Spatial Patterns of Drought Persistence in Xinjiang (A.R), China

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SPATIAL PATTERNS OF DROUGHT PERSISTENCE IN XINJIANG (A.R), CHINA

by

Guzhaliayi Sataer

A thesis submitted to the Graduate College in partial fulfillment of the requirements for the degree of Master of Arts Geography Western Michigan University June 2015

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Droughts have become one of the crucial hazards affecting Xinjiang, Northwest China, the biggest agricultural province and an important area for the grazing husbandry industry in China. Investigations about droughts in Xinjiang have been conducted from various perspectives by previous researchers. However, there are very few studies that focus on drought persistence and seasonal drought frequency. These issues are particularly important as they influence water resource management and forecasting, crop yields, agricultural development and energy consumption. Seasonal drought persistence describes how well drought conditions persist from one season to next season and is expressed as probability of persistence. In this study, monthly precipitation from 50 weather stations will be converted to the Standardized Precipitation Index (SPI). Seasonal drought frequency is calculated as the total number of years in which drought occurs in each climate division. A logistic regression model is employed to further investigate drought persistence from one season to other, and the model outcome is the log odds ratio of drought occurrence in the given season for any given location. The expected outcome from the logistic regression model will help to improve the operational decision making for water resource management, hydropower operation, irrigation planning and herding activities in Xinjiang.
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CHAPTER I

INTRODUCTION

Problems Related to Global Drought

Drought is a very complex phenomenon in terms of duration, spatial extent and impact, and remains a poorly understood climate hazard (Wilhite et al., 2007).

Drought length is the time period from the beginning to the end of the drought. It usually takes 2-3 months for a drought to become established. Tannehill (1947) mentioned that drought is a creeping phenomenon which takes a long time period to accumulate and determine. Drought is also related to the drought severity of the event which is also related to a cumulative deficiency in precipitation (Sam, 2011 Pg7). The spatial extent is the spatial distribution of the drought that is how much area is covered by any given drought hazard. Most of the time making drought intensity maps to show the vulnerable areas is essential. Drought has devastating impacts spatially for greater than any other natural hazards such as flood and hurricanes. The spatial distribution of many droughts is for than other hazards. Drought also has an immense direct and indirect impact on economic and social activities including agricultural and tourism as well as recreation. Drought can reduce crop yields and rangeland and forest productivity, which also increases the chance of fire hazard and reduce the water levels which in turn will harms wildlife and fish. From 2001 to 2002, most of the regions in Canada experienced an extreme drought period that was unseen
for a hundreds of years. Total losses for agriculture products were 3 billion dollars for
the two years. Another report estimated the agricultural losses from growing season
droughts to be more than 5 billion dollars in the Canadian central provinces (Wheaton
et al., 1992).

It is estimated that the global economic losses caused by droughts are as high
as $ 6–8 billion US dollars each year, far more than any other type of meteorological
disaster (Wilhite, 2000). Drought and drought-associated heat waves over the years
from1980 to 2002 impacted most parts of United States, especially the southwest.
This damage is highlighted in terms of wildfires burning over 370,000 ha and insect
outbreaks damaging three million acres of pinyon and ponderosa pine (Cook et al.,
2007). The western part of United States has experienced severe drought since late
1999, and 50% of the area was under the threat of drought in 2002(Cook et al., 2007).
The drought in 2012 in Southern Michigan was the worst year for agriculture harvest
(Change 2012).

Farmers saw 20 to 30 percent of the normal crop production in this year.
Africa is the second largest continent in the world and the most droughts vulnerable.
A continuous 60 years drought forced millions to leave their homes to escape drought
in Kenya, Ethiopia and Somalia (Tutton, 2011). Drought problems not only occur in
the Western world, but it also happens in many regions of Asia. For example, 18
percent of Yunnan Province in China faced persistent water shortages, and 2.5 billion
dollar worth of crops were lost. In Yunnan around 20 million people are faced with
insufficient water resources to drink, not to mention limited participation in agricultural activities. The total economic losses caused by severe drought in Southwest China are 1.61 billion dollars (Nature, 2010). In 2008 an extreme drought occurring in Northern China contributed in the loss of 10 million hectares of crops, including over 3 million hectares completely destroyed, which was only small part of the damages. More than 4 million people and 2 million livestock also faced water shortages. In Anhui Province alone the economic loss increased to 2.2 billion dollars (Hui and Song, 2009).

**Drought in Northwest China**

The rapid development of industry brought many benefits to the world economy, and improved human life as well. However, industrialization brought new environmental issues at the same time. As we know, the great smog in London during the month of December of 1952 was one of the first warnings that the environment had changed. After that human society faced global warming, climate change, floods and droughts. Extreme climate events have devastating effects on environment, economy and human health. Thus it is essential to understand the mechanisms of variable climate hazards to allow for the development of mitigating measurements against natural disasters (Benjamin, 2011).

Northwest is considered as an important agricultural region in China. But studies show that agricultural in Northwest is heavily influenced by climate extreme events, and drought is one of the incidents. Drought affected crop area and drought
destroyed crop land 360600 and 266000 ha from 2000 to 2007 respectively (Wen, 2005), and also consist increasing trend after 2000. Drought also became the major challenge for water resource management and water use policy that could effect on agricultural irrigation and human activities as well (Lu, 2003).

Northwest China has large, fertile and concentrated farm land, which is typically used for gravity irrigation for and large scale cultivation. Northwest China is the major producing area of cotton. Cotton, beets and fruit are the major economic crops in the region. The output of cotton harvest 838.31 kg per mu (0.067 hectares) has surpassed the world record in 2012 (Tang, 2012). Frequently occurring natural disasters, especially droughts and floods, have damaged lots of properties and ruined many lives in the past decade in this region. The incomes of the local people have also been reduced by these disasters. In recent decades, there is a magnifying trend of the drought and flood calamities in this region (Jiang, 2004).

Thus, understanding spatiotemporal patterns of seasonal drought persistence or the tendency for drought to continue from one time period to another period is significant to agricultural development, to water supply management, and last but not least to human health and economy. Investigating drought predictions and developing indicators to improve operational decision- making for water supply, transportation, hydropower, and irrigation is very important for the continued prosperity of this region.
Drought Studies

Droughts have become one of the crucial hazards affecting Xinjiang A.R in Northwest China (Figure 1). Xinjiang is the biggest agricultural province and an important area for pastoral husbandry in China. Investigations about droughts in Xinjiang have been conducted from various perspectives by many researchers. However, there are very few studies that focus on drought persistence and seasonal drought frequency. This research is particularly important as droughts influence water resource management and forecasting, crop yields, agricultural development and energy consumption. This research has the following two main objectives. 1) Identify and investigate spatial drought patterns of seasonal drought frequency and persistence in Northwest China; 2) Employ logistic regression to further investigate the odds and probability of droughts persisting from one season to the next.

Seasonal drought persistence describes how well drought conditions persist from one season to the next season and is expressed as a probability of persistence.

In this study, monthly precipitation from 50 weather stations will be converted to the Standardized Precipitation Index (SPI) for the years from 1957 to 2012. Seasonal drought frequency is calculated as the total number of years in which drought occurs in each climate division. Logistic regression models are employed to further investigate drought persistence from one season to other, and the model outcome is the log odds ratio of drought occurrence for any given location in any given season. The expected outcome from the logistic regression model will help to improve the operational decision making for water resource management, hydropower...
operations, irrigation and herding activities in Xinjiang.

Chapter Summary

This thesis is structured as six chapters. The first chapter describes the severe drought impacts and offers a brief description of the current study. The second chapter provides a review of previous studies of drought monitoring and prediction. The third chapter offers the background information and presents the data and methodology that were employed in this study. The fourth chapter discusses the results. And last chapter offers conclusions and identifying area where future work is needed.
CHAPTER II

REVIEW OF LITERATURE

Introduction

How droughts impact the environment and human beings was summarized in chapter one. It is also important to know the definition of drought and how droughts are measured and monitored across the regions and nations. This review of literature will consist of four sections. Section one will discuss some common existing definitions of droughts used by climate researchers. Section two will discuss how global drought measurements are made. Section three will discuss drought monitoring and prediction in China, and introduce the drought index that has been commonly used in China. Section four will discuss the previous drought studies conducted by scholars in Xinjiang, Northwest China including studies on precipitation patterns, climate change and drought measurement techniques. The last section will discuss the potential importance of this research and projected outcomes.

A Definition of Drought

Drought is a complex phenomenon which is hard to accurately define in terms of its spatial variations and dependent context (Quiring, 2009; Sam, 2011; Wilhite, 2007). In most drought studies, scholars describe drought via two main categories. The two types are conceptual and operational drought. The former is conceived as a
temporary lack of water caused by abnormal climate such as climate change, poor agricultural management and, last but not least, human activities which are necessary to all of us but do not exclusively explain what the drought is (Kallis, 2008). There are three types of conceptual drought. Meteorological droughts (weather, specifically abnormal precipitation deficits), agricultural droughts related to soil moisture deficiencies and poor water resource management, and hydrological droughts that refer to abnormal groundwater, lake deficits etc., water supply droughts that mostly chase back to the human activities and water resource management so that poor water supply systems cannot meet demand (Kallis, 2008). There are six evaluation criteria for those conceptual droughts (Keyantash & Dracup, 2002). Robustness refers to the implication of a range of physical condition and feature. Tractability implies the practical aspects of the drought index. Transparency is related to objective clearness and rationality behind the drought index. Sophistication is vital perspective for understanding physical motion and is related to the quality of data and accuracy of assessment method. The last is dimensionality which is the relationship between the drought index but not sequent data treatments and the physical world (Keyantash and Dracup, 2002).

Operational droughts are, on the other hand, more practical and specific. When defining operational droughts, the researchers most figure out the beginning, end, and degree of severity of drought (Quring, 2009). In most cases, it is hard to define operational drought in terms of large variations or ranges in geographic locations and climate quite different from region to region. Employing the general definition of
operational drought can lead to mischaracterization of drought conditions and incorrect drought responses, therefore it is important to define operational droughts according to local conditions or local levels of drought indices (Wu et al., 2007; Quring, 2009).

**Global Drought Monitoring and Prediction**

Drought is considered as one of the most costly and least understood natural disasters (Kao and Govindaraju, 2010). It is a global phenomenon that can occur in all types of landscapes, often leading to a large amount of economic loss as mentioned in the previous chapter. Thus it is a popular research topic among the scholars from many disciplines.

McKee (1993) created a new drought monitoring index-standard precipitation index (SPI), which produces probabilities of drought and, estimates the average precipitation and precipitation deficits during droughts. Kogan (1995) measured and detected drought in United States and including its time of its onset, intensity, duration, dynamics and impacts on vegetation by employing vegetation condition index (VCI) which can be obtained from satellite data.

Zhe and Tan (2013) came up with another new drought monitoring method (MPDI1) that is a combination of the soil moisture component using the Perpendicular Drought index (PDI) and a vegetation component using the Perpendicular Vegetation index (PVI), which is developed in NIR-Red reflectance space. They mentioned in the end that MPDI1 had great potential for surface drought
estimation that provided correct and effective information about surface drought in the soil-plant continuum. Dastorani et al., (2011) in their drought study in Iran employed two drought indexes (SPI and Reconnaissance Drought index (RDI)) to show the drought severity in Iran. They found both drought indexes had similar results on predicting the effect of drought in different regions of Iran, but the RDI resolved more climatic parameters such as evapo-transpiration which is important in calculating water resource losses. Two years later, in another drought study, Kousari et al.,(2014) also used different time series of RDI (3, 6, 9, 12, 18 and 24 monthly time series) trends to calculate drought severities. The results showed there were decreasing trends in long time series (12, 18 and 24 monthly time series) DRI as compare to short time series showing an important decreasing trends in DRI corresponding to increasing trends in drought severities. This is one of the threats for water resource management in Iran (Kousari et al., 2014). Multivariate Standardized Drought Index (MSDI) was also employed in a study of the continental United States and also showed MSDI was appropriate for high probability drought detection as compared to individual drought indices such as precipitation and soil moisture. This study mentioned that further drought studies should be based on multiple source of information to improve drought detection and monitoring (Hao and Aghakouchak, 2014). Ford and Labosier (2013) examined the spatial patterns of drought frequency and persistence in the Southeastern United States by using a logistic regression model which employed SPI to calculate the odds and probability of drought persisting from one season to another. This study also mentioned logistic regression models could be
applied across any region and climate regime for probabilistic seasonal drought forecasts, however long and continuous datasets are required for logistic regression models. Scholars in India investigated drought by using ARIMA linear stochastic models and multiplicative Seasonal Autoregressive Intergrated Moving Average (SARIMA) models which used SPI values as an input dataset. The significant results of these models can be used to forecast droughts with up to 2 months of lead time in India (Mishra and Desai, 2005).

**Drought Studies Across China**

Chapter one provided some examples of severe drought incidents in Southwest, Northern, Central and Northwest China, and their devastating economic and social impacts as well. Thus, Chinese scholars focus upon drought studies in China. In recent years central China has experienced many severe droughts, especially in Shanxi Province. Sun et al., (2008) developed a drought monitoring approach by using Vegetation Temperature Condition Index (VTCI), and figured out how the time series profile in VTCI measured in cropland does respond under both the rain-fed and irrigated conditions. The results showed that VTCI was the effective method for monitoring drought after crops turn green. Also under the rain-fed conditions, the time series VTCI had a more significant response to recent precipitation than irrigated conditions due to the different irrigation practices. Employing remote sensing technique is widely used all around the globe, China is no exception. Dong et al, (2013) investigated severe drought from 2008 to 2009 Northern China by using
Chinese HJ-1 satellite images together with NASA Moderate Resolution Imaging Spectro-radiometer (MODIS) data which include the Vegetation Index and the Water Index. The results indicated a combination of HJ-1 data and MODIS data was very effective for monitoring drought and soil moisture. After one year another similar drought study in Southwest China from 2000-2010 also used MODIS remote sensing data (Drought Severity Index (DSI)), and also tested the performances of the DSI by comparing its estimated value for the different time series of SPI. The outcome of the study showed that there were strong correlations between the DSI droughts patterns estimated with different time scales of SPI. Therefore DSI was the appropriate data to monitor the drought conditions over the study region and any similar regions (Zhang and Yamaguchi, 2014). In the research related to the 2011 severe drought impacting much of North China, Lu et al., (2014) came up with a Weighted Average of Precipitation method (SWAP) which can measure drought from daily to weekly, monthly periods. The model is even flexible enough to measure longer time scales. The SWAP index overcame the difficulty of complexity and limitations of PDSI as well as the longtime scale considerations of SPI. Results revealed that SWAP has the ability to measure day to day variation of spring drought in the Yangzi River basin, and also gave detailed information about the potential onset, duration and end of droughts. In a recent drought study developed by He et al., (2015) that employed the Comprehensive Drought Index (CI) for drought in the Haihe River basin from 1961 to 2011. The authors found that CI was an effective index to demonstrate the duration, frequency and severity of meteorological droughts in each station in the Haihe River
basin.

**Drought Research for Northwest China**

As noted earlier, employing remote sensing technique is a common method to investigate and monitor drought. Zhang and Jia (2012) applied a new multi-sensor Microwave Intergraded Drought Index (MIDI) which integrated Tropical Rainfall Measuring Mission (TRMM)-derived precipitation, Advanced Microwave Scanning Radiometer for EOS (AMSR-E) derived soil moisture, and AMSR-E derived land surface temperature for monitoring short time meteorological droughts for semi-arid regions. The results revealed that MIDI is an appropriate index for measuring short time meteorological drought over grassland of which improving cropland monitoring for Northern China and similar regions across the globe. Li et al., (2006) examined the regional history of droughts (1645-2002 AD) by calibrating with PDSI. Their study revealed not only extreme droughts incidents through long-term history, but also showed the long-term drought variability patterns. Eventually, it was deemed reasonable to apply a combination of tree-rings analysis and PDSI in investigating long-term drought patterns. Scholars are progressively more interested in precipitation and temperature changes that are related to climate change in Northwest China. Li et al., (2010) found higher concentrations of precipitation in South Xinjiang but lower concentrations in North Xinjiang by employing daily precipitation data for the period of 1961–2008 based on data from 50 rain gauge stations. Jiang et al. (2002) studied the statistical and fractal features of flood and drought disasters in Xinjiang, and
found that the flood and drought disasters in Xinjiang increased significantly after the 1980s. Zou and Zhang (2008) used daily precipitation and mean temperature series from 1951 to 2006 to conclude that the area affected by drought in Northwestern China significantly decreased after the middle of 1980s. Zhang et al., (2012) using the SPI value, argue that the south Xinjiang seems to be getting wetter in summer, while the southern parts of the south Xinjiang seem to be getting drier in the spring. Middle-east Xinjiang is identified as having a slightly dry tendency. Clearly, precipitation and seasonal drought variability in the Northwest China is not well understood. There are still many deficiencies regarding drought prediction either by season or a single for drought persistence and seasonal drought frequency. These factors are particularly important as they influence water resource management and forecasting, crop yields, agricultural development and energy consumption. Seasonal drought persistence describes drought conditions that persist from one season to next season. Seasonal drought persistence for each climate division and season (winter-spring, spring-summer, winter-summer) combination are expressed as the probability of persistence, calculated as the total number of years of drought exhibition divided by the total number of years in which drought occurs during the first season in that climate division. It is been clearly seen that we can calculate the probability of summer drought occurrence once a given spring SPI value is known. Thus, understanding the spatiotemporal patterns of seasonal drought persistence or tendency for drought to continue from one time period to another period (month-month, season-season, year -year) is significant to the agricultural
development, water supply management and human health conditions facing any region, including Xinjiang.
CHAPTER III

DATA AND METHODOLOGY

Study Area

Xinjiang A.R is located in the innermost center of the Eurasian continent, within the northwest part of the People’s Republic of China and covers both semiarid and arid areas. There are three mountain ranges running east-west from north to south. These consist of the Altai Mountains, the Tianshan Mountains, and the Kunlun Mountains. There are two major basins situated between these three great mountain ranges; the northern Junggar Basin which consists of mostly steppe and semi-desert, and the southern Tarim Basin which is considered to be as a more typical basin desert. Figure 1 the macro-region is a typical mountain–basin system including permanent snow and ice, high mountain forests, middle mountain forest–grassland, low mountain desert, agricultural oasis and shrub–grassland biomass (Wu et al., 2010).
The climate of Xinjiang Autonomous Region is typical of inner-continental land masses, with a wide daily temperature range, low precipitation and low humidity. It has been dry-warm from the end of the little ice age to the 1980s. During the past twenty years, it has changed to a warm-wet climate region (Shi et al., 2007). According to Wu et al., (2010), the annual precipitation of North Xinjiang is range from 100 to 500 mm with great variability, while South Xinjiang records only 20 to 100 mm. Annual average temperatures in north Xinjiang range from 4°C to 8°C, and in south Xinjiang from 10°C to 13°C. In the hottest month of July, the temperature in the Turpan basin to the north can reach as high as 48.9°C. However, in the coldest
month, the temperature can be as low as $-51.5^\circ$C in Fuyun in northern Xinjiang. On average, according to Wu (2010) south Xinjiang has from 200-220 frost-free days, whilst less than 150 days in the further north.

Northwest China has large expenses of fertile and concentrated arable land, which is appropriate for gravity irrigation and large-scale cultivation. Currently, Northwest China is the major producing area for cotton, sugar beets and fruit which are the major economic crops in the region.

Data

The raw data sets consist of daily precipitation amounts for the period from 1957-2012 for 55 surface meteorological stations. The data was downloaded from the China Meteorological Data Sharing System of China Meteorological Administration (CMA) (http://www.cma.gov.cn). After data cleaning 43 stations were selected for this study. The cleaning up process included identifying obvious errors in precipitation data, such as missing values and values less than 0 mm. It used ArcGIS 8.3 identify the location of each station and excluded a few stations which had almost the same longitude and latitude as other stations. After rejecting 12 stations, 43 stations finally were selected in this study. The locations of 43 stations are plotted in Figure 2.
Figure 2. Meteorological stations used in this study and location of Xinjiang, China

Drought indices are normally used to identify moisture conditions in any given region, to detect the onset of drought and to measure the severity and geographic extent of droughts (Alley, 1984). There are several drought indices as noted earlier, which are commonly used by scholars including PDSI, DSI, DIMI, CI and SPI. The
Standard Precipitation Index (SPI) was used in this research. This study classified meteorological drought which is defined as a period in which SPI reaches a value of -1.0 or less, based on the SPI (McKee, 1993). SPI has been used in a multitude of drought related studies, and is considered as a spatially invariant indicator of drought (Meng et al., 2013). Guttman (1998) found that SPI is able to show how drought in one region compares to drought in another region. Previous researches indicate the SPI is essentially a standardizing transformation of the probability of the observed precipitation. It can be computed for a precipitation total observed over any duration desired by a user (1-month SPI, 6-month SPI). Guttmann (1998) and Hayes et al. (1999) compared SPI with the Palmer Drought Severity Index (PDSI) and concluded that the SPI has marked advantages of statistical consistency, and the ability to describe both short-term and long-term drought impacts through the different time scales of precipitation anomalies. Also, due to its intrinsic probabilistic nature, the SPI is the ideal candidate for carrying out drought risk analysis (Guttmann, 1998). Cancelliere (2007) developed an SPI-based drought forecasting methodology under the hypothesis of uncorrelated and normally distributed monthly precipitation aggregated at various time scales. Livada and Assimakopoulos (2007) used the SPI to examine the spatial and temporal variability of drought in Greece. Patel (2007) similarly employed SPI to examine spatial patterns of meteorological drought in Gujarat India. Ford and Labosier (2013) employed the SPI to examine the spatial patterns of drought persistence in the Southeastern United States. Zhang et al., (2012) used the SPI to evaluate the drought events and trends in Northwest China and mentioned the
appropriateness of employing SPI in drought conditions in Xinjiang. Wu et al., (2001) also applied SPI to the areas of arid and semi-arid climate with severe droughts and flooding. Results indicted SPI performed well in those regions including the capital of Xinjiang A.R, Urumqi.

Methodology

At least 30 years of precipitation data are required for calculating SPI. Average periods are calculated by using the different time scales of a period of n months where the n can be 1, 2, 3, 6, 12, 24, 36 or 48 (McKee et al., 1993). For each month the new value is calculated from previous months, then fitted to a Gamma function in order to calculate a probability of precipitation occurring within the period. After calculating the probability of precipitation which for the location being used SPI is calculated along with an estimate of the inverse normal to compute the precipitation deviation from a normally distributed probability density (McKee et al., 1993; Bartels 2014). The probability of precipitation of the location being studied is fitted to the normal distribution with a zero mean and standard deviation. This method can then identify abnormal years which compared to normal years. The timescale for drought prediction is the period as precipitation indices are analyzed and compared to normal precipitation indices for any given location. Timescale selection mostly depends on the purpose of a particular drought study or the type of drought research. Meteorological drought research commonly uses 1, 2, or 3- month timescales. Agricultural drought commonly uses 1, 3, or 6 month timescales and hydrological
drought work mostly adopted longer timescales such as 12, 24, 36 or 48 months (Edwards 1997; Bartels 2014).

For this work, the 1-month SPI was calculated from the monthly precipitation accumulated by daily precipitation observation at 43 weather stations across Xinjiang to examine meteorological drought. These dates were processed using the JAVA computer program. The precipitation data set was obtained from CMA, and the data were converted to excel format from the JAVA program output file .exe format in order to be read properly by FORTRAN 77. FORTRAN was used to read the data and convert the precipitation data to the corrected SPI index. There is a scale used to classify the precipitation during that time period according to the SPI index. Drought incidents take place when the SPI is continuously negative and the value equal or less than -1.00. Table 1 shows the SPI ranking system developed by McKee et al., (1993) which commonly used among the scholars for this type of research.

Table 1. SPI Ranking System Developed by McKee et al., (1993).

<table>
<thead>
<tr>
<th>SPI Value</th>
<th>Drought Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.99&lt;SPI&lt;0.00</td>
<td>Mid Drought</td>
</tr>
<tr>
<td>-1.49&lt;SPI&lt;-1.00</td>
<td>Moderate Drought</td>
</tr>
<tr>
<td>-1.99&lt;SPI&lt;-1.50</td>
<td>Severe Drought</td>
</tr>
<tr>
<td>SPI&lt;-2.00</td>
<td>Extreme Drought</td>
</tr>
</tbody>
</table>

SPI-based drought is analyzed seasonally at each climate station. Seasonal
drought frequency is measured as the total number of years in which drought SPI<0 occurs in each climate division. The climate divisions included: (1) December, January, February (Winter); (2) March, April, May (Spring); (3) June, July, August (Summer); (4) September, October, November (Fall). For example, if the climate exhibits 15 years in which drought happens in winter during the total number of 56 years, the drought frequency probability is 15/56 or 27%.

Seasonal drought persistence demonstrates drought conditions which persist from one season to next. In this study, drought persistence is described as winter-spring, spring - summer, summer - fall, and fall – winter. Seasonal drought persistence for each climate station and season combination are expressed as the probability of persistence, calculated as the total number of years expressing drought persistence from one season to season combination divided by the total number of years in which drought occurs during the first season in that climate division. For instance, if the climate exhibits 15 years in which drought happens in winter and drought condition persist into spring during the 10 of those years, the drought persistence probability is 10/15 or 66%. For this study SPI is considered as a binary variable: drought occurrence=1 and no drought occurrence=0. Drought persistence is calculated to describe the influence of moisture conditions in one season on moisture conditions in the coming season (Ford and Labosier, 2013).

Logistic regression models will be used this study. For similar research, logistic regression has been used to further examine the persistence of drought from one season to next season (Peng, 2002). Logistic regression models are commonly used to
investigate the relationship between binary dependent variables and one or more independent variables (Ford and Labosier, 2013). Kutner (2005), mentioned that logistic regression is the more appropriate analysis method with a binary dependent variable which instead of using an ordinary least squares regression with a binary dependent variable can lead to issues of non-normally distributed errors and predicted values which do not range from 0 to 1. Furthermore, logistic regression uses the independent variables to predict the logit transformation of the dependent variable (Christopher, 2013). The logistic regression model (1) takes the form of:

\[
F(t) = \frac{e^t}{1 + e^{-t}} = \frac{1}{1 + e^{-t}}
\]  

(1)

\(t\) as a linear function of an explanatory variable \(x\), the logistic function can be written as (2):

\[
\pi(x) = \frac{e^{\alpha + \beta x}}{e^{\alpha + \beta x} + 1} = \frac{1}{1 + e^{-(\alpha + \beta x)}}
\]  

(2)

The inverse of the logistic function, the logit model is (3):

\[
g(x) = \ln \frac{\rho}{1 - \rho} = \alpha + \beta x
\]  

(3)

Where \(\rho / (1 - \rho)\) is the odds ratio of the occurrence of drought, \(\alpha\) is the Y intercept and \(\beta\) is the regression coefficient. Logistic regression model do not require normally distributed residuals, but instead assume that the distribution of errors
between the actual and predicted dependent variables is binomial (Christopher, 2013). Because in this study 3-month SPI observations are independent, the binominal assumption is met (Peng, 2002). The logistic function is useful because it can take an input with any value from negative infinity to positive infinity, whereas the output $\rho$ is confined to values between 0 and 1, and hence is interpretable as a probability. In this study, I employ a logistic regression model in which the binary dependent variable is drought occurrence in a given season (1=drought, 0=no drought) and the lone independent variable is the SPI value for in the previous season. The model outcome is the log odds ratio of drought occurrence in the given season and the slope ($\beta$) of the logistic regression represents the relationship between the independent and dependent variables. For example, when the $\beta$ value is negative, the odds of drought occurrence in a given season are negatively related to the SPI value in the previous season. In other words, an increase in the previous season’s SPI would decrease the odds of drought occurring in the subsequent season.
CHAPTER IV

RESULTS AND DISCUSSION

This chapter of the thesis discusses the results of the analyses from the both spatial and temporal aspects. The spatial aspects are demonstrated through map anomalies whereas the temporal aspects are discussed through graphs. The first part of the chapter includes the overall discussion of precipitation in the region with the map and charts. The second part is the discussion of drought frequency and related explanations by maps and graph. The third part of the output includes drought persistence maps and related explanations through maps and graphs as well. Last but not least, a set of odds radio maps are included to further explain the persistence of meteorological drought from one season to the next. Logistic regression model results identify significance among winter-spring seasonal patterns in the Northern region and Southern region, spring-summer Northern region and Southern region, and winter-summer for a combined regional analysis.

Precipitation Variation

Precipitation and snowmelt from snowpack are the major sources of surface water in the study area (Li et al., 2010). In Xinjiang, water vapor primarily comes from three sources: the Pacific water vapor in the east, the Atlantic and the Arctic Ocean water vapor in the mainly west and the Indian Ocean in the south (Dai et al.,
Despite the fact of being considered as a mountain-basin system far from the ocean, there are significant differences in climate and land cover /land use from North to South across Xinjiang. Agriculture is the main consumer of water in Xinjiang and accounts for up to 90 % of the total water use in Xinjiang (Li et al., 2010). Xinjiang is divided by the Tianshan Mountains into Northern Xinjiang and Southern Xinjiang. Northern Xinjiang lies in the semiarid climate region with annual mean precipitation of 50-200 mm whereas Southern Xinjiang is located in the arid climate region with annual mean precipitation less than 50 mm. Because of the climate differences, Northern Xinjiang is significantly wetter than Southern Xinjiang (Zhang et al., 2012).
As be seen can see from the annual precipitation map of China (Figure 3) there is a significant variation in precipitation over North West China, Xinjiang (A.R). The annual average precipitation varies from 50 to 200 mm in the northern parts of Xinjiang and ranges from 50 mm or less in the southern parts of Xinjiang. In general, the Northern parts obtain precipitation from rainfall and snow fall, and the Southern parts obtain from melted water from snowy mountains. There are also large differences in monthly precipitation between Northern and Southern Xinjiang. For example, station 51241(54.56 N, 83.36E) within the Northern region has monthly precipitation around 6 mm or more than 6 mm. A similarly selected Southern station 51644(41.43N, 82.58E) has the monthly precipitation around 3-4mm or less.

Figure 4. Northern station (54.56 N, 83.36E) Source: Calculated by author
The significant precipitation variation between south and north regions is primarily due to the unique geographic location, landscape and human activities, which lead to different distribution of extreme events such as flood and drought.

**Drought Frequency**

Again drought frequency is calculated as the total number of months with SPI<0 divided by the total number of months for the period from 1957 to 2012. According to this method I calculated the seasonal drought frequency for 43 weather stations. Seasonal drought frequency is calculated as percentage of seasons in which drought (SPI<0) occurs over the whole study period for winter, spring, summer, and fall, respectively. Seasonal drought frequency during all seasons exhibits considerable spatial and seasonal variability.
Figure 6. Seasonal drought frequency for each climate stations as percent of total (1957-2012) years. Source: Calculated by author

Winter drought frequency (Figure 6) shows a strong north-south gradient. The majority of southern weather stations have experienced meteorological drought in less than 20% of winter seasons between 1957 and 2012, while most northern weather stations have experienced drought in 40-60% of winter seasons. Spring drought frequency (Figure 6) shows a strong north-south gradient. The majority of southern weather stations have experienced meteorological drought in less than 20% of spring seasons between the 1957 and 2012, while most northern weather stations have experienced drought in 40-60% of spring seasons. Summer drought frequency (Figure 6) shows north-south gradient but it is slightly different in that winter and spring
drought frequency distribution. The majority of northern and central weather stations have experienced meteorological drought in more than 40% of summer seasons between the 1957 and 2012, while southern weather stations have experienced drought in less than 20% of summer seasons. Fall drought frequency (Figure 6) also shows a strong north-south gradient. The majority of southern weather stations have experienced meteorological drought in less than 20% of fall seasons between 1957 and 2012, while northern weather stations experienced drought in 40-60% of fall seasons. In summary, summer drought probabilities were similar across the whole regions while probabilities in all other seasons showed a consistent north-south gradient.

**Drought Persistence**

Drought has devastating impacts on agriculture, industry and other human activities. If meteorological drought is strong enough to persist over a long-time period, it can affect soil moisture and evapo-transpiration rates and may lead to a hydrological or agricultural drought (Bond et al., 2008). Xinjiang, with its special climate and geomorphology, is considered as a drought vulnerable place with its high frequency and strong persistence (Zhang et al., 2012).

Again seasonal drought persistence is expressed as a probability of persistence and is calculated as the total number of years in which drought persists from one season to another divided by the total number of years in which drought occurs during first season. For example: if a station has 25 years with winter SPI <0 and 10 of the
following springs with SPI <0, the drought persistence probability is 10/25 or 40%. It is a reflection of persistence of moisture conditions from one season to another.

![Maps of seasonal drought persistence](image)

Figure 7. Seasonal drought persistence percent probability Source: Calculated by author

The above probability maps demonstrate the areas within Xinjiang that are more susceptible to prolonged meteorological drought. For instance, a 69% drought persistence probability in winter-spring (Figure 7) means a 69% of winter meteorological droughts in Xinjiang can persist to the spring. It can be seen that there are large spatial variations in seasonal drought persistence. A strong north-south difference is shown, with stations in the southern region having a lower probability of
winter-spring drought persistence than those in the north. Drought persistence probabilities show the same pattern as winter drought frequency, which indicates that spring drought occurrence in the northern region of Xinjiang is a function of moisture conditions in the winter more so than are those in the southern region. A similarly strong north-south difference is shown in spring-summer and winter-summer drought persistence. Drought persistence probabilities in Northern Xinjiang are generally larger than those in Southern Xinjiang.

I further investigated the temporal variation in number of months/year with SPI<0. The following charts correspond to the above drought frequency maps and drought persistence probability maps. A number of stations were selected in the study area (North Figure 8, South Figure 9).
Figure 8. Temporal variation in SPI<0 month in Northern Xinjiang Source: Calculated by author
Overall, the number of months with SPI<0 in each year varied from 2 to 11 months with an average of ~6 months in the north (Figure 8, Table 2), whereas the number of months with SPI<0 in each year varied from 1 to 7 months with an average of ~3 months in the south Xinjiang (Figure 9).

The following tables also show average months in which drought occurred per year for selected northern and southern stations in Xinjiang. The northern region averages 6 months of meteorological drought per year, while the southern part averages less than 6 months of meteorological drought per year (Tables 2, 3).

Table 2. Northern stations in Xinjiang, corresponding table to the Figure 8

<table>
<thead>
<tr>
<th>Station ID</th>
<th>Station Name</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Average Month SPI&lt;0</th>
</tr>
</thead>
<tbody>
<tr>
<td>51068</td>
<td>Fu Hai</td>
<td>47.07</td>
<td>87.28</td>
<td>5.963636</td>
</tr>
<tr>
<td>51133</td>
<td>TaCheng</td>
<td>46.44</td>
<td>83</td>
<td>5.890909</td>
</tr>
<tr>
<td>51186</td>
<td>Qing He</td>
<td>46.6</td>
<td>90.23</td>
<td>5.963636</td>
</tr>
<tr>
<td>51243</td>
<td>Karamay</td>
<td>45.37</td>
<td>84.51</td>
<td>5.963636</td>
</tr>
</tbody>
</table>
Table 2-continued

<table>
<thead>
<tr>
<th>Station ID</th>
<th>Station Name</th>
<th>Latitude</th>
<th>Longitude</th>
<th>SPI &lt;0</th>
</tr>
</thead>
<tbody>
<tr>
<td>51288</td>
<td>BeiDa Shang</td>
<td>45.22</td>
<td>90.32</td>
<td>5.872727</td>
</tr>
<tr>
<td>51365</td>
<td>Narat Lake</td>
<td>44.12</td>
<td>87.12</td>
<td>5.722222</td>
</tr>
<tr>
<td>51542</td>
<td>Byimbullah</td>
<td>43.02</td>
<td>84.09</td>
<td>5.836364</td>
</tr>
<tr>
<td>52101</td>
<td>BaLitang</td>
<td>43.36</td>
<td>93.03</td>
<td>5.767857</td>
</tr>
</tbody>
</table>

Table 3. Southern stations in Xinjiang, corresponding table to the Figure 9

<table>
<thead>
<tr>
<th>Station ID</th>
<th>Station Name</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Average Month SPI&lt;0</th>
</tr>
</thead>
<tbody>
<tr>
<td>51628</td>
<td>Ahsu</td>
<td>41.1</td>
<td>80.14</td>
<td>4.890909</td>
</tr>
<tr>
<td>51730</td>
<td>Alar</td>
<td>40.33</td>
<td>81.16</td>
<td>2.388889</td>
</tr>
<tr>
<td>51720</td>
<td>Kecheng</td>
<td>40.3</td>
<td>79.03</td>
<td>4.113208</td>
</tr>
<tr>
<td>51765</td>
<td>Tekanlek</td>
<td>40.38</td>
<td>87.42</td>
<td>1.821429</td>
</tr>
<tr>
<td>51811</td>
<td>Shayar</td>
<td>38.26</td>
<td>77.16</td>
<td>3.267857</td>
</tr>
<tr>
<td>51818</td>
<td>Pishang</td>
<td>37.37</td>
<td>78.17</td>
<td>3.444444</td>
</tr>
<tr>
<td>51828</td>
<td>Hotan</td>
<td>37.08</td>
<td>79.56</td>
<td>2.946429</td>
</tr>
</tbody>
</table>

Source: Calculated by author

Drought Occurrence Odds Ratio

Logistic regression model outputs

In order to fully understand the influence of one season’s moisture conditions on the next season, this study employs a logistic regression model. Peng (2002) described logistic regression as a means to examine the persistence of meteorological drought from one season to the next. Ford and Labosier (2013) used the SPI to examine spatial patterns of drought persistence in the Southeastern United States. Tahl and Demuth (2009) employed logistic regression to assess the impact of atmospheric circulation patterns to stream flow drought. The model is the model used to explore
the relationship between a binary dependent variable that is is drought occurrence in
given season and the independent variable (SPI) in the previous season.

The model binary dependent variable is the drought occurrence in a given
season (drought=1, no drought=0) and the independent variable is the SPI in the
previous season. To fully understand relationship between the previous season SPI
and the drought occurrence in a subsequent season, this study uses the logistic
regression model. The logistic regression will be tested included: winter to spring,
spring to summer, winter-summer for Southern Xinjiang, Northern Xinjiang and
whole region separately. The following section will describe each model and test
significance of each model result.

Figure 10 shows the relationship between the spring drought occurrence and
winter SPI. The stations with odds ratio <1 (in green and blue with star shape,
negative) decreases odds ratio of drought occurrence in spring when the winter SPI
increases, while those stations with odds ratio >1 (in pink with circle) show a positive
increase in the odds ratio of drought occurrence in spring when winter SPI increases.
The relationship between spring drought occurrence and winter SPI is less than 1
(negative, if converted to log scale) for most stations across the north of Xinjiang.
This suggests that a one unit increase in winter SPI in the Xinjiang region is
associated with less odds of a drought occurrence in spring. Many of the extremely
low odds ratios (<0.5) in the north indicate that a winter drought reduces the odds of a
spring drought by 50%-98%.
The spring-summer map (Figure 10) shows the change in the odds ratio of summer drought occurrence given a one unit increase in spring SPI. The relationship between the summer drought occurrence and spring SPI is ~1 (nearly neutral) for the most stations across the Xinjiang. A few stations scattered across the region have small (strongly negative if converted to log scales) odds ratios, suggesting that an increase in spring SPI in the Xinjiang region reduces the odds of drought occurrence in summer.
The Winter-summer portion of the map (Figure 10) shows the change in the odds ratio of summer drought occurrence given one unit increase in winter SPI. The relationship between summer drought occurrence and winter SPI is ~1 (nearly neutral) (Figure 10) for most stations across the Xinjiang. This suggests that a one unit increase in winter SPI in the Xinjiang region typically does not affect, or actually decreases, the odds of drought occurrence in summer. However two stations, in the central east portion of the study area, showed a strongly positive association between winter and summer drought.

I further examined the significance of the odds ratio shown in Figure 10 and found that the odds ratios are significant at a 90% confidence level for most of stations in northern Xinjiang while they are not significant in most of the stations in southern Xinjiang.

**Winter-Spring Relationship**

My results show that a statistically significant relationship exists between winter SPI and spring drought occurrence for 4 of 8 stations tested in northern Xinjiang (Table 4). For example, station 51068, 51076, 51133, 51243 are statistically significant at the 90% confident level which means the logistic regression model can predict spring drought from the winter SPI, however the nagerkereck $R^2$ for most stations is not high due to the single variable in the model. The beta value is negative, indicating that the higher the winter SPI, the less likely a spring drought is to occur. In similar examples from the south stations 51628, 51818 and 52313 are also statistically
significant at the 90% confident level compared while the others are not. Among the 1 of 8 stations showing significance, the betas vary from positive to strongly negative indicating mixed winter-spring linkage in the region (Table 5).

Table 4. Winter-Spring model, northern region in Xinjiang (statistically significant at 90% confident level stations are highlighted)

<table>
<thead>
<tr>
<th>Station ID</th>
<th>Station Name</th>
<th>R²</th>
<th>B</th>
<th>Sig</th>
<th>Exp(B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>51068</td>
<td>FuHai</td>
<td>0.182</td>
<td>-1.305</td>
<td>0.01</td>
<td>0.271</td>
</tr>
<tr>
<td>51076</td>
<td>Altay</td>
<td>0.261</td>
<td>-1.444</td>
<td>0.003</td>
<td>0.236</td>
</tr>
<tr>
<td>51133</td>
<td>Qoqak</td>
<td>0.13</td>
<td>-1.045</td>
<td>0.026</td>
<td>0.352</td>
</tr>
<tr>
<td>51241</td>
<td>TuoLi</td>
<td>0.024</td>
<td>-0.363</td>
<td>0.324</td>
<td>0.695</td>
</tr>
<tr>
<td>51243</td>
<td>Karamay</td>
<td>0.174</td>
<td>-1.188</td>
<td>0.011</td>
<td>0.305</td>
</tr>
<tr>
<td>51365</td>
<td>Shi Hezi</td>
<td>0.062</td>
<td>-0.679</td>
<td>0.121</td>
<td>0.507</td>
</tr>
<tr>
<td>51542</td>
<td>Byimbullah</td>
<td>0.062</td>
<td>-0.616</td>
<td>0.116</td>
<td>0.54</td>
</tr>
<tr>
<td>52101</td>
<td>Balitang</td>
<td>0.035</td>
<td>-0.494</td>
<td>0.231</td>
<td>0.61</td>
</tr>
</tbody>
</table>

Source: Calculated by author

Table 5. Winter-Spring model, southern region in Xinjiang (statistically significant stations at the 90% confident level stations are highlighted)

<table>
<thead>
<tr>
<th>Station ID</th>
<th>Station Name</th>
<th>R²</th>
<th>B</th>
<th>Sig</th>
<th>Exp(B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>51628</td>
<td>Ahsu</td>
<td>0.06</td>
<td>1.034</td>
<td>0.128</td>
<td>2.813</td>
</tr>
<tr>
<td>51644</td>
<td>Kucha</td>
<td>0</td>
<td>0.061</td>
<td>0.927</td>
<td>1.063</td>
</tr>
<tr>
<td>51730</td>
<td>Alar</td>
<td>0</td>
<td>-0.026</td>
<td>0.983</td>
<td>0.974</td>
</tr>
<tr>
<td>51720</td>
<td>Krcheng</td>
<td>0.041</td>
<td>-1.054</td>
<td>0.214</td>
<td>0.349</td>
</tr>
<tr>
<td>51811</td>
<td>Shayar</td>
<td>0</td>
<td>-0.06</td>
<td>0.947</td>
<td>0.942</td>
</tr>
<tr>
<td>51818</td>
<td>Pishan</td>
<td>0.186</td>
<td>-4.466</td>
<td>0.093</td>
<td>0.011</td>
</tr>
<tr>
<td>51828</td>
<td>Hotan</td>
<td>0.015</td>
<td>-0.747</td>
<td>0.504</td>
<td>0.474</td>
</tr>
<tr>
<td>52313</td>
<td>Hongliuhe</td>
<td>0.062</td>
<td>-0.923</td>
<td>0.126</td>
<td>0.397</td>
</tr>
</tbody>
</table>

Source: Calculated by author
To sum up, the logistic regression model is not useful when describing the southern region which means there are other factors that have more influence on drought conditions. As I mentioned in the previous section, precipitation variation may contribute to the poor model performance in the southern region due to arid conditions and less overall precipitation seasonally and annually. The Tianshan Mountains specifically can block the water vapor from the North Atlantic and Arctic Oceans as well as from the Caspian and Mediterranean Seas in the southern region in the summer (Dai et al., 2006). Greater discussion on this issue will follow in the concluding chapter. The following figures will demonstrate the same process for different climate divisions such as spring-summer and winter-summer models for both north and south region.

**Spring-Summer Relationship**

I further examined the logistic relationship between spring SPI and summer drought occurrence in northern and southern Xinjiang. Overall, statistically significant relationship at the 90% confident level was not found in most stations tested for both northern and southern Xinjiang between spring SPI and summer drought occurrence (Tables 6, 7).

<table>
<thead>
<tr>
<th>Station ID</th>
<th>Station Name</th>
<th>Nagelkerke R²</th>
<th>B</th>
<th>Sig</th>
<th>Exp(B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>51068</td>
<td>FuHai</td>
<td>0.044</td>
<td>-0.635</td>
<td>0.185</td>
<td>0.53</td>
</tr>
</tbody>
</table>
Table 6 - continued

<table>
<thead>
<tr>
<th>Station ID</th>
<th>Station Name</th>
<th>Nagelkerke R²</th>
<th>B</th>
<th>Sig</th>
<th>Exp(B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>51076</td>
<td>Altay</td>
<td>0.029</td>
<td>-0.473</td>
<td>0.283</td>
<td>0.623</td>
</tr>
<tr>
<td>51133</td>
<td>Qoqak</td>
<td>0.007</td>
<td>-0.245</td>
<td>0.585</td>
<td>0.782</td>
</tr>
<tr>
<td>51241</td>
<td>TuoLi</td>
<td>0.05</td>
<td>-0.607</td>
<td>0.16</td>
<td>0.545</td>
</tr>
<tr>
<td>51243</td>
<td>Karemay</td>
<td>0.084</td>
<td>-0.826</td>
<td>0.067</td>
<td>0.438</td>
</tr>
<tr>
<td>51365</td>
<td>Shi Hezi</td>
<td>0.03</td>
<td>-0.496</td>
<td>0.273</td>
<td>0.609</td>
</tr>
<tr>
<td>51542</td>
<td>Byimbullah</td>
<td>0.001</td>
<td>0.1</td>
<td>0.829</td>
<td>1.105</td>
</tr>
<tr>
<td>52101</td>
<td>Balitang</td>
<td>0.002</td>
<td>-0.147</td>
<td>0.752</td>
<td>0.863</td>
</tr>
</tbody>
</table>

Source: Calculated by author

Table 7. Spring-Summer model, southern region in Xinjiang (statistically significant at the 90% confident level stations are highlighted)

<table>
<thead>
<tr>
<th>Station ID</th>
<th>Station Name</th>
<th>Nagelkerke R²</th>
<th>B</th>
<th>Sig</th>
<th>Exp(B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>51628</td>
<td>Ahsu</td>
<td>0.012</td>
<td>-0.447</td>
<td>0.496</td>
<td>0.64</td>
</tr>
<tr>
<td>51644</td>
<td>Kucha</td>
<td>0.004</td>
<td>-0.23</td>
<td>0.67</td>
<td>0.795</td>
</tr>
<tr>
<td>51730</td>
<td>Alar</td>
<td>0.012</td>
<td>-0.479</td>
<td>0.481</td>
<td>0.62</td>
</tr>
<tr>
<td>51720</td>
<td>Kecheng</td>
<td>0.015</td>
<td>0.435</td>
<td>0.436</td>
<td>1.545</td>
</tr>
<tr>
<td>51811</td>
<td>Shayar</td>
<td>0.079</td>
<td>-1.245</td>
<td>0.079</td>
<td>0.288</td>
</tr>
<tr>
<td>51818</td>
<td>Pishan</td>
<td>0.039</td>
<td>-0.975</td>
<td>0.229</td>
<td>0.377</td>
</tr>
<tr>
<td>51828</td>
<td>Hotan</td>
<td>0.053</td>
<td>-1.116</td>
<td>0.142</td>
<td>0.328</td>
</tr>
<tr>
<td>52313</td>
<td>HongLiu He</td>
<td>0.02</td>
<td>-0.545</td>
<td>0.362</td>
<td>0.58</td>
</tr>
</tbody>
</table>

Source: Calculated by author

Winter-Summer Relationship

In Table 8, stations 51133, 51241, 51365 are statistically significant at 90% confident level which means the logistic regression model can predict summer drought from the winter SPI, however the nagelkerke R² for most stations are not high due to the single variable in the model. While very few of the stations are significant, most are negative, indicating that the primary trend in this region is a lack of summer drought following a winter drought. In the Southern region (Table 9) none of the
stations are statistically significant at the 90% confidence level. To sum up, logistic regression model is not the best fit model for the southern region or the northern region for predicting drought winter-summer persistence.

Table 8. Winter-Summer model, northern region in Xinjiang (statistically significant at 90% confident level stations are highlighted)

<table>
<thead>
<tr>
<th>Station ID</th>
<th>Station Name</th>
<th>Nagelkerke R²</th>
<th>B</th>
<th>Sig</th>
<th>Exp(B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>51068</td>
<td>FuHai</td>
<td>0.018</td>
<td>-0.36</td>
<td>0.396</td>
<td>0.698</td>
</tr>
<tr>
<td>51076</td>
<td>Altay</td>
<td>0.004</td>
<td>-0.14</td>
<td>0.699</td>
<td>0.869</td>
</tr>
<tr>
<td>51133</td>
<td>Qoqak</td>
<td>0.089</td>
<td>-0.833</td>
<td>0.062</td>
<td>0.435</td>
</tr>
<tr>
<td>51241</td>
<td>TouoLi</td>
<td>0.097</td>
<td>-0.769</td>
<td>0.055</td>
<td>0.464</td>
</tr>
<tr>
<td>51243</td>
<td>Karemay</td>
<td>0.011</td>
<td>-0.259</td>
<td>0.512</td>
<td>0.772</td>
</tr>
<tr>
<td>51365</td>
<td>Shi Hezi</td>
<td>0.154</td>
<td>-1.152</td>
<td>0.018</td>
<td>0.316</td>
</tr>
<tr>
<td>51542</td>
<td>Byimbullah</td>
<td>0</td>
<td>-0.045</td>
<td>0.903</td>
<td>0.956</td>
</tr>
<tr>
<td>52101</td>
<td>Balitang</td>
<td>0.024</td>
<td>0.41</td>
<td>0.316</td>
<td>1.508</td>
</tr>
</tbody>
</table>

Source: Calculated by author

Table 9. Winter-Summer model, southern region in Xinjiang (statistically significant at the 90% confident level stations are highlighted)

<table>
<thead>
<tr>
<th>Station ID</th>
<th>Station Name</th>
<th>Nagelkerke R²</th>
<th>B</th>
<th>Sig</th>
<th>Exp(B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>51628</td>
<td>Ahsu</td>
<td>0.017</td>
<td>0.538</td>
<td>0.4</td>
<td>1.713</td>
</tr>
<tr>
<td>51644</td>
<td>Kucha</td>
<td>0.011</td>
<td>-0.46</td>
<td>0.495</td>
<td>0.631</td>
</tr>
<tr>
<td>51730</td>
<td>Alar</td>
<td>0.005</td>
<td>-0.434</td>
<td>0.661</td>
<td>0.648</td>
</tr>
<tr>
<td>51720</td>
<td>Kecheng</td>
<td>0</td>
<td>0.036</td>
<td>0.964</td>
<td>1.036</td>
</tr>
<tr>
<td>51811</td>
<td>Shayar</td>
<td>0.026</td>
<td>-0.773</td>
<td>0.298</td>
<td>0.462</td>
</tr>
<tr>
<td>51818</td>
<td>Pishan</td>
<td>0.007</td>
<td>-0.418</td>
<td>0.601</td>
<td>0.658</td>
</tr>
<tr>
<td>51828</td>
<td>Hotan</td>
<td>0.025</td>
<td>-0.751</td>
<td>0.316</td>
<td>0.472</td>
</tr>
<tr>
<td>52313</td>
<td>HongLiuHe</td>
<td>0</td>
<td>0.053</td>
<td>0.917</td>
<td>1.055</td>
</tr>
</tbody>
</table>

Source: Calculated by author

Overall, the logistic regression model results suggest that the odds ratios are
statistically significant at a 90% confidence level over 50% of the northern stations from winter to spring means a logistic regression model can be used to predict spring drought conditions in the northern region based on information from winter precipitation conditions. The logistic regression model approach is not useful when predicting summer droughts using a previous season’s SPI, particularly for the southern Xinjiang.
CHAPTER V

CONCLUSION

Summary

Droughts have become one of the crucial hazards affecting Xinjiang A.R, Northwest China, the biggest agricultural province and a very important area for the husbandry industry in China. Investigations about droughts in Xinjiang were conducted from various perspectives by previous studies. However, there are very few studies that focus on seasonal drought frequency. The information on seasonal drought frequency is important as it influences water resource management and forecasting, crop yields, agricultural development and energy consumption. This study had two main objectives: 1) identify spatial patterns of seasonal drought frequency and persistence in the Northwest China; and 2) employ logistic regression to investigate the odds and probability of drought persisting from one season to the next.

This study used daily precipitation data to calculate the SPI. The study area has a large precipitation variation, which contributes to the spatial and temporal variability in drought frequency persistence and also logistic regression model results across Xinjiang A.R.

The results suggest a strong north-south gradient in the distribution of droughts. The stations from the northern Xinjiang experience droughts over 40% of
the study period, while the stations from the southern Xinjiang had drought over 20% of the time (Figure 6).

Seasonal drought frequency is calculated as the total number of years in which droughts occur at each climate station. Probability values are calculated for three periods: winter-spring, spring-summer and winter-summer. Drought persistence describes the influence of moisture conditions in one season on moisture conditions in the following season (Ford and Labosier 2013). The distribution of drought persistence shows stronger patterns in northern Xinjiang than in southern Xinjiang (Figure 7).

A logistic regression model was employed to further investigate drought persistence from one season to other, and one of the model outcomes is the odds ratio of drought occurrence for the given season. The expected outcome from the logistic regression model could help improve the operational decision making for water resource management, hydropower operation, and irrigation and herding activities in Xinjiang. The odds ratio map shows the change in the odds ratio of drought occurrence given one unit increase in the previous season’s SPI. The odds ratio between drought occurrence and previous season’s SPI is <0 for most stations across Xinjiang. This suggests that a one unit increase in previous season’s SPI in the Xinjiang region can reduce the odds of drought occurrence in the following season, and also for those stations that with odds ratio <0.5 a one unit increase in the previous season’s SPI reduces the odds of subsequent drought by 50%-98%.

There are total six logistic regression models reported in this research:
winter-spring north, winter-spring south, spring-summer north, spring-summer south, winter-summer north and winter-summer south. The results show the odds ratio for most of the northern stations are statistically significant at the 90% confidence level especially for the winter-spring which indicates that logistic regression model approach can predict the drought occurrence in the northern Xinjiang. The models are not significant at 90% significance level over most of the southern stations suggesting that winter SPI is not a good predictor of spring drought in southern Xinjiang.

Overall, drought frequency and drought persistence over all seasons exhibit considerable spatial and temporal variability across the Xinjiang with a strong north-south gradient. This might be due to the precipitation variation from north to the south due to the geographic location that is arid and semi-arid and topography (mountain-basin system). In general, Northern Xinjiang has more precipitated than Southern Xinjiang (Zhang et al., 2012; Ling, Xu and Fu 2013). In Xinjiang, water vapor primarily comes from three sources: the Pacific water vapor to the east, the Atlantic and the Arctic Ocean water vapor in the mainly west and the Indian Ocean in the south (Dai et al., 2006). But most of the time of the Tianshan Mountains blocks water vapor from the Atlantic and Arctic Oceans which leads to the variation in precipitation between the north and south (Zhang et al., 2012).

Other factors that impact drought frequency and persistence include global warming human activities such as over grazing, excessive agricultural irrigation and deforestation. Meanwhile, along with population growth, the economy and income levels increased. To meet demand, urbanization and other infrastructure occurred
along Tarim river basin (Zhao et al., 2006). Over the past 22 years the Tarim River had lost 60.60% water area and 60.50% of the high coverage grasslands, while saline land and sandy land had increased tremendously by 131.42% and 20.30% respectively (Chen et al., 2013). Agriculture based on irrigation activities accounts for the main used of water in Xinjiang up to 90 % (Li et al., 2010).

**Future Research**

Further exploration of drought persistence would involve the use of more variables and, perhaps, on increase in the time span in corporate in this study. Including more variables such as elevation, surface temperature and runoff may be helpful to improve drought model prediction by increasing the Negalkerke $R^2$ and to find more correlation between the different climate divisions in Xinjiang. Many studies suggested that logistic regression required a long period and continuous dataset, thus a long term dataset is important in order to improve the predictability of drought (Ford and Labosier, 2013; Edward and Makee, 1997). Best water resource management practices are also beneficial to improve the logistic regression model prediction in the Tarim River Basin. Better management can mitigate the malfunctioned-hydro climate system in the river basin and help to get back to a normal river basin eco-hydrology.
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