity of drought at least once/year in the contiguous U.S.

3.3.2. Drought characteristics across spatial scales in the U.S

The study also investigated how droughts evolve at five different spatial scales: contiguous U.S., HPR, ND State, SCCD in ND, and Grant County in ND. The areal coverage of weekly drought intensity categories was plotted with time for the study period (2000 – 2014). USDM also provides similar graphical plots based on their traditional statistics, which is a percent of an area that is in or worse than a certain drought category. However, the purpose of this part of the study was to analyse how areal extent of different intensity categories evolved with different spatial scales. Spatiotemporal behaviour of the drought during the period December 20, 2005 to October 23, 2006 (44 weeks) was further investigated. This was one of the periods in which all intensity categories occur at least in some part of the contiguous U.S., and for all spatial scales considered.

Based on years 2000 - 2014 (783 weeks) of USDM weekly data, the drought characteristics for different spatial scales: contiguous U.S., HPR, ND State, SCCD in ND, and Grant County in ND were derived. The following drought characteristics were extracted:

3.3.2.1. Number of events

A drought event was defined as the occurrence of “greater than zero” drought intensity coverage anywhere in the considered area in any week during the study period. However, occurrences in consecutive weeks were considered as one event. Total number of drought events for the different intensity categories (D0, D1, D2, D3 and D4) were determined.

3.3.2.2. Total duration

The total number of weeks (not necessarily consecutive) in the study period in which the area covered by different intensity categories (D0, D1, D2, D3 and D4) were greater than zero.

3.3.2.3. Maximum duration

This was the maximum number of consecutive weeks that were subject to a drought event as defined previously. This was extracted for each drought intensity category (D0, D1, D2, D3 and D4).

3.3.2.4. Minimum, maximum, and average percentage area coverage

Minimum and maximum weekly percentage area coverage of different drought intensity categories (D0, D1, D2, D3 and D4) were identified over the study period. The average of weekly percentage area coverage was also calculated for different intensity categories over the study period, that is, 2000 to 2014.

3.4. Results and Discussion

3.4.1. Drought occurrences in the contiguous U.S.

Drought occurrence (in number of weeks) in the contiguous U.S. is shown in Figure 3.2. Fig. 3.2 shows the distribution of drought occurrences for intensity categories D4, D3, D2, and D1 during years 2000 to 2014 (783 weeks). Mapping the occurrences of drought using USDM data helps identify the areas that are vulnerable to droughts. In the contiguous U.S., during years 2000 to 2014 about half of the (51.7%) area had experienced D4, and almost the entire area (99.8%) had D1 at least once (Figure 3.2). D2 and D3 drought occurred at least once in 86.4% and 97.4% of the area respectively. The southern part of the contiguous U.S. has experienced all intensity droughts in the study period, and some areas including areas in north-eastern part have been free of high intensity droughts (D4 and D3). Each drought occurrence had different spatial pattern. Parts of several counties Wilbarger, Wichita, and Baylor in Texas; and Tillman in Oklahoma experienced with a range of 168-156 weeks (out of 783 weeks) D4 intensity drought (Figure 3.2). Other areas affected by D4 at least 96 weeks during years 2000 to 2014 can be found in Colorado, Idaho, Montana, New Mexico, Oklahoma, Texas, and Utah states (Figure 3.2). Frequent occurrences of D3 are mostly in western U.S. Parts of counties: Pershing and Humboldt in Nevada; and Apache in Arizona experienced D3 drought between 223 to 231weeks out of 783 weeks. The areas that had been hit by D3 more than 130 weeks during years 2000 to 2014 can be found in Alabama, Arizona, Colorado, Georgia, Idaho, Kansas, Montana, Nebraska, Nevada, New Mexico, Oklahoma, Oregon, South Carolina, South Dakota, Texas, Utah, Wyoming states (Figure 3.2).

D2 occurred mostly in the western part of the U.S similar to D3. Parts of Arizona, California, Nevada, and Oregon states have been in D2 condition at least 312 weeks out of 783 weeks (Figure 3.2). Figure 3.2 also shows that most of the eastern states were in D2 less frequently. Some areas in Ohio, New York, Pennsylvania, Vermont, and West Virginia have never been under a D2 drought. Occurrences of D1 can be seen almost in the entire contiguous U.S. Some parts of Nevada, and Oregon were in D0 at least 335 weeks out of 783 weeks (Figure 3.2).

Overall, the western part of the US experienced droughts frequently compared to the east (Figure 3.2), however, spatial patterns of occurrences varied significantly. For example, Alabama was the only state that was in D4 entirely at least once during years 2000 to 2014 but with relatively less frequency, whereas parts of Oklahoma and Texas were in D4 category very frequently. Some parts of Colorado were in D4 category frequently whereas some parts have never experienced D4. The characteristics of drought can be understood and/or interpreted differently observing from different spatial scales perspective. For example, southeast part of Colorado is exposed to higher intense drought frequently compared to the north central part of the state. Considering the value of drought index reported for the state, it is possible that the reported value may reflect the drought condition differently for each state. One may get a completely different picture of the drought conditions from the state level compared to a county or climate division. The drought information of a smaller area such as at the county extents could be masked when the drought is reported at the state level.

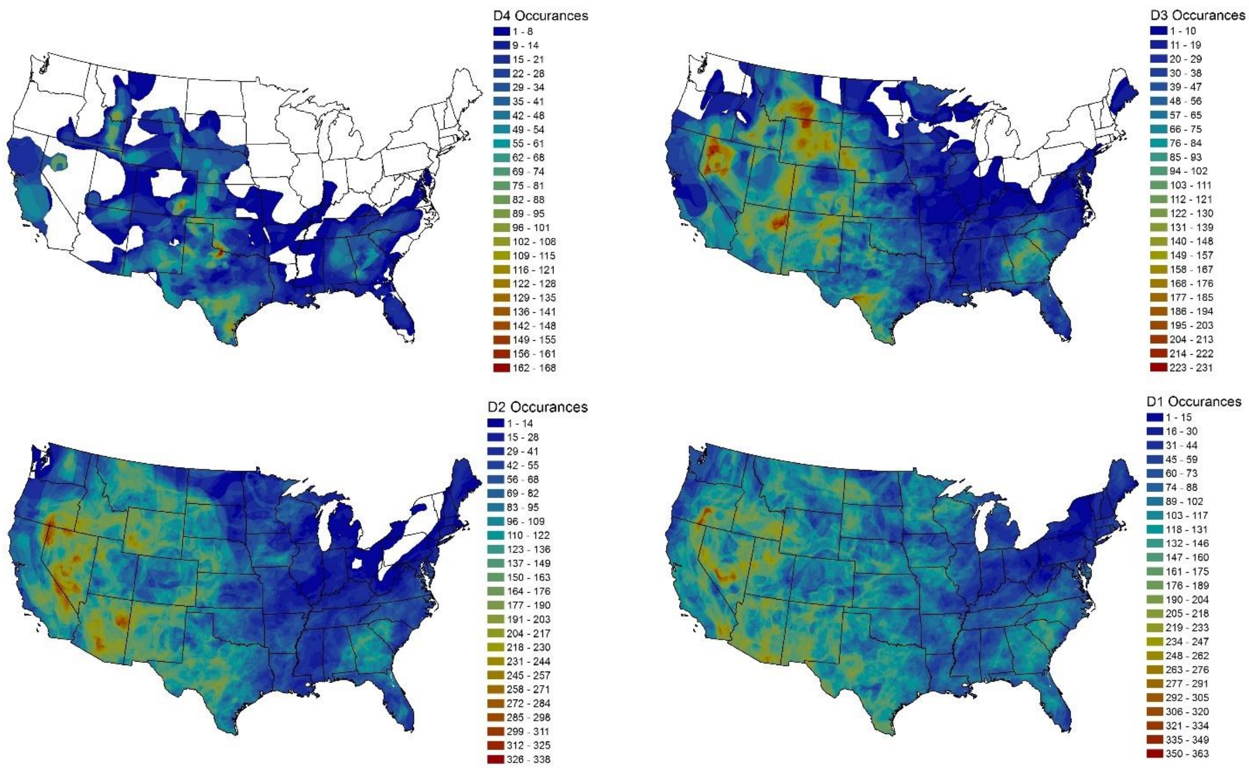


Figure 3.2: Drought occurrences (in weeks) of intensity categories D4, D3, D2, and D1 during the years 2000 through 2014 (783 weeks).

The variation of areal coverage of droughts in the contiguous U.S. on an annual basis was also analysed. The percentage area covered by different drought intensity categories for each drought during specific years are tabulated in Table 3.1. In the contiguous U.S., 16.9 % of the area experienced exceptional drought (D4) at least once in the year 2012 whereas none of the areas had D4 in 2010. In 2012, the extreme drought (D3) occurred in 42.6 % of the area at least once, and only 4.4 % area had D3 in 2010. The percentage areal coverage ranges for severe drought (D2) from 67.5 in 2012 to 20.1 in 2009, moderate drought (D1) 81.6 in 2012 to 42.8 in 2014, abnormally dry condition (D0) 91.2 in 2001 to 62.6 in 2014. Figure 3.3 shows the highest intensity drought that an area has experienced for each year from 2000 to 2014 in the U.S.

Table 3.1: The percentage areal coverage of different drought intensity categories in the contiguous U.S.

Year	Drought intensity categories				
	D4	**D3**	**D2**	**D1**	**D0**
2000	6.2	17.8	43.7	70.8	90.1
2001	0.8	16.6	41.0	63.2	91.2
2002	12.3	38.3	58.7	77.5	90.1
2003	7.4	34.5	53.5	58.4	63.0
2004	5.4	23.0	36.4	46.1	63.0
2005	2.4	14.5	37.6	64.0	90.3
2006	5.6	27.7	49.0	68.4	82.8
2007	6.2	24.1	50.8	70.5	89.0
2008	4.2	12.5	36.5	60.4	80.9
2009	2.2	5.7	20.1	47.5	78.1
2010	0.0	4.4	22.5	54.1	86.6
2011	16.1	24.3	33.9	47.6	70.3
2012	16.9	42.6	67.5	81.6	83.9
2013	11.7	33.5	58.5	66.6	72.0
2014	7.3	19.0	31.8	42.8	62.6

Although the total areal coverage may be the same in different years, it may be distributed differently in those years (Figure 3.3). For example, in the year 2011 and 2012, the total percentage area coverage of D4 intensity is 16.1 and 16.9 respectively (Table 3.1). It is spread out in 2012 whereas in 2011 it is concentrated in one region (Figure 3.3). This type of spatial characteristics of drought significantly influences drought management and resource allocation, and emphasizes the need of addressing drought at different spatial scales. Also from

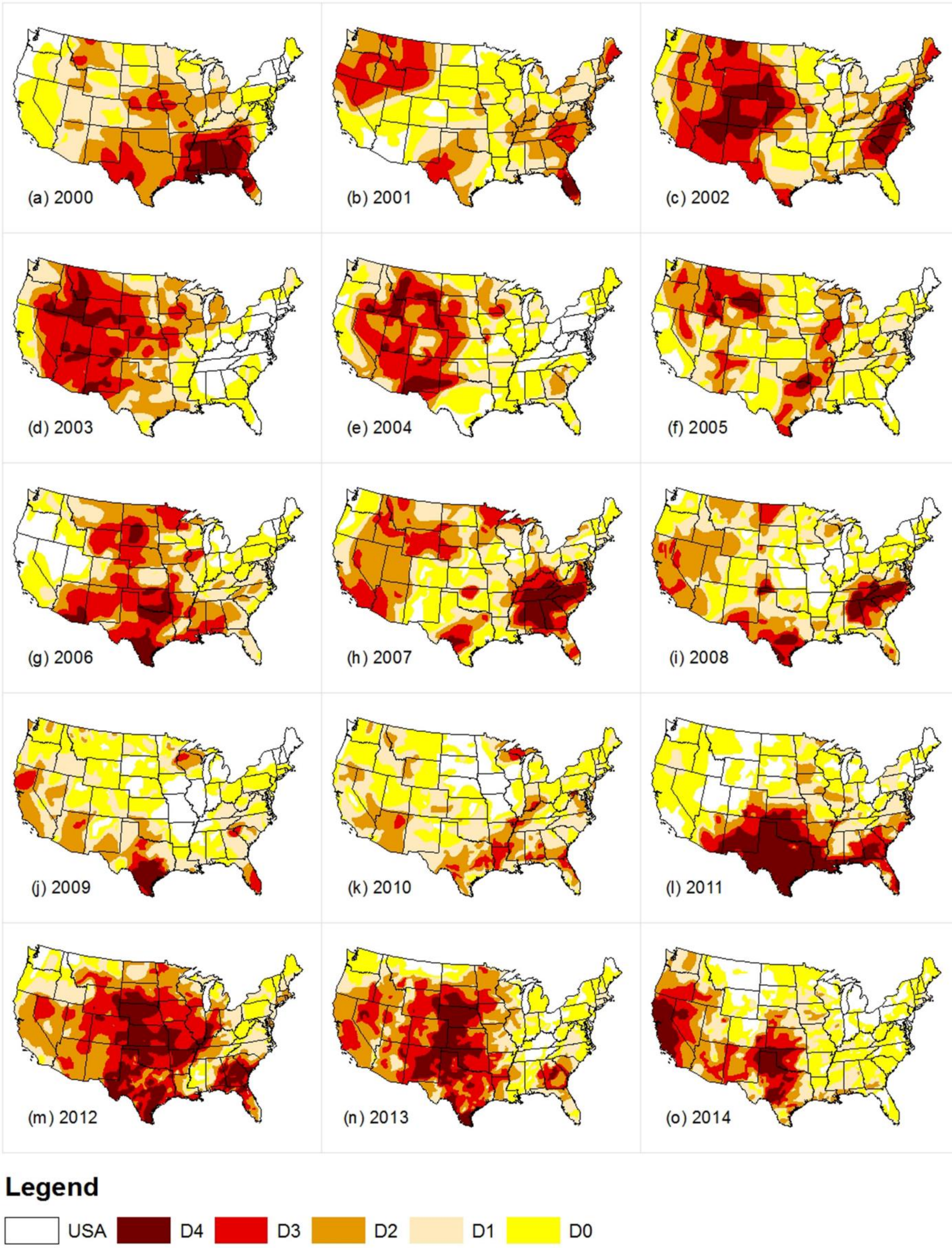


Figure 3.3: Areal coverage of the highest intensity of drought that an area experienced for years 2000 – 2014.

these yearly maps, the progression and onset of intensifying drought in the state of California can be seen in the years 2011 and 2014. In Texas D4 intensity drought occurred in the years 2009 and 2011, but not in 2010.The maps in Figure 3.3 are helpful in extracting information of this type of areal extent and pattern of droughts over the years in a region. In general, the contiguous U.S. was covered by higher intensity droughts in 2012 whereas in 2010 had less coverage by higher intensity droughts. Over the study period, occurrence of drought in the contiguous U.S. varied spatially, and a state like Texas had repeatedly experienced higher intensity drought.

3.4.2. Spatial propagation of drought intensity categories across spatial scales in the U.S.

Figure 3.4 (a-e) shows how the areal extent of different intensity categories evolved at different spatial scales. In HPR and contiguous U.S. scales, several long episodes of drought can be seen at different intensity levels (Figure 3.4d-e). The onset, progress and termination of drought were gradual for larger scales such as HPR and contiguous U.S. However, it can be seen from Figure 4 a-c that for the smaller scales, the duration of certain intensity drought was short and had sudden onset and termination. At the greater spatial scales, it was observed that the dynamics were smoother than those observed for the smaller spatial scales. This may be because at the greater spatial scale, i.e. at the contiguous U.S. scale, when a given sub-area changes its intensity category (e.g. from D3 to D2), another sub-area could assume D3 category, leading to a diminished D3 areal coverage. This occurrence becomes more and more unlikely as the spatial scale decreases due to more homogenous hydrological conditions allowing sudden variations of the area coverage of certain drought intensity. Recognition of this feature is important from a drought management perspective across scales because the small scales are subject to sudden drought and can be unnoticed at larger spatial scales.

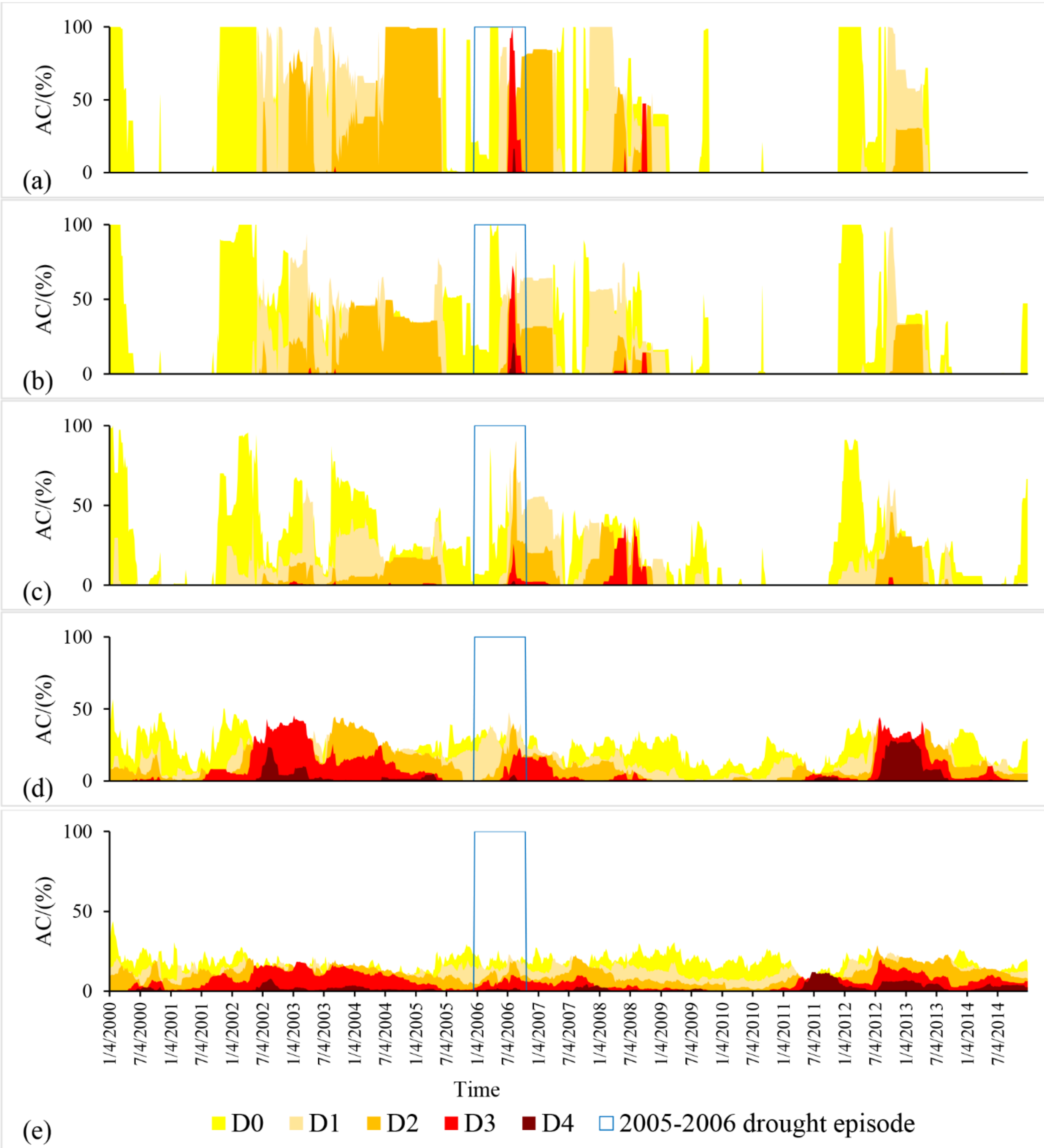


Figure 3.4: Propagation of areal coverage (AC) of different intensity category droughts over (a) Grant county, ND (b) SCCD, ND, (c) ND State (d) HPR, and (e) Contiguous U.S.

From the Figure 3.4 it can be seen that the Dec 20, 2005 to Oct 23, 2006 shown in box, was the only period where all the categories were present in all spatial scales considered. D4 occurred at least in some part of the contiguous U.S throughout the 44 week period, and D4 existed 8 weeks in HPR, 5 weeks in ND, 5 weeks in SCCD in ND, and 2 weeks in Grant County in ND.

Figure 3.5 (a-e) shows the area that had experienced drought at least once during Dec 20, 2005 to Oct 23, 2006 period (44 weeks) at different intensity levels. Figure 3.5(f) shows the highest intensity drought that an area has experienced within the same time frame. The areal coverage maps show that more intense droughts (D4 and D3) occur as spatially disjointed areas, and less intense droughts were spatially connected. It should be noted that the coverage was for the whole 44 weeks drought period considered, and might not be spatially connected at any given week. The spatiotemporal features of drought propagation significantly change with spatial scale. A same drought may appear to have different characteristics when viewed at different spatial scales, and that need to be considered in drought management.

3.4.3. Characteristics of droughts across spatial scales in the U.S.

Figure 3.6 shows the characteristics of drought occurrences of different USDM intensity categories and at different spatial scales in the U.S.: number of drought events, total and maximum duration, and maximum, average, and minimum areal coverages. From the number of events and total duration it can be concluded that at any given time in the time frame (2000 – 2014), at least some part of contiguous U.S. experienced; no drought (None), D0, D1, and D2 conditions (Figure 3.6a-b). Extreme drought (D3) and exceptional drought (D4) drought persisted continuously 269 and 196 weeks respectively in the contiguous U.S. to their maximum duration (Figure 3.6c). Contiguous U.S. experienced D3 drought for 751 weeks out of 783 weeks, as three separate events, D4 drought 590 weeks out of 783 weeks as nine different events (Figure 3.6a-b).

The High Plains Region experienced the D0 condition throughout the study period. The "None" condition occurred 771 weeks in the region while D4 condition existed 332 weeks with

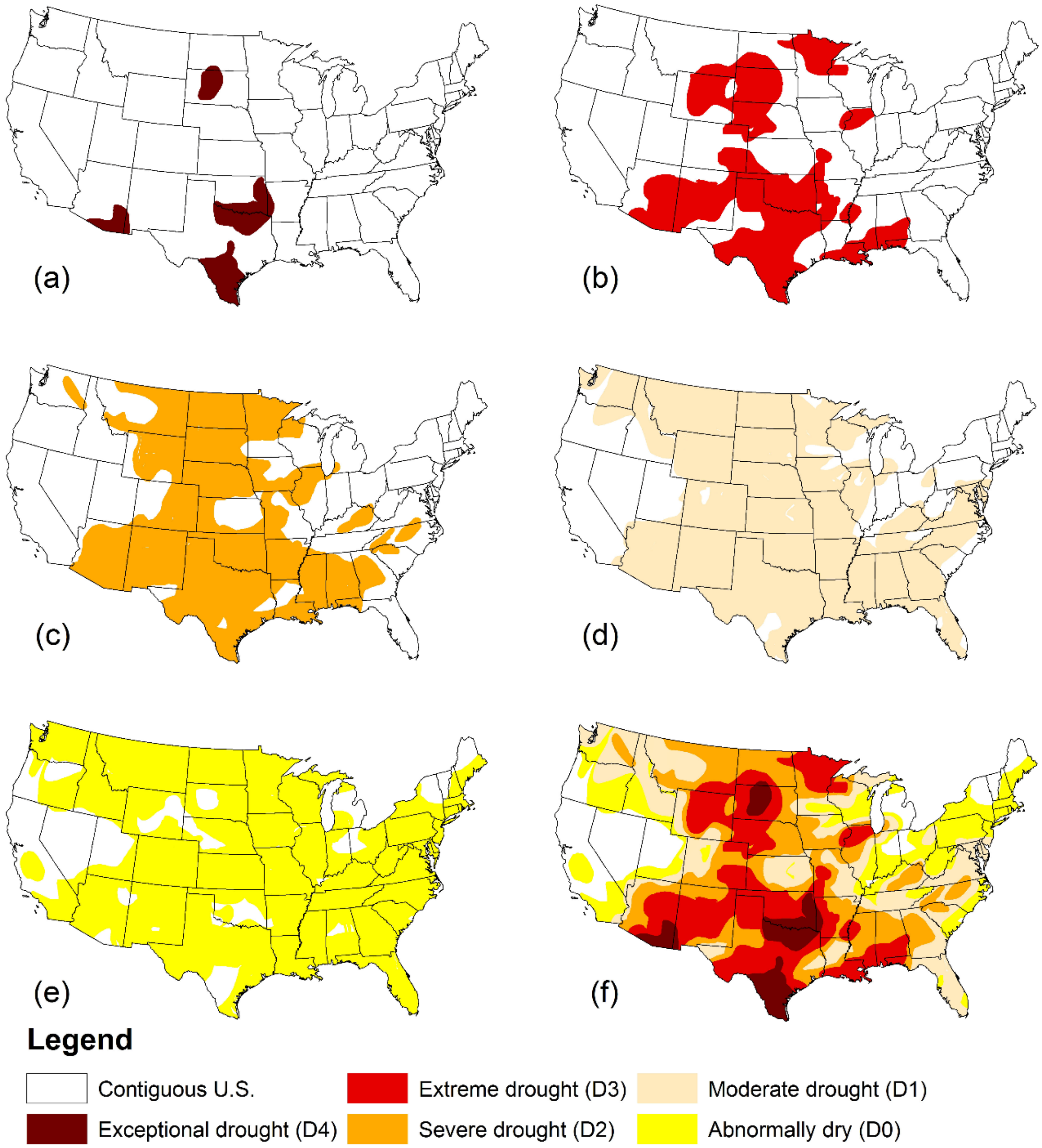


Figure 3.5: Areal coverage of drought during Dec 20, 2005 - Oct 23, 2006. (a) exceptional drought (D4), (b) extreme drought (D3), (c) severe drought (D2), (d) moderate drought (D1), (e) abnormally dry (D0), and (f) all categories.

the maximum duration of 154 weeks (Figure 3.6b-c). The North Dakota state experienced the absence of all drought conditions at least once in the past (Figure 3.6b,f). The state had its 100 % of area covered by “None” and D0 conditions at their maximum coverages (Figure 3.6d). The state has experienced the D4 category only once for a duration of 5 weeks with a maximum areal coverage of 2.4 % (Figure 3.6a-d). The South Central climate division in ND experienced the “None” condition for 539 weeks, and has experienced the D4 condition only for about 5 weeks as a single event with a maximum coverage of 21.32 % (Figure 3.6a-d). The Grant County in ND is covered 100% by None, D0, D1, D2, and D3 conditions at their maximum coverages (Figure 3.6d). The county experienced the D4 condition only once for a 2 weeks period with the maximum coverage of 16.36% (Figure 3.6c-d).

The number of events for D0 condition appears as increasing from a larger spatial scale to smaller spatial scale. However, for all other drought conditions numbers of events do not show any relation with spatial scales (Figure 3.6a). The total and maximum duration for all conditions are decreasing from larger to smaller spatial scales (Figure 3.6b-c). It was an expected observation since smaller spatial scales are subset of larger spatial scales. The average areal coverage of drought conditions did not show any trend with spatial scales (Figure 3.6e). The maximum percentage area coverages were increasing from the larger spatial scales to smaller spatial scales for “None”, D0, and D1 conditions (Figure 3.6d). All the spatial scales had been free of D4 and D3 at least once as seen in the minimum area percentage coverage. All the spatial scales except contiguous U.S had been totally covered by D0 or higher intense drought at least once (i.e., zero percentage covered by “None”) whereas contiguous U.S 80.75% covered by D0 or higher intense drought at least once (i.e., 19.25% covered by “None”). The minimum percentage area coverages of D0 for the contiguous U.S and HPR were 5.42% and 0.38%

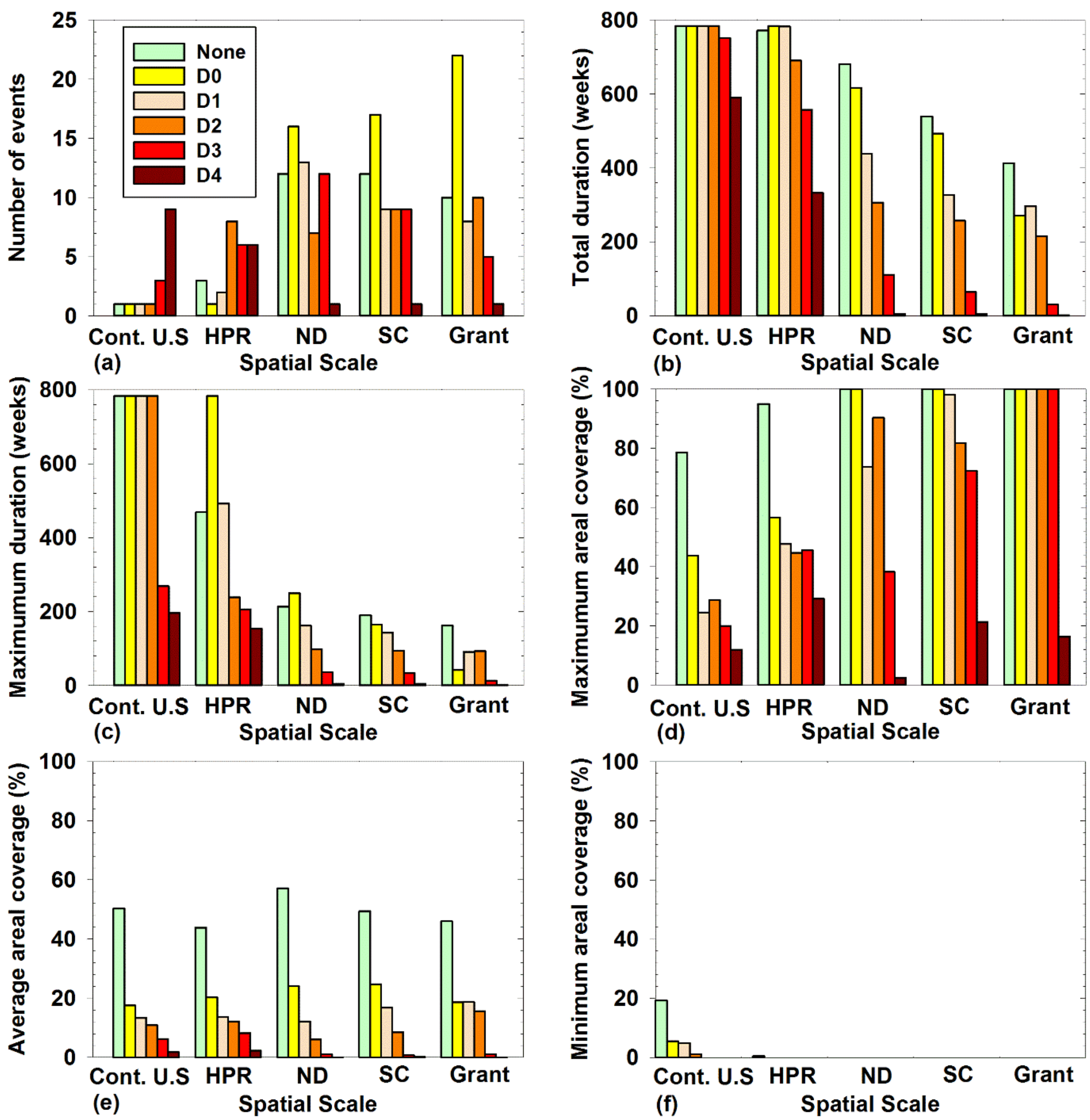


Figure 3.6: Comparing spatial scales with: (a) number of events, (b) total duration (weeks) (c) maximum duration (weeks) (d) maximum areal coverage, (e) average areal coverage, and (f) minimum areal coverage for each intensity category and "none" condition.

respectively. The other spatial scales were devoid of D0 category at least once. A section of contiguous U.S. was covered by D1 and D2 categories, at 4.80% and 1.08% areal extents respectively, and all the other spatial scales were free of D1 and D2 at least once. In general, the minimum areal percentage coverages are decreasing towards the smaller spatial scales (Figure 3.6f).

3.5. Conclusion

This study shows that southern and western parts of contiguous U.S. experienced higher intense drought frequently whereas northeast part less frequently. A combination of hydro-climatology and management practices of those areas could be the driver for the obtained spatial distribution and frequency of droughts. The spatial distribution of areal coverage of droughts of different intensities also varied significantly from year to year. The propagation of different intensity drought shows dissimilar patterns across different spatial scales. Depending on the size of the governing unit such as a county or state, an understanding of this scale-dependency is important for drought management and resource allocation.

The spatiotemporal characteristics of drought under different spatial scales show that the total duration, average percentage area, and maximum percentage areas are decreasing with increasing intensity for all spatial scales; and in the smaller spatial scale, the drought persists for a smaller duration compared to larger spatial scale. There have been discussions about appropriate temporal scale for reporting drought. It may be useful to consider a finer temporal scale for smaller spatial scales and larger temporal scaling for larger spatial scales. This study demonstrates that there is clear variation in the drought characteristics such as intensity coverage, duration, and occurrence at different spatial scales. The findings emphasize that drought management and resource allocation policies need to be developed for different spatial scales, even for smaller administrative units such as a county. In order to manage drought impact in any administrative areal unit in any geographic location better, the dependence of drought characteristics on spatial scales need to be studied at that location to derive drought characteristics appropriate for that scale.

CHAPTER 4. UNCERTAINTY IN DROUGHT REPORTING ACROSS DIFFERENT SPATIAL SCALES

4.1. Introduction

Drought is a spatially and temporally varying natural hazard. It is crucial to understand both the spatial and temporal characteristics of droughts and the uncertainty involved in the computations used for reporting of drought conditions for effective drought management and for developing mitigating measures. The characteristics of droughts are mostly studied using drought indices that represent the drought condition of specific spatial units (e.g., state, climate division, county, and watershed). For example, Karl (1983) reported spatiotemporal characteristics of drought for the U.S. using state-wide PDSI; Hayes et al. (1999) investigated the 1996 drought in the U.S. using the climate division scale SPI; variation of droughts and their impacts are studied in North Dakota, U.S. using a refined county-level drought index from U.S. Drought Monitor data (Leelaruban et al., 2012). An integrated multivariate standardized drought index (i.e. standardized Palmer drought index-based joint drought index, SPDI-JDI) was developed by Ma et al. (2015), and evaluated at the climate division scale in Texas, U.S. Fontaine et al. (2014) investigated the drought plan and program from Western States of the U.S., and found that most of the states use defined spatial unit such as watersheds or climate divisions to assess droughts. However, the concerns of reporting droughts in such coarse scale has been discussed by many researchers (Duncan et al., 2015; Fontaine et al., 2014; Svoboda et al., 2015). Duncan et al. (2015) stressing the need of high spatial resolution data for drought planning and management. They showed the differences in PDSI between climate division and 0.5° by 0.5° latitude/longitude resolution scales for the Pacific Northwest U.S. Svoboda et al. (2015) argued that it is necessary to have the drought information at a finer spatial scale even though information at course scale such as climate division is useful for a generalized perspective.

Drought is a geospatial phenomenon. Even though it is appropriate to consider drought as a regional phenomenon for administrative or management purposes, it is necessary to study the spatial characteristics of droughts in detail to get a clear understanding of this phenomenon. Typically, drought indices are reported for different governing units (county, climate division, watershed, etc.) based on computations using meteorological and hydrological data obtained from individual stations. The computation for reporting involves interpolation and aggregation of the data for specific spatial units which will introduce uncertainty in the reported products. The users of drought monitoring products must be aware of such uncertainty; but Dow et al. (2009) noted that even many savvy users did not fully recognize the uncertainty created by interpolation and aggregation of drought information in “local” maps.

Spatial data interpolation is a vital part in drought monitoring and reporting. Deterministic and geostatistical techniques are the two types mainly used for spatial interpolation. The deterministic techniques are solely based on deterministic mathematical functions whereas geostatistical techniques utilize mathematical and statistical approaches to interpolate values at concerned locations from known values at surrounding locations. These techniques are widely used in many fields including meteorology, water resources, agriculture, soil sciences, mining engineering, public health, etc. The detailed review of spatial interpolation methods and their application in environmental sciences can be found in literature (Li and Heap, 2008, 2011, 2014). Li and Heap (2008) listed and discussed over 40 different spatial interpolation techniques from geostatistical, deterministic, and combined category. Li and Heap (2011) compared and assessed the performance of 72 interpolation methods/sub-methods from

53 comparative studies. Li and Heap (2014) also compared 25 different spatial interpolations methods based on their features and theory.

Chang (1991) used the kriging method to study the drought of Scioto river basin, Ohio. Kriging is an interpolation technique in which measured values are weighted to predict a value for unmeasured location. The weights are derived based on the statistical relationships (i.e., spatial covariance) among the measured points. Chang and Teoh (1995) used kriging to characterize groundwater drought for the same study area. Akhtari et al. (2009) evaluated different spatial interpolation methods for SPI and Effective Drought Index (EDI), and found that Ordinary Kriging (OK) is the most desirable method. Ali et al. (2011) used the various geostatistical techniques to estimate the spatial distribution of station-wide indices. They used OK, Inverse Distance Weighting (IDW), and Thin Plate Smoothing Spline methods to interpolate the SPI and EDI indices based on 27 climatic stations in Iran. They found that SPI can be interpolated with IDW with power two, and OK method is suitable for EDI. Bonaccorso et al. (2003) developed a methodology to design a drought monitoring network based on kriging technique and automated data acquisition rainfall stations in Sicily. They used the Root Mean Square Error (RMSE) of the SPI to analyse the capability of the current system to monitor the drought. Though geostatistical techniques are used in drought studies, full advantage has not been taken of the recently developed advance features of spatial analysis tools. A better understanding of spatial distribution and dependency of drought phenomenon can be obtained using these tools. In the U.S., many rely on National Oceanic and Atmospheric Administration (NOAA)'s National Centers for Environmental Information (NCEI) drought indices including the SPI on a climate division scale. The county-level drought information from Western Regional Climate Center's WestWide Drought Tracker (WWDT) is another popular source for drought data. Drought is often reported at course resolution level to administrative units. However, drought can vary significantly within such a coarse resolution (county/climate division). This study addresses this issue, and models the spatial variability of drought using geospatial analysis techniques IDW and OK. IDW is widely used deterministic interpolation technique. OK is a very popular, and robust method (Oliver and Webster, 2014). OK is also widely used in several similar studies (Akhtari et al., 2009; Ali et al., 2011; Li and Heap, 2011). In addition, the uncertainty associated with considering drought across different spatial scales is quantified. In this study, SPI, an indicator of meteorological drought, with time scale of one month is used. The analysis is conducted for the North Dakota State for three selected spatial scales namely: county, climate division, and state. However, the proposed methodology is applicable to any region of interest using different drought indices. The finding could be helpful to understand spatial characteristics of droughts better, and to develop better drought monitoring networks.

4.2. Data

This study utilizes the Standardized Precipitation Index (SPI) data from Drought Risk Atlas (DRA) of the National Drought Mitigation Center (NDMC) (Svoboda et al., 2015). SPI is a well- recognized drought index especially for station-based drought reporting. This study involves interpolation of station data of SPI extracted from the archives of DRA for the state of North Dakota (ND), U.S (Figure 4.1). SPI-1 is chosen for this study. However, SPI with anytime scale can be used with same methodology used in this study. The period August 2012 is used for the analysis to demonstrate the method. Three different spatial scales namely: county (Grant, ND), climate division (South Central), and state (ND) were chosen to quantify the uncertainty associated with reporting drought in regional scales (Figure 4.1). Drought is commonly reported at these three spatial scales.

4.2.1. Standardized Precipitation Index (SPI)

SPI is a meteorological drought index developed by McKee et al. (1993, 1995) based on the probability distribution of temporal precipitation data. World Meteorological Organization (WMO) published a user's guide for SPI in 2012 which contains background information, description, strength and weakness, interpretation, and methods of computing SPI (Svoboda et al., 2012). According to Guttman (1998), SPI may indicate wetness and dryness better than Palmer index, another popular index used in the U.S. One of the major advantages of SPI is that it is comparable spatially and temporally because of the standardizing procedure used in the computation (Quiring and Papakryiakou, 2003; Steinemann et al., 2005). The SPI is calculated based on the historical precipitation data. A gamma distribution is fitted to the precipitation data and then normalized. Several authors discuss the usability and/or applicability of SPI (Guttman, 1998; Guttman, 1999; Hayes et al., 1999; Heim, 2002; Keyantash and Dracup, 2002; Mishra and Singh, 2010; Narasimhan and Srinivasan, 2005). SPI can be calculated for different time units such as SPI-1, SPI-2, etc., where 1, 2, etc., are months. The timescale is set by different lengths of moving averaging windows. The defined moving average window (time scale) will capture precipitation anomalies corresponding to that timescale which will reflect the different drought categories. For example, SPI indicates the meteorological, agricultural, and hydrological drought condition when it is calculated based on time units of one or two months, between one to six months, and between 6 to 24 months respectively (Svoboda et al., 2012).

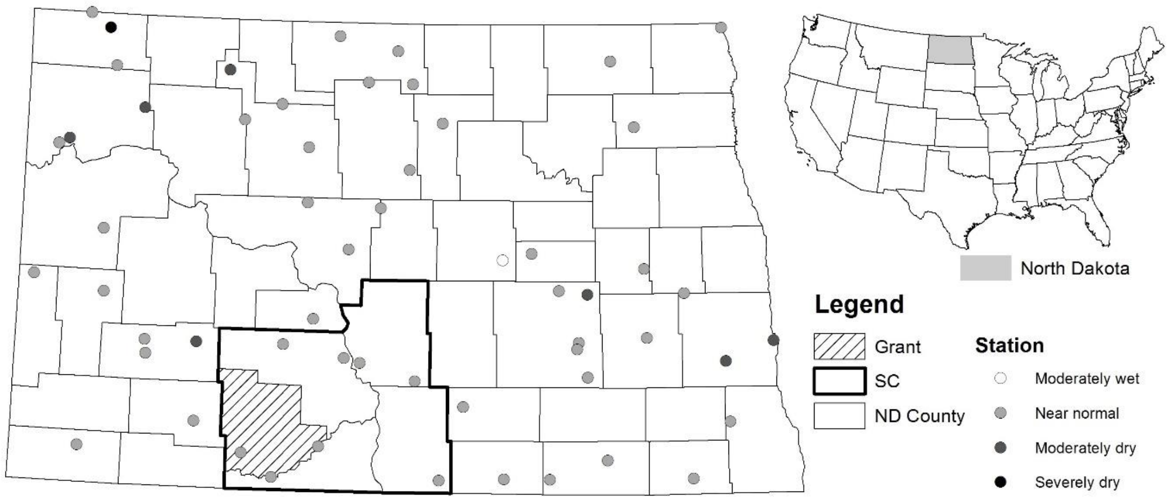


Figure 4.1: The selected stations in ND and severity level of drought based on SPI-1 for August, 2012.

4.2.2. Descriptive statistics of the data

In the NDMC DRA there are 57 stations which provide the historical SPI for the state of North Dakota. The selection procedures of these stations can be found in Svoboda et al., (2015). The SPI-01 drought index was archived station by station for August 2012. A GIS shapefile was created for station locations, and August 2012 SPI-1 is joined with the shapefile. Figure 4.1 shows the location and drought severity level based on SPI-1 for the stations: One station with severe drought condition (-1.5 to -1.99), seven stations with moderately dry condition (-1.0 to -1.49), forty-eight stations with near normal condition (-.99 to .99), and one station with moderately wet condition (1.0 to 1.49). The station-based SPI data was analysed for its statistical properties (Table 4.1). Values of skewness around zero and kurtosis around three imply that the data follow normal distribution. The histogram and minimum deviations from the straight line of normal Q-Q plot further support that data is normally distributed (Figure 4.2). The data also passed the *Kolmogorov-Smirnov* normality test in which the null hypothesis is data follow normal distribution. The *P-value* was 0.094 and greater than significance level of 0.05.

Therefore, the null hypothesis is not rejected. The normally distributed data is ideal to use in geostatistical analysis (Negreiros et al., 2010; Robinson and Metternicht, 2006; Webster and Oliver, 2007).

Table 4.1: Descriptive statistics of SPI-01 (August 2012) from 57 stations data.

Parameter	**Value**
Minimum	-1.81
Maximum	1.41
Mean	-0.28
Median	-0.16
Standard Deviation	0.62
Skewness	-0.017
Kurtosis	3.17

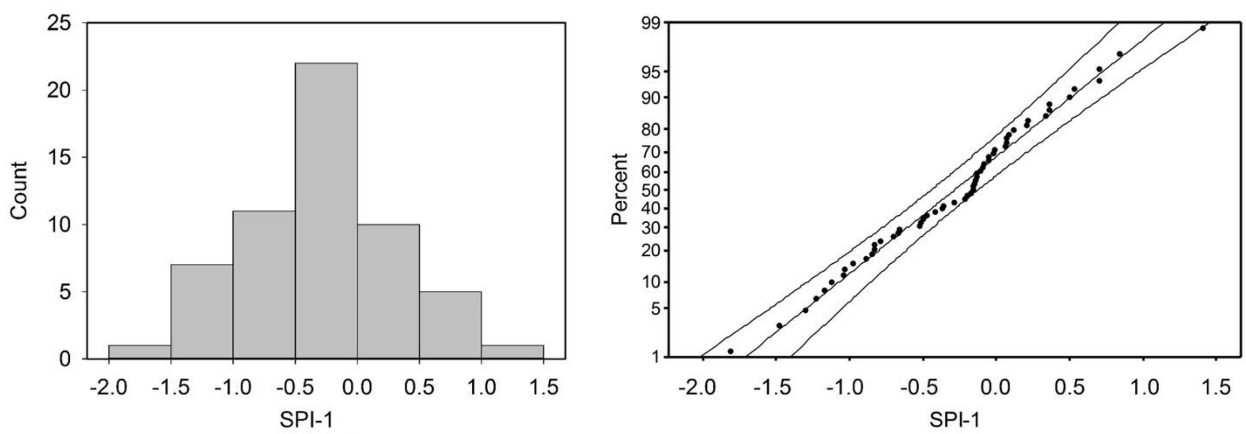


Figure 4.2: Histogram (left) and Normal Q-Q Plot (right) with 95% confident interval for SPI-1 (August, 2012).

4.3. Methods

Two widely used interpolation methods were used to interpolate the station-based SPI-1. IDW is a simple and quick interpolation method with less assumption about the data. Whereas kriging has been proven to provide the best linear unbiased estimates. The comparison between these two interpolation methods is a common topic of research. However, the findings are not consistent (Li and Heap, 2011). This study used both methods and compared the performances.

The interpolated surface of SPI-1 from both methods were used to quantify the uncertainty of drought reporting across different spatial scales.

4.3.1. Spatial interpolation

The Inverse Distance Weighting (IDW) and Ordinary Kriging (OK) methods in ArcGIS 10.3® were used for the spatial interpolation and to analyse the spatial characteristics of SPI-1data for the month of August 2012 from 57 stations in North Dakota, U.S.

4.3.1.1. Inverse Distance Weighted (IDW)

IDW is a distribution-free, nonlinear deterministic interpolation method based on the assumption that variables that are nearby are similar than those that are far away. The interpolation value at any location will be calculated by summing the weighted contributions from neighboring sampling points (Eq. 4.1).

$$\hat{z}(s_o) = \frac{\sum_{i=1}^{N} z(s_i) d_{io}^{-p}}{\sum_{i=1}^{N} d_{io}^{-p}} \tag{4.1}$$

where; $\hat{z}(s_o)$ is the predicted value at un-sampled location s_o , $z(s_i)$ is known value at location s_i, d_{io} is the distance between location s_i and s_o, N is the sample size, p is the power values. The optimum p value is used to interpolate the SPI-01 values for August 2012 from 57 station in ND. The optimum p value is chosen based on the cross validation parameter Root Mean Square Error (RMSE). Cross-validation is widely used to evaluate the performance of geospatial interpolation methods by comparing the predicted value with the observed value. (see section 4.3.1.3).

4.3.1.2. Kriging

Matheron (1963, 1965) formulated the kriging method based on Daniel Krige's approach to predict ore grades from spatially correlated sample data of gold mines of South Africa (Krige, 1951, 1966). The term "kriging" is adopted for a family of generalized least-squares regression algorithms. The spatial autocorrelation is a prerequisite for the application of kriging (Goovaerts, 1999). The spatial autocorrelation measures degree of dependency among observations in space. There are several kriging methods available: simple, ordinary, universal, cokriging, kriging with an external drift, indicator, disjunctive, and probability kriging. The detailed discussion of mathematics behind the different kriging methods can be found in several text books and software program manuals (Goovaerts, 1997; Johnston et al., 2001; Krivoruchko, 2011; Webster and Oliver, 2007). OK assumes a constant, but unknown, mean and estimates the mean value. Kriging models (SI, OK, and UK) predict $\hat{z}(s_o)$, using the sum of weighted (λ_i) values, $z(s_i)$, in the nearby N locations using the linear equation (Eq. 4.2).

$$\hat{z}(s_o) = \sum_{i=1}^{N} \lambda_i z(s_i) \tag{4.2}$$

Kriging uses one of several available theoretical semivariogram models fitted to empirical semivariogram to define the weights (λ_i)(Johnson et al., 2001). The empirical semivariogram will show how the data are related with distance. The empirical semivariogram for a separation distance of *h (lag)* can be derived from Eq. 4.3. The theoretical semivariogram model equations can be found in Johnston et al. (2001) and Krivoruchko (2011).

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2 \tag{4.3}$$

where $N(h)$ is the number of pairs of data points separated by lag distance (h); $z(x_i)$ and $z(x_i + h)$ are the values of the variable at locations (x_i) and $(x_i + h)$ respectively. The semivariogram depicts the spatial autocorrelation at various distances (Deutsch and Journel, 1998). A suitable theoretical semivariogram model needs to be fitted to the empirical semivariogram in kriging procedure.

The figure 4.3 illustrates the typical semivariogram parameters c and α, the partial sill and range respectively. The detailed descriptions of these parameters can be found in several geostatistical analysis literature sources (Johnston et al., 2001; Krivoruchko, 2011; Negreiros et al., 2010).

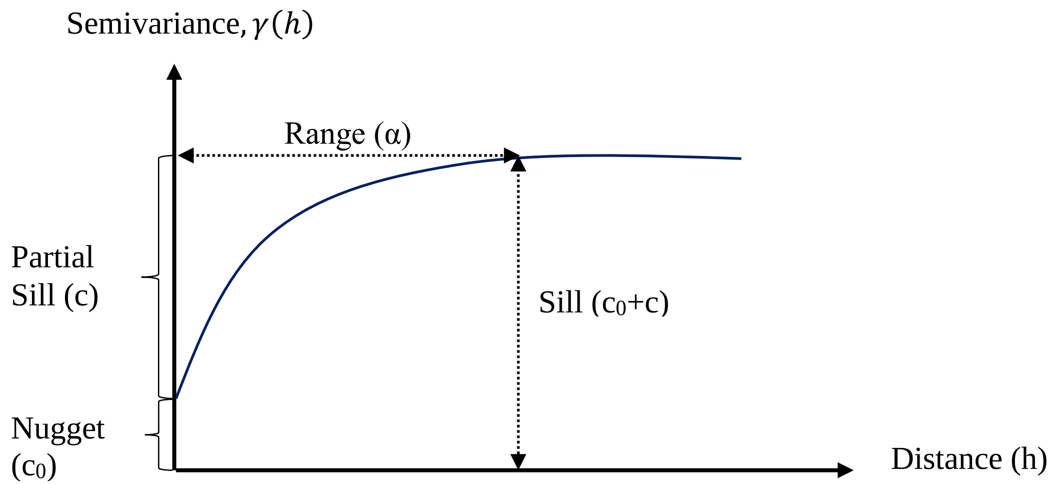


Figure 4.3: Illustration of semivariogram parameters.

In this study, the parameters such as number of lags, lag size, nugget, range, and partial sill (Fig. 4.3) for each semivariogram model were optimized using ArcGIS 10.3®.

ArcGIS 10.3® was used to explore the different semivariogram models such as Circular, Spherical, Tetraspherical, Pentaspherical, Exponential, Gaussian, Rational Quadratic, Hole Effect, K-Bessel, J-Bessel, and Stable to create the interpolated surface from SPI-1 data by OK method. Cross validation was used to choose the most suitable semivariogram model. The detailed description about the modeling and cross validation steps are discussed in section 4.4.1.

4.3.1.3. Cross-Validation

For cross-validation, the observed value of a variable from a location will be removed, and will be predicted using the observed values from the rest of recording locations. This process, will be iterated for all observation location. The cross-validation parameters are the statistics of the differences between the observed and predicted values. Mean Error (ME), Root Mean Square Error (RMSE), Average Standard Error (ASE), Mean Standardized Error (MSE), and Root Mean Square Standardized Error (RMSSE) were computed including prediction standard error ($\hat{\sigma}(s_i)$) (see Eqs. 4.4 – 4.8).

$$ME = \frac{\sum_{i=1}^{n}\left[\hat{Z}(s_i) - Z(s_i)\right]}{n} \tag{4.4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left[\hat{Z}(s_i) - Z(s_i)\right]^2}{n}} \tag{4.5}$$

$$ASE = \sqrt{\frac{\sum_{i=1}^{n}\hat{\sigma}(s_i)^2}{n}} \tag{4.6}$$

$$MSE = \frac{\sum_{i=1}^{n}\left[\frac{\left[\hat{Z}(s_i) - Z(s_i)\right]}{\hat{\sigma}(s_i)}\right]}{n} \tag{4.7}$$

$$RMSSE = \sqrt{\frac{\sum_{i=1}^{n}\left[\frac{\left[\hat{Z}(s_i) - Z(s_i)\right]}{\hat{\sigma}(s_i)}\right]^2}{n}} \tag{4.8}$$

The overall performance of prediction was assessed based on following criteria (Krivoruchko, 2011):

a) The ME should be near zero for an unbiased prediction method. However, it is a weak diagnostic since it does not measure the error magnitude.

b) The smaller RMSE is a better since it indicates how closely the model predicts the observed values.

c) The ASE should be small and close to RMSE. ASE and RMSE are two different estimates of prediction error. Similar values of these parameters indicate that the variability in prediction is assessed correctly.

d) MSE value should be close to zero.

e) RMSSE should be near to one. It implies that prediction uncertainty estimation is consistent.

The performance of IDW is assessed only using criteria (a) and (b) whereas kriging was assessed using all the criteria.

4.3.2. Quantification of uncertainty in reporting drought at different spatial scales

The state of North Dakota, South Central Climate Division in ND (SCCD, ND), and Grant County in ND are the areas selected to represent different spatial scales for this study (Figure 4.1). The procedure consisted of the following steps:

1. 4km × 4km grid points were created for the selected spatial scales (i.e., Grant County, SCCD, and ND).
2. The best interpolated surface of SPI-1 from among the ones produced by the selected interpolation methods (see section 3.1) was chosen based on cross-validation.
3. The interpolated values from selected surface are extracted to fine scale grid points (4km × 4km) using "*GA layer to point (Geostatistical Analyst)"* tool in ArcGIS 10.3®.
4. The attribute values of SPI-1 from grid points were exported to Microsoft EXCEL®.
5. The reported values of SPI-1 for August 2012 were acquired form NOAA's NCEI, and for county from Western Regional Climate Center's WWDT for the selected spatial scales.
6. The following parameters were computed for the selected spatial scales:
    a. Mean, Standard Deviation, Maximum, Minimum, and Range of SPI-1 from gridded points.

b. For each grid point the difference between reported spatial scale value and interpolated surface values (ΔSPI) were calculated and its variation is quantified as an indicator of uncertainty in drought reporting.

$$\Delta SPI = SPI_{interpolated\ value\ for\ grid\ point} - SPI_{reported\ value\ for\ grid\ point\ under\ considered\ spatial\ scale}$$

4.4. Results and Discussions

4.4.1. Spatial interpolation of SPI-01

The IDW interpolation was performed using ArcGIS 10.3®. An optimized value of 1 was found for p (Table 4.2). The possible reason may be the low skewness values of SPI-1 for August 2012 (-0.017) (Kravchenko and Bullock, 1999; Robinson and Metternicht, 2006). Table 4.2 summarizes the cross-validation parameters for IDW and OK. OK was performed using different semivariogram models. Based on the cross-validation parameters, the “OK with circular semivariogram” model could be recommended (Eq. 4.9a-c). It has the lowest MSE, RMSSE value closest to one, and the smallest difference between ASE and RMSE. The values of RMSE is fairly the same for all the models, therefore making it difficult to pick the best one. Circular model has the lowest ASE and close to RMSE and also produced the mean square error closer to mean kriging variance and therefore recommended for further use in this study (Oliver and Webster, 2014). It should be noted that the overall performance of prediction is not solely dependent on the selection of semivariogram model even though it is the key component in kriging. Li and Heap (2008) discussed the factors that influence the performance of spatial interpolation such as size, density, and spatial distribution of data. However, the cross validation parameters can be used as an additional tool to determine an appropriate semivariogram model (Akhtari et al., 2009; Oliver and Webster, 2014).

Equation 4.9 (a-c) describes the circular semivariogram model.

$$\gamma(h) = c_0 + c\left(1 - \frac{2}{\pi}\cos^{-1}\left(\frac{h}{\alpha}\right) + \sqrt{1 - \frac{h^2}{\alpha^2}}\right) \qquad 0 < h \le \alpha \qquad (4.9(a))$$

$$\gamma(h) = c_0 + c \qquad h > \alpha \qquad (4.9(b))$$

$$\gamma(0) = 0 \qquad (4.9(c))$$

Figure 4.4 shows the empirical semivariogram, and fitted circular model. The empirical semivariogram is derived based on the sample data (SPI-1 of August 2012 from 57 stations in ND using equation 4.3. The optimized model has (a) 12 number of lags with lag size of 29.69 km

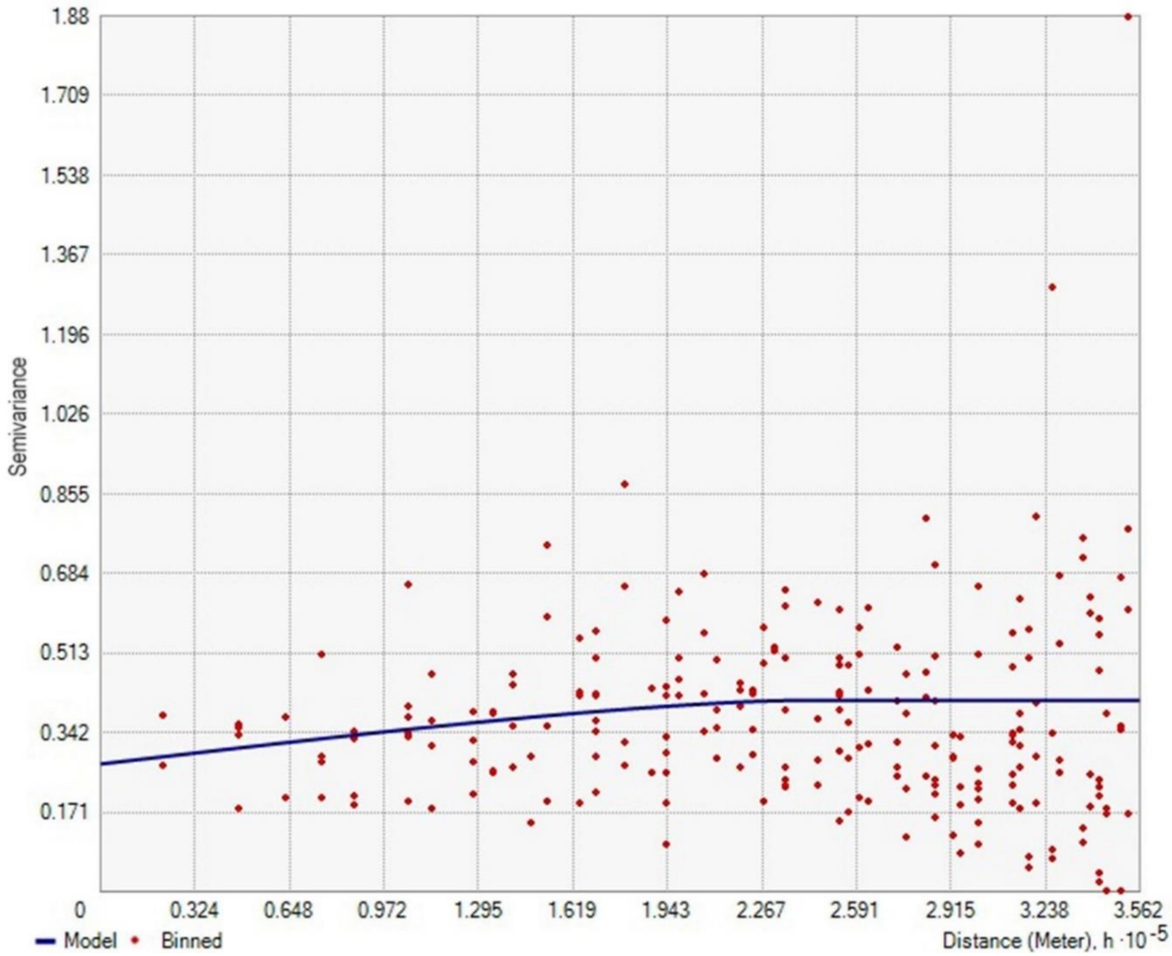


Figure 4.4: The empirical semivariogram and fitted circular model (Eqn.4.9 a-c) (binning is used to average semivariance data by distance and direction based on lag size).

(b) nugget value of 0.2744, an indication of data variation at distances smaller than closest sampling interval (c) range of 237.48 km, the maximum distance that the selected data has spatial dependence, and (d) partial sill of 0.1363, amount of variation of the spatial process. The number of lag and lag size control the way semivariogram values are being grouped. According to Robinson and Metternicht (2006) at least 300 samples are needed to detect anisotropy in which semivariogram function may change not only with distance but also with direction. The directional effect is not considered in this study.

Table 4.2: Cross-validation parameters for IDW and OK.

No		ME	RMSE	MSE	RMSSE	ASE	ASE-RMSE
	Power (p)	IDW					
1	1	**0.00867**	**0.56693**	**-**	**-**	**-**	**-**
2	2	0.01982	0.58339	-	-	-	-
3	3	0.02318	0.61011	-	-	-	-
	Semivariogram Model	Kriging					
1	Circular	-0.00076	0.57989	**0.00002**	**0.98947**	**0.58827**	**0.00838**
2	Spherical	**-0.00036**	0.57811	0.00187	0.95551	0.60796	0.02985
3	Gaussian	-0.00140	0.58014	0.00063	0.96539	0.60390	0.02376
4	Exponential	0.00130	0.57422	0.00334	0.95409	0.60543	0.03121
5	K-Bessel	0.00176	0.57388	0.00371	0.95532	0.60388	0.03000
6	Tetraspherical	0.00043	0.57619	0.00283	0.94790	0.61085	0.03466
7	Stable	0.00315	0.57240	0.00522	0.94899	0.60631	0.03391
8	Pentasherical	0.00113	0.57487	0.00369	0.94240	0.61298	0.03811
9	Rational Quadr	0.00289	**0.57231**	0.00525	0.94346	0.61025	0.03794
10	J-Bessel	0.00238	0.57420	0.00561	0.93144	0.61894	0.04474
11	Hole Effect	0.00447	0.58145	0.00895	0.93024	0.62583	0.04438

The RMSE value of IDW ($p = 1$) is lower than OK with circular semivarigram model in this study. However, unlike kriging, IDW will not provide the statistical measure of the accuracy of the predictions which can be used to evaluate the uncertainty of the predictions. The selected data sets for this study follow normal (Gaussian) distribution and kriging is an optimal predictor, and therefore, kriging is more appropriate for this study.

Both IDW with $p = 1$ and OK with circular semivarigram model were selected for interpolating the SPI-1 for further analysis. Figure 4.5 and Figure 4.6 depict the predicted surface of SPI-1 for August 2012 from IDW ($p = 1$) and OK (with circular semivariogram model) respectively. Even though both predicted surfaces look similar, the IDW produced *bull's-eye* effect where the highest values are assigned to points that are near the sampled locations. This is one of the disadvantages of IDW especially if the distribution of sample data points is not even. However, IDW is widely used due to its simplicity.

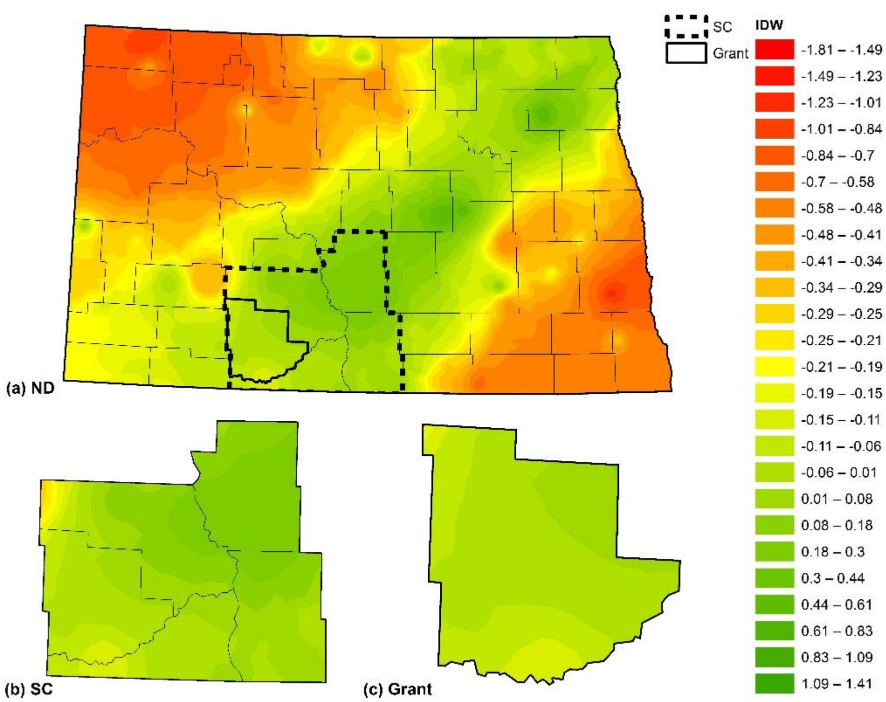


Figure 4.5: The interpolation surface SPI-1 for August 2012 in ND using IDW**.**

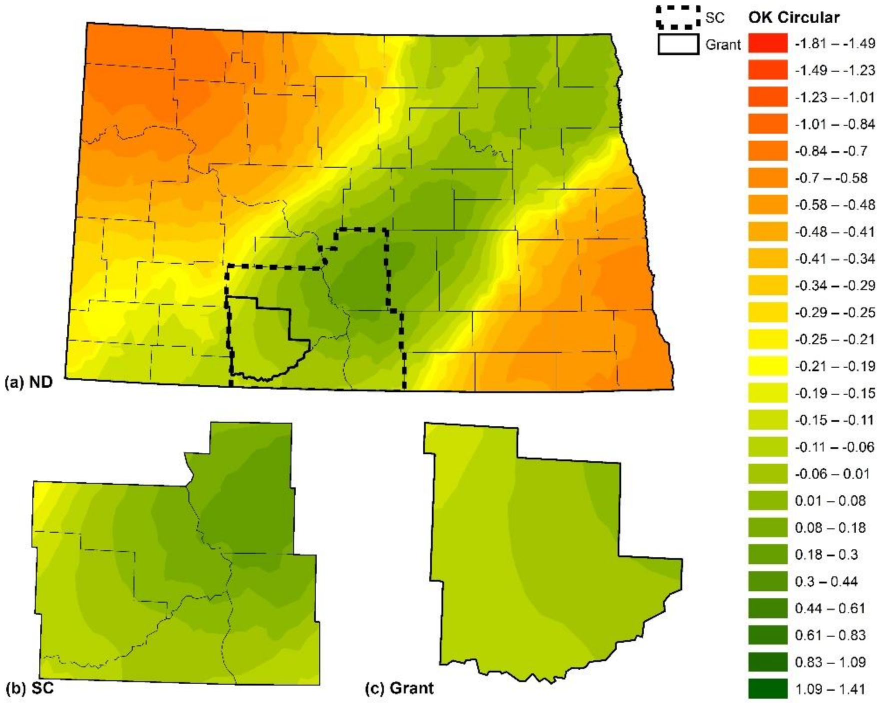


Figure 4.6: The interpolation surface SPI-1 for August 2012 in ND using OK with circular semivariogram model.

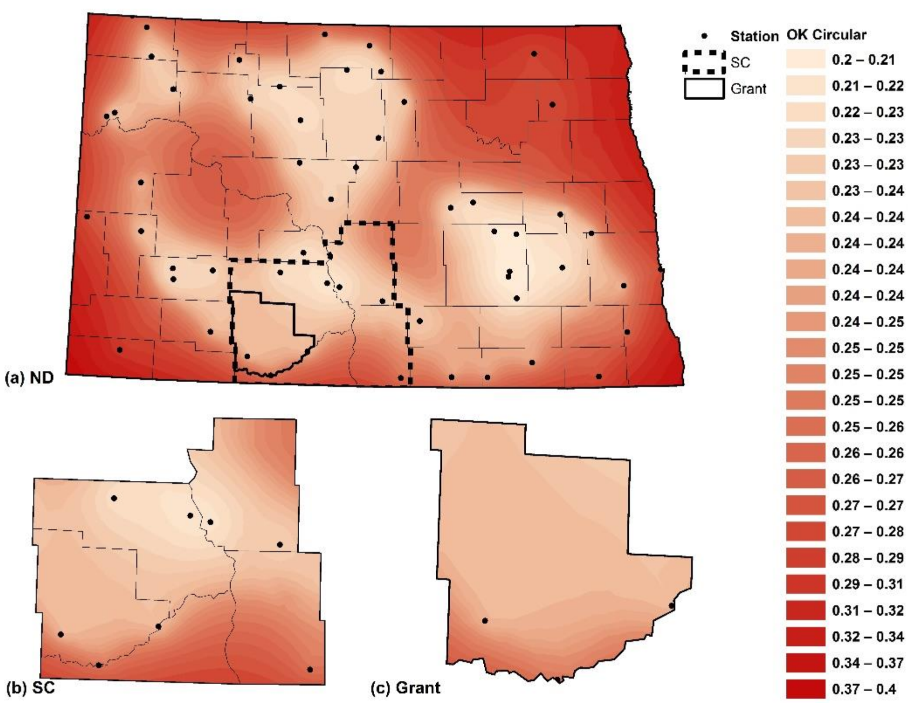


Figure 4.7: The prediction standard error surface of SPI-1 for August 2012 in ND using OK with circular semivariogram model.

Figure 4.7 shows the prediction standard error surface of SPI-1 for August 2012 from OK model. The prediction standard errors indicate the uncertainty associated with prediction. The higher the error the higher the uncertainty with prediction values. The standard error values vary between 0.2 and 0.4. In general, the error values can be related with the proximity and distribution of stations (Figure 4.7). The additional monitoring station in the locations that has the higher error (uncertainty) can improve the prediction and lead a better drought monitoring network. However, several trails are required using data representing different months and years to design a monitoring network, and such analysis is beyond the scope of this study.

4.4.2. The variation of drought within different spatial units

The drought conditions in SPI are generally reported as a regional phenomenon. The most of the drought indices are reported for administrative unit levels such as county, climate division, or state. However, droughts as a geospatial phenomenon may have a significant variation within such spatial units. This study quantifies the variability of droughts within three selected spatial units: county, climate division, state; and also the uncertainty associated with drought when it is reported to those spatial units. IDW with $p = 1$, and OK with circular semivariogram model were identified as suitable methods to interpolate the SPI-1 of August 2012 (see section 4.4.1). The significant parameters that reveal the variability of drought within selected spatial scales and among the selected interpolation models are summarized in Table 4.3.

Table 4.3 summarizes the number of grid points (4 km ×4km) within each spatial scale considered. The interpolated values for each grid point from the prediction surfaces (IDW and OK) were extracted to calculate the listed parameters. The reported values for each spatial scale is obtained from reliable drought reporting sources and compared with computed values (see also section 4.3.2). The average predicted values are ideally expected to be close to reported values.

Across all scales, there are disagreements between reported values and average values, though not large, indicating fairly good agreement between the reported and interpolated values. The average values of both interpolation methods also agreed. The standard deviation (StD) of predicted values from both interpolated methods are similar. The StD of predicted values are increasing with increasing spatial size for both methods. This is a clear evident that uncertainty in drought reporting will increase with increasing spatial size. The table provides the maximum, minimum, and range of predicted values. These values significantly differ between both methods. The range of predicted values, another indicator of uncertainty of drought at different spatial scales, also increasing with increasing spatial size. Even though the range highly depends on the selected interpolation method (Table 4.3) both methods agreed that uncertainty in drought reporting is increasing with increasing spatial size.

Table 4.3: Summary statistics of predicted and reported values of SPI-1 (August 2012).

	IDW			OK with circular semivariogram		
Spatial Scale	Grant	SCCD	ND	Grant	SCCD	ND
Reported value	-0.10	0.06	-0.61	-0.10	0.06	-0.61
No of grid points	4321	20701	183451	4321	20701	183451
Average	-0.04	0.07	-0.25	-0.05	0.04	-0.25
StD	0.05	0.13	0.28	0.04	0.11	0.26
Maximum	0.09	0.67	1.29	0.04	0.25	0.25
Minimum	-0.39	-0.39	-1.73	-0.16	-0.22	-0.84
Range	0.48	1.05	3.01	0.20	0.48	1.09
ΔSPImaximum	0.19	0.61	1.90	0.14	0.19	0.86
ΔSPIminimum	-0.29	-0.45	-1.12	-0.06	-0.28	-0.23
+ΔSPI (%)	91.95	45.14	87.79	91.00	39.29	89.12
-ΔSPI (%)	8.05	54.86	12.21	9.00	60.71	10.88
Sum of sq ΔSPI	25.47	328.01	38751.41	15.68	253.85	36570.20

The other set of parameters on ΔSPI are to quantify the uncertainty associated with spatial scale. The maximum and minimum values of ΔSPI for each spatial scale for both interpolation methods are listed in Table 4.3. These values indicate how extremes of the predicted values are deviating from reported values. The percentage of values predicted above (+ΔSPI, %) and below (-ΔSPI, %) the reported values are also shown. For the state and county, the values are mostly above the reported values; and the majority of values are below the reported value in climate division. The sum of square values of ΔSPI is also a measure of uncertainty with reporting drought in different spatial scales (Table 4.3).

Figure 4.8 shows the predicted values distribution from both methods for each spatial unit. The statistics are derived from the extracted values from 4 km ×4km grid points. The information from the Figure 4.8 is useful to understand the variation of drought within a defined spatial scale thus emphasizes the uncertainty with reporting drought in a different scale. For example, OK predicted 1.58% values of SPI less than -0.75; 20.88% values are in between -0.75 and -0.50; 22.54% values are in between -0.50 and -0.25; 34.65% values are in between -0.25 and 0; 20.32% values are in between 0 and 0.25; and 0.03% values are greater than 0.25 for the ND. This clearly indicate the range of variation within a spatial scale (see also Figure 4.5 and Figure 4.6). The range/variation of values is increasing with increasing spatial size (Figure 4.8). The information (Figure 4.8) is also useful to compare the distribution of predicted values from both methodologies. In general, the overall distribution of predicted values looks similar in both IDW and OK for this study. However, there is a noticeable difference in the both end of plots which indicates that the high and low end prediction values from both methods are dissimilar.

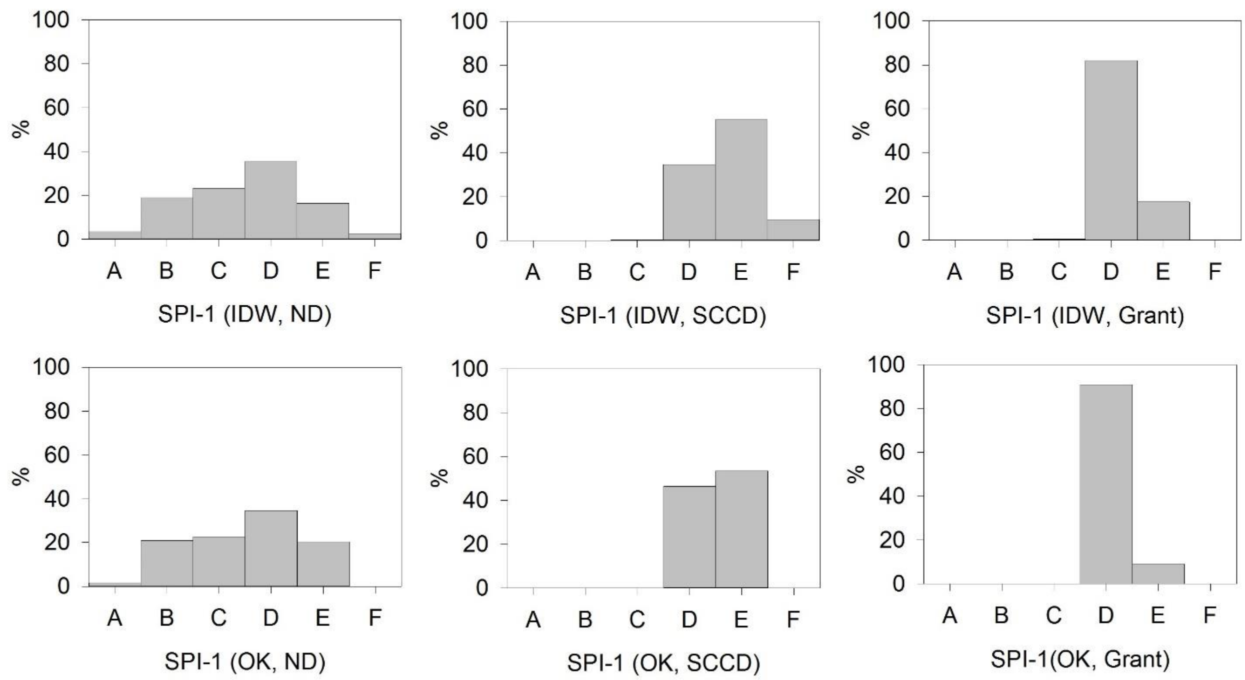


Figure 4.8: Percentage of predicted values (SPI-01, August 2012) from IDW and OK for each spatial scales. (A: SPI<=-0.75; B: -0.75<SPI<=-0.5; C: -0.5<SPI<=-0.25; D: -0.25<SPI<=0; E: 0<SPI<=.25; F: 0.25>SPI).

4.5. Summary and Conclusion

A precipitation-based drought index, SPI-1, interpolated from data from 57 stations for the month of August 2012 was used for estimating uncertainty in reported droughts across three different spatial scales in ND, U.S. Inverse Distance Weighting, a deterministic interpolation method; and Ordinary Kriging, a geostatistical method, were used for interpolation to obtain SPI-1 on a grid. First, it was confirmed that data followed normal distribution. An optimized p of 1 was used for IDW method using the cross-validation parameter RMSE. OK method with different semivariogram models were explored for the best performance. Based on the cross-validation analysis, circular semivariogram was chosen as the best model to be used with the selected data set. IDW method produced lower RMSE than OK, However, OK, unlike IDW, could provide statistical measures of accuracy and uncertainty of predictions (Johnston et al., 2001; Robinson and Metternicht, 2006). Also, OK can produce the optimum prediction surface when data follows a normal distribution such as in this study (Negreiros et al., 2010; Robinson and Metternicht, 2006; Webster and Oliver, 2007).

Uncertainty associated with reported drought index was estimated for the selected three spatial scales. Results showed uncertainty in the reported values increased with the size of spatial units for which drought is reported. The variations of drought values are significant enough to change on their category within a coarse spatial scales (Figure 4.8). The extracted values of SPI-1 from the interpolated surfaces (IDW with $p = 1$; and OK with circular semivariogram model) using 4 km ×4km grid points were used to assess the variation of droughts. The predicted values were compared with reported values from commonly used drought reporting sources. The deviation of predicted from reported values for each spatial scale were quantified as a measure of uncertainty.

The performance capability of the interpolation methods used in this study cannot be generalized for other data and other network of stations because the performance depends on the distribution of stations and data characteristics. However, this study proposes a methodology that can be used to quantify the variation of drought within a spatial unit and the uncertainty associated with different spatial scales from interpolated surface. This study also emphasizes the possibility of using the prediction standard error surface from kriging to improve the drought monitoring station network. Several studies have highlighted the need of reporting drought in finer scales (Duncan et al., 2015; Fontaine et al., 2014; Svoboda et al., 2015). As Duncan et al. (2015) reported the availability of higher resolution drought indicator are limited, and not utilized consistently in drought planning even when it is available. The proposed methodology can be used to analyse any drought index in any region of size and location. Though reporting drought as one value for a specific governing unit is useful for the general purpose of administrative management, drought should be studied as a geospatial phenomenon to understand its implications in terms of its spatial characteristics. It is also recommended that uncertainty information be provided with drought monitoring products when it is reported in coarse scales.

CHAPTER 5. EXAMINING THE RELATIONSHIP BETWEEN DROUGHT INDICES AND GROUNDWATER LEVELS[1]

5.1. Introduction

Establishing a parametric linkage between groundwater level fluctuations and drought is vital for water monitoring and management. In most areas, groundwater is used as an alternative water source during drought events. Groundwater and drought have inherent complexities, yet are relatively concomitant. Although drought is contextual without a universally accepted definition (Wilhite and Glantz, 1985) its central theme is related to a period of water deficiency in relation to demand. Since it is inherently difficult to identify or predict drought's onset and offset, indices are predominantly used (Dracup et al., 1980; McKee; Tallaksen et al., 1997). These indices are utilized categorically to identify and monitor drought (Steinemann et al., 2005). The four types of drought generally recognized include (i) meteorological, (ii) agricultural, (iii) hydrological, and (iv) socio-economic drought (AMS, 2013; Wilhite and Glantz, 1985). The first two types, that is, meteorological and agricultural droughts, are defined on the basis of precipitation and soil moisture deficits respectively (AMS, 2013; Wilhite and Glantz, 1985). On the other hand, hydrological drought is applicable to shortfalls on surface/subsurface water supply whereas socioeconomic drought is associated with the

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Part of this chapter was published in the Proceedings of the World Environmental and Water Resources Congress (Leelaruban, N., Padmanabhan, G., Droughts-Groundwater Relationship in Northern Great Plains Shallow Aquifers, Proceeding of the World Environmental and Water Resources Congress 2015, pp. 510-519. DOI: 10.1061/9780784479162.046).

[1]The material in this chapter was co-authored by Navaratnam Leelaruban and Dr. G Padmanabhan. Navaratnam Leelaruban had primary responsibility for constructing data base conducting analysis. Navaratnam Leelaruban was the primary developer of the conclusions that are advanced here. Navaratnam Leelaruban also drafted and revised all versions of this chapter. Dr. G. Padmanabhan assisted in discussion; and served as proofreader and checked the analysis conducted by Navaratnam Leelaruban.

supply and demand of some economic good (AMS, 2013; Wilhite and Glantz, 1985). Mishra and Singh (2010) suggested that groundwater deficit should be classified as a type of drought in addition to the aforementioned four types. Groundwater drought can be defined only in terms of groundwater level decline due to difficulties of quantifying groundwater storage, recharge, aquifer type and areal extents (Chang and Teoh, 1995; Eltahir and Yeh, 1999).

Various authors emphasize the need for evaluating the relationship of stream flow and groundwater with meteorological variables based drought indices (Chen et al., 2002; Chen et al., 2004; Haslinger et al., 2014; Jan et al., 2007; Lorenzo-Lacruz et al., 2010; Mall et al., 2006; Panda et al., 2007; Tirogo et al., 2016; Vasiliades and Loukas, 2009; Vicente-Serrano et al., 2012). The relationship of stream flow with drought indices has been studied by several authors. For example, Haslinger et al. (2014) established a methodology for directly relating various meteorological drought indices and stream flow data for northern Austria gauging stations. These indices included: (i) Standardized Precipitation Index (SPI), (ii) Standardized Precipitation Evapotranspiration Index (SPEI), (iii) Palmer's Z-Index, and (iv) self-calibrating Palmer Drought Severity Index (scPDSI). Vasiliades and Loukas (2009) used Palmer drought indices to ascertain hydrological drought using simulated river discharges and soil moisture for riverine systems in Thessaly, Greece. Vicente-Serrano et al. (2012) extensively studied the correlation between select drought indices and stream flow data from 151 basins worldwide. Lorenzo-Lacruz et al. (2010) evaluated the performance of SPI and SPEI drought indices to correlate river discharge, investigate reservoir storage, and determine reservoir release. The knowledge base of studies linking drought and groundwater levels is limited, although Mall et al. (2006) emphasized the need to study the impact of climate change and drought on groundwater resources in depth. Most studies have used precipitation and temperature to study drought relationship with groundwater levels. For example, Panda et al. (2007) reported the relationship between monsoon rainfall and groundwater fluctuation. Tirogo et al. (2016) reported the groundwater response to rainfall for a study area in Burkina Faso, West Africa. The relationship between groundwater level fluctuation and rainfall was also studied for a selected well in Central Taiwan by Jan et al. (2007). Chen et al. (2004) found that groundwater levels greatly depended on precipitation and annual mean temperature, with a delayed response time. An empirical model developed by Chen et al. (2002) linked annual precipitation and average temperature to groundwater levels based on water budget and groundwater flow. The relationship between drought indices and groundwater level fluctuation has not been explored much in the past.

This study differs from the aforementioned studies because this study focused on groundwater response to drought by deriving a parametric relationship between drought indices and groundwater data. Bloomfield and Marchant (2013) developed a Standardized Groundwater Level Index (SGI) incorporating an approach similar to the computation of SPI using groundwater level data from select wells in United Kingdom. Mendicino et al. (2008) proposed a Groundwater Resource Index (GRI) for drought monitoring and forecasting. This was based on a simple water balance model approach. Li and Rodell (2014) empirically derived a groundwater drought index (GWI) based on Catchment Land Surface Model (CLSM) output. Li and Rodell (2014) found strong regional correlation between CLSM (Koster et al., 2000) based GWI and in situ data based GWI, and both GWIs displayed a higher correlation with SPI-12 and SPI-24. However, CLSM requires substantial modeling effort. Other studies have used remote sensing techniques to quantify the groundwater storage decline (Castle et al., 2014; Famiglietti et al., 2011; Rodell et al., 2009; Voss et al., 2013). Most of these studies used precipitation and temperature as indicators of drought. Groundwater systems are influenced by many factors including hydrological properties of recharge area, hydraulic properties of aquifer, and climate variables. Therefore, deterministic approaches to quantify groundwater level dynamics require aquifer properties, recharge rates, amongst other factors. Due to limitations of such data, deterministic approaches may be difficult to implement (Chen et al., 2002) which leaves statistical analyses as a viable alternative.

In this study, groundwater level data from the U.S. Geological Survey Ground-Water Climate Response Network (USGS CRN) wells was used. Wells in this network have the least anthropogenic-induced disturbances (Cunningham et al., 2007). A total of 8 indices were tested and a correlation matrix was developed between groundwater levels and drought indices to evaluate the capability of indices to elucidate dynamics of groundwater level fluctuations. The seasonal variability of groundwater level, and its relationship with drought was also studied for selected wells. An event by event analysis was also conducted to capture the specific behaviour of groundwater level fluctuation during individual drought episodes. Duration of drought events and lag times of groundwater responses with respect to onset and termination of drought events were also studied.

5.2. Study Area and Methods

5.2.1. Study area and groundwater levels data

The study area and the selected well locations are shown in Figure 5.1. Criteria for the selection of CRN wells included: (a) located in unconfined aquifers or near-surface confined aquifers, (b) had minimum artificial influences (e.g. pumping, irrigation, canals, and artificial recharge), and (c) have never gone dry (Cunningham et al., 2007). Thirty-two USGS CRN wells from the Great Plains States of the U.S. were analysed. One well located in Colorado (CO), two wells from Kansas (KS), five wells in Montana (MT), six wells in Nebraska (NE), five wells in

North Dakota (ND), two wells in Oklahoma (OK), six wells in South Dakota (SD), and five wells located in Texas (TX)) (Figure 5.1). The beginning of time span of groundwater level data was chosen based on the beginning of available consistent groundwater level records. December 2013 was chosen as the end of time span.

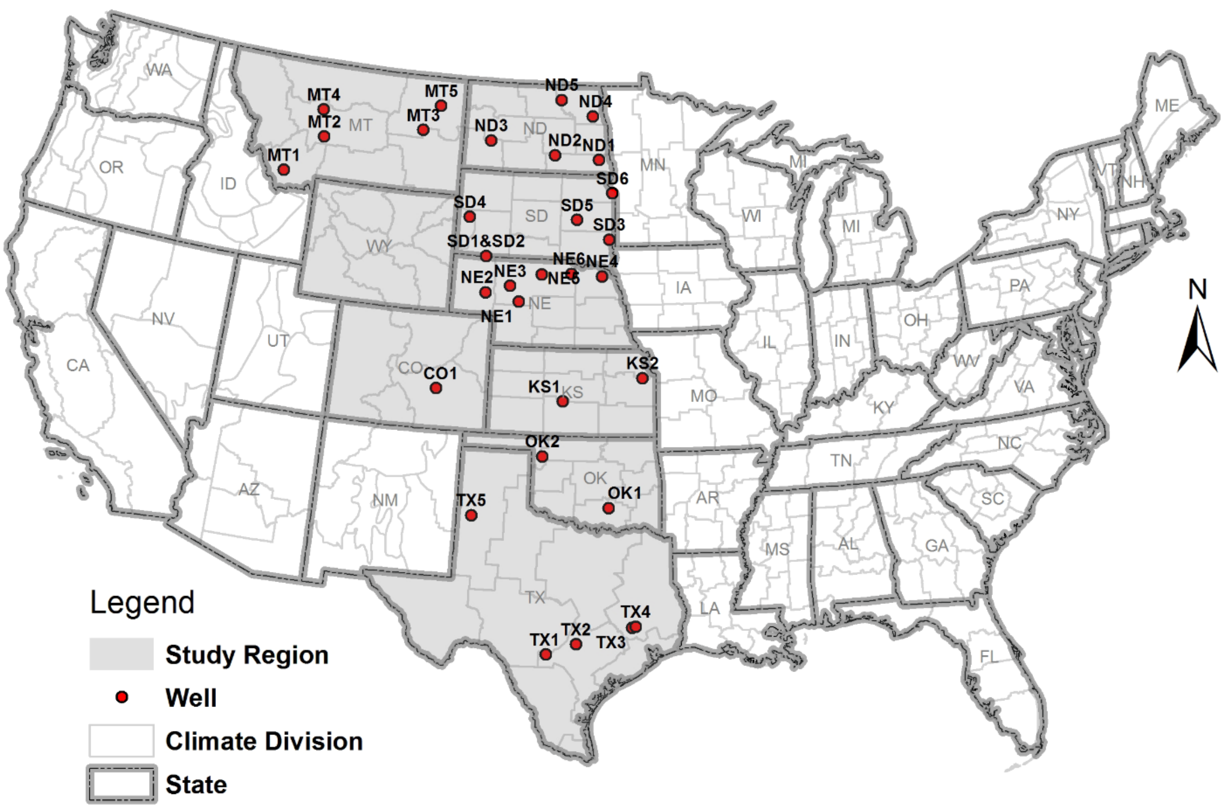

Figure 5.1: Study area showing selected wells' locations.

5.2.2. Drought indices

Palmer Drought Severity Index (PDSI) (Palmer, 1965), Palmer Hydrological Drought Index (PHDI) (Karl, 1986), Standardized Precipitation Index (SPI) (McKee et al., 1993; McKee et al., 1995); and meteorological parameters such as Precipitation (PCP) and Average Temperature (TMP) were used in this study. The Monthly values of PDSI, PHDI, SPI, TMP, and PCP were derived from National Oceanic and Atmospheric Administration (NOAA) National

Climatic Data Center (NCDC) [Currently part of NOAA's National Centers for Environmental Information (NCEI)]. The NCDC maintains historic data from 1895 to present in climatic division scale. NOAA's Gridded Climate Divisional Dataset (nCLIMDIV formerly known as Traditional Climate Division Dataset (TCDD) data) from NOAA NCDC were also used in this study. nCLIMDIV replaced the previous Traditional Climate Division Dataset (TCDD) in March 2014. The detailed description and major impacts of this transition can be found in Fenimore et al. (Fenimore et al., 2011). Vose et al. (2014) discussed the improvement in the nCLIMDIV data and suggested that this can be used in applied research and climate monitoring.

5.2.3. Groundwater level - drought indices correlation

The linear relationship between monthly median depth to water level from land surface, *b*, and corresponding monthly values of PCP, TMP, PDSI, PHDI, SPI-06, SPI-09, SPI-12, and SPI-24 indices was analysed using Pearson correlation coefficient. SPI can be calculated for multiple timescales which indicate the impact on different water sectors. In this study, SPI with timescales of at least six months was used since it was suitable for analyzing hydrological drought impact such as groundwater decline (Svoboda et al., 2012). Drought indices used for each well were for the respective climate division where the well was located.

5.2.4. Monthly groundwater variation and its correlation with SPI-24

The monthly variations of groundwater levels, and correlations between SPI-24 with *b* were studied for select wells. The rationale for focusing on SPI-24 is its inherent concomitancy with groundwater levels. A subset of wells which had at least 25 years records of monthly groundwater level data was demarcated from the rest of the dataset. This was done to identify the seasonal variability of groundwater level and its relation to drought.

5.2.5. Groundwater level fluctuation for specific drought events

For each well, the duration in number of months under moderate or more severe drought conditions were derived based on SPI-24. Drought is reported moderate or more severe when SPI-24 ≤ -0.8 by NOAA's NCEI. Therefore, the drought events for each well were delineated based on SPI-24 ≤ -0.8 for at least 30 consecutive months. Corresponding groundwater *b* values were also noted. From this data, groundwater level decline and, lag and recovery time of groundwater level in relation to the selected drought events were determined.

5.3. Results and Discussions

The Pearson correlation coefficients between *b* and climate indices such as PCP, TMP, PDSI, PHDI, and SPI for 6, 9, 12, and 24 monthly scales are shown in Figure 5.2. The results show that precipitation and temperature have relatively low correlation with groundwater level. Twenty-nine out of 32 wells show *r* for *b* and precipitation in the range -0.3 to 0.21. The highest correlation of *b* and precipitation (-0.51) is observed for well OK2. The *r* values of *b* and temperature vary between -0.23 and 0.19. Precipitation, by and large, correlates negatively as expected. Temperature, on the other hand, shows a positive and negative correlation with *b*.

Since *b* correlates negatively with drought indices; the more negative the index value, the more severe the drought. The more negative the indices, the greater the depth to groundwater. The PHDI and SPI-24 displayed better correlations with groundwater levels, albeit inconsistently (Figure 5.2). 12/32 wells show *r* value of -0.6 or better with SPI-24; nine wells show *r* of -0.6 or better with PHDI. Detailed description of *r* with indices follows: NE4 and NE5 displayed *r* of -0.9 and -0.8, for SPI-24. For (i) wells KS2 and MT5 with respect to SPI-24; (ii) OK1 with respect to PHDI; (iii) OK2 with respect PDSI; and (iv) TX2 with respect to SPI-9 *r* was $-0.8 \leq r \leq -0.7$. For wells KS1, MT2, ND5, NE2, SD3, & SD4 with SPI-24, *r* was $-0.7 \leq r \leq -0.6$ similar to wells ND1 and ND3 with respect to PHDI. The correlation values for wells MT1 and SD6 considering SPI-24; and CO1 with respect to SPI-9 r can be expressed as $-0.6 \leq r \leq -0.5$. Four wells (ND4, SD5 & TX4 with SPI-24; and MT3 with SPI-12) correlation values ranged between -0.5 and -0.4; one well (ND2 with SPI-24) with a correlation value of -0.32; 4 wells (TX3 with SPI-24; NE3 & SD2 with PHDI; and TX1 with SPI-12) correlation values between -0.3 and -0.2; and one well (NE6 with SPI-24) with a correlation value of -0.05. Wells MT4, NE1, SD1, and TX5 displayed positive correlation values with respect to drought indices. Some factors that can possibly be attributed to the inconsistent correlation may be due to each wells' heterogeneity owing to various geophysical and hydrological conditions. We can still unequivocally state that the results show that drought indices can be used as a proxy indicator of groundwater levels.

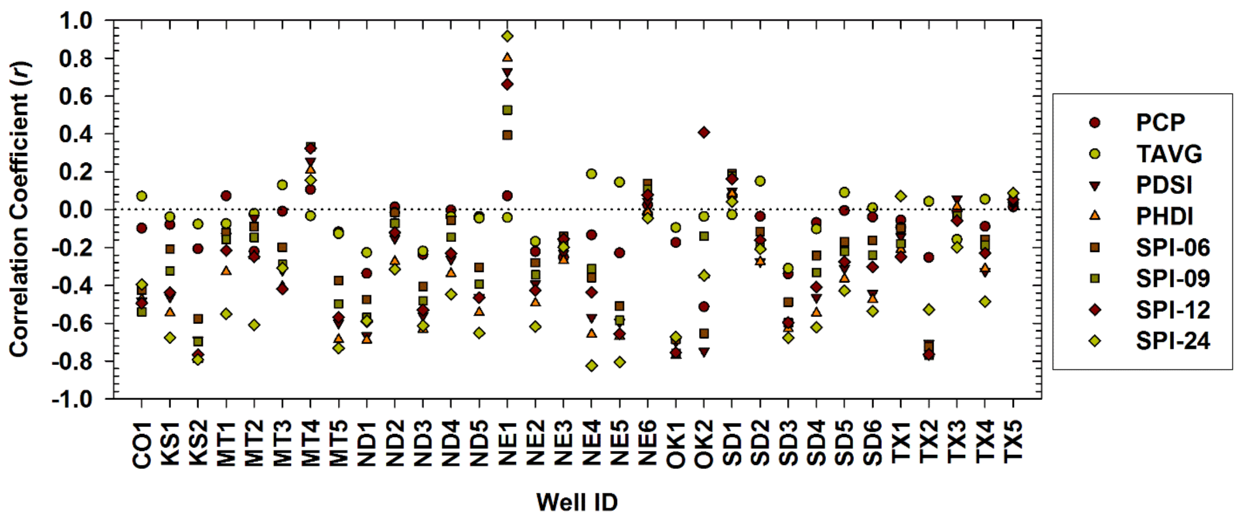

Figure 5.2: The Pearson correlation coefficient, r, between groundwater level (b) and drought indices.

Based on the results of overall correlation between b values and drought indices, SPI-24 index is a viable candidate in monitoring groundwater level fluctuations during a discernible drought. SPI is a simple index based on solely precipitation records. A study of groundwater level responses to SPI will be advantageous in groundwater management and monitoring during discernible drought episodes owing to the fact that precipitation records are widely available. Thus, SPI-24 may be regarded as a proxy and/or a direct measure of groundwater levels. The variation of *b* and SPI-24 for four wells that displayed positive correlation as opposed to the expected negative *r* is shown in Figure 5.3. From Figure 5.3, we can see that the *b* values are not reflecting any drought conditions. The inclusion of these wells in the CRN network may need further reconsideration beyond the scope of this study.

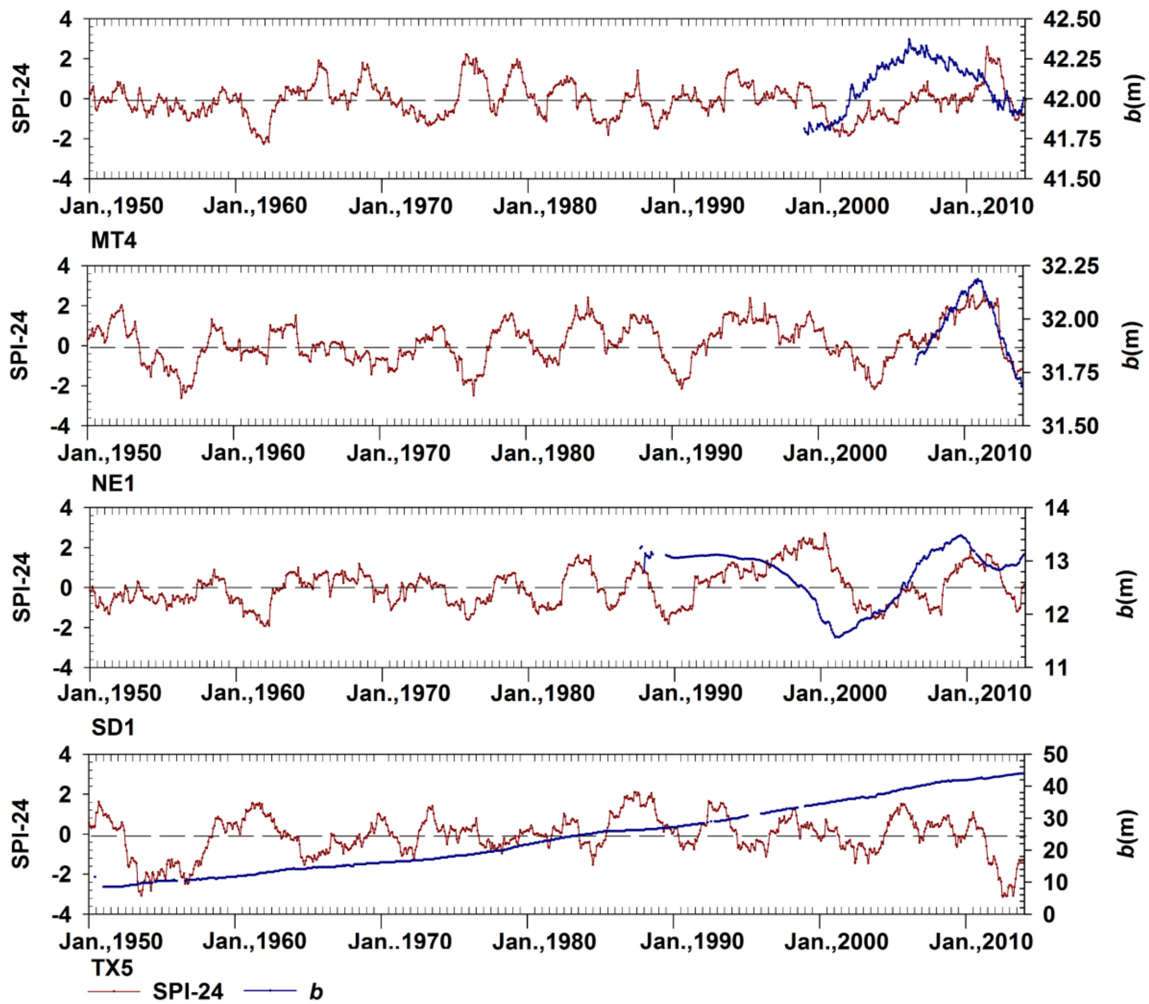

Figure 5.3: The variation of 24-month Standardized Precipitation Index (SPI-24) and depth to water level, *b*, for wells MT4, NE1, SD1, and TX5.

The variation of groundwater level and its correlation with SPI-24 were further analysed in a monthly time basis for a select set of wells. The selected wells were KS2, ND1, ND2, ND3, ND4, ND5, NE6, OK1, and TX2. These wells had at least 25 years of reported monthly records. TX5 had more than 25 years of monthly records for each month but was not used for this part of study because its water level variation was declining irrespective of any established drought episodes (Figure 5.3). The tabulated results in Table 5.1 include correlation coefficient values between SPI-24 and, *b*, for each month, *r'*, and average values of depth to water level from land surface (*b*), μ.

Figure 5.4 shows variation between *r'*, and μ. The μ values for well KS2 vary between 6.03 m in June and 6.39 m in February. The *r'* values for KS2 vary between -0.84 in January and -0.75 in September. The μ and *r'* values for KS2 well are relatively stable, and groundwater level had a strong linear correlation with SPI-24. The highest differential value for *r'* is observed for ND1 where *r'* values range between -0.75 for the month of January and -0.57 for May and June months. On the other hand, μ value varies between 1.97 m in February and 1.18 m in May. The highest differential μ value was observed for OK1 well where the highest μ was 34.49 m for October and lowest μ value was 32.14 m for June months. μ values for ND4 vary between 7.14 m for September and 7 m for June which was the lowest differential μ value. The *r'* values for NE6 are very low for all the months over the entire period. Overall for all the wells, μ values were low during summer months, that is, from May to August. This study did not explore any general specific patterns for seasonal variability of *r'*. The *r'* values are relatively the same throughout the year for the studied wells. It implies that drought influence the groundwater regardless of the season of the year for the studied wells. Knowing the variation of groundwater level and its correlation with drought in monthly basis will be helpful in identification of seasonal groundwater availability and its susceptibility to drought, and to better planning and utility of groundwater resources.

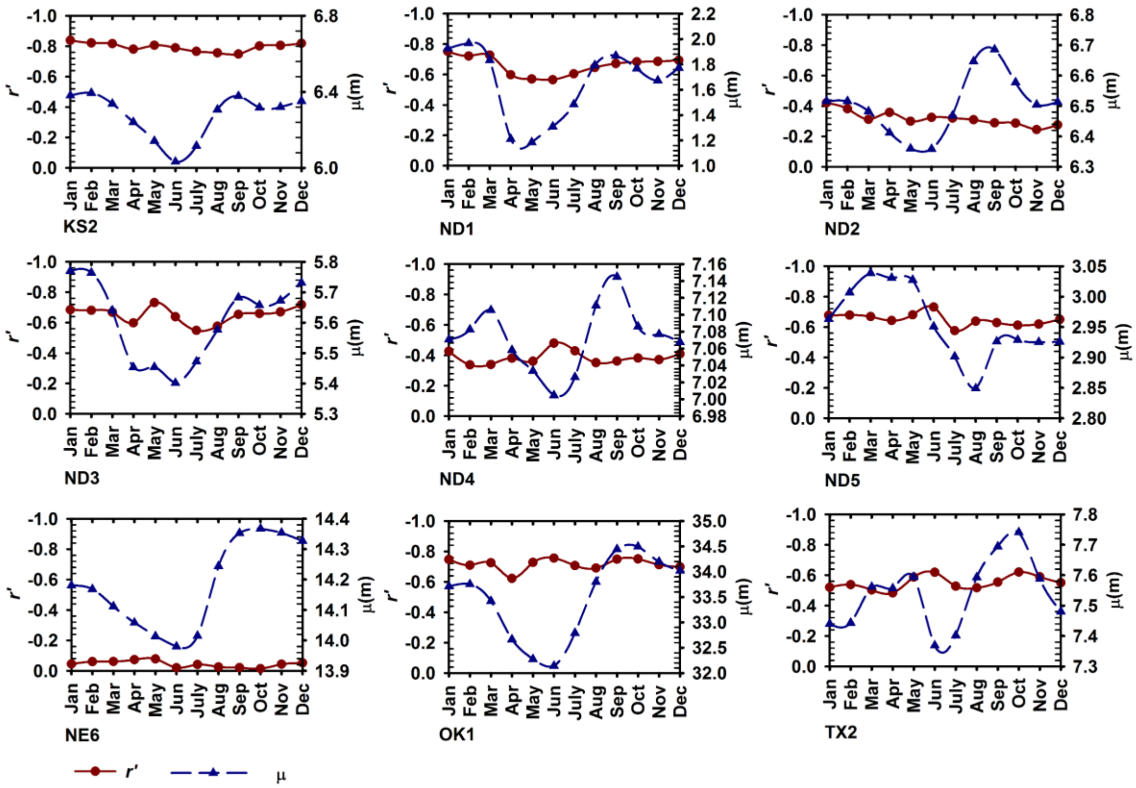

Figure 5.4: Monthly variation of *r'* and μ.

To study the effects of drought duration on groundwater decline, seven different events were identified that could satisfy the criteria of SPI-24 ≤ -0.8 in the area surrounding the well for at least 30 consecutive months. This was also complementary with complete well data spanning a similar time frame of 30 months. Table 5.2 shows the timeline of drought events (year and month of starting and ending), duration of drought events (number of months under moderate or more severe drought), and available monthly median records of groundwater level records within established drought events.

Table 5.1: Correlation coefficients between SPI-24 and b (*r'*), sample size (n), and average of monthly median values (μ).

ID (time frame)	Pr	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec
KS2	*r'*	-0.84	-0.82	-0.82	-0.78	-0.81	-0.79	-0.77	-0.76	-0.75	-0.80	-0.81	-0.82
(1953 – 2013)	*n*	61	60	61	61	61	61	61	61	61	61	61	60
	μ	6.38	6.39	6.34	6.24	6.14	6.03	6.12	6.31	6.38	6.32	6.32	6.35
ND1	*r'*	-0.75	-0.72	-0.73	-0.60	-0.57	-0.57	-0.60	-0.65	-0.67	-0.68	-0.69	-0.69
(1964 – 2013)	*n*	49	44	48	49	46	47	47	47	47	48	48	49
	μ	1.92	1.97	1.83	1.21	1.18	1.31	1.48	1.79	1.87	1.77	1.67	1.77
ND2	*r'*	-0.42	-0.38	-0.31	-0.36	-0.30	-0.33	-0.32	-0.31	-0.29	-0.29	-0.24	-0.28
(1979 – 2013)	*n*	29	28	33	33	35	35	35	35	34	35	35	32
	μ	6.52	6.52	6.48	6.41	6.36	6.36	6.47	6.65	6.69	6.58	6.50	6.51
ND3	*r'*	-0.68	-0.68	-0.67	-0.60	-0.73	-0.64	-0.55	-0.58	-0.65	-0.66	-0.67	-0.72
(1969 – 2013)	*n*	36	37	39	36	32	42	39	41	36	44	40	36
	μ	5.77	5.76	5.64	5.45	5.45	5.40	5.47	5.58	5.68	5.66	5.67	5.73
ND4	*r'*	-0.43	-0.34	-0.34	-0.38	-0.36	-0.48	-0.43	-0.35	-0.36	-0.38	-0.37	-0.41
(1966 – 2013)	*n*	45	45	47	46	46	46	45	46	47	46	47	47
	μ	7.07	7.08	7.11	7.06	7.03	7.00	7.03	7.11	7.14	7.09	7.08	7.07
ND5	*r'*	-0.68	-0.68	-0.67	-0.64	-0.68	-0.73	-0.58	-0.64	-0.63	-0.61	-0.62	-0.65
(1981 – 2013)	*n*	31	29	29	31	33	33	30	31	30	33	32	31
	μ	2.96	3.01	3.04	3.03	3.03	2.95	2.90	2.85	2.93	2.93	2.93	2.93
NE6	*r'*	-0.04	-0.06	-0.06	-0.07	-0.08	-0.02	-0.04	-0.02	-0.02	-0.01	-0.04	-0.05
(1967 – 2013)	*n*	46	46	47	47	47	47	46	46	47	47	47	47
	μ	14.18	14.17	14.11	14.06	14.01	13.98	14.02	14.24	14.35	14.37	14.35	14.33
OK1	*r'*	-0.75	-0.71	-0.73	-0.62	-0.73	-0.76	-0.71	-0.69	-0.75	-0.75	-0.71	-0.70
(1960 – 2013)	*n*	52	52	52	54	52	53	54	52	53	54	53	54
	μ	33.71	33.75	33.42	32.66	32.27	32.14	32.79	33.80	34.44	34.49	34.20	34.02
TX2	*r'*	-0.52	-0.54	-0.50	-0.48	-0.59	-0.62	-0.53	-0.52	-0.55	-0.62	-0.59	-0.55
(1981 – 2013)	*n*	28	25	30	28	27	27	29	27	28	28	27	26
	μ	7.44	7.44	7.56	7.56	7.59	7.37	7.40	7.59	7.69	7.74	7.59	7.48

Pr- Parameters; *r'*-correlation coefficient; *n*-number of monthly records; μ-average values of monthly median records in meters.

Table 5.2: Pertinent data showing selected drought events and number of groundwater level records.

	Drought Events			
ID	Start	End	Duration	# Records
KS2	195307	195710	52	52
MT1	200006	200304	35	35
MT4	200006	200302	33	32
ND3	198905	199207	39	39
ND4	198807	199106	36	36
ND5	198807	199106	36	35
NE2	193508	193808	37	30

The monthly SPI-24 values variation with temporal groundwater levels is shown in Figure 5.5(a-1 to g-1). The *x*-axis shows the year and month. The time frame commences two years before the beginning of drought, and ends two years after the drought event. As such, we can extract information on lag and recovery times of groundwater levels to drought. From Figure 5.5 (a-2 to g-2), we can see the relationship between *b* and duration, *d*, of a moderate or more severe drought, that is, SPI-24 ≤ -0.8 condition. Wells MT1, MT4, ND3, ND4, and ND5 display a prominent linear relationship with respect to the duration of drought events ($r > 0.9$) compared to wells KS2 and NE2 (Figure 5.5: a-2 to g-2). Table 5.3 shows the results of: (i) total groundwater decline values during each drought event, (ii) correlation coefficient between depth to water level and duration, *r*, (iii) fitted linear regression model equations for depth to water level with duration, and (iv) coefficient of determination, R^2. The total groundwater decline was determined from the difference in groundwater levels at the beginning and end of each drought event. The highest R^2 value was obtained for well ND5 which indicated that 97.41% of variation in groundwater level may be attributed to duration of moderate or more severe drought, that is, SPI-24 ≤ -0.8 conditions. Well NE2 displayed the lowest R^2 value of 39%. The water levels for wells KS2 and NE2 started to recover a few months ahead of the end to the associated drought event thus displaying a relatively low linear correlation value (Figure 5.5).

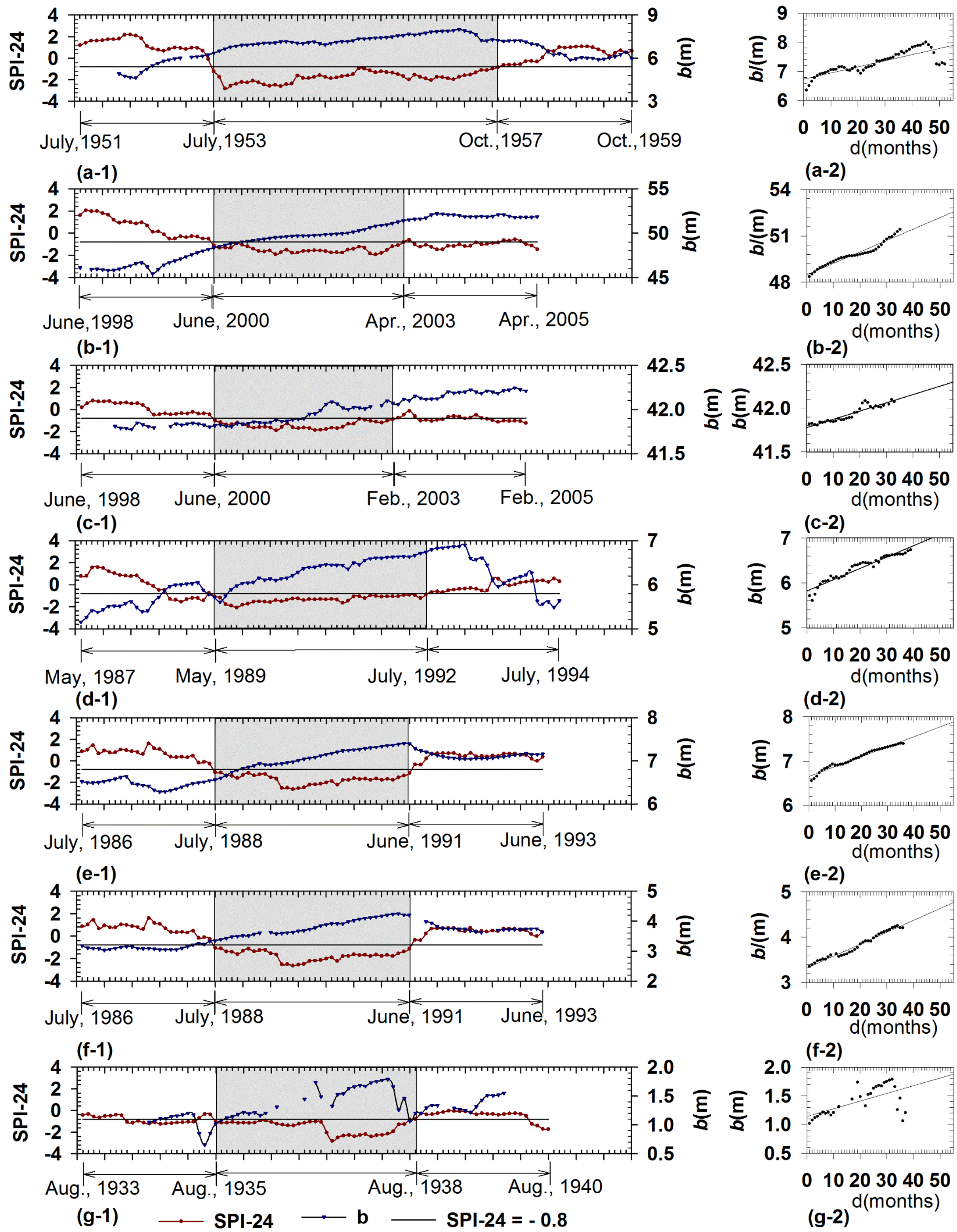

Figure 5.5: The variation of *b* with SPI-24 and duration (*d*) of selected drought events for (a) KS2, (b) MT1, (c) MT4, (d) ND3, (e) ND4, (f) ND5, and (g) NE2.

Table 5.3: The relationship between *b* and duration (*d*) of drought events.

ID	Time Frame		Total Drop (m)	r	Regression model	R^2 (%)
	Start	End				
KS2	195307	195710	0.90	0.831	$b = 0.021d + 6.734$	69.08
MT1	200006	200304	3.05	0.976	$b = 0.074d + 48.478$	95.34
MT4	200006	200302	0.25	0.933	$b = 0.009d + 41.779$	87.11
ND3	198905	199207	1.02	0.962	$b = 0.025d + 5.825$	92.51
ND4	198807	199106	0.84	0.986	$b = 0.022d + 6.653$	97.30
ND5	198807	199106	0.85	0.987	$b = 0.026d + 3.318$	97.41
NE2	193508	193808	0.19	0.625	$b = 0.013d + 1.143$	39.00

The depth to water level increased or continued to remain high even after the end of a drought event for wells MT1 and MT4. The consequent drought pattern after the defined drought event may be the reason for this type of anomaly. Wells MT4 and ND3 show a lag in response to a drought event. In general, we can surmise that the groundwater decline was linear during established drought events defined as moderate more severe, that is, SPI-24 ≤ -0.8. However, there was variation in groundwater responses before the onset and offset of drought events.

Drought impacts all water dependent sectors, and causes vast economic losses and environmental issues. Hays et al. (2011) emphasizes that an impact assessment is vitally important for decision making, responding, and understanding vulnerabilities of drought. Above ground hydrological responses to drought using stream flow data is a vastly studied area compared to studies of influences of drought on groundwater resources. This study investigated the possibility of utilizing drought indices in exploring groundwater level responses to drought. It should also be recognized that inherent challenges also face establishing an uncontested parametric relationship between drought indices and groundwater dynamics due to complex nature of aquifers such as varying depth, properties of aquifer and recharge area, and possible anthropogenic influences.

5.4. Summary and Conclusion

This study explored the relationship between groundwater levels and drought indices for wells located in the Great Plains States of the U.S. The groundwater level data from USGS CRN wells with minimum anthropogenic disturbances were used. Thirty-two wells were selected for the study. The correlation matrix of the drought indices and depth to groundwater levels (monthly median values) was calculated and used to identify which reliable drought indices were necessary in monitoring groundwater responses to drought. It should be noted that drought indices used in this study were derived from NOAA NCDC for each climate division where a well was located. It would be more appropriate to consider indices with areal coverage of recharge area of each well although this would be impractical. Regardless, this study found that drought indices fairly reflected groundwater responses to drought. The PHDI and SPI-24 indices superseded other indices used in this study and displayed a higher correlation with groundwater level. Li and Rodell (2014) also reported that SPI-24 is a promising drought index in studying groundwater responses to drought.

The seasonal variability of groundwater levels, and correlation of groundwater levels with SPI-24 were also studied for selected wells especially those that had adequate data. The correlation between average values of monthly median depths to water level remained relatively the same throughout the year. The fluctuations of groundwater levels for specific drought events were also examined. Drought events, for this purpose, were defined by a SPI-24 threshold of less than or equal to -0.8, a category used for moderate or more severe drought. There were seven drought episodes identified using at least 30 months of groundwater level records. During each defined drought event, the duration of drought events was found to have significant influence on groundwater levels response to drought, displaying a prominent linear relationship to groundwater decline. A set of regression equations were developed to establish the relationship between drought duration and depth to water level from land surface for the selected seven drought events. Based on R^2 values, for four wells (MT1, ND3, ND4, and ND5) more than 92% of the variation in groundwater can be explained by the drought duration. Decline and recovery times were also discernible for groundwater levels for the defined drought episodes with respect to each well location. For example, wells MT4 and ND3 had a lag time from the start of a drought event to when the groundwater level decline was perceptible, whereas wells KS2 and NE4 began to recover prior to end of the drought event.

Observation of groundwater level fluctuation is essential for groundwater monitoring and management. However, there is a deficiency of *in situ* observation due to practical limitations of establishment and maintenance of observatory well networks. Alternatively, establishing a relationship between groundwater and meteorological drought indicators as accomplished in this study will be useful in groundwater monitoring and management. Such a study could enable managers to have an estimated groundwater level during drought based on well-established and readily available drought indices from the widely used source, NOAA NCDC. In addition, the current understanding of interaction between drought and groundwater is limited. A study like this can be helpful to understand the response of groundwater levels to various characteristics of drought such as intensity and duration. However, the relationship between drought and groundwater levels may be region- specific and thus needs to be studied for each region of interest.

CHAPTER 6. QUANTIFYING IMPACT OF DROUGHTS ON BARLEY YIELD IN NORTH DAKOTA, USA USING MULTIPLE LINEAR REGRESSION AND ARTIFICIAL NEURAL NETWORK[1]

6.1. Introduction

Impact of drought on various sectors has long been recognized. Agriculture is one of the major sectors that experiences significant loss during drought events. Agriculture also is the first sector to be affected at the onset of drought because crops at various stages of their growth depend on water and soil moisture (Narasimhan and Srinivasan, 2005). Impact of drought on agriculture has been studied by several investigators (Lott and Ross, 2006; Li et al., 2009; Mishra and Cherkauer, 2010). Li et al. (2009) studied the drought risk for global crop production under current and future climatic conditions by using historical crop yield and meteorological drought. It is anticipated significant losses in yields of major crops in the future due to drought events. There was $145 billion loss in crop production across the U.S. during the last three decades (Lott and Ross, 2006). A better understanding of the historical drought damages and drought-yield relationship could help reduce any future losses. According to Thomson et al. (2005) crop yield variability is mainly influenced by local weather and climate rather than by large scale climatic

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This chapter was extracted from a published article in NNW (Odabas, M.S., Leelaruban, N., Simsek, H., Padmanabhan, G., 2014. Quantifying Impact of Droughts on Barley Yield in North Dakota, USA Using Multiple Linear Regression and Artificial Neural Network. Neural Network World, 24(4): 343-355. DOI: 10.14311/NNW.2014.24.020).

[1]The material in this chapter was co-authored by Navaratnam Leelaruban, Dr. Odabas, Dr. Simsek and Dr. G. Padmanabhan. Navaratnam Leelaruban had primary responsibility for conducting literature review, constructing data base, and conducting analysis. Navaratnam Leelaruban was the primary developer of the conclusions that are advanced here. Navaratnam Leelaruban also drafted and revised all versions of this chapter. Dr. Odabas helped in implementing Artificial Neural Network model. Other co-authors assisted in discussion; and served as proofreader and checked the analysis.

patterns. The State of North Dakota, U.S, is a leading producer of many crops. Particularly, it is a leading producer of barley in the nation accounting for 24% of nation's barley production. Since North Dakota is also a drought prone state, it is important to study the drought-barley yield relationship in particular (Karetinkov et al., 2008; Leelaruban et al., 2012).

Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) models are both widely used in many areas for prediction and classification purposes. MLR is a traditional statistical technique, and it has an established methodology. However, ANN is relatively a recent computational modeling tool that is used to solve many complex real world problems due to its remarkable learning and generalization capabilities (Basheer, 2000; Paliwal and Kumar, 2009). ANN has been used in water quality and water resources area to estimate evaporation, evapotranspiration, rainfall, runoff, and nutrient transportation (Tokar and Johnson, 1999; Tayfur and Guldal, 2006), accounting and finance (Lenard et al., 1995), health and medicine (Reggia, 1993; Ottenbacher et al., 2001), engineering and manufacturing (Feng and Wang, 2002; Yesilnacar and Topal, 2005), marketing (Fish et al., 1995; Ainscough and Aronson, 1999), agriculture (Ayoubi and Sahrawat, 2011, Kaul et al., 2005), and forestry science (Aertsen et al., 2010; Ostendorf et al., 2001). ANN has also been used in several drought forecasting studies (Rezaeianzadeh et al., 2016; Belayneh et al., 2014; Barua et al., 2012).

There are ample information in the literature about the application and capabilities of ANN and MLR (Ainscough and Aronson, 1999; Ayoubi and Sahrawat; 2011, Mekanik et al., 2013; Paliwal and Kumar, 2009; Pao, 2008, Yilmaz and Kaynar, 2011). A detailed review of neural networks and statistical techniques can be found in Paliwal and Kumar (2009). A comprehensive list of comparative studies of applications of neural networks and other statistical techniques from various fields can be found in their study. They also discuss the capabilities of each method. Mekanik et al (2013) investigated the capabilities of ANN and MLR to forecast long-term seasonal spring rainfall in Victoria, Australia using lagged El Nino Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD). They found that ANN is a better model to find the pattern and trend of observations, and generally had lower error compared to MLR.

Kaul et al. (2005) conducted a study to predict the corn and soybean yield using field-specific rainfall, and Soil Rating for Plant Growth (SRPG), and concluded that ANN has a better prediction capability compared to MLR. Ayoubi and Sahrawat (2011) used ANN and MLR to predict the biomass and grain yield of barley in relation to soil properties. They found that ANN outperformed MLR. There are numerous studies on quantifying barley yield using different input characteristics and methodologies (Ayoubi and Sahrawat, 2011; Mkhabela et al., 2011; Ogunkunle and Beckett, 1988; Ostergard et al., 2008). For example, Mkhabela et al (2011) developed statistical models to predict the yield of different crops including barley using MODIS NDVI data for Canadian Prairies. However, the relationship between different drought conditions and barley yield has not been studied using ANN to the best of authors' knowledge. Though MLR models have been used, the complex nature of drought-yield relationship need better methods of prediction and interpretation (Leelaruban et al., 2012).

ANN methodology is a non-linear data driven self-adaptive approach. ANN can identify and learn correlation patterns between variables (independent) and corresponding target variables (dependent) when the underlying relationship is unknown and consequently can predict the dependent variables based on new independent variable data sets (Suo et al., 2010). Basically, ANN performs the function of nonlinear mapping or pattern recognition. If a set of input data corresponds to a definite signal pattern, the network can be trained to give correspondingly a desired pattern at the output. The network has the capability to learn and estimate the output (Bose, 1994).

The objective of this study is to quantify and compare the impact of different drought conditions on barley (*Hordeum vulgare* L.) yield using the MLR and ANN models. Though there are few studies relating yield with climate variables using ANN and MLR, the method has not been used to quantify the drought impact on barley yields to the best of our knowledge. In addition, this study uses the U.S. Drought Monitor data which account for areal coverage and severity of drought. This drought data is relatively new (2000- present), and has not been used for similar past studies. North Dakota State is one of the leading producers of barley in U.S. Therefore, it is only appropriate to use data from North Dakota. However, the methodology used in this study can be used for other areas.

6.2. Data and Methods

6.2.1. Drought Data

This study uses USDM data (see section 2.2.2).

6.2.2. Crop Data

Barley is one of the major agricultural crops grown in North Dakota. County-by-county yield data of barley is derived from USDA National Agricultural Statistics Service (NASS) web portal for the study period (2000 – 2012) (http://www.nass.usda.gov/). Generally, Barley planting will start in later part of April, and harvesting end in early part of September in North Dakota. Figure 6.1 shows the North Dakota counties and barley yield in 2010. North Dakota is one of the north-central states of the U.S and has 53 counties.

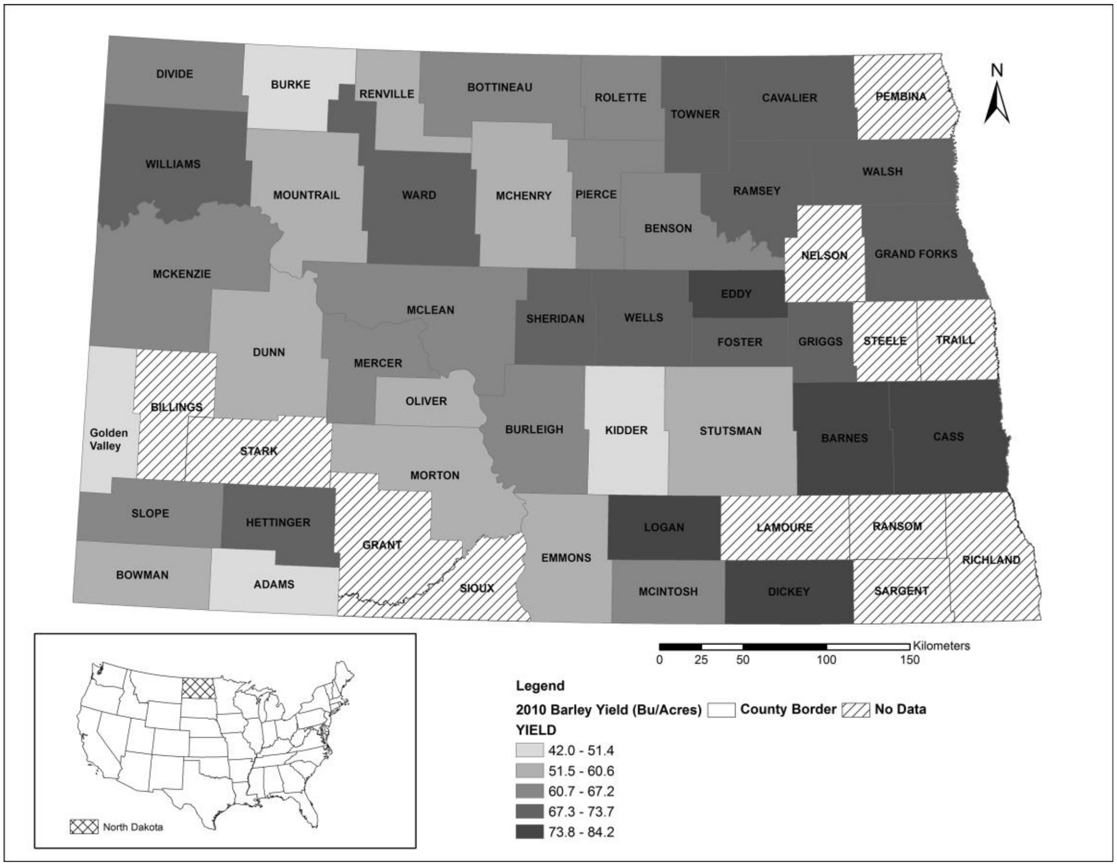

Figure 6.1: The North Dakota counties and barley yield in bushel/acres (1 bushel = 0.03524 m^3; 1 acre = 4046.86 m^2) for year 2010 (barley yield data is derived from USDA NASS web portal).

Table 6.1 shows the barley yield details in ND, U.S. for years 2000 to 2012. For each year, number of counties reported yield (out of 53 counties in ND), average yield, maximum and minimum yield, and corresponding counties are listed. Figure 6.2 shows the average yield variation of barley yield for year 2000 to 2012. The maximum average yield is reported in 2009 (69.22 bu/acres), and minimum average yield is reported in 2002 (40.02 bu/acres) in ND.

Table 6.1: Barley yield (in Bushel/acres) details in ND, U.S. for year 2000 – 2012.

Year	Number of county reported	Average yield	Maximum yield (County)	Minimum yield (County)
2000	53	54.91	71.4 (Pembina)	42.3 (Divide)
2001	53	55.68	66.0 (Slope)	46.0 (Burke/Mckenzie)
2002	51	40.02	55.7 (Traill)	12.6 (Grant)
2003	53	57.60	77.8 (Steele)	29.9 (Grant)
2004	51	59.02	81.6 (Dickey)	27.3 (Grant)
2005	51	53.50	73.3 (Emmons)	40.0 (Divide)
2006	48	46.15	68.6 (Traill)	21.8 (Emmons)
2007	51	53.17	63.3 (Emmons)	37.5 (Richland)
2008	40	54.75	81.1 (Traill)	23.9 (Mckenzie)
2009	41	69.22	91.0 (Emmons)	51.0 (Bowman)
2010	41	64.92	84.2 (Dickey)	42.0 (Golden Valley)
2011	27	43.47	67.1 (Ramsey)	23.3 (Morton)
2012	31	59.01	79.8 (Traill)	31.0 (Slope)

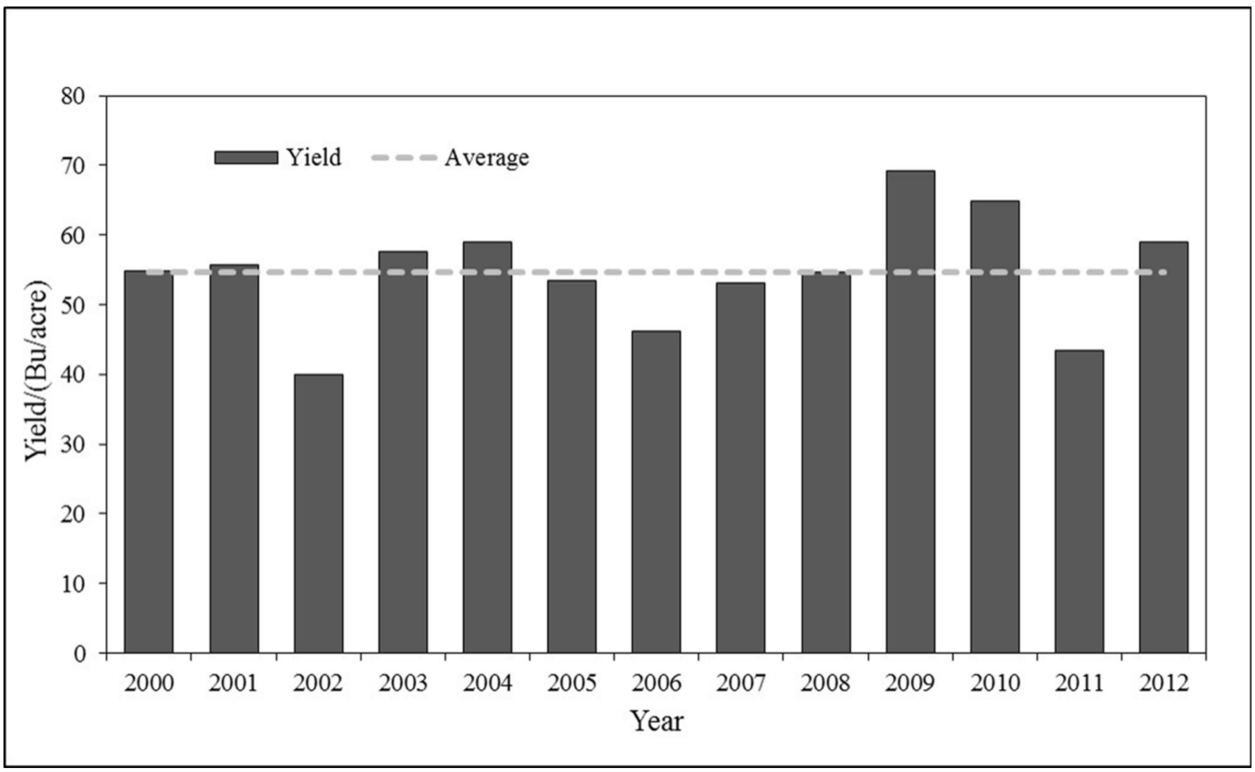

Figure 6.2: Annual average barley yield in ND, U.S. for year 2000 – 2012.

6.2.3. Multiple Linear Regression (MLR)

MLR is a statistical method used to investigate the relationship between several independent variables and a dependent variable. A linear regression model assumes that the relationship between the dependent variable and the *p*-vector of regressors is linear, where p is the number of independent variables. Thus the model takes the form

$$y_i = \beta_1\chi_{i1} + \ldots + \beta_p\chi_{ip} + \varepsilon_i = \chi_i{}'\beta + \varepsilon_i \; i = 1, \ldots, n \tag{6.1}$$

where ′ denotes the transpose, so that $x_i'\beta$ is the inner product between vectors x_i and β. The y_i is called the *regressand* or *dependent* variable. The decision as to which variable in a data set is modeled as the dependent variable and which are modeled as the independent variables may be based on a presumption that the value of one of the variables is caused by, or directly influenced by the other variables. The χi is called regressor or independent variable (Weisberg, 2005). To ascertain the dependency of barley yield on drought categories, Eq. (6.1) was utilized. Average values of A_{D0}, A_{D1}, A_{D2}, A_{D3}, and A_{D4} were calculated between planting and harvesting period from collected data for different drought intensity categories of areal coverage values, where A_{D0}, A_{D1}, A_{D2}, A_{D3}, and A_{D4} are percentage area coverage values for D0, D1, D2, D3, and D4 respectively. Then panel data set was constructed using barley yield, Avg(A_{D0}), Avg(A_{D1}), Avg(A_{D2}), Avg(A_{D3}) and Avg(A_{D4}). For i=1, 2, … 53 counties and t=1, 2, … 13 years (2000-2012) of observation.

$$Yield_{it} = \alpha_0 + \alpha_1 \times Avg(A_{D0})_{it} + \alpha_2 \times Avg(A_{D1})_{it} + \alpha_3 \times Avg(A_{D2})_{it} + \alpha_4 \times Avg(A_{D3})_{it} + \alpha_5 \times Avg(A_{D4})_{it} + \varepsilon \tag{6.2}$$

where $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$ coefficients were tested for statistical significance at the 5% level fitted models of equation 6.2. Though drought is a continuous phenomenon in terms of space and intensity, the drought monitor data account for areal coverage of drought for defined drought intensity categories. Therefore, it is appropriate to use the drought monitor data to quantify the impact of different drought intensity categories on barley yield.

6.2.4. Artificial Neural Network (ANN)

ANN has been widely used to model complex and non-linear processes and systems (Suo et al., 2010). ANNs are non-linear data driven self-adaptive systems that can identify and learn correlated patterns between input data sets and corresponding output values, even when the underlying data relationship is unknown. ANN resembles human brain in two respects; the network acquires knowledge through a learning process, and the interconnection strengths known as synaptic weights are used to store the knowledge (Bekat et al., 2012; Yilmaz and Kaynar, 2011). The ANN can be explicitly programmed to perform a task by manually creating the topology and then setting the weights and thresholds of each link. The process of determining weights and biases is called training. The observed data set used to train the ANN is called the training data set. The training data set consists of input signals assigned with corresponding target (desired) output. The network training is an iterative process. In each iteration weights coefficients of nodes are modified using new data from training data set. The weight coefficients and biases are adjusted in each iteration so as to minimize the error of prediction of target value. In this study, Levenberg-Marquardt (LM) algorithm was used to train the network.

The Levenberg-Marquardt (LM) algorithm is an intermediate optimization algorithm between the Gauss–Newton (GN) method and Gradient Descent (GD) algorithm (Arfken, 1985). It combines the speed of the Newton algorithm with the stability of the GD method.

6.3. Results and Discussion

In this study, the ANN and MLR models were compared for their performance in explaining the influence of drought conditions on the variability of barley yield in North Dakota.

In the MLR analysis, the yield of barley was used as the dependent variable and drought conditions were used as the independent variables.

The following tables list parameters derived from MLR model (Eq. 6.2) for barley using MINITAB® statistical software (Table 6.2, 6.3 and 6.4).

The regression equation can be written as;

$$Yield = (58.6) - 0.0688 \times Avg(A_{D0}) - 0.0959 \times Avg(A_{D1}) - 0.191 \times Avg(A_{D2}) - 0.239 \times Avg(A_{D3}) - 5.16 \times Avg(A_{D4}) \tag{6.3}$$

Negative values for coefficients suggest that yield reduces with increasing drought severity as expected.

Table 6.2: Results of analysis of variance.

Source	DF	SS	MS	F	P
Regression	5	12656.2	2531.2	18.88	0.000
Residual Error	585	78439.6	134.1		
Total	590	91095.8			

Table 6.3: Results of regression analysis.

Predictor	Coefficient	SE coefficient	T	P	VIF
Constant	58.6	0.7584	77.24	0.000	
$AvgD_0$	-0.0688	0.0265	-2.60	0.010	1.176
$AvgD_1$	-0.0959	0.0380	-2.52	0.012	1.494
$AvgD_2$	-0.191	0.0483	-3.95	0.000	1.579
$AvgD_3$	-0.239	0.0657	-3.64	0.000	1.171
$AvgD_4$	-5.16	2.4930	-2.07	0.039	1.009

$S = 11.5795$ $R^2 = 13.9\%$, $R^2\ (adj) = 13.2\%$

Table 6.4: Pearson correlation matrix.

	AvgD0	AvgD1	AvgD2	AvgD3
AvgD1	0.264			
AvgD2	-0.119	0.472		
AvgD3	-0.128	0.091	0.361	
AvgD4	0.016	0.046	0.054	0.084

Table 6.2 shows the Analysis of Variance (ANOVA) results for the regression model (Eq. 6.2). The ANOVA table lists the Degree of Freedom (DF), Sum of Square (SS), and Mean Square (MS) for regression model and residual error. The Mean Square for Error (MSE) for the regression model is 134.1. It is high for barley yield value prediction. Overall average barley yield in North Dakota for the study period is only 54.67 bu/acre (1 US Bushel = 0.03524 m^3 and 1 acre = 4046.86 m^2). Thus, prediction results will be unreliable (Table 6.2). However, global F-test indicates that MLR is useful. The observed significance level for F statistic ($p = 0.000$) implies there is strong evidence that at least one of the model coefficient is nonzero, and overall model is useful to predict yield (Table 6.2).

Table 6.3 shows the estimated coefficients for the regression model (Eq. 6.3), estimated standard error (SE) of coefficients, t-test statistic values, P-values, and Variance Inflation Factor (VIF) for coefficients. Results of regression analysis show that all the drought categories coverage has a significant influence in barley yield (Table 6.3). The observed significant values (p-values) in t-tests for all individual coefficients show that all the drought severity coverage categories are significant (at $\alpha = 0.05$) in barley yield prediction (Table 6.3). Negative values suggest that yield reduces with increasing drought severity as expected. Multiple coefficient of determination (R^2) for this model implies that only 13.9 % variation in yield can be explained by drought severity coverage (Table 6.3). It should be noted that the study area experienced only few D4 drought conditions during growing period of barley within the selected time frame for this study.

Low values of Variance Inflation Factor (VIF) for coefficient (<10), and Pearson correlation values between the drought severity coverage categories (Table 6.4) suggest no serious multicollinearity in the model.

The ANN scheme for the problem at hand is shown in Figure 6.3. ANNs can detect the important features of the input-output relationships with the help of nodes in the hidden layer. The hidden layer and nodes are very important for ANN. The nodes in the hidden layer capture the pattern in the data used (Mishra and Desai, 2006). Best fitting results were obtained for the five inputs AvgD0, AvgD1, AvgD2, AvgD3, and AvgD4, and the one output (yield of barley) using one hidden layer and ten neurons with logsig transfer function, $y=1/(1+e^{-x})$. For many practical problems where we need to approximate any function that contains a continuous mapping from one finite space to another, there is no reason to use any more than one hidden layer. The number of neurons used was determined by trial and error. Transfer functions

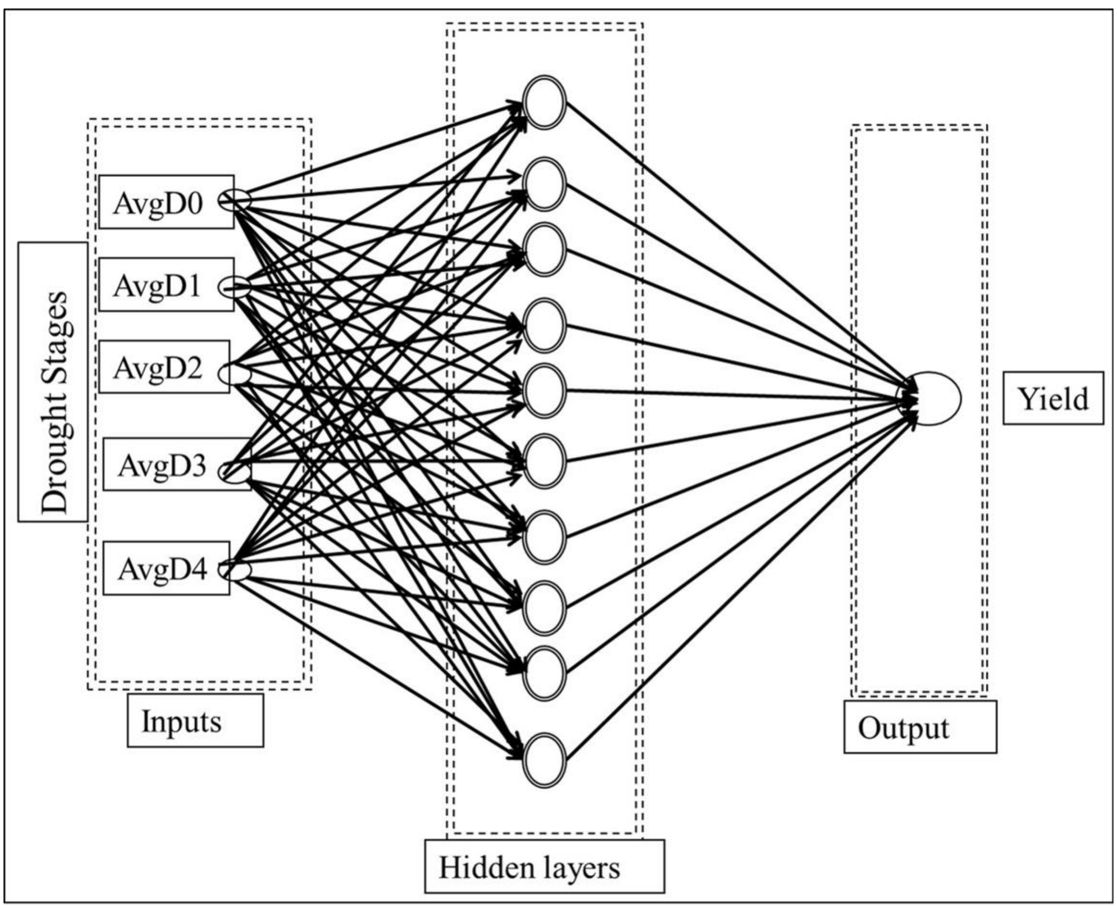

Figure 6.3: ANN Scheme for the study problem.

calculate a layer's output from its net input. The function logsig generates outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity. Logsig function is generally used when the network is used for pattern recognition problems such as this.

Predetermined values for the output error (MSE) and maximum iteration number were set to 0.001 and 1000 epoch, respectively. MATLAB® software was used for this analysis. Since the accuracy of estimation is highly dependent on covering all level of data, the randomization process was repeated until a satisfactory level of data distribution was reached. The training process will be completed when all weighing indices are fixed and the ANN model can accurately estimate the output data as a function of input values (Kawashima and Nakatani, 1998). Randomly chosen 70% of the data set (414 data) was selected as training data for ANN model. The rest 30% of data set (177 data) was used for testing and validation. An output error of 0.007 mse was determined for generated outputs by logsig transfer function with a maximum iteration number of 300 epochs. The R^2 of ANN was found 0.61 for training, 0.59 for testing, 0.61 for validation and 0.60 for all (Figure 6.4). The MSE value of ANN model for the barley prediction is 4.523 for all data.

Zaefizadeh et al. (2011) conducted a research to predict yield in barley using MLR and ANN methods. They determine the relationship between genotypes and genotype interaction in the environment and its impact on barley yield. They stated that ANN is more effective than MLR for the estimating barley yield since the error for the estimation of barley yield was higher in MLR compared to the error in ANN method. Many researchers agree that ANN is superior to MLR with regard to prediction accuracy since the accuracy in ANN increases as the dimensionality and nonlinearity of the problem increases (Basheer, 2000; Paliwal and Kumar, 2009). Overall, many researchers agree that ANN is an intelligence technique and it is superior to MLR in some aspects.

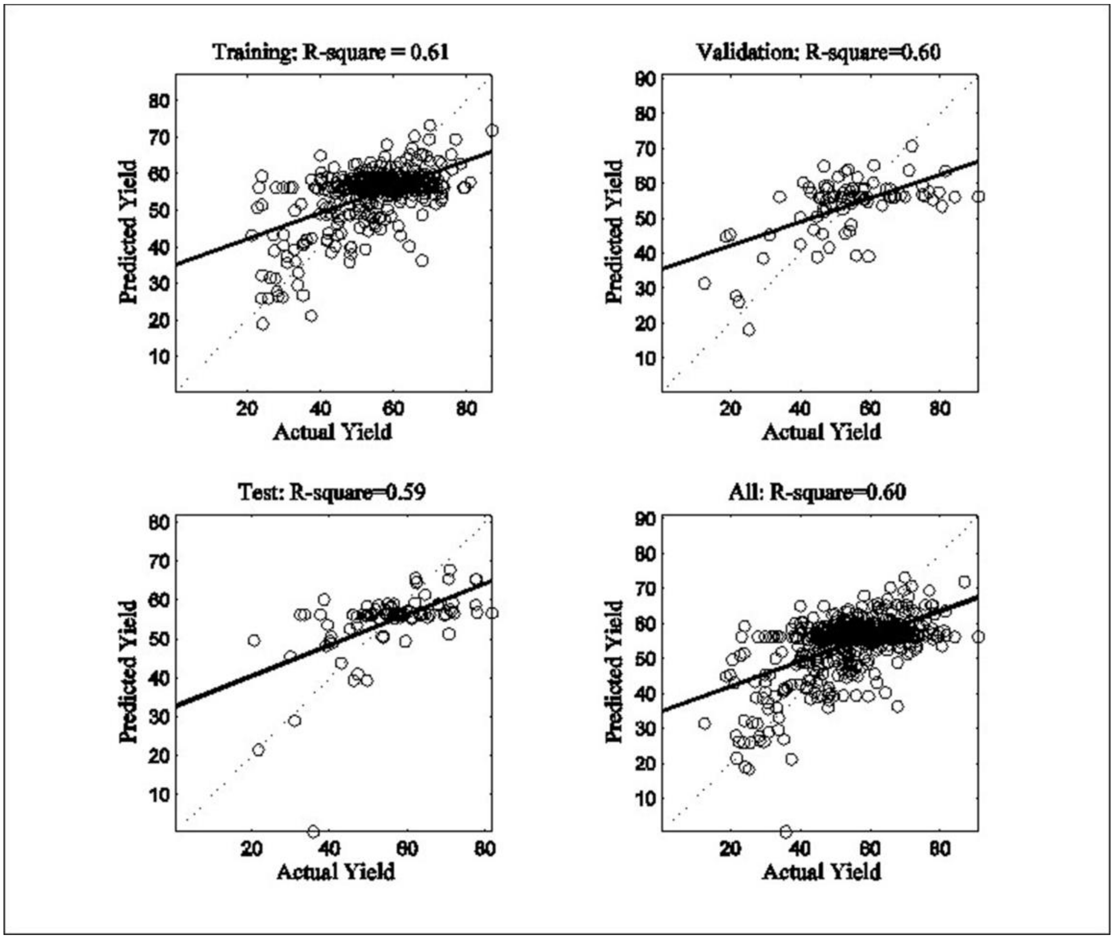

Figure 6.4: The relationship between actual and predicted yield of barley using ANN.

The precision of the approximation is based on the number of iterations of the simulation done. But the relationship between iterations and precision depends on the relationship between the input and output variables. According to R^2 results, ANN model has been found to quantify better the impact of the different drought conditions on barley yield.

6.4. Conclusion

This study quantified the impact of drought on barley yield in North Dakota, U.S., using MLR and ANN models and compared the results. The developed ANN model is trained using different drought conditions. The ANN model coefficient of determination (R^2) indicates that 60 percent of the variation in yield can be explained by drought whereas only 13 percent by multiple regression. It should be noted that barley yield also depends on other variables such as soil characteristics, and management practices. A perfect prediction model should account for all the variables that influence the yield. However, quantification of drought impact on yield is vital in order to develop more powerful predictive models. Massive parallelism, distributed representation, learning ability, generalization ability, and fault tolerance are some of the attractive features of ANN. When the input and output of the system are complicated (multiple input and output, nonlinearity, etc.), ANN can perform better with the help of its inherent structural advantages. Overall, the information processing capabilities and the ability to recognize and learn from input and output regardless of the problem's dimensionality and nonlinearity makes ANN a more efficient method compared to MLR for estimation of impact of different drought conditions on barley yield. While finding of this study emphasis the need of similar studies in different part of the world in order to proper mitigation strategies to address the drought, this study demonstrates how recent computational tools such as ANN can be effectively used to address this kind of problems. The issues associated with and caused by drought have started to be very real even in world regions where these problems have not been viewed, as yet, important. As drought becomes one of the foremost problems of modern agriculture, the application of ANN or in combination with MLR to investigate the impact of droughts on crop yields would be a promising subject for further research.

CHAPTER 7. OVERALL CONCLUSIONS

This study involved two important aspects of drought research: drought characteristics, and drought impact. The emphasis of the first part of the study was on spatial characteristics of droughts, and uncertainty associated with reported drought indices across different spatial scales. The emphasis on the second part was on the impact of droughts on crop yields and groundwater resources.

Drought monitoring and management rely heavily on drought severity indices. This study used U. S Drought Monitor data, a relatively new drought indicator which accounts for areal coverage and severity of drought. However, this data base is available only from the year 2000. Since then, though it became the most popular drought data base in the U.S., it has been found difficult to use and interpret for management purposes in its original form. A refined county-level drought severity and coverage index (I_{SC}) was developed in this study, which can be used for administrative purposes. The county level was chosen because it is an appropriate scale for drought monitoring and management in the U.S. An improved version of I_{SC} called Crop Specific Drought Severity-Coverage index ($I_{SC,AG}$) based on the statistical relationship between crop yields and USDM intensity converges was also developed. These indices (I_{SC} , $I_{SC,AG}$) can be very helpful for drought management administration purposes. The proposed indices I_{SC} and $I_{SC,AG}$ were also used to study drought occurrences at a county level in ND, and to assess the crop yields and their susceptibility to drought. The transition probabilities of various crop yield response from a period of less severe drought to more severe drought conditions determined by $I_{SC,AG}$ were estimated by modeling crop yield as a Markovian process. Crops like corn, durum wheat, and hay (all) display greater tendency to transit to lower yields whereas probability of spring wheat transitioning from higher yield to lower yields is relatively low in response to reduced wetness (more severe drought).

An understanding of drought occurrences and their characteristics such as intensity, duration, frequency, and areal coverage, and their variations on different spatial scales is crucial to plan for droughts in different regions and in different sized areas. Therefore, the above-mentioned characteristics of droughts in the contiguous U.S were studied using USDM data (2000-2014) across different spatial scales. The findings emphasized the need for studying drought characteristics from the perspectives of different spatial scales. The study also investigated how the weekly percentage area under different intensity categories propagates with time, and extracted the spatiotemporal characteristics of different drought intensity categories at different spatial scales. There is a clear variation in the drought characteristics such as intensity coverage, duration, and occurrence at different spatial scales. The results emphasize that drought management and resource allocation policies need to consider drought analysis across different spatial scales around the region of interest.

This study also demonstrated a methodology to quantify the uncertainty in reported drought indices. The characteristics of drought are mostly studied using drought indices that represent the drought condition of specific spatial units such as state, climate division, county, and watershed. However, drought is a geospatial variable and can have a significant variation within such a unit. Geostatistical tools can be used effectively to model the spatial characteristics of droughts and to quantify uncertainty in drought reporting at different spatial scales. In this study, uncertainty associated with drought reports across spatial scales was quantified. Results showed uncertainty in the reported values increased with the size of spatial unit for which drought is reported.

The impact of drought on groundwater resources was modeled using linear regression. Of the several drought indices, SPI-24 was found to correlate the best with groundwater levels. The correlation of average monthly groundwater levels with SPI-24 remained relatively the same for all the studied wells. The duration of drought also had significant correlation with groundwater level declines. It is important to monitor groundwater levels during drought for groundwater management. However, there is a deficiency of *in situ* observation wells. Therefore, establishing a relationship between groundwater levels and well-established meteorological drought indicators as accomplished in this study will be useful in groundwater monitoring and management.

This study also investigated the effect of different drought conditions on Barley yield using Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) methods. Though MLR method is widely used, the ANN method has not been used in the past to investigate the effect of droughts on barley yields. This study shows that the ANN model performs better than MLR in estimating barley yield. ANN is proposed as a viable alternative method or in combination with MLR to investigate the impact of droughts on crop yields. The results from ANN model indicate that 60 percent of the variation in yield can be explained by drought whereas only 13 percent by multiple regression.

There are several studies that have been conducted in the past on drought characteristics and impact. However, this study differs from other studies in terms of the following approaches. (a) integrating severity, impact (crop yield), and spatial coverage for county scale (b) capturing the drought characteristics and their variation across different spatial scales perspectives (c) quantifying uncertainty in drought reports, and (f) employing geostatistical, and ANN tools in drought studies.

Drought is a continuing threat all over the world to all the water dependent sectors. It is one of the least understood natural hazards which continue to attract attention of researchers. This study is one among them to further the knowledge base in drought research. The following topics are suggested for future study:

(a) Use of kriging to quantify uncertainty in reporting drought and thereby to improve drought monitoring networks was discussed in chapter 4. This requires several trials using different indices and for different time spans. A comprehensive study on this topic is recommended

(b) The application of ANN for quantifying drought impact is demonstrated using drought intensity coverages and barley yield. The study can be extended for different indices and impact sectors using ANN, and

(c) As discussed in Chapter 2, average values (first moment) of drought indices were used for representing the drought condition of the time span (time between planting and harvesting) to quantify the drought impact on crop yield. Variance (second moment) was not considered in this study, though it is also recognized to be a significant parameter to represent drought condition for the type of studies as the present one. Variance, in addition to average, could also be included in future studies to develop relationships between drought and crop yield.

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