Statistical Relationship between Drought Indices and NDVI at Regional Scale

by

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A Thesis Submitted to the Faculty of the
DEPARTMENT OF HYDROLOGY AND WATER RESOURCES

In Partial Fulfillment of the Requirements
For the Degree of

MASTER OF SCIENCE
WITH A MAJOR IN HYDROLOGY

In the Graduate College
THE UNIVERSITY OF ARIZONA

2002
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ACKNOWLEDGEMENTS

Without the assistance of a number of individuals, this thesis would not have been possible. In particular, I would like to thank my advisor, Dr. Bisher Imam who has given me his unreserved support and understanding. I would like to thank him sincerely. I would also like to thank Dr. Soroosh Sorooshian, for his guidance, support and patience. Many thanks also go to Dr. Bart Nijssen for being in my committee and his generous help in reviewing this thesis. I would like to say a very special thank you to Mr. Park Gi-Hyeon for his great friendship, and his help with programming questions; Mrs. Eve Halper for her assistance in GIS code writing and Mr. Ray Brice with for his computer related assistance; Andrea K. Sedek for her time and effort in helping editing this thesis.

I would like to acknowledge the support from NASA Grant NAG5-8503-HyDIS) and Raytheon (Grant NAS5-60000, Subcontract No. 3000623).

This thesis and the whole course of my Mater’s studies came to be because of the ever-present support and encouragement from my family especially my brother Hamid and his wife Renée. I would like to thank Rachida my fiancée for her encouragement and patience during this period of study.
DEDICATION

This thesis is dedicated to the souls of my parents, ALI and Zehira Boudjeloul.
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ABSTRACT

The potential contribution of easily accessible satellite data to the detection and quantification of regional droughts, in the absence of reliable meteorological data, is the objective of this study. The former statement can be investigated by identifying the characteristics of vegetation response to dry-wet cycles. The relationships between several "palmer-based" drought indices that are derived from meteorological data, and the concurrent time series of a coarse resolution departure of Normalized Difference Vegetation Index were used to investigate the feasibility of using remote sensing data in monitoring and observing drought conditions at spatial resolutions higher than the currently used in drought monitoring methods. Methods of investigation included cross-correlation between drought indices and both regional averaged and land-cover stratified departure NDVI, as well as spectral analysis of each type of time series.

The analysis showed a positive relationship between drought indices used and most vegetation covers and even a stronger relationship for particular vegetation covers such as open shrublands and needleleaf forest. Spectrum analysis detected a similar signal from both series that is related to ENSO events. This signal is observed at low frequency variability in departure NDVI and drought indices.
CHAPTER ONE
INTRODUCTION AND MOTIVATION

1.1 Introduction:

The 42nd session of the United Nations assembly declared the last 10 years of the twentieth Century as the International Decade for Natural Disaster Reduction (IDNDR). The declaration, which was adopted on the 11th of December, 1987, reflected the awareness of the wide gap between the scientific and technical understanding of natural disasters, and the development/implementation of internationally coordinated efforts for disaster warning, prevention, and mitigation.

Nearly 85% of all natural disasters are directly related to/or associated with extreme weather events (Obasi 1994). Among these events is drought; and drought is the most damaging environmental phenomenon. The impact of the most recent large area severe drought (1988) on the U.S economy has been estimated at $40 billion, which is 2-3 times the estimated losses from the 1989 San-Francisco earthquake (Riebsame et all 1990). Similarly, the 1991-1992 growing season in southern and eastern Africa, which was the worst since the beginning of the century, was a direct result of a prolonged regional drought that covered 2.6 million square miles. According to the United Nations
Department of Humanitarian Aids (1993), this drought has adversely affected the lives of 24 million people.

The magnitude, spatial extent, and duration of droughts are key factors in determining the likely economic and societal impacts of any drought event. However, the vulnerability to events of similar characteristics varies widely between developing and developed countries. Wilhite (1993) and Kogan (1997) noted that timely availability of drought information leads to substantial reduction in losses of life and property due to severe droughts. Yet, in most developing countries, where meteorological networks are sparse at best, such information are rarely, if at all, available.

In recent years, satellite data have become widely available at various spatial and temporal scales. For example, daily precipitation estimates (Sorooshian et al. 2000), vegetation characteristics (Townsend, 1994, and Smith and Kalluri, 1994) and several other data sets are now available at global scales and resolutions that are adequate for monitoring drought conditions. Therefore the development of drought monitoring tools that can benefit from such data holds the potential for improving the timeliness and access to drought information without the cost of extensive ground monitoring stations.

Satellite measurements of meteorological variables such as precipitation and temperature; require an extensive amount of ground data for validation. In addition, their use in drought monitoring requires substantial investment in hydrologic models, model
validation, and calibration not to mention that only few years of high quality data sets are now available. On the other hand, satellite derived vegetation characteristics data sets, which rely on the spectral characteristics of vegetation, and are available for periods exceeding 20 years, can yield an initial insight into the effects of soil moisture deficit, a key variable in many drought quantification tools, on the overall condition of vegetation. Investigating the former hypothesis is the main objective of this thesis.

As mentioned above, this thesis is motivated by the need to develop a satellite-based drought monitoring tools. The objective is to contribute to the development of such tools through detailed analysis of existing widely used drought indices and information that can be generated from widely used satellite vegetation data. As much, this work focuses on the potential contribution of easily accessible satellite data to the detection and quantification of regional droughts.

To accomplish these objectives, time-series of several widely used drought indices such as the Palmer Drought Severity Index (PDSI), derived from meteorological data, will be analyzed in conjunction with concurrent time series of a coarse resolution Normalized Difference Vegetation Index (NDVI), derived from the Advanced Very High Resolution Radiometer (AVHRR) imagery. The objective of the analysis is not to identify the characteristics of drought episodes, but to identify the characteristics of vegetation response to dry-wet cycles so that satellite data can be directly used to monitor drought in the absence of reliable meteorological data. The analyses will be conducted at
regional scales, but with focus on the spatial variability of vegetation, as vegetation type is likely to respond differently to climatic conditions. Finally, this thesis presents an approach for using Geographic Information System software (GIS) to combine various data layers such as NDVI, vegetation classes, and climate regions in drought analysis.
CHAPTER TWO

BACKGROUND

II.1 Objective:
The objective of this chapter is to survey conceptual and applied definitions of drought, and to provide a survey of different measures developed to assess drought conditions. The survey will cover individual variables such as rainfall, temperature, or stream flow and complex indices such as Palmer drought severity index (PDSI), Standardized precipitation index (SPI), or Crop moisture index (CMI) derived by combining two or more variables. Finally, the potential use of satellite imagery products as a measure of drought will be briefly discussed in context of the research objectives of this thesis.

II.2 Drought Definition and Impacts

II.2.1 Introduction:
The study of drought and its impact has received substantial attention from farmers, scientists, decision-makers and the general public since the dawn of civilization. Drought has occupied a prominent role in ancient scriptures, legends, and mythologies. While concepts such as drought preparedness and predictability can be read from ancient Egyptian writings, other civilizations were not as fortunate as the Egyptians, and have vanished due to a persistence of long duration drought. According to a recent study by David Hodell (2001), the collapse of the 3800-year-old Maya civilization appears to be
caused by a cyclical brightening of the sun, which created a severe drought that lasted for more than 150 years.

The question arises now, is whether similar risk continues to threaten today’s civilization, and if so, to what extent, since droughts have severely affected ancient civilizations in the past. In the past 3 years starting from 1999, Central and Southwest Asia have been experiencing a persistent severe drought that represents one of the largest regional droughts in recent times. According to the International Research Institute report (Shardul et al, Nov 2001), in parts of Afghanistan, Iran, Pakistan and Tajikistan, the ongoing drought is considered to be the most severe threat to the region over the past 50-100 years. Another example of ongoing severe drought is the current drought striking North Korea, which is the worst since the beginning of records, nearly a century ago. Recently, the state news agency (KCNA, 2001) reported that no harvest is expected from farmland in several hundred thousands of hectares. Consequently, the country is expected to face its worst food shortages in three years, making it increasingly dependent on the outside world to help feed its starving people (BBC news, 2001).

Wilhite (1998) classified drought studies into four separate categories in an effort to improve the quantitative and qualitative understanding of this phenomenon. The first category studies the causes of drought and the effects of atmospheric circulation on drought occurrence. The second category deals with issues of temporal and spatial characteristics of drought such as frequency, intensity, and spatial patterns. The third category investigates the impacts of drought. Finally, the fourth category focuses on responses, and reduction of the impacts caused by drought.
Notwithstanding the above-mentioned studies, defining a drought event based on severity, magnitude and duration continues to be a subjective exercise. Unlike other natural phenomena, which have an agreed upon quantitative measure, such as the Richter scale that is used worldwide to quantify earthquakes, drought has been a difficult phenomenon to determine and define. Some define it by rainfall amounts, vegetation conditions, soil moisture, and levels in reservoirs or stream flow.

(Tannehill, 1947) refers to drought as a creeping phenomenon, "We have no good definition of drought. We may say truthfully that we scarcely know a drought when we see one. We welcome the first clear day after a rainy spell. Rainless days continue for a time and we are pleased to have a long spell of such fine weather. It keeps on and we are a little worried. A few days more and we are really in trouble." The previous quote highlights the differences in opinion between climatologists regarding the onset of drought, the declaration of an end to drought, and occasionally the existence or not of a drought event among decision makers, due to the lack of a universally accepted definition. A practical solution to this dilemma is to consider a locally varying definition of drought (Wilhite, 2000). For example, a 700-mm annual rainfall in semi-arid countries is considered to be a record in contrast with Northern Europe, where this amount would constitute a dry year. This illustrates the difference between drought and aridity. Aridity describes a region, which is naturally restricted to low rainfall, and is a permanent feature of that climate. However, drought is a temporary aberration/departure from the long-term climate conditions of a specific region leading toward deficit in moisture. Nonetheless, there have been some agreements about functional definitions of drought on a regional
scale. These definitions can be categorized as either conceptual or operational (Wilhite and Glantz 1985).

II.2.2 Drought Definition:

Conceptual definitions are highly useful in establishing drought policies. They are formulated in general terms to help people understand the concept of drought. For example, the Encyclopedia of Climate and Weather (Schneider 1996) defines drought as, “an extended period- a season, a year, or several years- of deficient rainfall relative to the statistical multi year mean for a region.” Another general definition, “Drought is a protracted period of deficient precipitation resulting in extensive damage to crops and therefore, loss of yield.” (NDMC website).

The conceptual definition of drought gives a general description of the phenomenon but fails to guide the detection, onset and end of drought. Operational definitions, on the other hand, guide the identification of the beginning, the degree of severity, and the termination of drought periods. Operational definition can be used to estimate potential impacts of drought and to calculate the probability of the varying intensity and extent of drought (Kenneth C. Dagel, K. C., 1997). Operational definition is based on mathematic indices to decide when drought starts and how long it will last. For example, to determine the severity, and duration of drought, the degree of departure from the average of precipitation or some other climatic variable over some time period is calculated. The common approach compares the current situation to the historical average, often based on a 30-year period.
II.2.3 Types of Drought:

Wilhite and Glantz (1985) divide different types of drought into the following groups: meteorological, hydrological, agricultural, and socioeconomic. The relationship between these types of drought is shown in Figure 2.1, as well as the sequence of occurrence of each type of drought.

The departure of precipitation from the standard and the duration of the dry period usually define a meteorological drought. Definitions of meteorological drought must be considered for a specific region and conditions, since the atmospheric conditions that result in deficiencies of precipitation are highly variable from one region to another. For example, some definitions of meteorological drought are defined as a number of days where frequent precipitation events, in an area, are less than some specified threshold. This latter definition can be true for areas where precipitation is expected to fall on a daily basis such as tropical rainforests, but cannot be applied, without modifications to areas that are characterized by seasonal precipitation periods. Nevertheless, meteorological measurements are the first indicators of drought.

Agricultural drought deals with lack of moisture in the soil to satisfy the needs of crops and growth development from emergence to maturity. Accounting for susceptibility of plants during different stages of development improves the descriptive quality of agricultural drought, where emphasis is placed on precipitation shortage, reduced ground water level, reservoir, and soil moisture deficit. For example, moisture deficiency in topsoil at the beginning of the growth season may delay germination, leading to a reduction of final yield per hectare. However, if topsoil moisture is sufficient
for early growth demands, moisture deficiencies in subsoil during the same stage may not adversely affect the final yield if subsoil moisture is restocked or if the rainfall meets plant water needs during the reminder of the growing season.

**Hydrological drought** refers to deficiencies in surface and subsurface water supplies (i.e. stream flow, reservoir and lake levels, ground water). The duration and severity of hydrological drought is often based on a watershed or river basin scale. This drought occurs after certain duration of the other types of droughts (agricultural and meteorological). Because a lack of moisture in this phase will take more time to show in the ground water levels, it causes a phase shift in quantitative drought index when compared to other indices. Hydrological drought deals with moisture deficiency in the hydrological system as a whole. Other factors also can contribute to hydrological drought besides the atmospheric conditions. Changes in landscape, land use, and construction of dams also have significant impacts on the drought. Such changes may not only have a great effect on the immediate region, but may also impact the downstream region in terms of lack of moisture. The hydrological analysis of drought is harder to investigate than meteorological analysis because of the availability of short-term records of hydrological variables, as opposed to meteorological records. Hydrological analysis of drought is also difficult to assess because of changes in river regimes, due to significant human activities, such as construction of dams. A case study conducted in the UK (M.J. Santos, R. Verissimo, 2001) has shown, however, that hydrological drought return period is consistently lower or at least at the same range as the return period of meteorological drought.
Lastly, **socioeconomic drought** is the final type of drought. Generally, this type of drought becomes noticeable when water shortages start to affect people and their lives. Of all natural disasters, socioeconomic drought has the strongest link between human activities and weather conditions. It is associated with the supply and demand of economic goods such as food production, mining, and hydroelectric power, which are directly dependent on water availability and weather. This type of drought takes place when the supply of economic goods cannot meet the demand due to a shortcoming of precipitation over a particular region for an extended period of time. Demand for goods tends to increase as consumption rises due to population growth, improved production, and construction of reservoirs for water supplies. Therefore, the impact of drought will be much more significant in regions where the supply/demand balance is already disturbed. For example, in Uruguay in 1988-89, drought resulted in significantly reduced hydroelectric power production because power plants depended more upon daily natural conditions than on reservoir storage. Naturally, expensive imported oil, coupled with stringent energy conservation measures, was essential to meet the nation’s energy needs (NDMC website).

### II.2.4 Drought Sequence

Wilhite (2000) argues that the sequence of drought occurrence begins with the meteorological drought caused by precipitation deficiency. Prolonged meteorological drought can cause an agricultural drought as the precipitation deficit propagates into soil moisture deficit and reduces crop production. Meteorological drought may also be followed by hydrological drought, which can affect river flows, levels at lakes, and
aquifer recharge. Combined, these effects translate into deficit of water supply resulting in lack of water for domestic uses and environmental sustainability. A prolonged period of the latter will then cause socioeconomic changes that may reach the level of famine, as well as cause migration and large refugee situations. Figure 2.1 shows the relationships of occurrence of each type of drought in time.

Figure 2.1 Relationship between various types of drought and duration of drought events (Wilhite 2000).
II.3 Drought Measurements

II.3.1 Historical
The earliest measurement of drought consisted of the common meteorological and hydrological variables including precipitation, temperature, evapotranspiration, soil moisture, and stream flow. Occasionally a measure would be derived that combined some of these variables in an index summarizing many of these data sets in one composite value, which is more useful for decision-making over a certain area. In the last two decades and, after the significant advances in satellite remote sensing tools, applications were developed using remote sensing data to assess the general moisture availability conditions. Results of these applications indicate the potential use of satellite imagery to detect drought occurrences and to monitor the evolution of drought on regional scales (Kogan, 1997; William, 1994).

However, early drought quantification methods were largely based on precipitation deficit or its accumulated departure from normal over a given period of time within a specific region, factoring modest incorporation of temperature in the computation. Heim (2000) conducted a survey of these early measures. He listed the following examples for drought measurement in the US:

1- Fifteen consecutive days with no rain.
2- Twenty-one days or more with precipitation less than one third of normal.
3- Annual precipitation that is less than 75% of normal.
4- Monthly precipitation that is less than 60% of normal.
5- Any amount less than 85% of normal.
Similar criteria have been employed around the world:

1- Bali: a period of six days without rain.

2- Britain: fifteen consecutive days with less than 1 mm.

3- India: rainfall half of normal or less for a week, or actual seasonal rainfall deficient by more than twice the mean deviation.

4- Libya: annual rainfall that is less than 180 mm.

5- Russia: ten days with total rainfall not exceeding 5 mm.

Marcovitch (1930) derived an equation incorporating both temperature and precipitation to compute a drought index:

\[
\text{Drought Index} = N^2 (100/R)^2/2
\]

Where \( N \) is the total number of two or more consecutive days above 90 F, and \( R \) is the total summer rainfall for the same month.

Noticeably, the drought indices described above only indicate the initiation of drier than normal conditions. As such, occasionally, a drought can be considered as ended while the actual land surface conditions may continue to display moisture stresses. Clearly, to say that a drought is occurring, one needs to include water demand versus available supply. Thorntwaite and Mather (1995) stated, “We cannot define drought only as a shortage of rainfall, because such a definition would fail to take into account the amount of water needed. Furthermore, the effect of a shortage of rainfall depends on whether the soil is moist or dry at the beginning of the period … [Agricultural] drought does not begin when rain ceases but rather only when plant roots can no longer obtain moisture in needed amounts.”
In response to this and similar arguments, other indices were developed to provide a precise approach to measure drought. The crop moisture index, for instance takes into account the departure from the long-term normal condition of water availability.

II.3.2 Composite Drought Indices

As mentioned before, many drought indices summarize a suite of hydrologic and meteorological variables such as rainfall, soil moisture, temperature, and snowpack in one comprehensive value. Such indices can provide a better decision-making support to resource managers. Drought indices were developed to describe the climatic condition of a particular area in space and time, by monitoring the physical process of the climatic parameters that contribute to the shortage of moisture (V.K Lohani and Loganathan, 1997). The World Meteorological Organization (WMO) defines a drought index as, “An index, which is related to some of the climatic effects of a prolonged and abnormal moisture deficiency.” Basically, with respect to accuracy, there is not a significant difference in these indices. However, some indices are better suited than others for certain uses. For example, the Palmer drought severity index has been widely used by the U.S. Department of Agriculture to determine when to grant emergency drought assistance, but as argued by the National Drought Mitigation Center (NDMC), it performs better when working with large areas of uniform topography. Western states, with mountainous terrain and the resulting complex regional microclimates, find it useful to supplement Palmer index values with other indices such as the surface water supply index, which takes snowpack and other unique conditions into account. Presently, Colorado is monitoring its water resources using a combination of different drought
indices such as the standardized precipitation index, the surface water supply index, and a suite of Palmer’s method based indices (Hayes 2000).

The percent of normal index is a simple index that is mostly suited to the needs of TV weather anchors and the general public. The calculation of this index is based on dividing the actual precipitation by a long-term mean precipitation, typically taken as a 30-year mean and multiplied by 100. The disadvantage of this index is that the mean precipitation is often not the same as the median precipitation, which is in fact the precipitation exceeded by 50% occurring in a long-term record. The precipitation usually follows an exponential, abnormal distribution in which the median and the mean are not the same. Use of the percent of normal comparison implies a normal distribution where the mean and median are considered to be the same. This disadvantage can be seen where there is severe monsoon precipitation, in which heavy rainfall is seen in only a few hours, causing higher mean. As a consequence, the impression will be left that this area is relatively wet while in the rest of the year the area is quite dry.

The standardized precipitation index (SPI) was designed to measure the precipitation deficit for different time scales. The calculation of the SPI is based on a long-term record that is fitted to a probability distribution and then transformed to a normal distribution. A drought event occurs any time the SPI is continuously negative and reaches value of -1. The disadvantage of this index is that the values based on preliminary data may change. Table 2.1 summarizes the range of values of the SPI.
Table 2.1 Standardized Precipitation Index

<table>
<thead>
<tr>
<th>SPI Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.0 +</td>
<td>Extremely wet</td>
</tr>
<tr>
<td>1.5 to 1.99</td>
<td>Very wet</td>
</tr>
<tr>
<td>1.0 to 1.49</td>
<td>Moderately wet</td>
</tr>
<tr>
<td>-.99 to .99</td>
<td>Near normal</td>
</tr>
<tr>
<td>-1.0 to -1.49</td>
<td>Moderately dry</td>
</tr>
<tr>
<td>-1.5 to -1.99</td>
<td>Severely dry</td>
</tr>
<tr>
<td>-2 and less</td>
<td>Extremely dry</td>
</tr>
</tbody>
</table>

Palmer designed the crop moisture index (CMI) after the calculation of the Palmer drought severity index (PDSI). It is based on the previous values of CMI, mean temperature, and the total precipitation for each week within the Climate Division. The disadvantage of this index is that its main propriety that is based on monitoring week-to-week crop conditions may fail to monitor long-term drought conditions.

The purpose of developing surface water supply index (SWSI) was to compliment the PDSI by including snowpack, reservoir storage, and streamflow. It was designed by Shafer and Dezman (1982) to be an indicator of drought at a river basin scale. The SWSI varies between −4.2 and +4.2 with normal condition at zero. The disadvantage of this index is that the entire SWSI algorithm for that basin must be redeveloped when changes in the water management within a basin, such as flow diversions or new reservoirs, are made. Because the SWSI calculation is unique to each basin or region, it is difficult to compare SWSI values between basins or regions (Doeskenns et al., 1991).
The reclamation drought index (RDI) has been recently developed as a tool for monitoring drought, which allows states to seek assistance from the Bureau of Reclamation in order to reduce the impact of drought. This index includes the same inputs as the SWSI. The RDI ability to account for climate and water supply factors increases its strength. Yet, the index is not very useful for interbasin comparison. Table 2.2 lists the range of the RDI classification.

<table>
<thead>
<tr>
<th>RDI Classifications</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.0 or more</td>
<td>Extremely wet</td>
</tr>
<tr>
<td>1.5 to 4.0</td>
<td>Moderately wet</td>
</tr>
<tr>
<td>1 to 1.5</td>
<td>Normal to mild wetness</td>
</tr>
<tr>
<td>0 to -1.5</td>
<td>Normal to mild drought</td>
</tr>
<tr>
<td>-1.5 to -4.0</td>
<td>Moderate drought</td>
</tr>
<tr>
<td>-4.0 or less</td>
<td>Extreme drought</td>
</tr>
</tbody>
</table>

The Australian Drought Watch System uses the deciles index to provide assistance for ranchers and farmers during drought. The deciles index was developed by Gibbs and Maher (1967) arranging monthly precipitation data in deciles. It is very simple to compute, and requires fewer data. Its main disadvantage is that it requires a long climatic data record to be accurate. Figure 2.2 summaries the classification of deciles.
Keetch and Byram (1968) developed an index that relates recent weather conditions to potential or expected fire behavior. It is based on an 8 inches soil moisture capacity that is available in the upper soil layer, and can be used by vegetation for evapotranspiration. Factors in the index are maximum daily temperature, daily precipitation, antecedent precipitation, and annual precipitation. The advantage of the Keetch and Byram drought index (KBDI) is its simplicity of usage and familiarity among fire managers. The disadvantage remains in this index as long as it needs validation or calibration of the KBDI in areas outside the region of the southeastern United States. Without a proper recalibration of the drying tables (i.e. Table 2.3), KBDI could seriously overestimate the fire risk, particularly in the tropical regions, where weather is more moist (Regional Technical Assistance (RETA) report, 1997).
### Table 2.3 Keetch and Byram Index

<table>
<thead>
<tr>
<th>Index</th>
<th>Fire Danger</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 – 200</td>
<td>Low Fire Danger</td>
<td>Soil and fuel moisture is high.</td>
</tr>
<tr>
<td>200 – 400</td>
<td>Moderate Fire Danger</td>
<td>Fires more readily burn.</td>
</tr>
<tr>
<td>400 – 600</td>
<td>High Fire Danger</td>
<td>Fire intensity begins to significantly increase.</td>
</tr>
<tr>
<td>600 – 800</td>
<td>Extreme Fire Danger</td>
<td>Expect extreme intensity. Rapid response time to wildfire</td>
</tr>
</tbody>
</table>

### II.4 Drought Predictions:

After the extreme drought in India in 1877, Henry Blandford, then, the Director of the Indian Meteorological Service, found out that during the same time, high atmospheric pressure was occurring over Asia. His findings led to an extensive discussion and search for the causes of drought and its relationship to atmospheric pressure changes (Neville et al. 2000). During the early decades of the twentieth century, Gilbert Walker (1868-1958) conducted a study that showed large-scale atmospheric teleconnection patterns. His work indicated that north Australian summer rainfall could be predicted by an index he called the Southern Oscillation (what has later become known as El Nino-Southern Oscillation or ENSO). Subsequently many studies discussed the relationship between ENSO and climate, such as Quyale (1910, 1920), Grant (1956), and Troup (1965). Identification of these consistent relationships between ENSO and precipitation give a clear indication that seasonal meteorological drought may be predictable. Studies by Ropelewski and Halpert (1989, 1995) emphasized that there is a strong association of dry conditions, in large areas of the globe, with the warm or cold phase of ENSO. A recent study by Piechota and Dracup (1996) based on a harmonic analysis applied to Palmer drought index (PDSI)
states that there is a strong relationship between El Nino and severe drought especially along the Pacific Northwest part of the USA. It has been shown also that in Indonesia and Philippines, a strong prediction can be made about an upcoming drought once an ENSO event lasts for successive years (Harger, 1995).

However, an ENSO signal remains insufficient for regional drought prediction in many parts of the world because in these regions other factors predominantly affect drought conditions rather than ENSO episodes. Data from North Africa, for instance, does not support a strong relation between drought conditions and ENSO cycles in most years (Ward et al, 1993). Also, Northeast Brazil is influenced more by tropical Atlantic sea surface temperature patterns (Folland et al, 1991, Hastenrath 1995, Ward 1997) than by ENSO.

There are three major approaches to the challenge of climate prediction: statistical, conceptual, and numerical (Paulo and Iracema, 2000). Statistical methods usually analyze the time series in terms of periodicity and trends. For example, Pesti et al (1997) used a fuzzy rules approach to estimate precipitation based drought indices from climate patterns characteristics. Lohani and Loganathan (1997) used the PDSI in a non-homogeneous Markov chain model as an early warning system for drought. As the case in Markov chain models, this approach requires the availability of long time series in which synthetically generated time series (flow, precipitation) are used (e.g. Wijayaratne and Golub, 1991). The conceptual method requires a prior knowledge of the physical mechanism and interaction between the components of concern. The numerical method is based on continuity equations and thermodynamics. The best examples of this approach
are the General Circulation Models that are used to forecast the climate. They are computationally intensive.

II.5 Assessing Drought Using Satellite Data

Although the Palmer drought index is recognized as one of the best drought indices used in the USA, this index has found little acceptance outside of the United States (Kogan 1997). The search for a measure of drought that allows impact comparisons includes the potential use of remote sensing data. Satellite based technology has the advantage of real time monitoring of drought. It is based on analyzing vegetation properties that are highly related to the presence of moisture. Scientists began using satellite remote sensors to collect images of our planet's surface to quantify the concentration of green leaf vegetation around the globe. This concentration is interpreted by the vegetation index that is a measure of the vegetation greenness. The widely used vegetation index is the normalized vegetation index (NDVI). The NDVI is believed to reflect the general patterns of vegetation distribution and the changes in vegetation greenness. It is calculated by taking the difference between the visible and infrared light reflections and then normalized by dividing it by the sum of them. A detailed description of this index is presented in chapter three. Annual variation of NDVI in a certain region may well indicate regional climatic impact caused by weather. According to the argument that the evolution of the surface greenness responds quite well to rainfall conditions, normalized difference vegetation index is utilized to analyze the drought episodes (Kogan, 1990). Recent studies have shown potential promise for drought assessment. For instance, Liu
and Juarez (2001) showed that the use of satellite-based normalized difference vegetation index (NDVI) provided a better correlation with ENSO compared to rainfall, and therefore a drought onset prediction model was constructed over area of Northeast Brazil. Moreover, satellite imagery can provide a regular, repetitive and regional view of most of the earth surface, as well as a permanent data archive, and cost effectiveness (Kogan 1997).

Most of the previous studies that included the use of satellite data were limited to point measurements. However, recent studies conducted at the regional scale showed encouraging results for pursuing this method of studying drought. Rundquist et al. (2000) examined the strength of relationships between the NDVI and climatic data at the mesoscale. Mean monthly AVHRR NDVI data for 1988-1996 for the months of April through October for the State of Kansas, its nine climatic divisions (CDs), and dominant land cover types within each CD were used. Corresponding climatic and water budget data were obtained or derived from National Climatic Data Center. Temperature, precipitation, and NDVI were determined. Statistical analysis revealed favorable relationships between NDVI and climatic variables. The highest correlation coefficient (r) for the state as a whole was 0.53, between NDVI and estimated actual evapotranspiration. When examined by climatic division or major land cover type, relationships between NDVI and a drought index were statistically acceptable in most cases and ranged from 0.30 to 0.56.
Peters et al. (1991) examined the effect of the 1988 drought on vegetation dynamics by climatic division in Nebraska and concluded that AVHRR NDVI is useful in identifying vegetated areas that are most affected by water stress.

Kogan (1995) developed new indices to monitor drought based on the NDVI, the vegetation condition index (VCI) and temperature condition index (TCI). The results presented by Kogan were the first attempt to use both NDVI and thermal channels on a large area with very diversified ecological resources. These indices were also used for assessment of drought impact on regional agricultural production in South America, Africa, Asia, North America, and Europe. For this purpose, the average VCI-TCI values for a given region and for each week of the growing season were calculated and compared with yields of agricultural crops. The results showed a very strong correlation between these indices and yield, particularly during the critical periods of crop growth.

William et al (1994) used NDVI to study drought evolution in the South American continent. Vegetation response to drought was studied by inspection of the temporal and spatial evolutions of monthly drought area maps, which are delineated by NDVI values. The results show a well-defined regional dependence of the drought area variability. They also indicate that there is a potential use of satellite NDVI imagery to monitor drought occurrences as well as to study climatic variability on regional and continental scales.
CHAPTER THREE

METHODS AND DATA

III.1 Introduction:

This chapter will focus on the conceptual background of this study. This chapter will also describe detailed definition of variables, data sets, and tools used to conduct the analysis described in chapter 5. These include Palmer drought indices, IGBP land cover and normalized difference vegetation index. Data analysis tools used in this study including the steps followed to create monthly NDVI time series over the climate regions and by vegetation classes, are also discussed in this chapter.

III.2 Conceptual Framework

The potential usefulness of satellite data in drought monitoring presents a new opportunity in improving drought assessment. This potential has been presented by various studies, which translate information about moisture condition to vegetation stress and relate it to drought, especially at a regional scale. Normalized difference vegetation index (NDVI) is one strong measure of the vegetation condition that has been used in those studies. However most of the attempts to relate NDVI to drought use the absolute value of the NDVI index that translate the actual vegetation condition and not the departure of the vegetation condition, where drought differs from aridity and has a meaning of departure. The last argument suggests that this relation between drought and
remotely sensed vegetation condition would be based on a departure of normal vegetation condition. In this context, Kogan derived the Vegetation Condition Index (VCI) that introduces the deviation concept in assessing drought. VCI is based on subtracting the actual value of NDVI from the minimum NDVI calculated for each pixel from multiyear smoothed NDVI data. The argument of this study is different from the VCI method in terms of subtracting the average monthly NDVI from actual NDVI value for each pixel instead of subtracting the minimum NDVI value. This takes into the consideration that we are assessing drought, aside from normal conditions. This new value is called the departure NDVI (DNDVI). This new term (DNDVI) is computed and compared to Palmer drought indices. Furthermore, this study analyses this relationship by disaggregating the DNDVI for each land cover type that addresses the characteristics associated with the various land cover types. For example forests perform differently from shrubland during a period of drought and therefore reacts differently to drought effects in terms of time.
Figure 3.1 North America Land cover (from IGBP)

Figure 3.1 shows the variation of land cover classes over North America. This variation emphasizes the need to separate DNDVI for each land cover type, especially at a regional scale, where climate regions are large in the Western United States, because they may include various land cover types, without a highly dominant cover.

To conduct analysis of DNDVI as measure of drought, this study is based on the following premises:

1. Use established drought indices such as the PDSI, which are known to capture the long-term soil moisture memory similar to the memory associated with vegetation growth.

2. Conduct analysis at the same aggregation scale of drought index (i.e. climate regions).
3. Ensure accounting for land cover and vegetation type variability in the process as they affect seasonal changes in NDVI

The data used in this analysis are heterogeneous in terms of their spatial and temporal scale. Also data images have different projections. This was addressed by reprojecting some of the data layers to a common projection. In the following sections a detailed description of the data sets, and steps followed to obtain DNDVI time series, will be provided.

III.3 Palmer Drought Indices

III.3.1 Palmer Model

Palmer’s (Palmer, 1965) objective was to address the two key descriptors of drought, intensity of a drought and duration. His goal was to develop a comparative index that was independent from climatic regimes. Water balance equations are the starting point in Palmer’s model of drought progression. Identical to the water budget formulation of Thorntwaite and Mather (1955) in many respects, Palmer’s index introduced the balance between moisture supply and demand as the basis to identify an index moisture deficit or surplus for different components of the water budget. The transformation of deficit/surplus provides an index commonly known as the PDSI. The hydrologic mass balance presented in equation (3.1) must be satisfied.

According to Palmer, the procedure consists of carrying out a hydrologic accounting by month, for a long period of time in historical climatologic series:
\[ P + I_g = ET + O_s + O_g - (S_t - S_{t+1}) \]  \hspace{1cm} (3.1)

Where,

P: precipitation.

I_g: groundwater inflow.

ET: evapotranspiration.

O_s: outflow from surface runoff.

O_g: outflow from groundwater.

S: storage.

Underground water storage underground is divided into soil moisture storage and groundwater storage. Also Palmer added three potential terms. These potentials are Potential recharge (PR), potential runoff (PRO), and potential loss (PL), defined below.

Before the calculation of the PDSI, several parameters are derived from the input temperature and precipitation data by calculating quantities that are climatically appropriate for existing condition (CAFEC) (William, 1984). Other parameters, which are direct input in to the Palmer model, are the available water capacity (AWC) of the soil, and heat index terms used in the Thornthwaite equation (Karl, 1986), which depends on soil characteristics and the depth of the root zone. Soil moisture storage is divided into 2 layers; a surface storage layer (S_s) and underlying soil moisture storage layer (S_u). It is assumed that the upper layer contains 1 inch of moisture at field capacity, and the remaining (AWC - S_s) of moisture is assigned to the underlying layer at field capacity. Moisture is removed from the upper layer (S_s) at a potential evapotranspiration rate until
all the available moisture has been removed. Then, moisture starts to evaporate from the underlying layer ($S_o$) at a rate that is function of potential evapotranspiration and the ratio of water in storage to the total available water capacity (AWC).

**Potential Values:**

Palmer developed additional potential values from their respective actual values in a manner similar to potential evapotranspiration $PE$.

First, the potential recharge, $PR$, is defined as the amount of moisture needed to bring the soil to field capacity.

$$PR = AWC - S'$$  \hspace{1cm} (3.2)

Where $S'$ is the amount of available moisture in both layers of the soil at the beginning of the month (Palmer, 1965, pp. 9-10).

Second, the potential loss, $PL$, is defined as "the amount of moisture that could be lost from the soil provided that precipitation during the period were zero" (Palmer, pp.10).

$$PL = PL_s + PL_u,$$  \hspace{1cm} (3.3)

$$Where 
PL_s = \begin{cases} 
PE & PE < S'_s \\
S'_s & PE \geq S'_s 
\end{cases}$$  \hspace{1cm} (3.3.a)

And

$$PL_u = (PE - PL_s)S'_u / AWC$$  \hspace{1cm} (3.3.b)
The subscript \( s \) indicates surface layer and \( u \) for under layer as described before.

The last potential value is the potential runoff, PRO, "potential runoff is a function of the amount of soil moisture available and simply written as

\[
\text{PRO} = \text{AWC} - \text{PR} = S' \quad (3.4)
\]

This assigns potential precipitation as being equal to AWC" (Palmer, 1965, pp. 11).

Later on, Palmer suggested that potential runoff would generally be closer to 3 times the normal precipitation for the month. So \( \text{PRO} = 3P - \text{PR} \), where \( P \) is the normal precipitation during a month.

After defining the additional potentials, the next step is to derive the coefficients of evapotranspiration, recharge, loss, and runoff respectively noted as \( \alpha_i, \beta_i, \delta_i, \) and \( \chi_i \). These are parameters for each of the 12 months at each location.

- Coefficient of evapotranspiration

\[
\alpha_i = \frac{(\text{ET}_i)}{(\text{PE}_i)} \quad (3.5)
\]

Where \( \text{ET}_i \) and \( \text{PE}_i \) are the long-term mean of evapotranspiration and potential evapotranspiration for the month \( i \).

- Coefficient of recharge

\[
\beta_i = \frac{(\text{R}_i)}{(\text{PR}_i)} \quad (3.6)
\]
Where $R_i$ and $PR_i$ are the long-term mean recharge to the soil and potential recharge for the month $i$.

- Coefficient of Loss

$$\delta_i = (L_i)/(PL_i) \quad (3.7)$$

Where $L_i$ is moisture loss and $PL_i$ is its corresponding potential for the month $i$.

- Coefficient of Runoff

$$\chi_i = (RO_i)/(PRO_i) \quad (3.8)$$

Where $RO_i$ and $PRO_i$ are long term mean of runoff and potential runoff for month $i$.

The CAFEC (quantities as climatically appropriate for existing condition) for evapotranspiration, recharge, runoff, loss and precipitation can then be determined. They are denoted by a circumflex “^”.

CAFEC:

$$\hat{ET} = \alpha PE \quad (3.9)$$

$$\hat{R} = \beta PR \quad (3.10)$$

$$R \hat{O} = \gamma PRO \quad (3.11)$$

$$\hat{L} = \delta PL \quad (3.12)$$
\[ \hat{P}_i = ET_i + \hat{R}_i + RO_i - \hat{L}_i \]  \hspace{1cm} (3.13)

This says that the CAPEC precipitation for month \( i \), is the amount of precipitation needed to bring the water supply of the region up to the customary use expectations.

Palmer argued that it could be proven that the long-term average departure of the actual precipitation from the long-term average CAPEC precipitation is zero (Palmer 1965). After that the CAPEC precipitation has been calculated accordingly for each month \( i \), the subtraction from the actual precipitation provide a measure of departure of the moisture from normal.

\[ d = P - \hat{P} \]  \hspace{1cm} (3.14)

Departure \( d \) is weighted by another coefficient \( K \) that represents the climatic characteristic correction. The climatic characteristic \( K \) is needed to compute the moisture anomaly index, \( Z \), the departure of the soil moisture of a particular month from the average moisture climate of that month. The moisture anomaly index reflects short-term moisture deficiencies or excesses.

**Climate characteristic of \( K \):**

Initially, Palmer suggested using the standard deviation of \( d \) as a measure of climatic characteristic, but the results were not realistic. After considerable experimenting and in
view of that the K factor didn't work very well in some other climates, Palmer finally established a relationship for K that appears to give satisfactory results. This factor is considered, as a correction factor for the monthly departure d, which will facilitate the interpretation of the drought index between different areas.

\[
K' = 1.5 \log_{10} \left[ \frac{PE + R + RO}{P + L} + 2.80 \right] / D + 0.5 \quad (3.15)
\]

Where \( P + L \) represents average water supply, \( PE + R + RO \) represent the climatic moisture demand, and \( D \) is the monthly mean of the absolute values of d. The above factor (equation 3.15) was not reasonable and a further adjustment to its final form equation 3.16.

\[
K_j = \left( \frac{17.67}{\sum_{i=1}^{12} \frac{D_i K_i'}{D_i K_i'}} \right) K_j' \quad (3.16)
\]

It has been noticed that the weighting factor K tends to be large in arid region and small in humid regions.

The monthly moisture anomaly index, \( Z \), is defined as
\[ Z = dK \]  

(3.17)

The moisture anomaly index \( Z \) expresses a relative departure of the soil moisture of a particular month and location from the average moisture conditions of that month. Having established the value of \( K \), and the value of \( Z \), these values are used to determine the monthly PDSI such that:

\[ PDSI_i = 0.897 PDSI_{(i-1)} + \frac{Z_i}{3} \]  

(3.18)

Where the initial month \( (i = 0) \) in a spell of dry or wet weather are simply \( PDSI_i = \frac{1}{3} Z_i \) (Karl, 1986). This index is considered as a hydrological drought index. However, a meteorological drought index was also developed to determine whether the spell of anomalously dry or wet weather was over, and not to wait for the end of a drought or wet spell when the average moisture demand was satisfied. In order to accomplish this, the term \( Pe \) was developed in which it expresses the moisture received as a percentage of the moisture required to definitely terminate a drought or a wet spell (Palmer, 1965).

Palmer arbitrarily selected the classification scale of moisture condition based on his original study areas in central Iowa and western Kansas (Palmer, 1965). Figure 3.2 shows the classification for dry and wet Periods.
III.3.2 Other derivative of the original PDSI

In addition of the PDSI, and the Z index already described, additional drought indices definitions are used in the analysis including (Karl, 1986):

1. Palmer Hydrological Drought Index (PHDI)

This hydrological index is a modified version of the PDSI generated and used for water supply monitoring, and was first described by Karl (1986). This index is based on the principles of a balance between moisture supply and demand. Man-made changes such as increased irrigation, new reservoirs, and added industrial water use were not included in the computation of this index. The index generally ranges from -6 to +6, with negative values denoting dry spells, and positive values indicating wet spells. There are a few values in the magnitude of +7 or -7. PHDI values 0 to -0.5 = normal; -0.5 to -1.0 = incipient drought; -1.0 to -2.0 = mild drought; -2.0 to -3.0 = moderate drought; -3.0 to -
4.0 = severe drought; and greater than -4.0 = extreme drought. Similar adjectives are attached to positive values of wet spells. This is a hydrological drought index used to assess long-term moisture supply.

2. Modified Palmer Drought Severity Index (PMDI)

This modification of the Palmer Drought Severity Index is based on a probability-weighing factor for wet and dry terms. The modification purpose of the palmer drought index is to eliminate the rapid transition between positive and negative values when the probability of drought (wet) spell crossed 50% (Heddinghause and Sabol, 1991). The modification was made after concurrence with experts at the National Weather Service Climate Analysis Center for operational meteorological purposes. Operationally, three intermediate parallel index values are calculated each month, but only one value is selected as the PDSI drought index for the month based on occurrence probability. The PMDI and PDSI will have the same value during an established drought or wet spell (i.e., when first substantial rain after a prolonged drought), but they will have different values during transitional periods.

III.3.3 Limitation of palmer index

The PDSI index and its derivatives have been analyzed and criticized by many authors including Alley (1984), Karl (1983, 1986), and Nathaniel (1998). Alley noted that a number of arbitrary assumptions were made during the establishment of Palmer’s method. For instance, he noted that the palmer representation of runoff is very simple and therefore crude. He stated that the weighting factor (K) for standardization is based on
limited data and is weakly justified statistically. He also discussed the effect on the index of the arbitrary rules for determining the beginning and the ending of wet or dry spells as well as their intensity. Lastly, he was also concerned about the bimodality in the index distribution, which will limit the use of time series models in order to capture stochastic proprieties of the index. Nathaniel stated that the Palmer index is very complex, spatially variant, and difficult to interpret. He also mentioned the use of the initial conditions is critical, therefore he suggested to take a conservative approach by ignoring the first five years of the PDSI time series. Although Alley and others criticized this index, no other proposed index was shown to be better, and the availability of long history of using PDSI has contributed to its wide acceptance.

III.3.4 Drought Indices Data Used

The raw data for computing drought indices were obtained from the website ftp://ftp.ncdc.noaa.gov/. The required input data are temperature and precipitation on a monthly basis for each climate division. Another required input is the soil constant file, which contains soil layers water capacity, Thorntwaite coefficients for computing evapotranspiration, and the negative tangent of the latitude of the location. The Palmer FORTRAN code was also downloaded from the same website. After running the program the output was compared to the results found online by the National Climate Data Center, and the output was consistent with the online results. The output data are PDSI, PHDI, Zindex, and PMDI described above.
III.4 Pathfinder AVHRR Land NDVI Data

III.4.1 Definition

Many techniques have been developed to study quantitatively and qualitatively the status of the vegetation from satellite images. The Normalized Difference Vegetation Index, for example, is believed to reflect the general patterns of vegetation distribution and the changes in vegetation greenness. Chlorophyll causes considerable absorption of visible radiation, and the spongy mesophyll leaf structure causes considerable reflection of the near infrared radiation (Tucker 1979, Jackson et al. 1983, Tucker et al. 1991). Vegetation indices take advantage of the relatively unique spectral reflectance characteristics of green vegetation. AVHRR channel 1 (0.58-0.68 μm) or red-light senses an area of the spectrum that shows an inversely proportional relationship to the amount of chlorophyll in the plant canopy, and consequently shows an inverse relationship to the amount of green biomass present. On the other hand, AVHRR channel 2 (0.725-1.0 μm) or near-infrared senses a region of the spectrum with reflectance directly proportional to the density of photosynthetically active vegetation, and with less reflectance for active or dead vegetation. This high reflectivity in the near infrared is a result of scattering of incoming near-infrared radiation by the spongy mesophyll layer of the leaves. Vegetation indices are combinations of both of these spectral channels, in such a way that they reflect the contribution of vegetation, minimizing the contribution of other factors such as soil, lighting, atmosphere, etc. Also this combination discriminates many cover types that can fit one of the characterizations mentioned (e.g. a barren lava flow for low red reflectivity). The combination of the two is unique enough to allow the consistent
discrimination of vegetation, and the relative determination of vegetation vigor. A variety of vegetation indices using combinations of red and near infrared have been proposed and used. The most widely accepted vegetation index is the Normalized Difference Vegetation Index (NDVI). The NDVI formula in particular was originally termed the VI (Vegetation Index) (Rouse et al., 1973) and applied to Landsat MSS data (Tucker 1979). The formula for the NDVI is expressed as:

\[
NDVI = \frac{\text{channel}_2 - \text{channel}_1}{\text{channel}_2 + \text{channel}_1}
\] (3.19)

Figure 3.3 below illustrates the energy reflected in each of the visible and near-infrared band for vegetation stage.

![Figure 3.3 Reflectance Energy of Visible and Infrared frequency for Crop](From NOAA)
The range of values obtained by the NDVI is between -1 and +1. Only the positive values correspond with vegetated zones. The negative values, generated by a higher reflectance in the visible region than in the infrared region, are due to clouds and snow. The value of the NDVI can change depending on the land use, the season, and the climate of the area. Rock and bare soil have similar reflectance in the red and the near infrared, so these surfaces will have negative or near zero values. Figure 3.4 shows the percentage of reflectance at different wavelengths for green vegetation.

Figure 3.4 Typical reflectance and absorption characteristics of green vegetation. [Adapted from Swain and Davis 1978]
III.4.2 Description of the data

The NDVI continental data sets for a 19 year time series, from July 13, 1981 through December 31, 1999 were extracted from the Pathfinder Advanced Very High Resolution Radiometer Landcover (PAL) Global 8-km, 10-day composite. These data are provided by the Goddard Space Flight Center (GSFC). The data covers the time period from July 13, 1981 through December 31, an average of 36 images per year starting from 1982, except 1994, which had 27 observations due to the failure of the NOAA-11 satellite during the months of October, November, and December. The 8 km data set has been selected because of the regional scale at which drought is considered as regional phenomena. Also these data cover the entire globe and represent a fairly long time frame in case an extension of the analysis is to be performed.

The original PAL 10-day data are a composite data set, based on the maximum NDVI observed during an 8 to 11 day period, based on the month and year, or fewer than 8 days if there is a lack of data. The purpose of the compositing was to create a single image with minimal cloud and atmospheric contamination. Daily images collected over an 8 to 11 day period from the NOAA AVHRR Global Area Coverage (GAC) 1B data were combined into a single composite (GSFC, 2000). Pixels for the composite image were selected based on the maximum daily NDVI value within the 10-day period.
III.4.3 Source of Data:

These data were obtained from The Advanced Very High Resolution Radiometer (AVHRR) flown on NOAA-series satellite. The orbital period of about 102 minutes produces 14.1 orbits per day. Because the daily number of orbits is not an integer, the sub-orbital tracks do not repeat daily, although the local solar time of the satellite's passage is essentially unchanged for any latitude. The 110.8 degrees cross-track scan equates to a swath of about 2700-km. This swath width is greater than the 25.3 degrees separation between successive orbital tracks and provides overlapping coverage.

The bandwidths and Instantaneous field of view (IFOV) of the AVHRR instrument are given in the following table (Table 3.1).

<table>
<thead>
<tr>
<th>Channel</th>
<th>Wavelength (micrometer)</th>
<th>IFOV (milliradian)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.58 - 0.68</td>
<td>1.39</td>
</tr>
<tr>
<td>2</td>
<td>0.73 - 1.10</td>
<td>1.41</td>
</tr>
<tr>
<td>3</td>
<td>3.55 - 3.93</td>
<td>1.51</td>
</tr>
<tr>
<td>4</td>
<td>10.3 - 11.3</td>
<td>1.41</td>
</tr>
<tr>
<td>5</td>
<td>11.5 - 12.5</td>
<td>1.30</td>
</tr>
</tbody>
</table>
III.4.4 File Format and procedure

The original data were compressed when extracted from the NDVI continental Subsets CD. Once the pathfinder NDVI biweekly data provided by the Goddard Space Flight Center are uncompressed, the data are processed as 8-bit unsigned integer value. Importing the data to be viewed and processed was performed using ERDAS-Imagine tool software on a file-by-file basis. Necessary information of map info and sequences for correct registration are shown in figure 3.5.

Once all the images were imported and registered correctly, a cover of the climate regions of interest was used to clip out a subset of the continental North America data. To obtain the NDVI values from the scaled data value (Digital Number) the offsets must be subtracted from the scaled data value and the result multiplied by the gain. An AML code was written to do that using Arc Info GIS software.

\[
\text{NDVI} = (\text{DN} - \text{offset}) \times \text{Gain} \tag{3.20}
\]

Where Gain and offset represent data compression parameters.

Gain = 0.0079365 and Offset = 126.
Figure 3.5 Importing of NDVI data flowchart (NOTE: BSQ means that the input data are in band sequential format from multi-bands).
Since the US cover map used for subsetting the data is registered in Albers Conical Equal Area coordinate, and the NDVI images in interrupted goods Homolosine (IGH), the cover map was reprojected first to decimal degree (DD), then clipped in two parts north projection and south projection. The north projection was reprojected again from DD to Mollweide Region 1 of the IGH, and the south projection was also reprojected to Sinusoidal Region 3 of the IGH. After that, the two previous projections were merged into one image of the US cover and then converted into a grid. The parameters used for this procedure are provided by Steinwand (1994) (Table 3.2). The NDVI data were kept on their original projection because of the need to minimize the distortion resulting from reprojecting all the number of NDVI images as opposed to simply reprojecting the US cover map of climate regions. At this point we have NDVI grids and US cover map at the same projection. This will allow us to subset NDVI grids of North America to climate divisions of interest. Figure 3.6 and figure 3.7 describe the sequences of the reprojection method.
### Table 3.2 Interrupted Goode Homolosine Projection Parameters

<table>
<thead>
<tr>
<th>REGION</th>
<th>LATITUDE Range</th>
<th>LONGITUDE Range</th>
<th>PROJECTION</th>
<th>CENTRAL MERIDIAN</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>90N to 40 44'N</td>
<td>180W to 40W</td>
<td>Mollweide</td>
<td>100W</td>
</tr>
<tr>
<td>3</td>
<td>40 44'N to 0</td>
<td>180W to 40W</td>
<td>Sinusoidal</td>
<td>100W</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>REGION</th>
<th>GOODEs WINDOW (SL,SS,NL,NS)</th>
<th>LOCAL PROJECTION (Y,X) Upper Left</th>
<th>GOODE's PROJECTION (Y,X) Upper Left</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>12,156,414,412,572</td>
<td>9009410.83 -6740512.57</td>
<td>8673000.00 -17860000.00</td>
</tr>
<tr>
<td>3</td>
<td>4145,1,4530,15568</td>
<td>4529000.00 -8895512.57</td>
<td>4529000.00 -20015000.00</td>
</tr>
</tbody>
</table>

Radius of Sphere: 6370997 meters

<table>
<thead>
<tr>
<th>X shift (false easting):</th>
<th>MOLLWEID</th>
<th>SINUSOIDAL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-119487.43</td>
<td>-119487.43</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Y shift (false northing):</th>
<th>MOLLWEID</th>
<th>SINUSOIDAL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-336410.83</td>
<td>0.00</td>
</tr>
</tbody>
</table>
Project climate region cover (US) to DD units:
called: CR_DD

- clip CR_DD to only north part.
  - projection north: CR_DD --> CR_DD-N

- Project CR_DD-N to Mollweide Region 1
  (parameters from table) CR-N-M

- clip CR_DD to only south part.
  - projection south: CR_DD --> CR_DD-S

- Project CR_DD-S to Sinusoidal Region 3
  (parameters from table) CR-S-S

- Merge them back CR-N-M & CR-S-S CR-GOODE

- make Grid

- subsetting interested climate divisions

Figure 3.6 Flowchart for reprojecting US cover map from Albers to Homolosine.
Figure 3.7 Sequence of reprojecting US cover map from Albers projection to Sinusoidal and Mollweide projection
III.4.5 Final Data Product

After subsetting the 10-day composite NDVI grids into the climate divisions of interest, the 10-day composite NDVI grids were converted to monthly grids by taking the maximum value in the three images for every month. After that the average NDVI of each month was computed over the period of time given (1981-1999) which was subtracted from the correspondent months NDVI grid. This approach is based on the fact of comparing the departure NDVI statistics from the normal conditions since the Palmer Indices are presented as departure from the long term normal conditions as described in section III.3. This approach seems more realistic than just working with the absolute NDVI in order to measure drought conditions that are departure from the normal conditions. The new grids computed after subtracting the monthly average NDVI of each corresponding month of NDVI is called departure NDVI (DNDVI). Two sets of time series were generated from the DNDVI grids. The first set of time series are time series of DNDVI for the different climate regions in Arizona. The second set of time series are time series of DNDVI for each land cover type and within each climate region in Arizona. The final data products from the DNDVI grids are the maximum, minimum, mean, and standard deviation for every Monthly Departure NDVI grid. These steps were performed through AML scripts in ARC-INFO. The procedure of getting the time series of DNDVI is shown in the flowchart below in figure 3.8.
8KM NDVI grid for North America

8KM NDVI grid for Chosen climate Division

for each month
MONTHLY
MAX_grid = max(NDVI_grid)

Average monthly Grid
AVG_grid = SUM(MAX_grid)/N
N: number of years over the same month

DEVIMATION:
DV_grid (month(i)) = max_grid(month(i) - AVG_grid(month(i))

first analysis
climate division grid
grid computation:
zonalstats(climate division, DVgrid(month(i))

second analysis
IGBP land cover within the climate division
grid computation:
zonalstats(IGBP Landcover, DVgrid(month(i))

Output statistics for DV_grid
mean
maximum
minimum
standard deviation

total of 12 AVG_grid

Figure 3.8 Procedure in getting final DNDVI time series
III.5 International Geosphere Biosphere Programme (Global Land Cover)

III.5.1 Data Description

A variety of land use classifications have been developed for different purposes. The Simple Biosphere Model (SIB) (Seller et al. 1986), Simple Biosphere 2 Model, the Biosphere Atmosphere Transfer Scheme (BATS) (Dickinson et al. 1986), International Geosphere Biosphere Programme (IGBP), and USGS/Anderson are examples of this variety.

The land cover classification chosen in this study is the International Geosphere Biosphere Programme (IGBP) that is considered as one portion of a global land cover characteristics database. It was developed on a continent-by-continent basis where a combination of multitemporal AVHRR data, with other ancillary data sets, were used to produce a prototype land cover characteristics data base. While other land cover classification schemes include large number of land use classes, which can increase the complexity in this analysis, the IGBP classification includes 17 classes that represent a good mosaic of the land cover and will be the basis for the Common Land Model (CLM) under development. In addition, this land cover classification is accepted by the international community, which makes the analysis here transferable to other regions of the world. The map projection is in Interrupted Goode Homolosine, and has 1-km nominal spatial resolution.
The land cover classification system proposed consists of 17 general cover types selected based on the requirements of the IGBP Core Projects. These categories include similar categories to the philosophy that was described by Running et al. (1994) in which the classification consists of a simple combination of three primary attributes of plant canopy structure that are permanence of aboveground live biomass, leaf longevity, and leaf type (Running et al. 1994). These modifications stress the fact that the IGBP classification must be compatible with classifications systems currently used for environmental modeling (e.g., Simple Biosphere Model -- SiB, and Biosphere Atmosphere Transfer Scheme -- BATS). Also it had to provide, where possible, land use implications; and it has to represent landscape mixtures and mosaics (Belward, 1995).

III.5.2 Class Definition for IGBP (Global Land Cover Legend)

The following are brief land cover category definitions for each class as described by (Belward A. S, and Loveland, T., 1995)

1-Evergreen Needleleaf Forests: Lands dominated by trees with a percent canopy cover more than 60% and height exceeding 2 meters. Almost all trees remain green all year. Canopy is never without green foliage. Consist of needleleaf tree communities.

2-Evergreen Broadleaf Forests: Lands dominated by trees with a percent canopy cover more than 60% and height exceeding 2 meters. Almost all trees remain green year all year. Canopy is never without green foliage. Consist of broadleaf tree communities.
3-Deciduous Needleleaf Forest: Lands dominated by trees with a percent canopy cover more than 60% and height exceeding 2 meters. Consists of seasonal needleleaf tree communities with an annual cycle of leaf-on and leaf-off periods.

4-Deciduous Broadleaf Forests: Lands dominated by trees with a percent canopy cover more than 60% and height exceeding 2 meters. Consists of seasonal broadleaf tree communities with an annual cycle of leaf-on and leaf-off periods.

5-Mixed Forests: Lands dominated by trees with a percent canopy cover more than 60% and height exceeding 2 meters. Consists of tree communities with interspersed mixtures or mosaics of the other four forest cover types. None of the forest types exceeds 60% of landscape.

6-Closed Shrublands: Lands with woody vegetation less than 2 meters tall and with shrub canopy cover is more than 60%. The shrub foliage can be either evergreen or deciduous.

7-Open Shrublands: Lands with woody vegetation less than 2 meters tall and with shrub canopy cover is between 10-60%. The shrub foliage can be either evergreen or deciduous.

8-Woody Savannas: Lands with herbaceous and other understory systems, and with forest canopy cover between 30-60%. The forest cover height exceeds 2 meters.
9-Savannas: Lands with herbaceous and other understory systems, and with forest canopy cover between 10-30%. The forest cover height exceeds 2 meters.

10-Grasslands: Lands with herbaceous types of cover. Tree and shrub cover is less than 10%.

11-Permanent Wetlands: Lands with a permanent mixture of water and herbaceous or woody vegetation that cover extensive areas. The vegetation can be present in salt, brackish, or fresh water.

12-Croplands: Lands covered with temporary crops followed by harvest and a bare soil period (e.g., single and multiple cropping systems). Note that perennial woody crops will be classified as the appropriate forest or shrub land cover type.

13-Urban and Built-up: Land covered by buildings and other man-made structures. Note that this class will not be mapped from the AVHRR imagery but will be developed from the populated places layer that is part of the Digital Chart of the World (Defense Mapping Agency, 1992). It must be mentioned that this category generally underestimates the aerial extent in most Pathfinder data set (Dr B. Imam, personnel communication).

14-Cropland/Natural Vegetation Mosaics: Lands with a mosaic of croplands, forests, shrublands, and grasslands in which no one component comprises more than 60% of the landscape.
15-Snow and Ice: Lands under snow and/or ice cover throughout the year.

16-Barren or sparsely vegetated: Lands with exposed soil, sand, rocks, or snow, which never have more than 10%, vegetated cover during any time of the year.

17-Water Bodies: Oceans, seas, lakes, reservoirs, and rivers. Can be either fresh or salt-water bodies.

III.5.3 Projection Parameters of the IGBP (Global Land Cover)

The data dimensions of the Interrupted Goode Homolosine projection for the global land cover characteristics data set are 17,347 rows and 40,031 columns resulting in a data set size of approximately 695 megabytes for 8-bit (byte) images. Table 3.3 provides a summary of the map projection parameters used:

<table>
<thead>
<tr>
<th>Table 3.3 Interrupted Goode Homolosine projection parameters for IGBP map</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Projection Type:</strong></td>
</tr>
<tr>
<td><strong>Units of measure:</strong></td>
</tr>
<tr>
<td><strong>Pixel Size:</strong></td>
</tr>
<tr>
<td><strong>Radius of sphere:</strong></td>
</tr>
<tr>
<td><strong>XY corner coordinates (center of pixel) in projection units (meters):</strong></td>
</tr>
<tr>
<td><strong>Lower left:</strong></td>
</tr>
<tr>
<td><strong>Upper left:</strong></td>
</tr>
<tr>
<td><strong>Upper right:</strong></td>
</tr>
<tr>
<td><strong>Lower right:</strong></td>
</tr>
</tbody>
</table>
III.6 Analysis Procedure:

III.6.1 Analysis overview

After generating the final grids of monthly DNDVI and subsetting them by climate divisions, time series of the mean of the pixels of every monthly grid, maximum pixel, minimum pixel, and the standard deviation of the DNDVI were calculated based on climate regions as well as vegetation cover within each climate regions. To identify possible relationship between DNDVI spatial mean and various climate regions scale drought indices, first, a visual inspection of the timeseries was conducted. The objective of such inspection is to discern patterns in the data before subjecting the record to more quantitative analysis. It must be noted that visual inspection is not, by itself sufficient, as the human eye tends to create sometimes false impression of order (trend, cyclic behavior) in the data.

III.6.2 Analysis over a selected climate division

To establish the methods described in this thesis, and to ensure relevance to semi-arid regions, it was necessary to choose a climate region from a semi-arid region (Arizona) that has as many land cover types as possible in order to observe which land cover exhibits correlation with drought indices. In this phase correlations and crosscorrelations between the mean DNDVI and the Palmer drought indices were calculated over all climate regions in Arizona.

The Pearson product-moment correlation coefficient is probably the single most widely used statistic for summarizing the relationship between two variables. Alas,
simple correlation analysis can be misleading for physical phenomena that exhibit a dynamical, time varying response, and therefore methods using the cross-correlation function are more appropriate (Box and Jenkins 1976). The outcome of the cross-correlation as opposed to the simple Pearson correlation is that correlation analysis for application to time series summarizes the strength of the synchronous relationship only. However as for many of hydrological processes, this relationship can be delayed due to many factors. For example an annual time series of river discharge series might contain input from several past years rainfall and since this relationship between the discharge and rainfall time series does not need to be contemporaneous, the simple correlation coefficient does not measure this lagged effect.

To study the lagged relationship and where these relationships manifest most in time, we can use the cross-correlation functions. In this analysis we have used the cross-correlation function (CCF). The CCF is an asymmetric function in which a different value results from lagging one series forward or backward from the second series. Following Chatfield (1975), the sample cross correlation is given by:

$$r_{xy}(k) = \frac{c_{xy}(k)}{\sqrt{c_{xx}(k)c_{yy}(k)}}$$

(3.21)

Where $$c_{xy}(k)$$ is the cross-covariance function and is given by

$$C_{xy}(k) = \frac{1}{N} \sum_{t=1}^{N-k} (\mu_t - \bar{\mu})(y_{t+k} - \bar{\mu})$$

[k = 0,1,....,(N-1)]

(3.22)
\[ C_{uy}(k) = \frac{1}{N} \sum_{t=1-k}^{N} (u_t - \bar{u})(y_{t+k} - \bar{y}) \quad [k = -1, 2, \ldots, (N-1)] \]

Where \( \bar{u} \), \( \bar{y} \) are the sample means and \( c_{uu}(0) \), \( c_{yy}(0) \) the sample variances of observations on \( u_t \) and \( y_t \).

Confidence bands for the CCF in this study were computed for a 95% confidence limit.

**III.6.3 Analysis based on most dominate land Cover Type**

After finding which land cover type responds best to the drought index, PDSI and its derivatives (PMDI, PHDI, and Z index) were tested against the same land cover type to detect which index is more correlated to DNDVI.

It must be mentioned that the variables used in this study do not have the same geographical distribution. The Palmer drought indices are computed as a point record for region using weighted mean of temperature and precipitation provided by the national climatic data center (NCDC). The method of calculating these spatially averaged temperature and precipitation is not well defined as the number of stations included in the averaging may shift between years. Whether Thiessen polygons or isohyetal approaches are used cannot be discerned from available data as well. The DNDVI statistics were computed over a climate region using arithmetic averaging of spatially distributed raster data. As such, it is possible that they can be affected by the spatial variability, but at the same time smooth out these variabilities associated with seasonal differences in vegetation cycles among various vegetation types. Finally, the land cover type
distribution is based on the International Geosphere-Biosphere Programme – Data and Information Systems Land Cover Working Group. The IGBP land cover, which has the same spatial distribution as that of the NDVI (8km) is, similar to NDVI data sets, constructed from identifying the dominant land cover type within the 64 1 km pixels of the original 1 km data set. Therefore, for terrains known to exhibit substantial land cover diversity, this data set smoothes out variability within each climate region.

To improve the likelihood that correlation analysis between three heterogeneous data sets is representative of the particular land cover, the IGBP data set was analyzed extensively to identify two other climate regions outside of Arizona where a single land cover uniformly dominates the landscape (figure 3.9). Hence the two climate divisions chosen were:

- Climate division number 9 in Mississippi where the dominant land is 97 percent of evergreen broadleaf forest.
- Climate division number 4 in Iowa where the dominant land is 99 percent of croplands.
Figure 3.9 Climate divisions analyzed.

III.6.4 Spectral Analysis

An example of applying the spectral analysis method in drought is the study by Cook et al. (1997) in which they applied spectral analysis methods to relate tree-ring variations at hundreds of sites in North America to an index of area covered by drought (Cook et al. 1997). Their results showed some evidence for a bi-decadal rhythm in drought area that might be driven by interacting solar and lunar influences near the double sunspot and lunar nodal periods (D. Miko, 1999).
In our case we are applying this method to the mean NDVI data set generated over climate region 3 that has various land cover classes to observe important frequency variability within each vegetation type. Also, to compare results of the important frequency variability of the mean NDVI time series and the various drought indices and the precipitation time series and how they relate to climate anomalies (i.e. La Nina, El Nino).

In this section, and after quantitative identification of land covers that respond best to the drought index selected, a spectral analysis is performed on both DNDVI time series and drought. The objective of spectral analysis is to estimate and study the spectrum (Percival and Walden 1993), which isolate the variance of the timeseries as a function of frequency of recurrence. Understanding the frequency dependence may yield information about the underlying physical mechanisms, as well as information regarding significant cyclic behavior of both variables as they respond to the longer climatic oscillations.

The smoothed periodogram is one of many alternative methods available for estimating the spectrum that has been applied in this study. Some of these methods are listed in table 3.4. The main steps in estimating the spectrum are as follow:

- Compute discrete Fourier transformation
- Compute (raw) periodogram
- Smooth the periodogram to get the estimated spectrum.
Table 3.4 methods for estimating the spectrum (Dr D.M. Meko class notes, 1999).

<table>
<thead>
<tr>
<th>Method</th>
<th>Summary</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blackman-Tukey</td>
<td>Fourier transformation of smoothed Truncated autocovariance</td>
<td>Chatfield, 1975</td>
</tr>
<tr>
<td></td>
<td>Estimate periodogram by discrete fourier transform of time series; Smooth periodogram with modified Daniell filter</td>
<td></td>
</tr>
<tr>
<td>Smoothed Periodogram</td>
<td>Averaged periodograms of overlapped, windowed segments of a time series</td>
<td>Bloomfield, 2000</td>
</tr>
<tr>
<td>Welch's method</td>
<td>Use orthogonal windows (&quot;tapers&quot;) to get approximately independent estimates of spectrum; combine estimates</td>
<td>Welch, 1967</td>
</tr>
<tr>
<td>Multi-taper method (MTM)</td>
<td>Eigenvector analysis of autocorrelation matrix to eliminate noise prior to transformation to spectral estimates</td>
<td>Percival and Walden, 1993</td>
</tr>
<tr>
<td>Singular Spectrum Analysis (SSA)</td>
<td>Parametric method: estimate acf and solve for AR model parameters; AR model has theoretical spectrum</td>
<td>Vautard and Ghil, 1989</td>
</tr>
<tr>
<td>Maximum entropy (MEM)</td>
<td></td>
<td>Kay, 1988</td>
</tr>
</tbody>
</table>

Discrete Fourier Transform: Any time series can be expressed as the sum of sinusoids at the Fourier frequencies of the series:

\[ x_t = A(0) + \left\{ 2 \sum_{0 \leq j < n/2} \left[ A(f_j) \cos 2\pi f_j t + B(f_j) \sin 2\pi f_j t \right] \right\}, \quad t=0,1,\ldots,n-1 \]

\[ + \left\{ A(f_{n/2}) \cos 2\pi f_{n/2} t \right\} \quad (3.23) \]

Where the summation is over Fourier frequencies (cycle per month in this case)

\[ f_j = j/n, \quad j=1,2,\ldots,(n-1)/2 \]

And the last term in braces is included only if \( n \) is even (Bloomfield 2000).
The coefficients in (5.3) are the sine and cosine transformation that transform the time series \( x_t \) into a series of coefficients at its Fourier frequencies:

\[
A(f) = \frac{2}{n} \sum_{i=0}^{n-1} x_i \cos 2\pi ft \\
B(f) = \frac{2}{n} \sum_{i=0}^{n-1} x_i \sin 2\pi ft
\]

The discrete Fourier transform is the complex expression of these coefficients

\[
d(f) = \frac{A(f)}{2} - i \frac{B(f)}{2}
\]

And the magnitude is given by

\[
R(f) = |d(f)|.
\]

The magnitude measures how strongly the oscillation at frequency \( f \) is represented in the data. The strength of the periodic component is more often represented by the periodogram defined as

\[
I(f) = n[R(f)]^2 = n|d(f)|^2
\]

The periodogram is a wildly fluctuating estimate of the spectrum with high variance. Therefore, for a stable estimate, the periodogram must be smoothed. A Fortran code is used to generate the smooth periodogram for the time series of concern.
CHAPTER FOUR

CASE STUDY

IV.1 General Description of the Climate:

The Southern U.S is characterized by the importance of climate in all its aspects of life. The climate of the southeastern U.S can be described briefly by two words: dry and hot. However, a closer look shows the spatial and temporal (i.e. seasonal) variability of the region's climate. This variability is usually caused by the change in elevation from high-elevated plateau to the low deserts, and the wet and dry seasons that govern the region. In Arizona, for instance, this variability can clearly be noticed by comparing several places throughout the state that summarize most of the climatic, and topographic aspects of the state (Table 4.1, and Figure 4.1). Naturally, it can be concluded from the table and the precipitation map that the higher the elevation the lower the temperature and the higher the precipitation (snow or rain). Snowfall dominates higher regions while this form of precipitation is mostly non-existent in the low altitudes. The amount of precipitation in the mountainous regions (e.g. Flagstaff) is substantially higher than the precipitation in low-level areas. Combined with the temperature differences, this creates a distinguished vegetation type and density in each of the two regions. Vegetation over
Arizona consists mostly of desert shrub, grasslands, savannas, and needleleaf forests (Figure 4.4 and 4.5).

**Table 4.1** Climate summaries for selected cities in Arizona  
(Source: Western Regional Climate Center, 2000)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Flagstaff, AZ</td>
<td>7000</td>
<td>61.1</td>
<td>30.5</td>
<td>21.7</td>
<td>99.6</td>
</tr>
<tr>
<td>Tucson, AZ</td>
<td>2600</td>
<td>82.5</td>
<td>54.6</td>
<td>11.6</td>
<td>1.3</td>
</tr>
<tr>
<td>Phoenix, AZ</td>
<td>1100</td>
<td>85.7</td>
<td>59.3</td>
<td>7.7</td>
<td>0</td>
</tr>
<tr>
<td>Yuma, AZ</td>
<td>200</td>
<td>88.2</td>
<td>60.6</td>
<td>2.9</td>
<td>0</td>
</tr>
</tbody>
</table>

**Figure 4.1** Annual Average Precipitation over Arizona using the PRISM model
Figure 4.2 Seasonal variations of Temperature and Precipitation in Arizona.

Figure 4.2 illustrates further the seasonal variation of the state of Arizona temperature and precipitation. The temperature pattern shows that highest temperatures occur in summer (June, July, and August) when it reaches 80 °F and the lowest temperatures occur during the month of January when it drops to 41 °F in a cyclical pattern. Two wet seasons also characterize the precipitation pattern in the region. The winter season is driven mostly by frontal storms from the Pacific Ocean caused by El Niño and La Niña phenomena. This season tends to have lower intensity precipitation over a longer period of time and over a larger area. Snowfall also occurs in this season in higher elevations, which contributes mostly to the spring and early summer streamflow as the snowpack melts. For instance in the Flagstaff area where the elevation reaches 7000 ft.
the snow pack is estimated to be 99.6 inches. The summer season on the other hand is
governed by the North American monsoon. The monsoon is a result of a seasonal change
in atmospheric circulation patterns. Summer precipitation occurs in intense brief and
localized thunderstorms. Although it seems that most of the precipitation over the state of
Arizona falls in the summer where it reaches an average of 19.6 inches in July (figure
4.2) most of this precipitation evaporates due to the season high temperature, resulting in
limited runoff and infiltration. In conclusion, runoff in Arizona primarily results from
summer thunderstorms and winter precipitation. In the mountains, most of the winter
precipitation falls as snow.

IV.2 Water Resources:

Water is a critical issue for population growth in the Southwest. In this region of
limited water supplies, and growing population, the long-term availability and supply of
this resource is always crucial. Climate variability affects many of the region’s water
supplies. Surface delivery systems are dependent on annual rainfall amounts and the
minimization of evaporative loss. For example of the average 23.4 million ha-m (190
million acre-ft, 14.2 area inches, or 360 mm) of rain and snow that falls each year on the
Colorado River Basin, more than 90 percent evaporates or is used by plants (Hibbert
1979). Additionally groundwater depends on rainfall including snow mountain front
recharge and the infiltration of water into the ground. Serious problems are encountered
in parts of the state due to the decline of water levels in aquifers where extraction of
groundwater is immense. Some measures are taken to optimize groundwater recharge
capability in Arizona by recharging the water table from the surplus of the Colorado water river, which can extend the life span of the aquifer.

Surface water sources supply about 81 percent of the total water use in the United States. Despite the dominance use of surface water in the US, Arizona considerably relies on ground water as a supply source for its needs. According to the USGS data, groundwater contributes about 48 percent to Arizona’s water needs, and this percentage increases when surface water supplies are diminished by drought.

Figure 4.3 Water use by sector in Arizona 1963 and 1995
(Source: Hodge 1964 and Solly 1998)
The percentage of water used by different socioeconomic sectors in Arizona in 1963 and 1995 is presented in figure 4.3. Although agriculture is still the primary consumer of water in Arizona, there has been a decrease from 93 percent to 81 percent of water used by this sector, as the state increases in population, it requires a greater portion of this resource for municipal and power uses. Industrial uses also have been increasing by 2 percent over the same period.

Water availability becomes more crucial under dry periods where shortage of precipitation will be exuberated by rapid water loss from crops, evaporation, and increased urban and industrial use. A recent study on the sensitivity of the urban water sector in Arizona to drought has been conducted under the NOAA-funded Climate Assessment for the Southwest (CLIMAS) Project located at the University of Arizona. This study shows a scenario under certain assumptions that could create an imbalance of 36 percent between renewable supply and demand in a city like Tucson. The worst scenario case of 5-year drought could produce a 78 percent imbalance, while the ten-year scenario could result in a 75 percent imbalance (Carter et al. 2000).

IV.3 Climate Regions in the State:

The state of Arizona is divided into 7 climate regions (divisions) that are not homogeneously distributed in terms of size, population density and land cover. Climatic divisions are regions within each state that represents relatively homogenous climate conditions based on records that extended from the late 19th century to 1990. The climate
regions in Arizona are shown in Figure 4.4 with a land cover distribution according to the International Global Biosphere Programme.

**Figure 4.4** Land Covers Distribution within Arizona Climate Regions (Divisions)
Figure 4.5 shows quantitative distribution of the vegetation cover over the state of Arizona, which is dominated by about 57 percent of open shrubland, 18 percent of grassland, 13 percent of woody savannas, 10 percent of evergreen needleleaf forests. Figures 4.6 through 4.8 show a detailed vegetation cover of each climate region by itself. Climate region 2 is the largest division in the state and is dominated by open shrubland cover type that covers about 57 percent of the climate region area. Other land cover types also are presented and distributed almost evenly, needleleaf forest, woody savannas and grassland, which cover about 13-14 percent each. Some mixed forest type also exists (about 2 percent). The dominance of shrubland is typical in most of the climate regions except for climate region 3 and 4 where other vegetation covers are dominant. Most of the areas in these two climate regions are at high elevation plateau where there is a vegetation cover mosaic that includes needleleaf forest, woody savannas, grassland and
some mixed forest. Furthermore, the existence of shrubland on climate region 4 is negligible and needleleaf forest and woody savannas are highly dominant. Climate region 4 is the smallest in Arizona and it has the highest average annual precipitation of 19 in (482 mm) and a mean temperature of 60 °F (15 °C). Similarly, climate region 3, the second smallest region, has an average annual precipitation of 15.4 inches and a mean temperature of 58.5 °F. Climate region 3 and 4 show the effect of the altitude on the precipitation and temperature. Climate region 2 has the lowest mean temperature of 51.3 °F because it is located at higher altitude and includes mountainous area. The driest climate region in Arizona is climate region 5 that has the lowest average annual precipitation of 3.5 inches and a highest mean temperature of 71 °F. Most of climate region 5 is desert and flat.
Figure 4.6 Frequency Histogram of Land Cover for Climate Regions 1 and 2.
Figure 4.7 Frequency Histogram of Land Cover for Climate Regions 3 and 4.
Distinctive features are seen when looking to the topography of the climate regions in Arizona. Elevation ranges from 2 m in climate region 5 to over 3000 m in climate region 2. Table 4.2 and figure 4.9 summarizes the elevation, precipitation, and temperature distribution in each climate region. This variation in the climatic and
topographic distribution explains the variation range of the vegetation from desert shrub to needleleaf green forests.

![Elevation comparison of the climate regions in Arizona](image)

**Figure 4.9** Elevation comparison of the climate regions in Arizona

**Table 4.2** Topographic and climatic summaries by Climate Division

<table>
<thead>
<tr>
<th>Climate region</th>
<th>Area (km²)</th>
<th>Elevation (m)</th>
<th>Average Annual Precipitation (in)</th>
<th>STD of Precipitation (in)</th>
<th>Mean Temperature (F)</th>
<th>STD of Temperature (F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Climate 1</td>
<td>3.507</td>
<td>113 to 2394</td>
<td>1133.21</td>
<td>8.95</td>
<td>62.77</td>
<td>1.12</td>
</tr>
<tr>
<td>Climate 2</td>
<td>10.245</td>
<td>750 to 3596</td>
<td>1874.66</td>
<td>13.69</td>
<td>51.33</td>
<td>0.87</td>
</tr>
<tr>
<td>Climate 3</td>
<td>2.054</td>
<td>303 to 2355</td>
<td>1134.33</td>
<td>15.38</td>
<td>58.44</td>
<td>0.83</td>
</tr>
<tr>
<td>Climate 4</td>
<td>1.191</td>
<td>627 to 2316</td>
<td>1370.51</td>
<td>19.07</td>
<td>60.28</td>
<td>1.29</td>
</tr>
<tr>
<td>Climate 5</td>
<td>2.562</td>
<td>2 to 1695</td>
<td>309.06</td>
<td>4.36</td>
<td>71.28</td>
<td>0.89</td>
</tr>
<tr>
<td>Climate 6</td>
<td>3.635</td>
<td>134 to 2742</td>
<td>638.63</td>
<td>9.66</td>
<td>69.10</td>
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</tr>
<tr>
<td>Climate 7</td>
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<td>192 to 3164</td>
<td>1211.14</td>
<td>13.97</td>
<td>62.47</td>
<td>0.83</td>
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</tbody>
</table>
IV.4 Historical Drought records within each climate region

The difference between drought and aridity has been discussed in Chapter 2. This difference can be presented more quantitatively by differentiating between two indices, which are the mean moisture status and a drought index that indicates the departure from the mean.

The mean moisture status (MS) relates potential evapotranspiration to available water, and is expressed as the total available water minus the potential evapotranspiration. MS is a unique specific characteristic of a region (Steila, 1972), while the drought index represents the departure from the normal water availability over the same region. The moisture status monthly plot (Figure 4.10) over each climate region shows different behavior of the water stress due to topographic and climatic variability in each division. Climate regions 1, 2, 3 and 4 are characterized by a similar trend of monthly MS. In the beginning of the year, a rise in moisture recharge is observed until March when a withdrawal of soil water increase due to increase temperature and therefore MS becomes negative. This withdrawal will reach its maximum by July and MS will remain negative until November. Climate regions 5, 6, and 7 also show similar trends of soil water depleting by the beginning of the year. These trends of MS continue downward until they reach a negative minimum by July. Climate region 7 is different because it reaches its negative minimum by June. The southern regions (5, 6, 7) have less soil moisture recharge than the northern regions (1, 2, 3). Region 4 has the highest soil moisture accumulation. This difference in MS in terms of quantity and period is due to the effect of snowmelt that reflects the maximum MS in the spring (March) especially for climate
regions that are mountainous (climate 4, climate 3 and climate 2). During the spring, the soil has more moisture because the evaporation rate is low, and at the same time the snowmelt begins. This variation in degree of aridity within the regions cannot be interpreted as drought; it only shows the status of soil water that characterizes each climate division.

Figure 4.10 Mean Moisture Status over all climate regions (data from Steila, 1972).
Long time series of Palmer index from 1895 to 1999 are plotted on figure 4.11 showing the variability in drought event magnitude and existence. Persistence of drought is considered an important aspect in measuring drought. Persistence refers to the tendency duration for drought after it has been initiated. Table 4.3 provides information about the frequency of consecutive months of negative palmer index values for every climate division in Arizona. Longer drought periods are more likely to appear in the southern climatic divisions with a maximum sum of 24 consecutive dry months. Also short periods of drought that last more than 3 months occur more on the southern climate divisions. Climate region 1 has the lowest number of 68 droughts that range from 1 to 30 months of consecutive negative palmer index value. Conversely, climate region 5 has the highest number of 96. A highest frequency of negative values of palmer index exceeding 90 consecutive months was also recorded in all the climate regions and it started by the end of the last century.
Table 4.3 Frequency of consecutive months of negative Drought index values for Arizona (time series 1895-2000)

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<th>NE</th>
<th>NC</th>
<th>EC</th>
<th>SW</th>
<th>SC</th>
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Figure 4.11 Monthly Modified Palmer Index over all climate regions in Arizona
CHAPTER FIVE
RESULTS AND DISCUSSION

V.1 Introduction
Throughout this chapter, results of the different techniques used in this thesis will be presented, such as spectral analysis and cross-correlation between different data sets (Palmer indices, mean departure NDVI based on climate region, and mean departure NDVI based on vegetation class). A comparison is concluded between cross-correlation when using the climate region NDVI as a whole and when separated based on the vegetation classes. This will show the potential of remote sensing data as an alternative, or in conjunction with the classical accepted drought indices for monitoring, and possibly predicting the drought phenomenon.

The original data sets of the NDVI include a period of 3 months of missing data (1994). This was attributed to the failure of the NOAA-11 satellite. After generating the mean, minimum and maximum of DNDVI of each monthly grid, a time series was collected for the mean, minimum and maximum DNDVI. To keep the time series continuous on a monthly basis interpolation was made for the missing months. Missing data for the months of October, November, and December from 1994 were estimated at regional scale by assigning the temporal monthly mean of the data record (1981-1999) of each specific month that is missing. For example the temporal mean of the month of October was
computed from the time series record and assigned to the month of October 1994 that is missing.

The mean departure NDVI that is the arithmetic average of all pixels in a climate region actually shows the variation of the response in the vegetation growth better than the maximum pixel value in a climate region or the minimum pixel value of DNDVI (Fig 5.1). Working with the maximum and minimum departure NDVI can be misleading because extreme values of DNDVI (pixel) can be a result of specific conditions within that pixel (irrigation, near a source of water, fire) in the region that will contribute to either a significant increase or decrease of the NDVI pixel value.
V.2 Cross-correlation analysis

Visual inspection was conducted between different timeseries of Palmer indices and DNDVI for dominant vegetation cover timeseries in all regions. The moving average of 3 months of the DNDVI timeseries were plotted instead of the monthly timeseries to visualize better possible relationships and resemblance patterns between drought indices and DNDVI. This smoothing was made due to the high fluctuation of the monthly DNDVI timeseries. Results of PMDI timeseries with three different vegetation covers
that are grassland, open shrubland and evergreen needleleaf forest respectively are shown in figures 5.2. It is necessary to be reminded that the percentage of grassland in land cover 3 is about 35 percent, open shrubland in land cover 5 is 95 percent, and evergreen needleleaf forest in land cover 4 is 38 percent. The plots in Figs 5.2 show that there is consistent pattern between the DNDVI and PMDI, and that the DNDVI follows the dry-wet cycles most of the time with a phase shift that varies depending on the severity of drought or wetness event, whether it is a drying cycle or a wetting cycle, and the vegetation cover type. Open shrubland seems to be affected rapidly by the shift from dry to wet conditions. Grassland and evergreen needleleaf forest, however, follow the same patterns but with longer lag time. It appears that vegetation conditions are improving faster when going from drier conditions to wetter conditions. In contrast, when moving from wet periods to dry periods the vegetation conditions are likely to deteriorate but with lower rate than when it improves. Vegetation conditions in climate region 4 and 3 during the period of 1980-1983 do not follow that patterns because of the previous drought event prior to 1980 that might severely affected the vegetation to the point that even during that same period a substantial increase in moisture conditions did not follow up with an improve in vegetation conditions.
Figure 5.2 Timeseries of PMDI and different dominant vegetation covers within climate region 3, climate region 4 and climate region 5.
V.3 Discussion of Cross-correlation results

V.3.1 Climate Division Analysis

The results of the cross-correlation analysis for each climate region indicated positive relationship between departure NDVI and drought indices (see Figures 5.3-5.9). Also, in all climate regions, the Palmer modified drought index (PMDI) shows a slightly better correlation coefficient compared to the Palmer hydrologic index (PHDI) and the Palmer drought severity index (PDSI). The Z index on the other hand, had weaker relationships to departure NDVI and it never exceeded a coefficient correlation of 0.5. In fact, for climate region 2, 3 and 4 the relationship barely exceeded the bands of the confidence level. The Z index values reflected short-term moisture deficiencies or excesses while the PDSI, PMDI, PHDI responded slowly to the current moisture changes. This rapid fluctuation can be seen in the time series of Z index, and they even indicate favorable moisture conditions over a particularly wet or dry month in the midst of a serious long-term drought or wet period (Thomas R. Karl, 1986). On the contrary, most of the vegetations in the arid or semi arid regions exhibited slow response to short-term fluctuations of moisture deficiencies or excesses.

A delay response association between the variables was seen in all the climate divisions at different lags that are a fixed time displacement of one-month step. Climate divisions 1, 5,6 and 7 (Figure 5.4, Figure 5.6, Figure 5.7, and Figure 5.8) had their highest correlation coefficient at lag 1, which represents 1-month delay. This one-month delay is related to the dominant vegetation that covers these regions, which happen to be open
shrubland. Surprisingly, climate region 2, which is also dominated by open shrubland, showed the highest relationship at lag 10 (Figure 5.4). A closer look at the topography of climate region 2 indicates that it is located at high elevation in which the palmer drought indices did not perform well. Climate region 4 showed that the highest correlation was located at lag 10 in which the dominant vegetation cover is needle-leaf forest (Figure 5.6). It can be seen in climate 3 that there are 2 lags where the correlation is highest, at lag 1 and lag 10 (Figure 5.5). This was interpreted by the contribution of various vegetation covers that dominate climate region 3 as different vegetation types response differently to the water stress. Hence, it is worth mentioning that climate region 3 for example, has 35% cover of grassland, 33% of woody savannas, about 19% of open shrubland, 10% of needle-leaf forest, and 2.5% of mixed forest. For further understanding of the dynamic response of the vegetation to drought-wet cycles, an analysis based on segregating the vegetation covers for all climate regions was conducted, but will only be exemplified by presenting climate region 3.
Figure 5.3 Cross-correlation between NDVI-mean departure and drought indices for climate region 1
Figure 5.4 Cross-correlation between NDVI-mean departure and drought indices for climate region 2
Figure 5.5 Cross-correlation between NDVI-mean departure and drought indices for climate region 3
Figure 5.6 Cross-correlation between NDVI-mean departure and drought indices for climate region 4
Figure 5.7 Cross-correlation between NDVI-mean departure and drought indices for climate region 5
Figure 5.8 Cross-correlation between NDVI-mean departure and drought indices for climate region 6.
Figure 5.9 Cross-correlation between NDVI-mean departure and drought indices for climate region 7
V.3.2 Land Cover Analysis

Further improvements in the coefficient correlation and the dynamic response of the vegetation to water availability are noticed by analyzing the cross-correlation considering every vegetation type within climate region 3. Climate region 3 was chosen because it has various vegetation covers in which no vegetation type exceeds 35% of the total land cover. Five vegetation classes were considered that represent 95% of the total land. An improvement in the relationship in terms of lag is seen when consideration is given to the climate region for various vegetation covers as opposed to the relationship of the departure NDVI for the climate division as a whole. It can be seen that only one highest correlation coefficient exists when working with separate vegetation classes, instead of there being two lags of highest correlation when taking the whole climate division (Figure 5.10-514.). Open shrubland NDVI relationship to drought indices is stronger than the NDVI for the whole climate region especially PMDI of the whole climate division at lag 1 (Figure 5.12). Needle-leaf forest, on the other hand, shows a highest correlation coefficient with PMDI at lag 10 (Figure 5.10 and Figure 5.5) with a value of 0.37 while the value was 0.35 when the whole climate region was considered. Woody savannas, mixed forest, and grassland show higher correlation coefficient at lag 10 (between 0.31 and 0.37) (see tables in Appendix A). These finding suggest that open shrubland is more rapidly sensitive to moisture change after 1 month with a coefficient equal to 0.54 for
PMDI and departure NDVI. These results agree with previous study by Szilagyi et al. (1998) where NDVI relationships with precipitation greatly improved when a one month lag was introduced. Forests (mixed forest and needle-leaf forest) are less sensitive to moisture change, with delay of about 10 months. The correlation coefficient between PMDI and departure NDVI for mixed forest is 0.34 and 0.373 for needle-leaf forest. Grassland results show a delay in response of 10 months for drought event of a correlation coefficient equal to 0.32.
Figure 5.10 Cross-correlation between NDVI-mean departure and drought indices for evergreen needleleaf forest in climate region 3
Figure 5.11 Cross-correlation between NDVI-mean departure and drought indices for mixed forest in climate region 3
Figure 5.12 Cross-correlation between NDVI-mean departure and drought indices for open shrublands in climate region 3
Figure 5.13 Cross-correlation between NDVI-mean departure and drought indices for woody savannas in climate region 3
Figure 5.14 Cross-correlation between NDVI-mean departure and drought indices for grasslands in climate region 3.
The open shrubland shows a markedly high correlation coefficient of 0.73 within climate region 5 at lag 1 (fig 5.15) between the PMDI and departure NDVI for open shrubland. Also this coefficient is more than 0.5 over most climate regions that have a dominant vegetation cover of open shrubland. Climate region 2, in spite of the dominance of open shrubland, has a cross-correlation coefficient (CC) of 0.40 at lag 1. This is maybe due to the high elevation of climate region 2 in which the Palmer index do not perform well in isolating a drought signal because of the snow factor, which is not included in the Palmer model water budget. In Table 5.1, a summary of the results of the cross-correlation between PMDI and open shrubland for all climate regions is provided. Climate region 5 is 95% covered by open shrubland in a desert and with low elevation (Fig 4.9).

<table>
<thead>
<tr>
<th>Table 5.1 Cross-correlation between PMDI and Open Shrubland</th>
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</tr>
<tr>
<td>------</td>
</tr>
<tr>
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</table>
Figure 5.15 Cross-correlation between mean departure NDVI of the Open Shrubland and Palmer Drought Indices for Climate Region 5
After the remarkably improved results of the cross-correlation coefficient when separating the climate regions by land cover classes, IGBP data set was analyzed extensively to identify 2 other climate regions where a single land cover uniformly dominates the landscape. Hence, the two climate divisions chosen were climate division number 9 in Mississippi where the dominant land is evergreen broadleaf forest and covers 97 percent of the land, and climate division number 4 in Iowa where the dominant land is croplands and covers 99 percent of the land.

Surprisingly, the results showed a very low correlation coefficient between the PMDI and the DNDVI in spite of the homogeneity of the land cover within these climate divisions. It is necessary to say that for climate region 9 in Mississippi (Figure 5.16) that is dominated by evergreen needleleaf forest shows the highest coefficient at lag 12-13 with a value of 0.38 instead of lag 10. This suggests that the dynamic response of forests to drought is variable from semi arid regions to other regions (i.e. tropical), but still the effect of drought remains after several months, due to complicated factors that contribute to the leaf growth such as the elevation, type of trees, and geographic location. On the other hand, climate region 4 in Iowa (Figure 5.17) that is dominated by cropland showed no significant correlation between drought events and DNDVI. The irrigation mode in this climate region is probably the main factor for such observation, where the alternation
of NDVI is rather sensitive to the irrigation mode and cropping system than to the drought cycles.

![Graph showing cross-correlation between PMDI and NDVI_mean](image)

**Figure 5.16** Cross-correlation between NDVI_mean departure and PMDI for evergreen needleleaf forest in Mississippi-climate region 9 (97 % cover).

<table>
<thead>
<tr>
<th>LAG</th>
<th>Lag0</th>
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<tbody>
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<td>0.091</td>
<td>0.081</td>
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</table>

<table>
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<tbody>
<tr>
<td>Correlation Coefficient</td>
<td>0.131</td>
<td>0.174</td>
<td>0.226</td>
<td>0.232</td>
<td>0.237</td>
<td>0.237</td>
<td>0.214</td>
<td>0.215</td>
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</table>
**Figure 5.17** Cross-correlation between NDVI_mean departure and PMDI for cropland in Iowa-climate region 4 (99 % cover).

<table>
<thead>
<tr>
<th>LAG</th>
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</thead>
<tbody>
<tr>
<td>Correlation Coefficient</td>
<td>-0.08</td>
<td>-0.03</td>
<td>0.01</td>
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<td>0.03</td>
<td>0.016</td>
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<td>LAG</td>
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<td>Lag15</td>
</tr>
<tr>
<td>Correlation Coefficient</td>
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<td>0.03</td>
<td>0.026</td>
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</table>

**V.4 Discussion of the spectral analysis results:**

In this analysis it has been noticed that frequency variability occurs within various vegetation classes when using the mean NDVI time series. A comparison between these significant frequencies and the frequencies obtained using the modified Palmer index (PMDI) time series is being discussed.

The temporal characteristics of monthly series of mean departure NDVI have been studied in Arizona climate region 3, by means of spectral analysis, with the purpose of detecting major fluctuations, and oscillation modes. The same analyses were
conducted on the four Palmer Drought indices (PDSI, PHDI, PMDI, and Z index) to detect any similarities between the classical Drought indices time series and the mean departure NDVI.

![Spectra of Evergreen Needle-leaf Forest mean-departure NDVI for climate region 3](image)

*Figure 5.18 Spectra of Evergreen Needle-leaf Forest mean-departure NDVI for climate region 3*
Figure 5.19 Spectra of Mixed Forest mean-departure NDVI for climate region 3

Figure 5.20 Spectra of Open Shrublands mean-departure NDVI for climate region 3
Figure 5.21 Spectra of Woody Savannas mean-departure NDVI for climate region 3

Figure 5.22 Spectra of Grasslands mean-departure NDVI for climate region 3
Figures 5.18 through 5.23 present the results of the spectral analysis over each vegetation class within climate region 3. It can be seen that a positive and similar trend exists in the whole analyzed region for most of the vegetation classes. The spectral analysis shows dominant periodicity of 74 months that is about 6 years. The last figure (5.23) that presents the spectra of vegetation class 14 (cropland/natural vegetation mosaic) has a bimodal behavior in terms of dominant frequencies. The first dominant periodicity is about 111 months (9 ¼ years) and 37 months (3 years). The results of this last figure are
not taken into consideration because the low percentage of this land cover within climate region 3 (0.01%) makes it insignificant.

Figure 5.24 Spectra of PDSI time series for climate region 3
Figure 5.25 Spectra of PHDI time series for climate region 3

Figure 5.26 Spectra of PMDI time series for climate region 3
Similarly, the spectral analysis of Palmer drought indices time series shows low-frequency variability dominance. The importance of 6 years oscillation (Fig 5.24-Fig 5.27) is seen on the indices. Another low frequency that corresponds to 32-month periods is also an example of significant low-frequency variability especially in the PDSI and the Z index. The Z index also shows some significance variability that corresponds approximately to 12 months that emphasizes the seasonal variability.
The results of the spectral analysis of the drought indices compared to the results obtained from the deviation mean departure NDVI provide some evidence for an interconnection between the periodicity of the vegetation vigor and the drought events that are driven by similar effects that have the same periods. It is apparent that there is a common high variability frequency of 0.013 that corresponds to a period of 6 years. This finding shows a possible linking with the ENSO phenomenon.
Chapter 6

Conclusion

In this study, the relationships between several “palmer-based” drought indices and the departure of NDVI from its long-term mean were statistically investigated at regional scales. The study, which focused on semi-arid climate regions in the state of Arizona, utilized GIS tools to assess the feasibility of using remote sensing data in monitoring and observing drought conditions at spatial resolutions higher than the currently used drought monitoring methods.

With respect to the methods and tools used in this study, it was found that the differences between map models (i.e., projection system and resolutions), which result in intensive amount of effort to reconcile, are perhaps key factor hindering the extensive use of remote sensing based vegetation data in drought monitoring. Another factor is related to the absence of high resolution quantitative drought monitoring index, which creates a significant gap between the resolution of remotely sensed condition (from 1 km$^2$, to 64 km$^2$), and those of the drought calculation (climate regions; about 25,000 km$^2$). At such scale, the meaning of NDVI when averaged over the entire climate region is somehow vague. In summary, time series, generated from the monthly images introduced additional
uncertainties because of the averaging of the NDVI over a climate region in which there are heterogeneity of land covers, therefore averaging over land cover type would reduce these uncertainties.

Despite of the fact that averaging DNDVI for each land cover within each climate regions continues to pose a “many-to-one” analysis problem, this study was able to report the existence, both qualitatively and quantitatively, of a relationship between vegetation response and drought conditions. At the qualitative level, which can be discern through visual inspection, patterns of drought indices and NDVI time series, showed some of the characteristics of “cause-response” patterns. It was also observed that the magnitude of response is governed by a combination of antecedent conditions (Dry/Wet), and direction of change (getting dryer/getting wetter). The fact that drought index time series display strong short-term persistence (common to additive series), while DNDVI time series display a much wider short-term variability, has affected the consistency of visual inspection and statistical analysis was conducted to attain quantitative assessment of the response. These included cross-correlation between drought indices and both regional averaged and land-cover stratified DNDVI, as well as spectral analysis.

The crosscorrelation analysis shows an agreement between the NDVI data and Palmer drought indices as far as the spatial distribution is concerned for all climate regions except for the Z index where a lower correlation coefficient is noticeable. They all show above significance level relationship at different lags. The subscaling of NDVI data from climate division to vegetation cover type has improved the relationship between NDVI
and drought indices when running a crosscorrelation test. This test showed a positive relationship for most vegetations and it shows even a stronger relationship for particular vegetation covers such as open shrublands and needleleaf forest. Furthermore, this study highlighted the existence of a lag in NDVI response to drought event, and this lag actually varies depending on the vegetation cover, antecedent conditions, and direction of moisture condition change. The physical mechanism of the plants water extraction from soil explains the lag between DNDVI and drought indices that is one month in the case of shrublands and ten months in the case of forest. Since the lack of moisture affects the topsoil layers first, shrublands response to water lack is faster and shows after one month in which the roots of the shrublands obtain its water needs. Forests, on the other hand, respond slowly to the lack/improvement of moisture because its roots are deeper in the soil and that changes of moisture conditions water are not sensed immediately in the deep root zone.

Spectrum analysis of the data detected a similar signal that is related to ENSO events. This signal is observed at low frequency variability in DNDVI and drought indices. This finding strengthens the evidence for a similar, and underlying process that is affecting both the drought events and the vegetation growth.

Despite of the strong positive correlation found at this stage between Departure NDVI and drought events, the analysis could be improved further by reducing errors in the NDVI data, and by smoothing the post-processing time series. Data obtained from AVHRR sensors at low resolution are suitable for drought monitoring at regional and
continental scales due to the fact that drought is a regional event. In the absence of spatially distributed measures of drought, it can be said that, NDVI by itself is a crude indicator of drought, and needs to be related to other biophysical data in order to be useful, and considering its variation to the growing season.

At the conceptual level, however, the ability to identify the delay in vegetation response to wetting/drying conditions can be of significant benefit to forest managers and to fire managers. The ability to identify the lag-time separating improved/worsening moisture conditions and detectable change in vegetation vigor can help in improving the prediction of fire hazards.
Appendix A

Climate Region 3 with Dominant Vegetation Classes
Cross-correlation between departure NDVI and Palmer Drought indices
<table>
<thead>
<tr>
<th>CL3- Evergreen Needleleaf Forest</th>
<th>LAG 0</th>
<th>LAG1</th>
<th>LAG2</th>
<th>LAG3</th>
<th>LAG4</th>
<th>LAG5</th>
<th>LAG6</th>
<th>LAG7</th>
</tr>
</thead>
<tbody>
<tr>
<td>PDSI</td>
<td>-0.041</td>
<td>0.023</td>
<td>0.034</td>
<td>0.07</td>
<td>0.082</td>
<td>0.134</td>
<td>0.174</td>
<td>0.207</td>
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<tr>
<td>PHDI</td>
<td>0.132</td>
<td>0.199</td>
<td>0.215</td>
<td>0.239</td>
<td>0.26</td>
<td>0.297</td>
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<th>LAG2</th>
<th>LAG3</th>
<th>LAG4</th>
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<td>0.286</td>
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<td>0.252</td>
<td>0.239</td>
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<td>PMDI</td>
<td>0.269</td>
<td>0.302</td>
<td>0.318</td>
<td>0.308</td>
<td>0.272</td>
<td>0.224</td>
<td>0.224</td>
<td>0.205</td>
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<tr>
<td>ZINDX</td>
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<td>0.24</td>
<td>0.158</td>
<td>0.158</td>
<td>0.066</td>
</tr>
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</table>
REFERENCES


37. National Drought Mitigation Center website http://enso.unl.edu/ndmc/


42. Percival, Donald B. Andrew T. Walden, 1993, Spectral Analysis for Physical Applications, Cambridge University Press. Definition of spectrum in context of a sinusoidal model, 1.6-1.16].


47. Regional Technical Assistance RETA website http://www.haze-online.or.id


70. WMO (1975), Drought Lectures presented at the twenty-sixth session of the WMO Executive Committee, Special Environmental Report No. 5, WMO, Geneva


73. Western Regional Climate Center, Extensive sets of data with maps, articles, and analysis of weather and climate data and events for western U.S states. http://www.wrcc.dri.edu/ and http://www.wrcc.sage.dri.edu/
