Drought Forecasting for Small to Mid-sized Communities of the Southeast United States

by

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Abstract

Most of the climate variability in the Southeast United States has been attributed to El Niño Southern Oscillation (ENSO) and this climate variability has resulted in increased the stress on water resources of the region and drought is one of the most expensive outcomes of this climate variability. Drought is a major concern for small to mid-size communities in the Southeast as it poses a serious risk to the performance of water supply systems of such communities and may cause short term failures. In response, this study was undertaken to study the impact of ENSO on precipitation and streamflows and to develop a Community Water Deficit Index (CWDI) for forecasting drought in small to mid-size communities. The usefulness and value of this drought forecast information for water resource managers was then assessed. Results indicated a significant relationship between ENSO and precipitation and streamflow with dry conditions during winter months being associated with La Niña in the southern climate divisions of Alabama. It was found that this information can provide a basis for the water resource managers in Alabama to incorporate ENSO related climate variability in their decision-making. During a low precipitation and high temperature ENSO phase (La Niña), the loss of soil moisture through evaporation increases the dynamic demand of water due to increase in outdoor water use by the residents (lawn irrigation etc.). System Dynamics modeling software STELLA ™ was used to develop a model addressing the relationship between water supply and demand of a community and the CWDI was estimated as ratio of available storage and desired level of water storage in the reservoir of the community. The index was tested in two small to mid-size communities in the region and it demonstrated skill in monitoring and forecasting drought. Impact of climate variability on water demand of the community and how the knowledge of this forecast allows mitigation of negative impacts were studied. A multiple linear regression approach was used to predict per capita water demand based on daily precipitation, daily maximum temperature, and a one-day lag variable to account for temporal persistence in time series of water use. It was found that there is considerable accuracy in predicting water use based on climatic variables (R^2 values ranging from 0.62 – 0.84). The model was run using historical data to estimate volumetric and cost savings associated with the use of this drought forecast information and it was found that considerable savings could be made by using CWDI to plan ahead thus minimizing the drought vulnerability of community water systems.

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CHAPTER 1
INTRODUCTION

1.1 MOTIVATION

Only 2.5% of the earth's 1386 million cubic kilometers of water is freshwater, and only about 33% of this freshwater is available for human use. In spite of this determinate supply of water, total water consumption for human use has increased almost three-fold in the last 50 years and it is estimated that by 2025, five out of eight people will be living in conditions of water scarcity (Postel et al. 1996). This is the scenario without considering the effects of climate variability or change on the natural water resources.

Natural climate variability has significant impact on society—particularly water resources and agriculture. To minimize potential adverse consequences of natural climate variability, they must be identified, quantified, and understood. It is important to assess the climate's sensitivity to a variety of factors, particularly time scales that are of most concern to human beings and may vary from inter-annual to centuries. Many information sources, including instrumental records, visual observations, and paleoclimate data, bear witness to substantial variability in the earth's climate on time scales from years to centuries. To determine how climate variations, whether natural or anthropogenic, alter the occurrences, intensities, and locations of extreme events, is one of the highest priorities for decision makers. Since the hydrological cycle is linked closely to variations in climate, citizens and water resource managers both will have to deal with new challenges associated with both water quantity and quality. Natural climate variations, such as El Niño Southern Oscillation and the North Atlantic Oscillation, can significantly alter the behavior of extreme events, including droughts, hurricanes, floods, and cold waves (Intergovernmental Panel on Climate Change, IPCC 2001). As of now, there is limited understanding of the physical mechanisms that produce and maintain natural climate cycles, the extent to which these interact with each other, and how they may be changed in the future by anthropogenic climate changes. These changes make it difficult to efficiently adapt current societal practices, such as maintaining a municipal water supply, while continuing to provide clean and safe drinking water to an ever increasing population.

Global municipal water use over the past few decades has increased due to population growth (Bates et al., 2008). Water supply shortages depend on water availability and demand, which in turn depend on the physical, hydrologic, and climatological characteristics of the system. Water supply systems vary dramatically throughout the US and this variability impacts the appropriate management responses. During the past decade, the Southeast USA has experienced several severe droughts that have resulted in loss of agricultural productivity, increased wildfires, imposition of municipal water use restrictions, and conflicts among different water use sectors. The Southeast often suffers from the low surface water availability during summer months because of intra-annual climate variability, very high evapotranspiration rate, and increased demand by ever growing urban centers. Identifying the onset of a drought can be elusive, requiring detection of diminutions of supplies, escalations in demand, or both. It is difficult to say exactly what climate change effects will be, as climate signals are chaotic and noisy, encompassing annual, inter-annual, decadal, or much longer periods of variability. For both short and middle term risk management planning, inter-annual modes of climate variability and their seasonal expression are of interest. In this dissertation, the focus is on isolating, modeling and forecasting the effects of climate variability on hydrology in the southeastern United States. Variability for the purpose of this study is defined as fluctuations in climate from the monthly to seasonal and multi-annual scale, and will be quantified via standard climate indices.

1.2 El Niño Southern Oscillation (ENSO)

El Niño–Southern Oscillation (ENSO) phenomenon results from the interaction between large-scale ocean and atmospheric circulation processes in the equatorial Pacific Ocean and is one of the major factors influencing climate variations and has been linked to climate anomalies throughout the world. El Niño is the name given to the appearance of warm water in the Pacific Ocean off the coast of Equatorial South America and since fishermen usually first detected this ocean warming toward the end of December; it derives its name from the celebration of the birth of the Christ Child. The ENSO maintains an irregular 2-7 year periodicity that gives it a level of predictability, yet retains some variability in its occurrence, magnitude and climate consequences around the world (Cane, 2005). The term 'Southern Oscillation' was first used by Walker (1924) to describe fluctuations in pressure between the North Australian—Indonesian low-pressure trough and the Southeast Pacific subtropical high-pressure cell (Philander and Rasmusson, 1985). It is an irregular, inter-annual reversal of the gradient of mean sea-surface level atmospheric pressure between the eastern and western Pacific Ocean and is accompanied by a change in both the direction and intensity of trade winds, resulting in a change in the gradient of sea-surface temperature (SST). The pressure difference between Easter Island in the Southeast Pacific and Djakarta, Indonesia is called the Southern Oscillation Index (SOI) (Walker and Bliss, 1926). This index is defined as the normalized difference in monthly mean pressure anomalies between Tahiti (18°S, 150°W) and Darwin (12°S, 131°E) (Chen, 1982). It is positive if pressure is higher than normal in the Southeast Pacific and lower than normal to the north of Australia; this is usually the case during non-El Niño years. On the contrary, it is negative if there is below-normal pressure in the Southeast Pacific and above-normal pressure north of Australia.

The exact cause of El Niño is not known; however, several theories have been proposed. Hickey (1975) suggested that it is caused by a minimum in the zonal wind stress at longitudes west of 120°W and a minimum in the meridional wind stress east of 120°W. He correlated the decrease in southeast trades near Peru with El Niño and concluded that it is associated with a decrease in the coastal upwelling of the cold subsurface waters, thus leaving relatively warm water at the surface.

ENSO is comprised of three phases, a warm-El Niño, a cold-La Niña, and a Neutral phase. The terms “El Niño” (EN) and “La Niña” (LN) are used to describe respectively the warming and cooling of sea surface temperatures on the shores of the west coast of South America (Quinn 1994; Aceituno 1992). Approximately one-fourth of the time, El Niño pattern prevails, while La Niña pattern prevails another one-fourth of the time. During the remaining half of the time, the pattern is classified as neutral. El Niño concurs with the season of weak trade winds and reduced upwelling in the Southern Hemisphere. During El Niño events, low air pressure in the eastern Pacific weakens the atmospheric pressure gradient heading westward. This causes unusually high SSTs and increased convection in the central and eastern equatorial Pacific. During La Niña, trade winds strengthen, amplifying the SST gradient so that lower than average SSTs are recorded instead (Figure 1.1). The relative strength and precise oscillation of these warm or cool phase events depends on the strength of the mean winds, amount of heat generated by SST gradients from specific temperatures and humidity, how deep the thermocline is, and system dynamics. The theory as to why the oscillations remain between 2 to 7 years has not yet been comprehended (Fedorov and Philander, 2001). Global climate patterns develop over different time scales ranging from inter annual to decadal and interact with each other hence becoming the driving forces behind weather across the world. ENSO also interacts with other global patterns, such as the Pacific Decadal Oscillation (PDO) and North Atlantic Oscillation (NAO), and knowledge of these interactions could lead to improved weather and climate forecasts. This information can be used to increase confidence in predicting significant climatic events including winter storms, heat waves and droughts, and hurricane activity. Huang et al. (1998) reported that there is a significant interaction between NAO and ENSO during warm ENSO events from 1900 to 1995.

During relatively weak Niño3 SST anomalies, non-coherence between the NAO and ENSO occurs. This weakening or strengthening of NAO during a transitory or established ENSO phase is reportedly caused by Hadley cell variations. NAO intensification during mature ENSO phase leads to enhanced early winter temperature over the most northern and central Euro-Asia and more abundant winter snowfall over Northern Europe. When the NAO is in its negative (cold) phase, arctic air pushes further south into the United States but NAO phases can change at a temporal scale of 1-2 weeks and hence are not predictable.

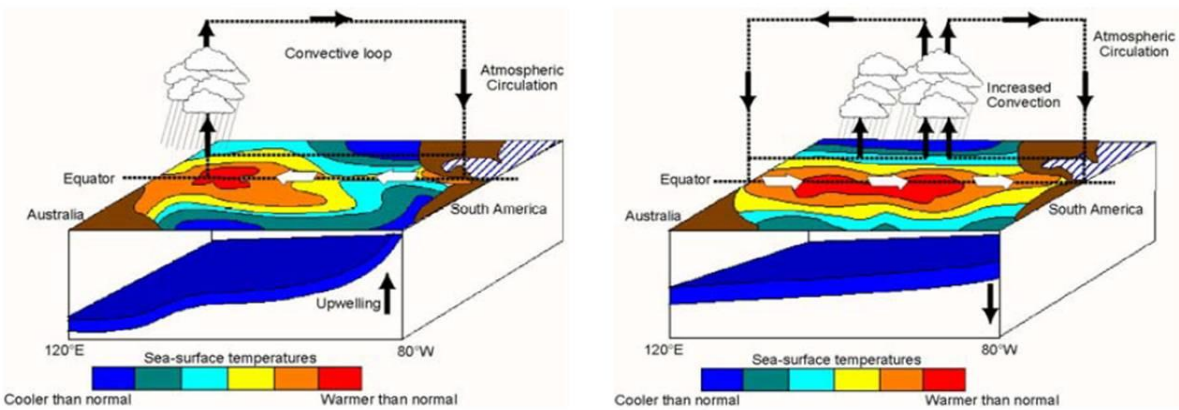


Figure 1.1. Neutral (left) and El Niño (right) conditions in the equatorial Pacific. As opposed to neutral conditions, during an El Niño event sea surface temperatures (SST) are warmer than usual, increasing convection of moist air into global circulation. During a La Niña event, cooler water decreases convection.(Source: TAO Diagrams).

As far as PDO is concerned, most of the studies on its relationship with ENSO have been inconclusive, conflicting, or confusing. However, a study conducted by Gershunov and Barnett (1998) shows that the global climate patterns resulting from ENSO are moderated by PDO and that the resulting climate patterns interact with each other. Highly positive PDO likely results in a strong El Niño signal; similarly, highly negative PDO results in a strong La Niña signal. Newman et al. (2003) report that these two signals interact with each other at all time scales and that PDO prediction might improve with improvement in ENSO forecast skills.

1.3 ENSO INDICES

Climate indices are researcher-created diagnostic monitoring tools that describe an important or significant pattern or state of a climate system and are generally represented as time series, with one index value representing a particular point in time. There are dozens of indices, which can describe any atmospheric event including monsoon precipitation, air pressure differences, sea surface temperatures (SSTs), hurricane activity, or solar radiation. Spatially averaged areas of sea surface temperatures in different parts of the world are particularly relevant to describing climate phenomena in specific locations, and El Niño/Southern Oscillation (ENSO) has proven to be one of the steadiest in describing low-frequency climate variability on both regional and local scales (Ropelewski and Halpert, 1986). An index is typically used to define the phase and strength of ENSO; however, there are several classes of indicators available to characterize ENSO phases. One class of indicators focuses on the atmospheric component of ENSO. These indicators, for e.g. the Southern Oscillation Index defined by the Australian Bureau of Meteorology or the US Climate Prediction Center, are based on the differences of mean sea level atmospheric pressure between two locations on the Eastern Pacific and Western Pacific (Troup 1965; Chen 1982; Ropelewski and Jones 1987). Another class of indicators focuses on the oceanic component. They are based on the monthly anomalies of sea surface temperatures (SSTs) recorded in different sectors of the tropical Pacific Ocean (Rasmusson and Carpenter 1982; Glantz 2001). Typical examples of such indicators are the Oceanic Niño Index (ONI) developed by the National Oceanic and Atmospheric Administration or the index developed by the Japanese Meteorology Agency (JMA). A third set of more complex indicators are based on combinations of these different factors, such as the trans-Niño index (TNI) (Trenberth and Stepaniak 2001) or the multivariate ENSO index (MEI) (Wolter and Timlin 1993). Each of these indices uses slightly different definitions of ENSO coordinates and phases and is most relevant to slightly different regions around the world. There is no agreement within the scientific community as to which index best defines ENSO years or the strength, timing, and duration of events. Indices that are commonly used to classify ENSO events include regional sea surface temperature (SST) indices (e.g., Niño-1, Niño 2, Niño-3, Niño-4, Niño-3.4, Japan Meteorological Agency (JMA), and the modified JMA) and the surface atmospheric pressure–based Southern Oscillation index (SOI).

The SST indices are temperature based; using mean SSTs within different regions of the equatorial Pacific calculated using a 100-year SST anomaly dataset. This method allows reconstruction of anomalies without any gaps in the time series. Niño-1 and Niño 2 regions are highly responsive to seasonal and El Niño induced changes whereas Niño 3 region is much less responsive to continental influences than Niño 1 and Niño 2 regions. In Niño 4 region, changes in SSTs are related to longitudinal shifts of strong east-west temperature gradients along the equator. JMA is located within the Niño-3 region (4°N-4°S and 150°-90°W) and is the 5-month running mean of spatially averaged SST anomalies. If monthly JMA values are 0.5°C greater (lesser) than the long term average for 6 consecutive months, the ENSO year of October through the following September is categorized as El Niño (La Niña), or neutral (all other values). Modified JMA has similar approach to JMA with its only drawback being that the summer months classified according to conditions in previous October rather than the actual conditions. In modified JMA the episode stops as soon as the temperature conditions are no longer met. Both JMA and modified JMA have similar results from September-March, however, significantly less (more) precipitation is recorded during El Niño (La Niña) episodes.

Prolonged periods of negative SOI values coincide with abnormally warm ocean waters across the eastern tropical Pacific typical of El Niño episodes and prolonged periods of positive SOI values are typical of La Niña episodes.

In addition to the aforementioned indices, several other indices have been proposed for the study of ENSO events. Two of these indices include the trans-Niño index (TNI) and the multivariate ENSO index (MEI). TNI consists of scaled difference between SST anomalies averaged in Niño 1+2 and Niño 4 regions and though it can show the formation of ENSO events but cannot capture their occurrence very well. TNI leads ENSO in Niño-3.4 by 3-12 months prior to 1976/77 and then lags and has been reported to be not a good index for identification of individual ENSO events. The MEI is a composite index using not only SST, but also surface air temperature, sea-level pressure, zonal and meridional surface wind, and cloudiness (Wolter and Timlin, 1993). It correlates well with SST and SOI based indices in identifying individual ENSO events.

Niño-3.4 region (5°N -5°S and 170°W - 120°W) of the Pacific has been reported (Trenberth and Hoar 1996) to be the main area where sea level pressure and temperature anomalies are very well-correlated with each other and for having the most relevance to the southeast United States, hence this index will be used in this research.

1.4 ENSO IMPACTS

The ENSO phenomenon is composed of complex environmental changes that have different influences throughout the world, and are somewhat related, statistically and physically, with the main regional precipitation-generating mechanisms (Waylen and Poveda, 2002). ENSO events are associated with climate extremes over many areas of the globe (Ropelewski and Halpert 1987; Halpert and Ropelewski 1992) and large-scale precipitation and temperature patterns influenced by ENSO have been examined in many areas of the world (Barsugli et al. 1999; McCabe and Dettinger, 1999). ENSO effects can range from significant to very little or no effect at all in different parts of the world (Molnar and Cane, 2007). Most pronounced signal of ENSO can be seen where this phenomenon was discovered i.e. equatorial South America, where El Niño years bring less than normal precipitation and La Niña years are associated with more than normal precipitation and cooler temperatures (Aceituno, 1988).

Australia experiences less rainfall during El Niño, especially during the winter in the interior of eastern Australia and during the northern Australian monsoon whereas La Niña years are often wetter (Nicholls et al., 1996). Investigations have also reported relationships between precipitation from the Indian Monsoon and El Niño events (Ropelewski and Halpert, 1987; Charles et al., 1997). As a critical component of Indian sub-continent water supply and agriculture, historic monsoon failures have often coincided with strong El Niño events (Kiladis and Diaz, 1989; Ropelewski and Halpert, 1987; Charles et al., 1997). Quinn et al. (1978) reported a relationship between El Niño and Indonesian droughts, particularly in the east monsoon season of May–October. In southeast and the eastern equatorial Africa, El Niño events bring greater than normal precipitation and cooler temperatures (Ropelewski and

Halpert, 1987; Halpert and Ropelewski, 1992).West and Central Europe may experience higher temperatures and lower precipitation during strong El Niño winters whereas northern Europe receives less precipitation. La Niña events bring higher precipitation to northern Europe (Fraedrich and Muller, 1992).

The Southern Oscillation influences temperature, precipitation and upper-level winds (Halpert and Ropelewski, 1986 during a particular year. Prior knowledge of the expected state of the equatorial Pacific Ocean gives a substantial source of predictability of seasonal climate variability over the Tropics (Palmer and Anderson 1994). Many studies have verified a relationship between ENSO and precipitation and streamflow (e.g. Redmond and Koch, 1991; Eltahir, 1996; Chiew et al., 1998; Berri and Flamenco, 1999; Simpson and Colodner, 1999). Significant ENSO correlations have been reported in different parts of North America that include studies that show West and south Canada and the northern United States experience warmer winters and less precipitation during El Niño events whereas the southwestern United States have greater than average precipitation during El Niño summers. During La Niña years most of these patterns are reversed (Rasmusson and Wallace, 1983; Ropelewski and Halpert, 1986; Halpert and Ropelewski, 1992).

The southeastern United States generally receives generous amounts of rainfall, with annual amounts in Alabama alone totaling 53 inches. The amount and timing of this rainfall can be quite variable, which has led to many water related disputes in the region. This region has shown cooling and warming temperature trends that have varied at an inter-decadal temporal scale making the southeast the only region in the country to show an overall cooling of 1-2 ºC

(Burkett et al., 2001). Rainfall trends in the last century have shown overall increases of 20-30% or more in Mississippi, Alabama, and Louisiana, with mixed results in Georgia and Florida. In the southeastern United States climate variability can be attributed to El Niño Southern oscillation (ENSO) phenomenon (Enfield et al., 2001; Glantz et al., 1991; Diaz and Markgraf, 2000; Schimdt et al 2001). During El Niño events, winter precipitation is anomalously high, but temperatures are low due to increased cloud cover, while summers tend to be dry along the southeast coast (Ropelewski and Halpert, 1986; Adams et al., 1995). This distinctive winter El Niño pattern in the region is caused as a result of deflection of the subtropical jet due to stronger Hadley Circulation over the eastern Pacific Ocean (Cane, 2005). ENSO influence on rainfall has a lagged effect on streamflows in the region, as Zorn and Waylen (1996) showed for the Santa Fe River in northern Florida.

Knowledge of what has happened during past ENSO events gives some hint of what might happen during a present or future event. This information gives a better approximation of the possible future climate than the assumption that seasonal conditions will be the same as average. Based on this knowledge of ENSO impacts in southeastern United States, I am analyzing the use of ENSO outlooks in drought forecasting and water resource management in the region.

1.5 Drought

Drought is a normal, recurrent climatic feature that occurs almost in every climatic zone around the world, causing billions of dollars in loss annually. According to the US Federal Emergency Management Agency (FEMA), the United States loses $6-8 billion annually on average due to drought (FEMA 1995). A drought is considered to be a period of abnormally dry weather that causes serious hydrological imbalance in a specific region (Burke et al. 2006). Drought may be a temporary condition where the amount of water from precipitation falls short of a threshold value. From meteorological point of view the threshold value can be normal precipitation. From hydrological perspective, the threshold value can be normal ground or underground water level. From an agricultural viewpoint, the threshold value is the when plant available water is less than atmospheric demand for evapotranspiration (ET). From socioeconomic standpoint, the threshold value water supply is less than the water demanded by the society. Drought basically starts from a deficiency of precipitation resulting in water shortage for a certain activity.

Linsley et al. (1975) defined hydrological drought as a period during which stream flows could not supply recognized uses under a given water management plan. Bryant (1991) ranked natural hazard events based on various characteristics, such as severity, duration, spatial extent, loss of life, economic loss, social effect, and long-term impact. He found that drought ranks first among all natural hazards. This is because, compared with other natural hazards like flood and hurricanes that develop quickly and last for a short time, drought is a creeping phenomenon that accumulates over a period of time across a vast area, and the effect lingers for years even after the end of drought (Tannehill 1947). According to IPCC, the frequency and severity of droughts could increase in some areas as a result of a decrease in total rainfall, more frequent dry spells and higher evapotranspiration (Frederick and Major, 1997).

A drought can occur due to a combination of natural causes, including precipitation and evapotranspiration imbalance over a long period of time, unusually high temperatures, or low precipitation, as well as human causes, including unsustainable demand/supply ratio and landuse changes. Water demand forecasts are needed for the design, operation, and management of urban water supply systems (Bougadis et al. 2005).

Drought management depends on indicators to detect drought and triggers to activate drought response. However, indicators often lack spatial and temporal transferability, comparability among scales, and relevance to critical drought impacts; triggers often lack statistical integrity and consistency among drought categories (Steinemann, 2003). Physical measures of a system such as reservoir level and groundwater supply are used as hydrological indicators to define drought triggers and their use requires comparison of forecast of demand and supply (Fisher and Palmer, 1997).

1.6 Significance of Drought in The Southeast United States

Unlike the western US where aridity is widespread and populations have developed approaches to deal with water shortages, the southeast USA finds itself ill-prepared to deal with drought. During the past decade, the southeast USA has experienced several severe droughts, which have affected the region adversely. For example, La Niña conditions in 1998 and 1999 were associated with a drought that lasted until 2000 in Florida and until 2001 in northern Georgia and Alabama. More recently, La Niña-like conditions during the winter of 2006 caused drought throughout the southeast that had an economic impact that ran in to billions of dollars in the region. As discussed earlier, in the southeast climate variability, and hence occurrence of drought, is greatly influenced by El Niño Southern Oscillation (ENSO) phase. Drier conditions in winter (La Niña) have an enormous impact in the region because of its dependence on water recharge during the cool season. Even without La Niña, the southeast suffers from low surface water availability during summer months because of intra-annual climate variability, very high evapotranspiration rates, and increased demand by ever growing urban centers. And since La Niña typically returns every two to seven years, drought is a recurring phenomenon in the southeast states, which emphasizes the importance of drought preparedness.

1.7 Drought Index

Based on the defined drought criteria, the intensity and duration of drought is expressed with a drought index. A drought index integrates various hydrological and meteorological parameters, such as rainfall, temperature, evapotranspiration (ET), runoff, and other water supply indicators into a single number and gives a comprehensive picture for decision-making (Narasimhan and Srinivasan, 2005; Hayes, 2006). Federal and State government agencies use drought indices to assess and respond to drought. Available drought indices vary among themselves in many respects, such as applicability (regions and conditions), basic concept (energy-balance- or water-balance-based), input requirements, purpose (monitoring crop water deficit or estimating crop yield), and target use (agricultural, hydrological, or socioeconomic). They also vary in terms of complexity, genericness (whether the parameters of these indices are crop-specific or not), and spatio-temporal resolution. Each index has been developed for a particular purpose and has specific features. Among various available drought indices, the Palmer Drought Severity Index (PDSI) (Palmer 1965), Standardized Precipitation Index (SPI) (McKee et al 1993), and Surface Water Supply Index (SWSI) (Shafer and Dezman 1982) are most widely used for water resources management and drought monitoring in the US and are discussed briefly below.

1.7.1 Palmer Drought Severity Index (PDSI)

Palmer Drought Severity Index (PDSI) was developed by Palmer (1965) as a meteorological drought index based on the criteria of beginning and end of a drought or wet spell. PDSI has gained a wide acceptance because the index is based on a simple lumped parameter water budget model. The input data needed for PDSI are monthly precipitation, monthly temperature, and average available water content of the soil for the entire catchment. It does not consider streamflows, lake and reservoir levels, human impacts such as irrigation, or other hydro-meteorological variables that affect droughts (Karl and Knight, 1985). The PDSI is also known as the Palmer Hydrological Drought Index (PHDI) as it is based on moisture inflow (i.e. rainfall), outflow as moisture loss due to temperature effect and storage as soil moisture content (Karl and Knight, 1985). The PDSI has been widely used for a variety of applications across the United States for monitoring drought and triggering drought relief programs (Loucks and van Beek, 2005). The capability of PDSI to provide a measure of abnormality of weather in a region, spatial and temporal representation of historic droughts, and current conditions in historical perspective are three major features that make it popular (Alley, 1984). Although the PDSI has been widely used within the US, several limitations of this application have been reported by Alley (1984), Karl and Knight (1985) and Karl (1986). PDSI does not do well in regions with extreme rainfall variability such as Australia and South Africa (Hayes, 2003) and is a poor indicator of soil moisture changes at temporal scales ranging from one to several weeks (Bruwer, 1990). Other limitations of PDSI include the use of Thornthwaite's method for calculation of potential evapotranspiration (ET), which has been reported to be the poorest performing method of estimating potential ET (Jensen et al., 1990). Since the water balance model used by Palmer (1965) is a lumped parameter model, it makes it difficult to spatially delineate the areas affected by drought (Balaji, 2004).

1.7.2 Standardized Precipitation Index (SPI)

Standardized Precipitation Index (SPI) was developed by McKee et al. (1993) to replace PDSI for Colorado, US. It is calculated as the difference between total precipitation and historical mean precipitation for a given time period divided by the standard deviation. This index is mainly a meteorological drought index based on the precipitation amount in a 3, 6, 9, 12, 24, or 48 month period. Observed rainfall during these time periods are first fitted to a Gamma distribution, and then transformed to a Gaussian distribution to obtain the value of SPI for that time scale. Since the SPI requires minimal input data it is widely used throughout the world (Hughes and Saunders, 2002; Hayes, 2003; Bhuiyan, 2004; Mishra and Desai, 2005; Bacanli et al., 2008). Despite of its popularity, it still has limitations as it does not consider many other hydro-meteorological variables that effect droughts, such as soil moisture, ET, reservoir storage, land use characteristics, crop species, crop growth stage, and temperature anomalies that are critical for drought monitoring. (Keyantash and Dracup, 2004; Smakhtin and Hughes, 2004).

1.7.3 Surface Water Supply Index (SWSI)

The SWSI was primarily developed as a hydrological drought index with an intention to replace PDSI for areas where local precipitation is not the primary source of water. The main aim for its development was to incorporate both hydrological and climatological features into a single index (Shafer and Dezman, 1982; Doesken et al., 1991). The SWSI is calculated based on monthly non-exceedance probability from available historical records of reservoir storage, stream flow, snow pack, and precipitation. Details on the computation of SWSI are presented by Shafer and Dezman (1982). The SWSI has been used to trigger the activation and deactivation of the Colorado Drought Plan along with reported use in other western states in the US. Its advantages include that it gives a representative measurement of surface water supplies across the basin. However, just like SPI, it does not consider some hydro-meteorological variables such as soil moisture content and potential ET along with having a bias involved in determining weights that are a part of SWSI calculations. Furthermore, the changes in the water management within a basin, such as flow diversions or new reservoirs, mean that the entire SWSI algorithm for that basin needs to be redeveloped to account for these changes making it difficult to maintain a homogeneous time series of the index (Heddinghaus and Sabol, 1991).

There are many other drought indices reported in literature but most have limited use. Some of these indices are briefly presented in Table 1.1. However, none of the drought indices discussed operates at a spatial scale that water resource managers of small to mid-size communities desire; nor do they consider the supply and demand balance or forecast drought.

This study is concerned with the possibility for developing a new hydrological drought index that is simpler and may perform better than the other drought indices available now.

1.8 Municipal Water Systems and Droughts

Domestic water use accounts for 8 percent of withdrawals and 6 percent of consumptive use in the United States (Solley et al. 1993). To serve an adequate quantity of water to a modern city in the Southeast US, a public water supply system is necessary and this supply system may depend on surface water, or groundwater, or both. The former may include water drawn from rivers, reservoirs, and lakes. A municipal water system may be defined as all the utility components and services involved in providing finished water to the water users (Shaw, 1993).

The water supply systems of many small- and mid-size municipalities depend on surface water sources. Due to this dependence on surfaces sources as well as due to fast growth of these communities they become extremely vulnerable to drought. Most of these cities have their water resources (lakes or reservoirs) in small watershed systems. Smaller systems and systems relying on surface water have greater sensitivity to climate variation than larger systems and systems relying on groundwater (O'Connor et al. 1999). Changes in land use, population growth, urban sprawl, and economic growth further worsen the situation (Varis et al., 2004).

Table 1.1: Some other Drought Indices

Drought Index	Definition	Use
Deciles (Gibbs and Maher, 1967)	Grouping monthly precipitation occurrences into deciles	Meteorological drought measurement within the Australian Drought Watch System
Keetch-Byram Index (Keetch and Byram, 1968)	Daily water balance, precipitation and soil moisture balanced in a water budget model	Estimates of forest fire potentials
Crop Moisture Index (Palmer, 1968)	A Palmer derivative, precipitation and temperature used in a water balance method across major crop-producing regions	Agricultural drought
Vegetation Condition Index (Kogan, 1995)	Calculated with satellite Advanced Very High Resolution Radiometer (AVHRR) radiance	"Health" of vegetation, drought detection and tracking
Reclamation Drought Index (Weghorst, 1996)	Calculated at river basin level, using precipitation, temperature, streamflow and reservoir levels.	Drought severity and duration by U.S Bureau of Reclamation
Effective Drought Index (Byun and Wilhite, 1999)	Amount of rain needed to overcome accumulated deficit	Used to monitors daily drought conditions in the United States
U.S. Drought Monitor (Svoboda, 2000)	Incorporates several drought indices and indicators to produce a weekly map	Multipurpose

Climate variability is not the only factor that affects the supply of and demands for water; other factors influencing supply and demand include population size, technology, economic conditions, and other social factors. In addition, household water demand fluctuates with climatic conditions, water prices, and use restrictions, and household income. Hughes et al (1994) in a study of urban water use in Utah found that potential ET and rainfall best explained the changes in residential water use attributable to climate. Changes in climate variables such as rainfall and temperature drive changes in both water supplies and demands. Fluctuations in weather conditions, along with normal loading conditions, may cause short-term failures in a system. Consequently, drought conditions subject municipal water systems to the combined effects of higher demands and lower supplies thus posing serious risk to the performance of these systems (Radwan and Shaw, 1994).

1.9 Problem Statement

Most of the drought indices already available are not designed to cater to the needs of water resource managers of small to mid-size communities (population less than 100,000). It is very important for water resource managers of the Southeast to have a water deficit index that operates at a fine spatial resolution; accounts for the balance of available water supply (dependent on climate variables such as precipitation and temperature) and water demands (dependent on time of the year, population, and climate variables); and should be able to forecast drought based on the climate variability signal ENSO that is prevalent in the southeastern United States.

Water balance in a watershed can be estimated accurately using hydrologic models. However, these models are difficult to apply because they require a large numbers of inputs and parameters that are difficult for users to obtain. Thus, a complex drought index derived from a hydrologic model is impractical for broader application. Another important consideration is that the index should be generic or customizable for any community, based on its water supply and demand systems. Generic indices also provide economy in both modeling and understanding (Reynolds and Acock, 1997). So in this study, a drought index is proposed that would be customizable for small to mid-size communities of the southeastern United States.

It is hypothesized that the proposed water balance-based, simple, generic, and high-resolution drought index would characterize hydrologic drought better than other drought indices that are available now and that, being simple and generic, the index would be more convenient for water resource managers, and would provide them with a tool that forecast drought 3-4 months in advance taking in to account the ENSO conditions. It would be more convenient for the users to apply this index and also, being relatively simple, the chance of its application as a web-based, decision support system would be high.

1.10 Dissertation Objectives

The objectives of this dissertation are:

1. To study the impact of El Niño Southern Oscillation on the precipitation and streamflows in Alabama for better water resource management.
2. To develop a drought index for forecasting drought for small to mid-size communities of the southeastern United States using the El Niño Southern Oscillation impact in the region.
3. To evaluate the value of the developed index by studying the use of this information for water resource managers of the region.

1.11 Dissertation Organization

This dissertation focuses on the above mentioned three objectives and is presented in manuscript format for those chapters discussing the methodology and results. Chapter 1 provides an introductory overview justifying this research, a review of literature and presents the research objectives. Chapters 2 through 4 present in manuscript format a discussion and response to the three objectives outlined for this research. Chapter 2 presents the details of study of impact of ENSO signal on precipitation and streamflows in Alabama. It establishes the different El Niño and La Niña patterns as observed over the past 52 years in the state of Alabama. This chapter has already been accepted for publication in Journal of Soil and Water Conservation (Sharda et al. 2011). Chapter 3 documents the development of Community Water Deficit Index (CWDI) as the drought index to forecast drought based on ENSO outlook. This chapter has been submitted for publication in Journal of Hydrologic Engineering (Sharda et al., 2012). Chapter 4 covers the quantification of value of drought forecast information for water resource managers. This chapter will be submitted in the Transactions of American Society of Agricultural and Biological Engineers for publication. Chapter 5 presents the conclusions of this research. Finally, Chapter 6 presents future research suggestions and practical implications of the research findings. Style manual or Journal used in the manuscript is Transactions of American Society of Agricultural and Biological Engineers (ASABE).

Chapter 2

Quantification of El Niño Southern Oscillation (ENSO) Impact on Precipitation and Streamflows for Improved Management of Water Resources in Alabama

2.1 Abstract

There is increased pressure on the water resources of the southeastern United States due to the rapidly growing population of the region. This pressure is further exacerbated by the severe seasonal to inter-annual (SI) climate variability this region experiences, most of which has been attributed to El Niño Southern Oscillation (ENSO). Understanding the regional impacts of ENSO on precipitation and streamflow is valuable information for water resources managers in the region. This study was undertaken to develop a clear picture of the effect of ENSO on observed precipitation and streamflow anomalies in Alabama to help water resource managers in the state with decision-making. The effects of ENSO on precipitation in eight climate divisions of Alabama were assessed using 59 years (1950-2008) of monthly, historical data. In addition, eight unimpaired streams, one in each climate division, were selected to study the relationships between ENSO and streamflow. Results indicate a significant relationship between ENSO and precipitation and streamflow. However, different parts of the state respond differently to ENSO. For precipitation, it was found that the relationship is significant during winter months with dry conditions being associated with La Niña in the southern climate divisions. A fairly strong relationship was also found during other months. Streamflows show a high variability and positive correlation during winter months in the southern climate divisions. These results

provide a basis for the water resource managers in Alabama to incorporate climate variability caused by ENSO in their decision-making related to soil and water conservation.

2.2 INTRODUCTION

Natural climate variability has a considerable impact on society, particularly on agriculture and water resources. To minimize its negative consequences, we must identify, quantify, and understand this variability (Climate Research Committee and National Research Council 1995). Natural climate variations caused by El Niño Southern Oscillation (ENSO), the Pacific Decadal Oscillation (PDO), and the North Atlantic Oscillation (NAO) can significantly alter the behavior of extreme events including floods, droughts, hurricanes, and cold waves (IPCC 2001).

The southeastern US is a region with a rapidly growing population including a reported 32% population increase between 1970 and 1990. This expanding urban population increases pressure on water resources in this region, which is exacerbated by severe seasonal to inter-annual (SI) climate variability. The climate variability in the Southeast is influenced greatly by ENSO (Enfield et al. 2001). ENSO is a coupled, ocean-atmospheric phenomenon that occurs in the equatorial Pacific Ocean and the atmosphere above it and results in varied climatic effects in different parts of the world (Roy 2006). The terms “El Niño” and “La Niña” describe the respective warming and cooling of sea surface temperatures off the shores of the west coast of South America (Quinn 1994; Aceituno 1992). Another important phenomenon that affects the climate in this region is PDO, which is a long-lived, ENSO-like pattern of Pacific climate variability that operates on a decadal time scale and can last up to 30 years. Gershunov and Barnett (1998a, b) reported that PDO has a regulating effect on ENSO, with typical ENSO signals being stronger during the strong phase of PDO. NAO has also been reported to impact temperatures in the region, with La Niña winters being colder than normal during its negative (cold) NAO phase. However, since NAO phase changes in a 1-2 week time scale, its effect is transitory. Tootle et al. (2005) reported that NAO might influence La Niña impacts on streamflow in the midwestern United States. However, the literature suggests that ENSO has the strongest impact on climate variables in the Southeast. Ropelewski and Halpert (1986) studied the response of precipitation and temperature to ENSO over all of North America and found that above-normal precipitation (normal precipitation being the mean of the available data) was associated with El Niño conditions in the southeastern United States during October through March. La Niña years were relatively warm and dry between October and April (Mearns et al. 2003). During warm (El Niño) events, winter precipitation was anomalously high, but temperatures were low due to increased cloud cover (Ropelewski and Halpert 1986).

The southeastern United States often suffers from low surface water availability during summer months due to high evapotranspiration rates and increased demand by ever-growing urban centers. Smaller water systems and systems relying on surface water sources have greater sensitivity to climate variability compared to larger systems or systems relying on groundwater sources or a combination of groundwater and surface water sources (O'Connor et al. 1999). This situation is further worsened by changes in land use, population growth and urban sprawl (Varis et al. 2004).

Past research has studied the relationship between precipitation and ENSO on global and regional scales. Many of these analyses have included Alabama (e.g., Ropelewski and Halpert

1986; Livezey et al. 1997; Gershunov and Barnett 1998a; Livezey and Smith 1999). Although such regional studies of climate variability provide a broad picture of potential impacts, they do not adequately address the spatial and temporal scale of variability on which decisions are based.

Various researchers have also studied the relationship between ENSO and the streamflow of different rivers (e.g., Amarasekera et al. 1997; Fu et al. 2007; and Zubair 2003). Although Alabama relies heavily on surface water resources, with 88% of its public water supply coming from surface water (USGS 2005; US Census data), little has been done to examine in detail the patterns of rainfall in Alabama. Streamflow integrates precipitation over the drainage basin and responds to precipitation by a temporally-variable combination of runoff and groundwater inputs (Schimdt et al. 2001). Abtew et al. (2009) reported that identifying connections of ENSO indices to a basin's or region's hydrology can aid in resource management decision-making. For example, a tool to manage food security in Indonesia has been developed utilizing the study of Naylor et al. (2004). They showed that four to eight months of sea surface temperature (SST) measurement can be used to predict and plan rice production in the region. Forecasting and managing flooding of the Brahmputra-Jamuna River in Bangladesh is based on a study of the relationship between SST and wet season flows of the river (Jahan et al. 2006).

The changes in precipitation and streamflow caused by ENSO have potential implications for the conservation of soil and water. For example, the inter-annual variability in precipitation in Alabama affects the availability of surface water resources in the state and may cause short-term failures in the system. This makes it all the more important from a water manager's perspective to study, in detail, the impact of ENSO on precipitation and streamflow in this part of the southeastern United States. Those who manage surface water resources in the state could potentially make explicit use of information about probable inter-annual changes in surface supplies based on a range of observed and forecasted ENSO parameters. For example, municipal water managers can impose timely water use restrictions and encourage water conservation based on ENSO forecasts, thus preparing consumers to deal with low water availability or hydrologic drought. This type of information is also important for agricultural water use where decisions about water withdrawals and irrigation can be made based on the impacts of ENSO on precipitation and streamflows. A recent study by Mondal et al. (2011) has shown that by using this information, an ecologically-sustainable surface water withdrawal prescription for irrigation can be developed.

Quantifying and understanding precipitation trends associated with climate variability is also important due to its direct link with droughts, floods, and soil erosion (Pruski and Nearing 2002). For example, knowledge of ENSO impacts on precipitation and streamflow can be used for implementing non-structural BMPs, such as riparian buffers, vegetated waterways, and live stakes to reduce erosion and sediment transport. ENSO-related climate variability can also affect water quality and impact ecosystems, health, and food availability (Keener et al. 2010). Therefore, understanding the impact of ENSO on precipitation and streamflow, the objective of this study, can provide valuable information to water resource managers.

2.3 MATERIALS AND METHODS

2.3.1 STUDY AREA

For this study, we selected the state of Alabama in order to explore the relationship between ENSO and precipitation and streamflow. However, the methodology presented here can be applied to other regions that are affected by ENSO or any other seasonal to inter-annual climate variability phenomenon. Alabama has a humid, subtropical climate with an average annual temperature of 17.8°C (64 °F) and average annual rainfall of 142 cm (53 in). The northern parts of the state, especially the Appalachian Mountains in the northeast, tend to be slightly cooler, whereas, the southern parts are slightly warmer. Rainfall in the state is also affected by tropical storms and hurricanes.

2.3.1.1 Precipitation Data

Monthly precipitation data for 49 stations (APPENDIX A), for a 59-year period of record, 1950-2008, spread over eight climate divisions in Alabama (Figure 2.1) were obtained from the National Climate Data Center, US Department of Commerce (http://www.ncdc.noaa.gov/oa/ncdc.html). Mean monthly precipitation from the stations in each climate division was summed. Climate divisions were adopted from the US Department of Agriculture Bureau of Agricultural Economics Crop Reporting Districts in 1949. The reason for adopting crop reporting districts as climate divisions was because crop production areas are strongly related with climate classification. There were minor revisions made in order to organize the data based on geography, drainage basins, river districts, and forecast areas of responsibility. In the 1950's, a standard national scheme based partially on climatic considerations was adopted (Guttman and Quayle 1996). The historical perspective associated with these climate divisions and the ease with which information from these divisions can be understood by stakeholders or water resource managers were important considerations in summing up the station data using the state's eight different climate divisions.

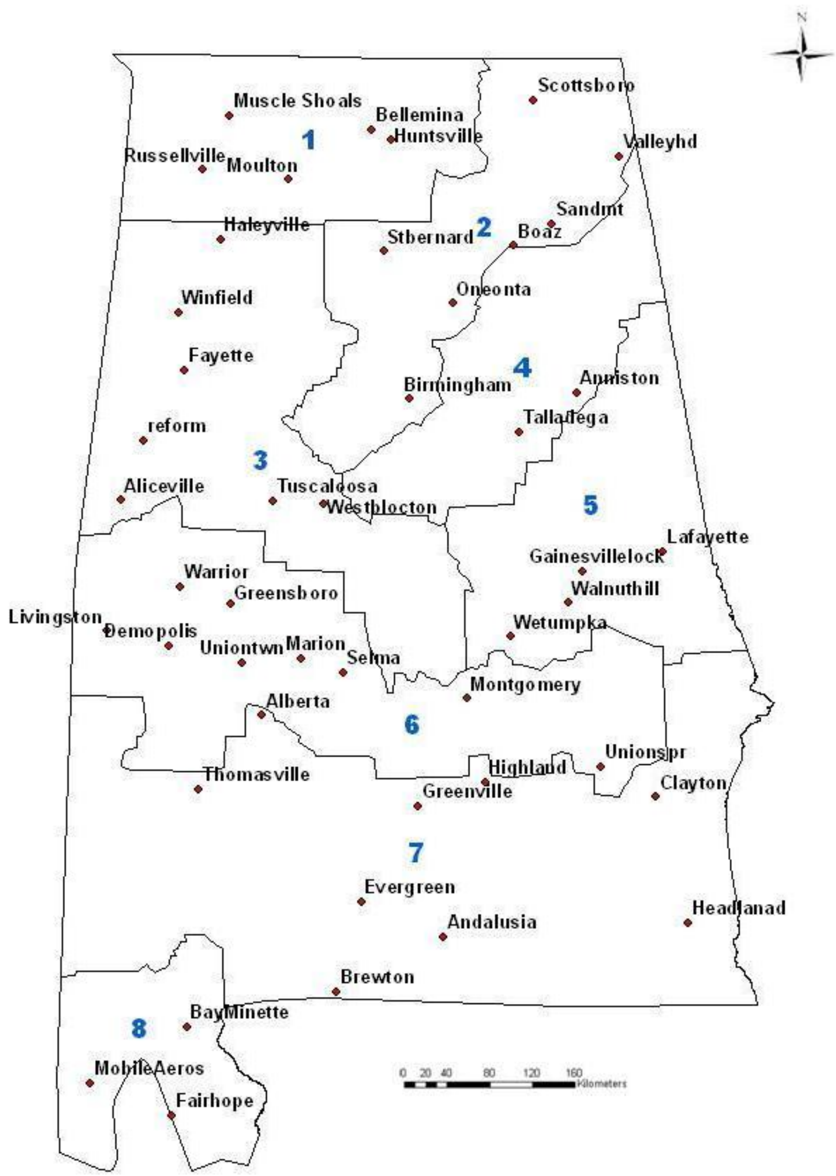


Figure 2.1. Climate Divisions of Alabama and stations in different Climate Divisions used for analyses.

It has been reported that higher than yearly time resolution may be desirable to study the relationship between precipitation and ENSO episodes (Redmond and Koch 1991).Therefore, to obtain the best correlation between precipitation and ENSO episodes, three-month mean precipitation data were used and referred to as the seasonal mean for the seasons of January-February-March (JFM), April-May-June (AMJ), July-August-September (JAS), and October-November-December (OND). In addition, two "municipal" seasons were selected for analysis. These are the wet season or growing season- December, January, February, March and April (DJFMA) - and the dry season - April, May, June, July, August and September (AMJJAS).

In Alabama, the wet season provides the most precipitation and the least evapotranspiration and is considered a recharge season by water managers. During this season, water managers allow reservoirs to fill so that they can supply water during the dry season. The rate of evapotranspiration and thus water consumption is the highest in the dry season. Further, if the wet season does not receive adequate rainfall, increased water consumption often exacerbates the negative effects of high evapotranspiration on water use.

2.3.1.2 Streamflow Data

The streamflow data were obtained from the United States Geological Survey (USGS) (USGS 2010). One unimpaired stream, with more than 30 years of past streamflow data, was selected in each climate division. The BASINS (Better Assessment Science Integrating point & Non-point Sources) model (EPA 2001) was used to select the streams (gauging stations) with minimal upstream human interventions, such as regulations and diversions, point source discharges, and dams. The data obtained from USGS were mean monthly streamflows in cubic meter per second (m3/s).

2.3.2 ENSO INDEX

The National Oceanic and Atmospheric Administration (NOAA) Niño 3.4 index was used to define the ENSO phase. This index is based on a three-month, extended reconstruction, sea surface temperature (SST) analysis (ERSST.v2), which includes average SST anomalies in the Niño 3.4 region (5°N -5°S and 170°W - 120°W) of the Pacific. This region has been reported (Trenberth and Hoar 1996) to be the main area where sea level pressure and temperature anomalies are very well-correlated. If the Niño 3.4 index is more than +0.5°C, the event is termed El Niño, and, if the index is less than -0.5°C, the event is termed La Niña. A neutral phase is defined when the Niño 3.4 index is between +0.5°C and -0.5°C. The NOAA Climate Prediction Center (CPC) assigns ENSO phase to a three-month period based on the SST anomaly, and this information is available on their website from 1950 to present (NOAA-CPC 2010).

2.3.3 ENSO PHASE ASSIGNMENT

Seasonal (JFM, AMJ, JAS, OND) ENSO information from 1950 – 2008 available from NOAA CPC was used. For the “municipal” seasons, the phase over the entire period was considered. For example, for DJFMA, we looked at the ENSO phases for NDJ, DJF, JFM, and FMA and, if there was no phase change during these months, it was assigned to DJFMA; otherwise, that particular year was deleted from the analysis. The same procedure was repeated for AMJJAS. Based on this method, the seasons for the entire period of 59 years (1950-2008) were classified as El Niño, La Niña or Neutral (Table 2.1).

Table 2.1: Number of years, by seasons, in each ENSO phase.

ENSO Phase	JFM	AMJ	JAS	OND	DJFMA*	AMJJAS**
El Niño	13	11	14	19	13	9
La Niña	17	16	12	19	16	12
Neutral	29	32	33	21	25	30

* Years 1964, 1965, 1972, 1978 and 2007 were deleted from the analysis.

** Years 1963, 1965, 1969, 1970, 1983, 1998, 2000 and 2004 were deleted from the analysis.

2.3.4 PRECIPITATION AND STREAMFLOW VARIABILITY

Historic mean monthly precipitation values for 49 rainfall stations of the state were downloaded and the monthly values were then added and averaged for each of the six seasons. These values were then averaged by ENSO phases (i.e., El Niño, La Niña, and Neutral). The station data were grouped according to climate divisions. The total, seasonal mean precipitation values for each climate division were analyzed, and standard deviation and coefficient of variation along with anomalies were calculated to study the precipitation variability during each ENSO phase. Seasonal precipitation anomalies were calculated by subtracting the seasonal mean monthly precipitation value of all the years from the value of that year. Seasonal streamflow anomalies were similarly calculated for the six seasons. The Environmental Systems Research Institute (ESRI) ArcMap 9.2 was used to create precipitation anomaly maps. Maps were created for each season for both the El Niño and La Niña phases using the ArcToolbox Natural Neighbor tool of interpolation.

Monthly mean streamflows (m^3/s) were used for each of the eight streams selected and analyzed for variability in a similar manner as precipitation for the six seasons. These values were then averaged over the months in a season to get seasonal mean streamflows for each year of the past data.

Analysis of variance (ANOVA) was conducted using Statistical Analysis System (SAS) software (SAS Institute, Inc., NC, USA) General Linear Model (GLM) procedure to ascertain if statistical differences existed in precipitation and streamflow during different ENSO phases. Means and standard deviations for these parameters were also calculated using the GLM procedure. Multiple comparisons of means for all parameters were conducted using the Least Square Difference (LSD) procedure. All statistical analyses were conducted using a 90% confidence interval.

2.3.5 Correlation Analysis

Correlation coefficients between the Niño 3.4 index and precipitation and streamflow anomalies were calculated using SAS to study the relationship between ENSO and precipitation and ENSO and streamflow. The Pearson correlation coefficient (r) measures linear association. The null hypothesis, H_0 - no correlation, was tested at a 90% level of significance for all the seasons for both precipitation and streamflow in each climate division using SAS. Because Pearson's correlation measures the linear association, and because it is difficult to establish an independent, identically distributed, normal relationship for hydrologic variables such as precipitation and streamflow (Xu et. al. 2004), Kendall's correlation (τA), which is a distribution-free rank correlation, was also calculated for the dataset. Kendall's rank coefficient does not require the variables to be normally distributed and is more efficient with high power (Kendall 1975).

Lag correlations of linear regression between streamflow and the Niño 3.4 index were calculated to quantify the strength of the relationship and to find if streamflow in the region showed a lagged response to ENSO, as has been observed in different parts of the world (Chiew et al. 1998). A significant lag correlation also indicates a potential for forecasting.

2.3.6 Composite Analysis

Composite Analysis is a sampling technique based on the conditional probability of a certain event such as El Niño or La Niña occurring. This analysis was performed on the dataset to find the conditional probability of El Niño, La Niña, and Neutral precipitation or streamflow being above, below, or near normal based on the historic data. Seasonal mean monthly precipitation and seasonal mean monthly streamflow data were used, and the analysis was performed for JFM, AMJ, JAS, OND, DJFMA, and AMJJAS for all climate divisions. Lower and upper terciles were calculated to obtain the cutoff points between above, near, and below normal precipitation and streamflow categories for each season using the 1971-2000 dataset. These tercile values were then compared with the precipitation and streamflow values for each month and season to find if the precipitation and streamflows were above, near or below normal. The number of each above, near or below normal precipitation/streamflow values were counted for each El Niño, Neutral, and La Niña event, and then the probability of occurrence was calculated.

2.4 Results and Discussion

2.4.1 Precipitation Variability

The results of seasonal precipitation variability are presented in Figure 2.2. The figure shows anomalies in total, seasonal precipitation values in El Niño and La Niña phases as compared with the normal precipitation for all eight climate divisions of the state for the six seasons analyzed.

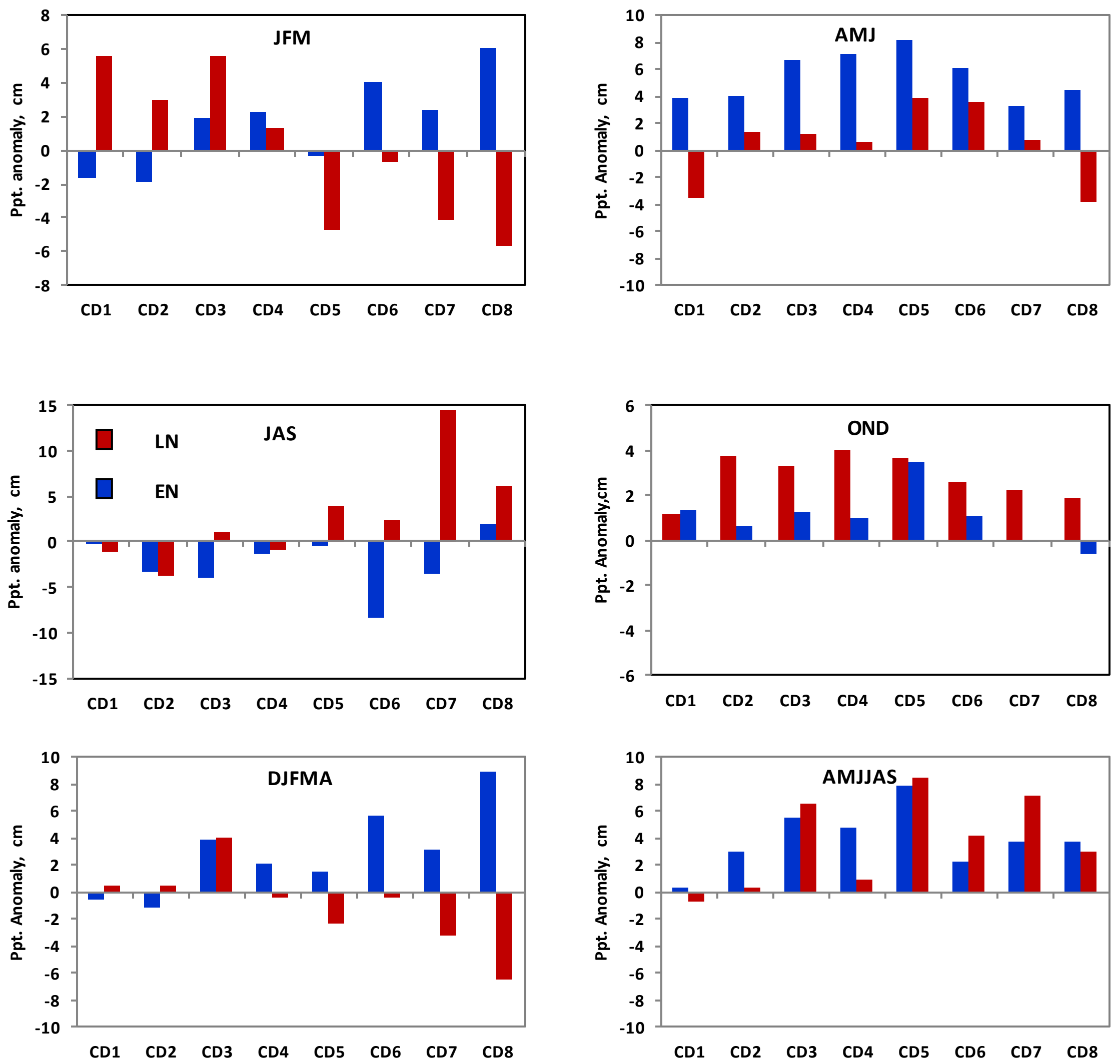


Figure 2.2. Anomalies in total seasonal precipitation in each climate division for the El Niño and La Niña phases for all the six seasons.

It was found that seasonal El Niño precipitation for JFM and AMJ was higher than normal precipitation (positive anomaly) and La Niña precipitation in the southern climate divisions 6, 7, and 8. The statistical analysis of total mean precipitation according to different phases indicates that the southern climate divisions of the state might have drier winters during La Niña with larger variability. Table 2.2 lists those results.

Table 2.2: Precipitation means and standard deviations for different climate divisions during El Niño and La Niña phases.

Climate Division	Season	El Niño Mean (cm)	El Niño Std. dev. (cm)	La Niña Mean (cm)	La Niña Std. dev. (cm)
CD1	JFM	35.84	10.57	43.28	12.27
	AMJ	35.64	11.46	32.39	9.09
	OND	35.15	11.48	33.35	9.86
	DJFMA	61.67	15.27	68.99	14.38
	AMJJAS	63.96	6.25	57.10	12.34
CD2	JFM	39.47	8.33	44.32	8.48
	AMJ	37.34	9.12	34.82	8.03
	OND	34.62	10.03	31.52	8.81
	DJFMA	67.26	13.11	68.78	11.00
	AMJJAS	69.72	8.99	67.08	11.25
CD3	JFM	43.21	9.83	46.89	8.48
	AMJ	41.05	13.61	35.61	7.42
	OND	35.38	8.36	33.30	7.95
	DJFMA	73.48	16.08	73.56	10.46
	AMJJAS	73.03	7.06	74.22	15.88
CD4	JFM	42.57	11.30	41.66	9.07
	AMJ	39.09	12.50	32.59	7.57
	OND	31.24	9.37	28.19	10.11
	DJFMA	67.28	13.82	64.80	11.94
	AMJJAS	67.18	10.11	63.35	13.34
CD5	JFM	41.10	6.71	37.87	12.17
	AMJ	35.71	9.25	32.44	12.88
	OND	29.08	7.19	28.98	8.86
	DJFMA	65.66	12.07	62.69	15.82
	AMJJAS	61.72	8.61	64.01	12.95
CD6	JFM	43.64	9.50	40.26	8.94
	AMJ	36.40	12.70	33.88	11.10
	OND	31.32	7.19	29.79	7.87
	DJFMA	69.85	14.05	65.41	10.01
	AMJJAS	65.00	11.15	66.93	16.71
CD7	JFM	44.81	7.49	39.62	11.61
	AMJ	40.41	11.48	37.64	12.50
	OND	34.93	7.19	32.36	8.61
	DJFMA	75.46	12.75	68.30	12.73
	AMJJAS	80.11	12.55	83.95	17.70
CD8	JFM	47.19	11.76	35.36	10.80
	AMJ	45.97	15.57	37.57	13.11
	OND	33.76	9.30	31.24	12.57
	DJFMA	75.62	18.44	60.12	13.23
	AMJJAS	95.78	19.63	94.97	19.20

It clearly showed the tendency for the average, seasonal El Niño precipitation to be more than La Niña precipitation in southern climate divisions of the state except during the growing season, which did not show a clear response. Most of the southern part of the state had wet (dry) conditions during the El Niño (La Niña) phases in JFM and DJFMA. During the wet season, La Niña precipitation was lower than El Niño and normal precipitation in the climate divisions 7 and 8. The precipitation anomalies were more prominent in the winter months for the southern part of the state.

For JAS, there was no clear response in any part of the state. El Niño precipitation was slightly less than normal in most of the state, whereas La Niña precipitation was near or slightly higher than normal. In climate division 8, both El Niño and La Niña precipitations in JAS were more than normal. These results agree with the findings of earlier research that indicate that ENSO teleconnection patterns exhibit strong, climatic signals during fall, winter, and spring months in the southeastern USA. However, these teleconnections show weak signals during the summer season (Leathers et al. 1991; Yin 1994). In climate divisions 6, 7, and 8, El Niño precipitations were, on an average, 10% higher than normal during winter months (OND, JFM and DJFMA) and La Niña precipitations were 8% lower than normal.

The opposite relationship was found in the northern climate divisions 1 and 2 during JFM. This relationship was, however, not clearly observed during OND and AMJJAS. Climate division 5 displayed higher La Niña variability than El Niño during all seasons. In climate divisions 1, 2, and 3, the El Niño precipitations were on an average 6% lower than normal precipitations during JFM, and La Niña precipitations were nearly 8% higher than normal. In other words, winter precipitation was generally higher (lower) than normal during El Niño conditions in the southern (northern) climate divisions of the state with lower variation as compared to La Niña precipitation, which was lower than normal with high variability.

These results are consistent with the findings of Ropelwiski and Halpert (1987), who reported higher than normal precipitation in the southeastern US during El Niño conditions in the winter months, and with the findings of Mondal et al. (2011), who found similar results for a South Alabama watershed. This information can be helpful to regional water managers when planning for water storage during the wet season. During La Niña, due to an expectancy of below normal precipitation in the climate divisions 6, 7, and 8, more water should be stored in the reservoirs, whereas in the northern part of the state, water storage should be reduced to make room for the coming higher runoff and precipitation. An opposite strategy could be adopted during El Niño conditions. Such a strategy can help water managers conserve water when scarcity is expected and release water when abundance is expected.

2.4.2 Precipitation Anomaly Maps

Precipitation anomaly maps were created as a tool for the water managers to see the spread of precipitation anomalies throughout the state. Figure 2.3 shows the precipitation anomaly maps for the entire state for three seasons, i.e., JFM, OND and DJFMA, for both El Niño and La Niña phases. The red color in the map indicates a dry condition or a negative precipitation anomaly and blue indicates a wet condition or more than normal precipitation. Based on the historic precipitation data, JFM received up to 13.9 cm (5.47 in) more than normal precipitation in the southern part of climate division 8 during El Niño and 9.4 cm (3.7 in) less than normal precipitation during La Niña. For JFM during El Niño, positive anomalies entirely covered climate divisions 6, 7, and 8 and most parts of climate division 5.

Southern parts of the climate divisions 2, 3, and 4 also had more than normal precipitation during El Niño in JFM, whereas climate division 1, the northeastern part of climate divisions 2 and 4, and the northwestern part of climate division 3 were drier than normal. An almost opposite trend was observed in La Niña conditions in JFM with positive anomalies extending up to the northern part of climate division 6. Negative anomalies were observed during OND in La Niña phase in southern climate divisions 7 and 6, extending up to climate division 5, although the eastern parts of climate divisions 5 and 7 were wet. Most of the central part of the state was dry in La Niña conditions and wet in El Niño, whereas the northwestern part of the state was wet (dry) during La Niña (El Niño).

During DJFMA, similar conditions as those during JFM existed in most of the state with lower than normal precipitation or drier conditions during El Niño moving further south. In La Niña, the eastern (eastern part of climate divisions 4 and 5) and southern (climate divisions 7 and 8) parts of the state were mostly dry, and wet conditions prevailed in Northwest and Central Alabama. No clear impact was observed during AMJ, JAS, and AMJJAS. These results agree with the results obtained through composite analysis and correlation studies (discussed below).

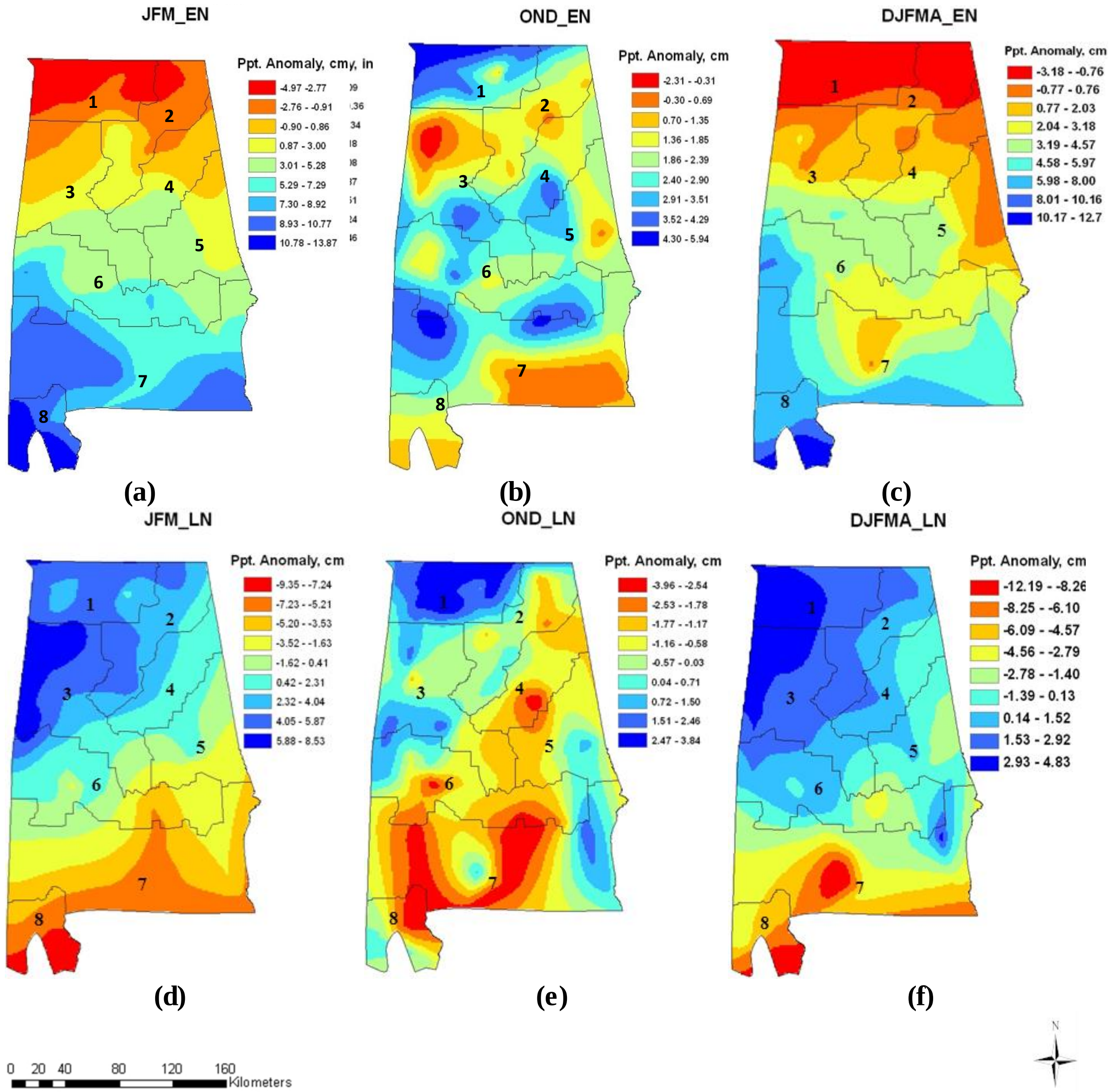


Figure 2.3. Precipitation anomaly distribution in the state during JFM, OND and DJFMA. Maps (a), (b), and (c) are for El Niño conditions and (d), (e), and (f) are for La Niña conditions.

These precipitation anomaly patterns can be attributed to the physical mechanisms underlying the ENSO phenomenon. During El Niño winters, the warm waters of the Pacific Ocean strengthen the jet stream and guide storms to California and along the Gulf Coast. These storms provide rain in the southern part of the state. During La Niña winters, the opposite occurs and the jet stream weakens and travels north making the winters drier than normal in the southern part of the state. These results agree with the general results found in studies conducted on the southeastern United States that concluded that the effect of ENSO is observed to be stronger in the South than the North and stronger in winter-spring than in summer-fall (O'Brien et al. 1999). These anomaly maps can be used to communicate impact of ENSO to the water managers of the state and how the anomalies spread throughout the state. A combination of anomaly maps and composite analysis can indicate the probability of how a certain set of precipitation conditions can occur in any region of the state depending on the ENSO phase.

2.4.3 Correlation Between ENSO and Precipitation

Table 2.3 presents the results of the correlation tests conducted at a significance level of 90% with the cells with an asterisk representing significant correlation. The results indicated that there was a significant correlation between ENSO and precipitation during winter months in climate divisions 7 and 8. Climate division 8 also demonstrated high correlation during AMJ. In climate division 4, a positive correlation existed between ENSO and precipitation anomalies during OND. A strong positive correlation was also indicated during DJFMA in climate divisions 4 and 5. In general, a positive correlation indicates that, during cool ENSO events (La Niña), precipitation tends to be below normal and, during warm ENSO (El Niño), it tends to be higher than normal. This relationship was stronger during winter months in climate divisions 7 and 8 and was reversed in the northern climate divisions. The negative association was also clear in climate divisions 1 and 2 during JFM and for OND in climate division 3. Both Pearson and

Kendall's correlations showed similar results in most climate divisions during all the seasons analyzed except for in climate divisions 3 and 4 during AMJ, for climate divisions 5 and 6 during JFM, and for climate division 3 during OND, when Pearson's correlation was significant and Kendall's was not. During AMJJAS, precipitation anomalies were found to be correlated with the ENSO signal in climate divisions 1, 5, 6, and 7. For JAS, the correlations were non-significant in all the climate divisions (not presented in Table 2.3.

Table 2.3. Pearson's (r) and Kendall's (τ) Correlation Analyses results between ENSO and precipitation.

Climate Division	JFM		AMJ		OND		DJFMA		AMJJAS	
	r	τ	r	τ	r	τ	r	τ	r	τ
CD1	-0.21*	-0.16*	0.07	0.02	0.02	0.04	-0.06	-0.07	0.16*	0.10*
CD2	-0.15*	-0.15*	0.08	0.04	0.13*	0.05	0.02	-0.02	0.04	-0.02
CD3	-0.09	0.07	0.11*	0.03	-0.10*	-0.10*	0.06	-0.01	0.01	-0.01
CD4	0.06	0.03	0.13*	0.04	0.19*	0.12*	0.13*	0.06*	0.01	-0.01
CD5	0.12*	0.09*	0.04	0.04	0.08	0.05	0.21*	0.17*	-0.16*	-0.11*
CD6	0.16*	0.07	0.00	-0.02	-0.03	-0.03	0.26	0.15	-0.09*	-0.09*
CD7	0.29*	0.18*	0.07	0.07	0.21*	0.11*	0.29*	0.19*	-0.17*	-0.09*
CD8	0.45*	0.27*	0.19*	0.11*	0.14*	0.10*	0.48*	0.32*	0.01	-0.02

*Significant correlation

2.4.4 Composite Analysis – Precipitation

Figure 2.4 presents the charts showing the probability of precipitation being below, near, or above normal during the three ENSO phases in all the climate divisions for JFM. Based on the historic data, during JFM, the chance that La Niña precipitation would be below normal was nearly 65% in climate divisions 7 and 8, 53% in climate division 5, and below 50% in the rest of the climate divisions. An interesting observation made through this analysis for the season of JFM was that in the Neutral ENSO phase the probability of precipitation being below normal was near or just above 50% for all climate divisions except in climate division 1 (31%).

During the wet season (Figure 2.5), it was observed that there was more than a 50% chance of La Niña precipitation being below normal in climate divisions 5, 6, and 7. El Niño precipitation had a higher probability of being below normal in almost all the climate divisions in the state; the expected result was that it would be above normal. Although the weather stations used in this study were distributed throughout the state, this result can still be attributed to great spatial variability of precipitation in the region and also to the calculation procedure of composite analysis (use of terciles instead of means).

It was found that climate division 8 shows, except for JAS, the effect of the ENSO phase in all of the six seasons studied, i.e., below (above) normal precipitation occurring during La Niña (El Niño). The lowest probabilities for El Niño (La Niña) precipitation being above (below) normal were obtained for AMJ in all the climate divisions. This result also matches the correlation analysis that showed the weakest correlation during this three-month period. For OND, Neutral phase precipitation had around a 50% chance of being below normal in climate divisions 2, 3, 4, and 5 with almost the same probability existing for El Niño precipitation to be above normal in climate divisions 3, 4, 7, and 8. No clear trend was observed in the composite analysis conducted for the growing season (AMJJAS) in all the climate divisions of the state.

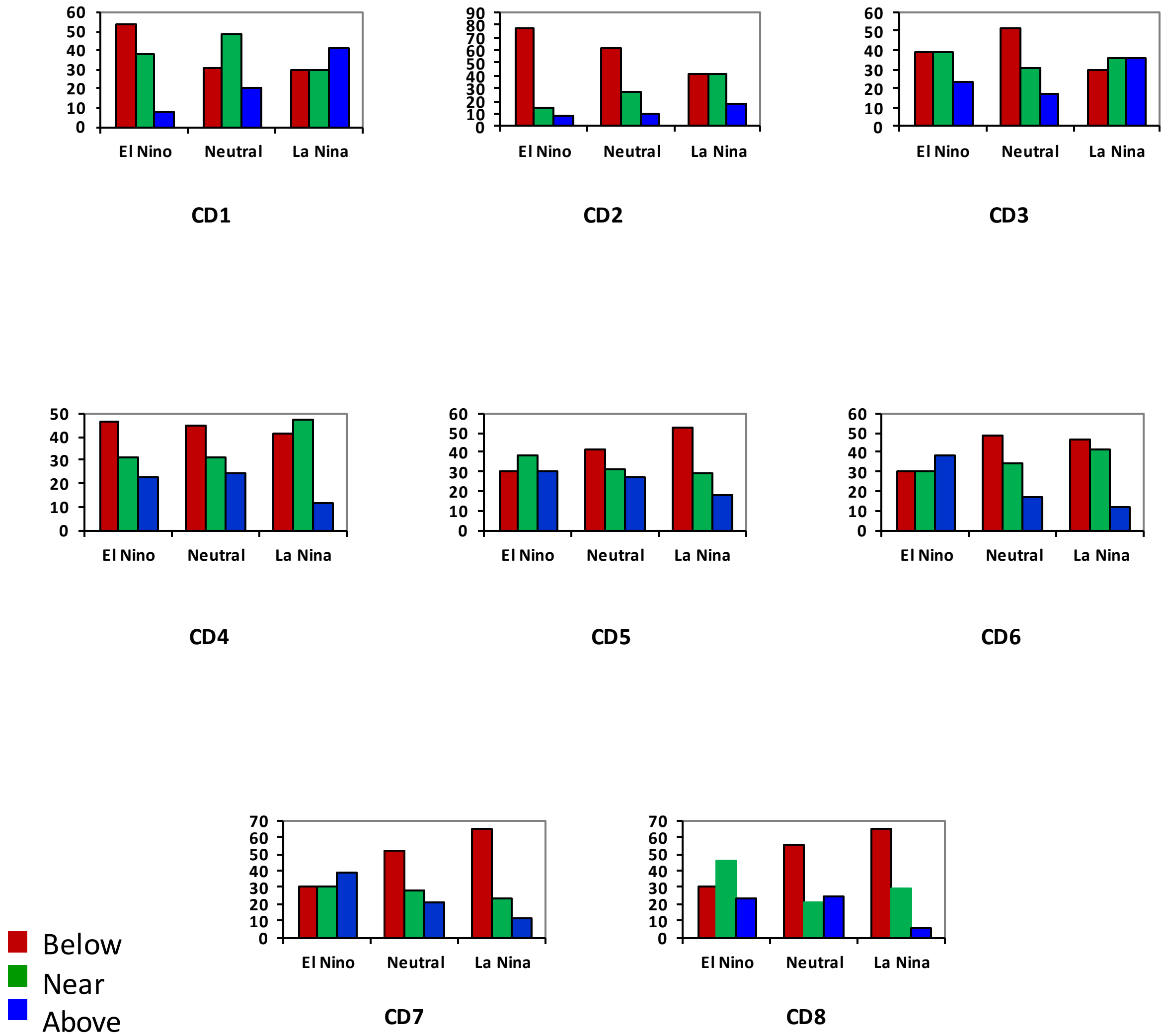


Figure 2.4. Conditional probabilities of precipitation during the three ENSO phases in different climate divisions (CDs 1 through 8) as obtained by the composite analysis for the JFM season.

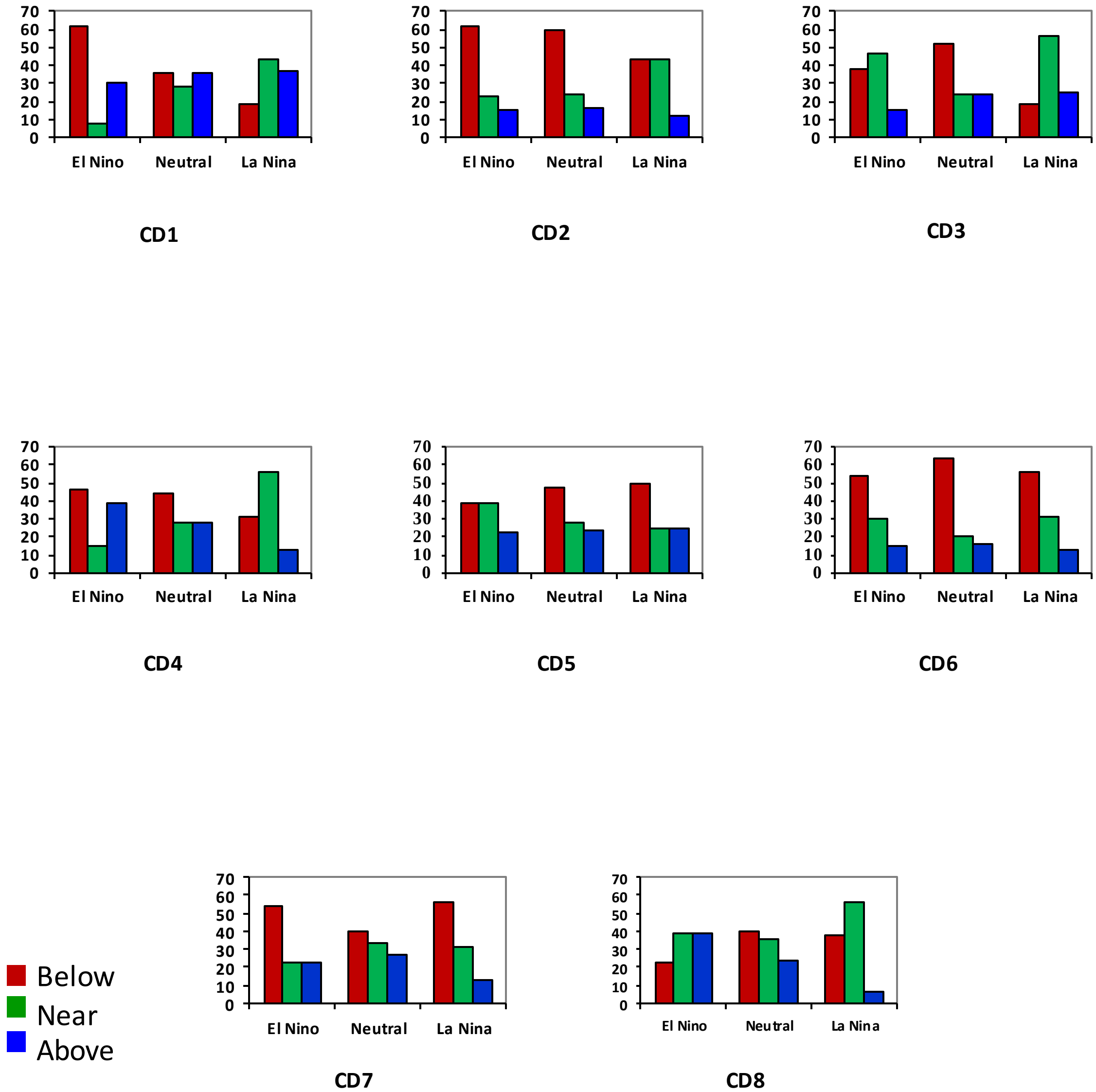


Figure 2.5. Conditional probabilities of precipitation during the three ENSO phases in different climate divisions (CDs1 through 8) as obtained by the composite analysis for the wet season (DJFMA).

2.4.5 Streamflow Variability

The streamflow dataset was comprised of data from eight streams or stream gauge stations, one in each climate division. These were the Flint River, Paint Rock River, Kelly Creek, Sipsey

Fork, Hillabee Creek, Noxubee River, Uchee Creek, and Chickasaw Creek in climate divisions 1, 2, 3, 4, 5, 6, 7, and 8, respectively. The mean monthly flows of all the streams being considered are shown in Figure 2.6. From the figure, it is clear that, for all the streams, most of the flow occurred from January through March with mean monthly streamflow being highest in March. Because December and April also had high flows and the clear impact of ENSO on precipitation was observed during this period or wet season (DJFMA), as discussed in previous sections, the relationship between ENSO and streamflow is presented only for this season. However, for correlation, all five seasons are discussed to show the strength of this relationship throughout the state of Alabama.

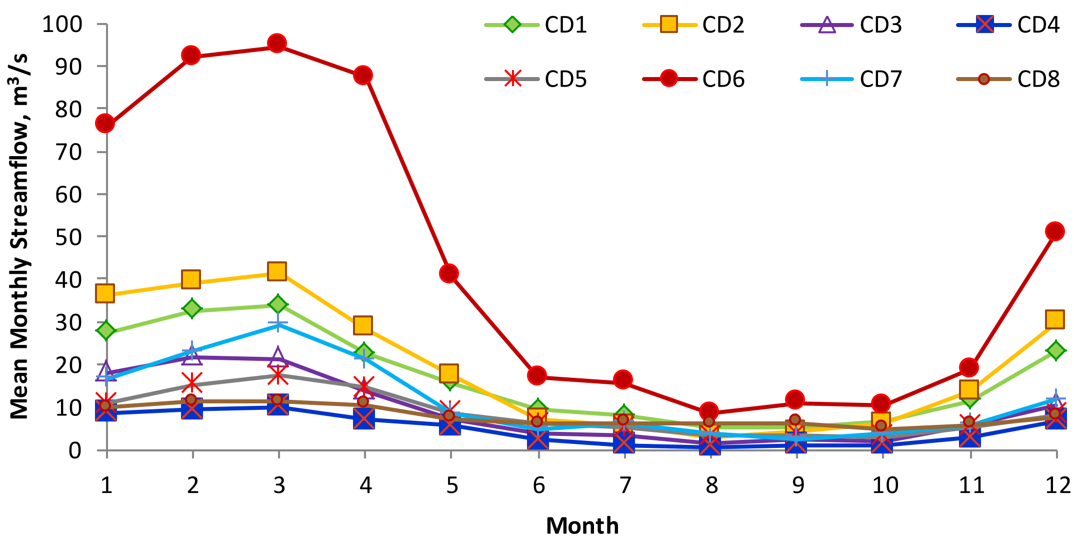


Figure 2.6. Mean monthly streamflows of all the streams used in this study. The names and watershed area for the streams in each climate division are: CD1 - Flint River (88577.6 ha), CD2 - Paint Rock River (82879.6 ha), CD3 - Kelly Creek (49986.8 ha), CD4 - Sipsey Fork (23853.8 ha), CD5 - Hillabee Creek (49209.8 ha), CD6 - Noxubee River (284121.7 ha), CD7 - Uchee Creek (83397.6 ha), and CD8 - Chickasaw creek (32374.8 ha).

The mean streamflows normalized by the drainage area according to different ENSO phases are presented in Figure 2.7 for the DJFMA season. El Niño streamflows were higher than Neutral and La Niña streamflows during this season in the southern climate divisions, and these results were similar to precipitation results. Streamflows were on an average 13% higher during El Niño than under Neutral conditions in climate divisions 5, 6, 7, and 8. In the northern part of the state, La Niña streamflows were higher than normal which was opposite to the trend in climate divisions 5, 6, 7, and 8, where La Niña streamflows were lower than Neutral ones. Climate division 4 streamflows did not show any response to ENSO for the wet season as the flow was almost the same in all of the three phases. The streamflows in climate division 6 displayed the highest variability in the state, which could be because the Noxubee River watershed in climate division 6, among all the watersheds used in this study, had the largest area and might experience higher rainfall spatial variability. These results were similar to but not in total agreement with the precipitation variability results. Dettinger and Diaz (2000) suggested that this difference between precipitation and streamflow response tp ENSO could be due to several reasons including: (i) precipitation freezing in a season and being released as snow-melt subsequently in a season of a different ENSO influence, (ii) different ENSO signals upstream of the stream-flow gauging station coupled with long, stream-flow travel time, (iii) storage in underground reservoirs, (iv) seasonality in evaporation, and (v) groundwater recharge–discharge mechanisms. Out of these, seasonality in evaporation is the most likely reason given the conditions in the state of Alabama.

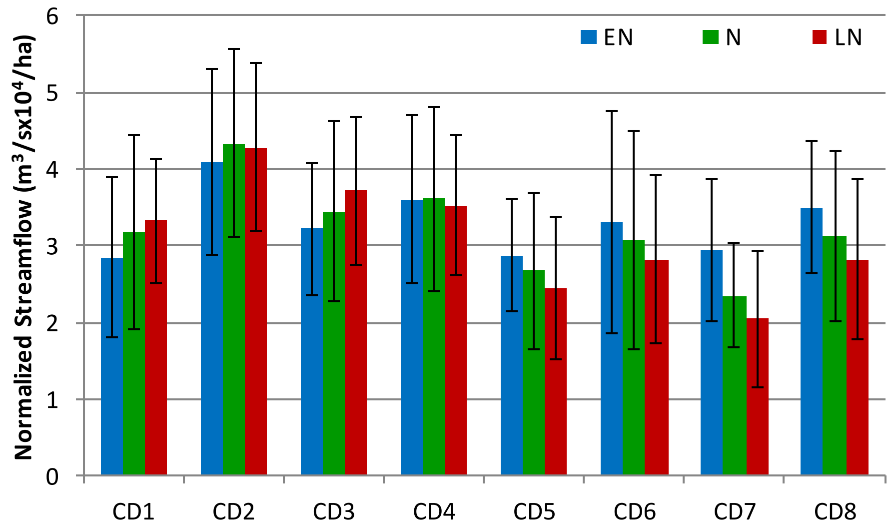


Figure 2.7. Mean monthly streamflow normalized by watershed area for DJFMA for different ENSO phases in each climate division. Also shown are standard deviation error bars. In the legend, EN = El Niño, N = Neutral, and LN = La Niña.

2.4.6 Correlation between ENSO and Streamflow

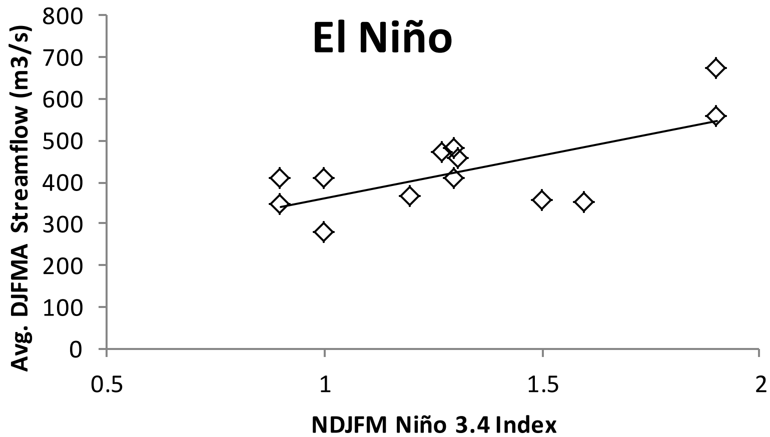
The results for correlation between ENSO and streamflow are presented in Table 2.4 with the cells with an asterisk representing significant correlations. During winter months, mean streamflows in climate divisions 5, 7, and 8 showed a positive correlation with the Niño 3.4 index at a 90% level of significance. Significant correlation between streamflows and ENSO was observed in climate divisions 1 through 4 during OND. Apart from this, climate division 1 had negative correlation for JFM and positive correlation during AMJ, which means lower (higher) streamflow during El Niño (La Niña) and higher (lower) streamflows during El Niño (La Niña), respectively.

Table 2.4. Pearson's (r) and Kendall's (τ) Correlation Analyses results between ENSO and streamflows.

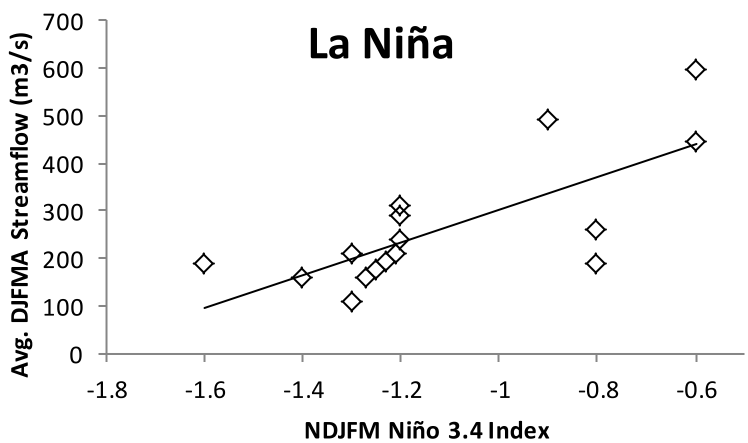
Climate Division	JFM		AMJ		OND		DJFMA		AMJJAS	
	r	τ	r	τ	r	τ	r	τ	r	τ
CD1	-0.25*	-0.17*	0.12*	0.10*	0.22*	0.06*	0.08	0.06	-0.03	-0.05
CD2	-0.13	-0.11	0.01	-0.01	0.17*	0.10*	0.03	-0.01	-0.11	-0.08
CD3	0.03	-0.01	-0.11	-0.05	0.16*	0.09*	-0.18	-0.14	0.01	-0.01
CD4	0.06	-0.01	0.06	-0.03	0.08*	0.09*	0.15	0.04	0.13	0.01
CD5	0.26*	0.19*	0.05	0.04	0.10	0.13	0.27*	0.18*	0.06	0.04
CD6	-0.12	0.07	0.06	0.03	-0.01	-0.03	-0.13	-0.13	-0.03	-0.10
CD7	0.41*	0.28*	-0.02	0.04	0.17	0.11	0.42*	0.26*	-0.09	-0.04
CD8	0.30*	0.17*	0.09	0.07	-0.09	-0.04	0.29*	0.18*	-0.03	-0.03

*Significant correlation

Lag correlation results are presented in Figure 2.8 for DJFMA in climate division 8. Lag correlation analyses showed that during El Niño events the streamflow anomalies had strong lag correlations with the sea surface temperature anomalies (Niño 3.4 index), with the correlation coefficients varying between 0.15-0.68, the strongest being for one-month lag correlations (Figure 2.8a). Three to four months lag correlations were also observed during La Niña events, with the strongest correlation coefficients for a one-month lag (Figure 2.8b). It was found that the highest correlations were obtained for a one-month lag period in most of the climate divisions. That is, the ENSO effect on streamflow was lagged by one month. Also, as was the case with correlations, the lag-correlations were different for different parts of the state. These correlations were relatively higher during the winter months and the recharge season (DJFMA) as compared with the summer and fall seasons. These results indicate that there is a potential for forecasting streamflow one month in advance, especially during winter months, which can be very helpful to the regional water resource managers.



(a)



(b)

Figure 2.8. Niño 3.4 versus streamflow plot showing one-month lag correlation for (a) El Niño (0.68) and (b) La Niña (0.74) for the climate division 8 for DJFMA (wet season).

2.4.7 Composite Analysis – Streamflow

The results of composite analysis conducted on ENSO and streamflow for the wet season are presented in Figure 2.9. It was found that there is more than a 52% probability for the La Niña streamflows to be below normal in the southern climate divisions 6, 7, and 8. A high probability of El Niño streamflow being near normal (56%) in climate division 1 and La Niña streamflow being near normal (67%) in climate division 3 was observed. Also, there is a 54% probability that the El Niño streamflow will be more than normal in climate division 7. These results are similar to but not as clear as those obtained for precipitation, which might also be due to the lagged response of streamflow to ENSO.

2.5 Summary and Conclusions

This study was undertaken to explore the impact of ENSO on precipitation and streamflow in the state of Alabama. The Niño 3.4 ENSO index was used to study the relationship using historic precipitation and streamflow datasets. Four seasons, JFM, AMJ, JAS, and OND, and two 'municipal' seasons, wet season (DJFMA) and growing season (AMJJAS), were used to group the monthly mean precipitation and monthly mean streamflows. The precipitation data were obtained from 49 stations, which were then grouped into eight climate divisions. For streamflows, one unimpaired stream was selected in each climate division. The results obtained are in broad agreement with previous studies conducted in the southeastern United States. However, this more detailed study of Alabama has resulted in some new observations, which can be put to effective use by managers of the state in their decision-making process related to soil and water conservation.

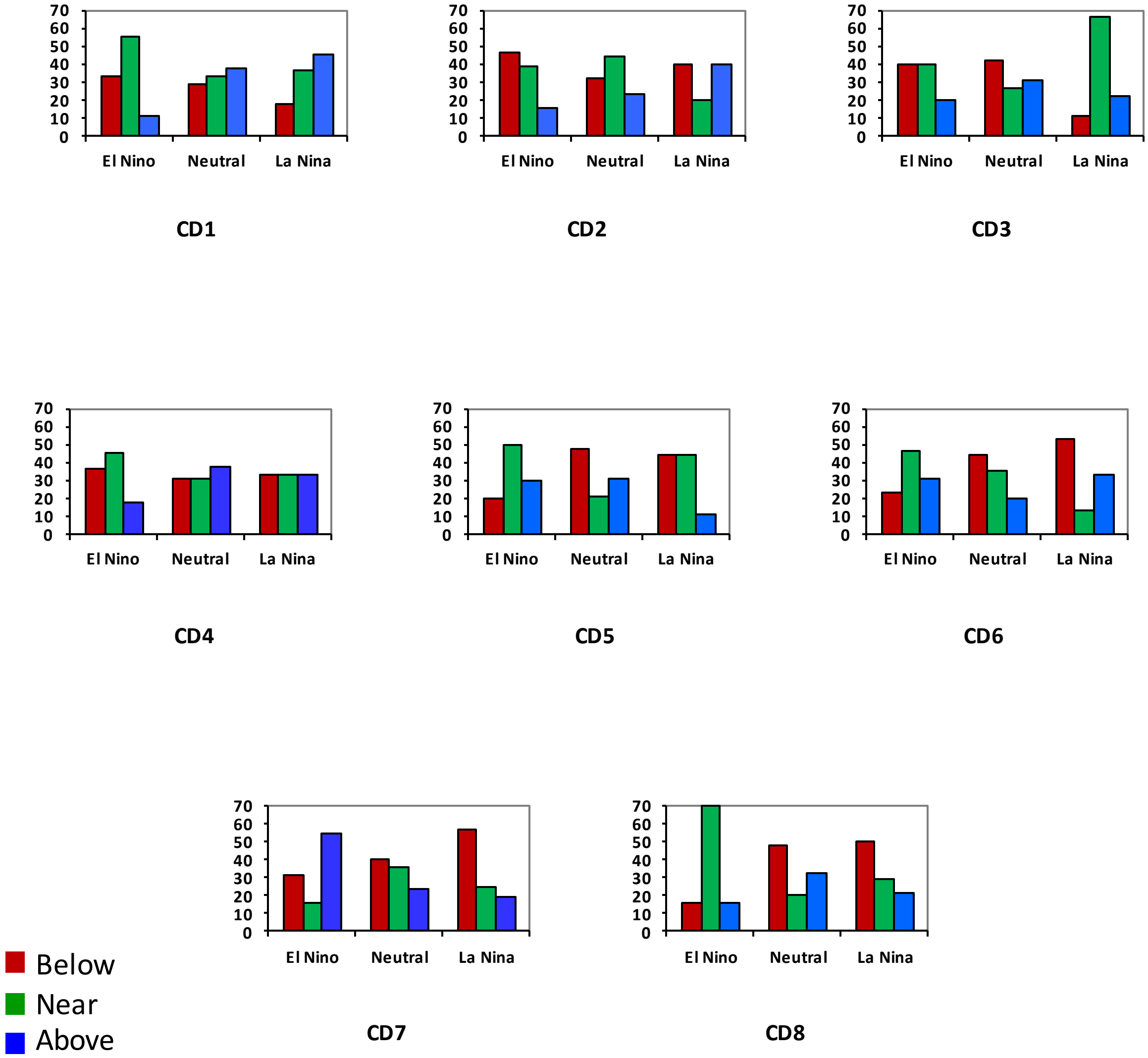


Figure 2.9. Conditional probabilities of streamflow during the three ENSO phases in different climate divisions (CDs 1 through 8) as obtained by composite analysis for the wet season.

Both seasonal precipitation and streamflows showed strong response to the inter-annual variability in the tropical Pacific Ocean represented in this study by Niño 3.4 SST anomalies. It was observed that dry conditions during winter months in the southern climatic divisions (6, 7, and 8) tend to be associated with La Niña. These climate divisions also showed a more than

50% decrease in La Niña precipitation during JFM. Significant correlation was found between Niño 3.4 and precipitation anomalies in climate divisions 7 and 8 during the winter months. Northwestern climate divisions demonstrated negative correlation in the winter months indicating an opposite effect as compared to 7 and 8. The correlation was not very strong or nonexistent for most of the central climate divisions during AMJ and AMJJAS. Climate divisions 7 and 8 had a high probability of precipitation that was below (above) normal for La Niña (El Niño) events during JFM, AMJ and OND. Most of the climate divisions had a high probability of neutral precipitation that was also below normal during the winter months, which is a very important factor for water resource management. The anomaly maps showed that dry La Niña events extend up to climate division 5 and some parts of climate division 6 during winter months. JFM and DJFMA showed the clearest impact of ENSO on precipitation anomalies from south to north.

La Niña streamflows were lower than normal and El Niño flows in climate divisions 6, 7, and 8 during the wet season, whereas there was opposite impact in climate divisions 1, 2, and 3. Streamflows showed a high variability in all the climate divisions and a strong positive correlation during winter months in the southern climate divisions. OND streamflows were also significantly correlated with ENSO in the northern climate divisions. There was more than a 50% probability that La Niña streamflow would be below normal in the southern climate divisions of the state. Lag correlations indicated that there was a one-month lag in the ENSO impact on streamflow and that the Niño 3.4 index can be used with some success to forecast streamflow in some parts of the state at least one month in advance.

In conclusion, the relationship between the Niño 3.4 index, precipitation, and streamflows are significant during the winter season in Alabama and that dry conditions during winter months in the southern climatic divisions (6, 7, and 8) of the state tend to be associated with La Niña. The streamflows show a high variability and a positive correlation and indicate a one-month lagged response to ENSO during winter months in the southern part of the state. These results also show that the state doesn't respond to ENSO uniformly with respect to precipitation and streamflow and that the impact is different in the South as compared with the North.

Knowledge of this pattern of seasonal variation in association with ENSO forecasts can help water resource managers of the state with decision-making. In particular, it can give them lead time for planning. This study can be used to convince state water managers to increase their use of seasonal ENSO forecasts in the decision-making process. The water managers can use the results of this study to assess ENSO impact on the precipitation and streamflow in their region and can get an idea of what the regional supply and demand of water will be. This advance knowledge combined with ENSO forecasts will lead to the mitigation of negative impacts by allowing managers to make timely water conservation decisions, thus curbing excessive water use when there is an ample supply and imposing timely water restrictions when there is a shortage. Also, this information can be used for agricultural irrigation scheduling, planning for point discharge of contaminants into streams, monitoring lake and reservoir water quality, predicting monthly nutrient loads in streams, and facilitating management in high risk seasons, implementing plant-based Best Management Practices (BMPs) for soil conservation. All of these uses have implications for soil and water conservation.

CHAPTER 3

DEVELOPMENT OF COMMUNITY WATER DEFICIT INDEX (CWDI) – A DROUGHT FORECASTING TOOL FOR SMALL TO MID-SIZED COMMUNITIES OF THE SOUTHEASTERN UNITED STATES

3.1 ABSTRACT

El Niño Southern Oscillation (ENSO) climate variability phenomenon greatly affects water availability in the Southeast USA. For example, it is well-known that La Niña conditions bring drought to this region. In the past decade, several severe droughts have adversely impacted the water resources of many communities in this region, especially those that rely on surface water systems. Since small- to mid-size communities are the most vulnerable to climate variability, this study was undertaken to develop a climate variability-based Community Water Deficit Index (CWDI) for use by water managers in these communities. While, drought indices can be useful tools for monitoring and forecasting purposes, currently available drought indices are not suitable for use in water supply systems for small to mid-sized communities. The CWDI was conceptualized keeping in mind that it should: (1) forecast hydrologic drought, (2) operate at a high spatial resolution, and (3) address both water supply and demand during droughts. System dynamics modeling software STELLA® was used to develop the modeling framework to estimate CWDI by evaluating differences in a community water supply and demand, and thus help predict the severity of an impending drought. Another important feature of the CWDI is its ability to evaluate how drought management policies can affect the severity of drought. CWDI was tested in two small- to mid-size communities of this region (Auburn, AL and Griffin, GA). The results indicate that the index not only can monitor drought in the studied water supply systems, but can also forecast ENSO-induced droughts in the region and be used in drought planning.

3.2 Introduction

As global climate systems evolve, there is an increasing need to understand how changes have been and will be manifested at regional and local scales. It has been reported in the literature that climate variability greatly influences water availability (Jenerette and Larsen, 2006). Water managers throughout the world are facing the increasing challenge of supplying water under the growing, combined stresses of population growth and climate variability.

Climate variability signals, such as El Niño Southern Oscillation (ENSO), Pacific Decadal Oscillation (PDO), Atlantic Multidecadal Oscillation (AMO) and North Atlantic Oscillation (NAO), and their relationship with hydrologic variables have been studied in the past and used in regional water resource planning (Battisi and Sarachik, 1995; Mantua et al., 1997). Of all these ocean-atmospheric phenomena, ENSO has been studied the most comprehensively, both at global and regional scales (Ropelewski and Halpert, 1987; Andrews et al, 2004; Schmidt et al., 2001). The ENSO is a coupled, ocean - atmospheric phenomenon that is centered over the eastern equatorial Pacific Ocean and maintains an irregular 2-7 year periodicity that gives it some level of predictability, yet it retains some variability in its occurrence, magnitude and climate consequences around the world (Cane, 2005). The ENSO can be divided into the cold (La Niña) and warm (El Niño), and Neutral phases. There are several accepted indices in use including the Niño 1 & 2, Niño 3, Niño 3.4, Niño 4, Multivariate ENSO Index (MEI), and Japan Meteorological Agency (JMA) index. Each uses slightly different definitions of ENSO coordinates and phases and is relevant to different regions around the world. In this study, the National Oceanic and Atmospheric Administration (NOAA) Niño 3.4 index was used for the definition of the ENSO phase. This index is based on a three-month, extended reconstruction, sea surface temperature (SST) analysis (ERSST.v3b), which includes average SST anomalies in the Niño 3.4 region (5°N -5°S and 170°W - 120°W) of the Pacific. This region has been reported (Trenberth and Hoar, 1996) to be the main area where sea level pressure and temperature anomalies are very well-correlated. If the Niño 3.4 index is more than +0.5°C, the event is termed as El Niño, and, if the index is less than -0.5°C, the event is termed as La Niña. A neutral phase is defined when the Niño 3.4 index is between +0.5°C and -0.5°C.

Droughts remain one of the most widespread effects of climate variability and cause considerable damage. The western US have been plagued with persistent droughts this century and have developed approaches to deal with this problem. The Southeast United States, however, has been long spared, but suddenly finds itself among the most rain-starved regions of the country (Manuel, 2008) and ill-prepared to deal with such. La Niña brings warm and dry conditions to this region between October and April (Mearns et al., 2003) and typically returns every two to seven years, making the Southeast vulnerable to ENSO-related droughts. In the winter of 2007, the arrival of La Niña resulted in drought throughout the Southeast and deficits in rainfall during the recharge period accentuated water resource concerns. Ryu et al. (2010) reported that different relationships between ENSO and hydrologic drought exist in different parts of the United States, and that the type of relationship, when established on a regional basis, can help water managers in minimizing the impact of hydrologic events associated with ENSO.

Various studies on application of ENSO to drought (Barlow et al., 2001; Ropelewski and Halpert, 1987; Karl and Koscielny, 1982) have been done in the past, but few have focused on hydrologic drought (Piechota and Dracup, 1996; Ropelwwski and Halpert, 1986) and ENSO-driven, hydrologic drought forecasting (Ryu et al., 2010).

Forecasts of ENSO-induced hydrologic droughts can provide insight to water managers to store more water during the recharge season, when lower than normal precipitation is forecasted, and to impose timely restrictions during the "growing season" when outdoor residential water use increases. In the Southeastern states, winter months constitute the recharge season and drier conditions during winter increases the odds of drought during the following spring and summer. The water supply in many of the small- to mid-size communities in the region depends on surface water sources, and management of water supply and demand during drought conditions is critical for these communities in order to meet daily demands and assure unbroken supply.

The ability to forecast drought conditions in advance is fundamental to mitigating the detrimental effects associated with droughts (Mishra et al., 2007). In recent years, various hydrologic drought indices have been developed including Total Water Deficit, Cumulative Streamflow Anomaly, Palmer Hydrological Drought Severity Index (PHDI), and Surface Water Supply Index (SWSI), among others. Although useful for managing many types of droughts on regional and big basin or watershed scales, these indices are of limited use to municipal water managers in small- to mid-size communities because of three main reasons: (1) high spatial variability of rainfall in the Southeast due to convective rains during the summer months and the relatively small size of these communities requires an index that can operate at a high spatial resolution; (2) management of municipal drought has two main components: supply and demand, both of which are affected by drought and are not adequately addressed by currently available indices; and (3) most of the currently available indices provide drought information that is based on past and current data, and do not forecast how the drought might progress based on future climate forecasts. Resolving these issues is crucial for developing a drought index that is useful for municipal water managers in these communities. Based on this background, this study was undertaken to develop a Community Water Deficit Index (CWDI) for small- to mid-size communities of the Southeastern United States for disseminating ENSO-based drought information. The novelty of this index lies in the fact that, unlike other available indices, it addresses both water supply and demand components, operates at a high spatial resolution, and forecasts drought 3 to 6 months in advance while utilizing the underlying climate variability signal in the region. The methodology presented in this paper provides a framework for general use across similar communities in this region but, at the same time, can be customized for use by a particular community.

A brief description of the concept of the model is first presented, followed by descriptions of the design of the model framework leading to forecasting the drought index, formulation of the model, use of STELLA for modeling, and the method and data used for forecasting drought with the CWDI.

3.3 Methodology and Model Development

Singh (1995) observed that all watershed models need to be packaged at the level of a user who is not necessarily a hydrologist and should be integrated with, or at least have the capability of being integrated with, social, economic and management modules. Keeping in mind that the end users of this model are the stakeholders, namely, water managers, water managers, a simple watershed modeling approach, based on the guidelines discussed earlier was applied to develop the Community Water Deficit Index (CWDI). CWDI is described here as a tool that can be used for better water management during drought. It is based on the balance between the water supply and demand according to the ENSO outlook in the region. The index is a result of integrating climatic factors, hydrological processes, and management parameters into a simulation model. Some assumptions have been made in the methodology to make the index simple to understand while not compromising its scientific merit. It is assumed that, irrespective of the source of water supply, each community has a reservoir to store water; the source of supply to this reservoir can be a river, a watershed draining into the reservoir, or supplemental supply from a groundwater well or purchased water; there is a supply watershed and a demand watershed; and the supply watersheds have minimal land cover changes making climate the driving factor affecting the supply of water.

3.3.1 MODELING FRAMEWORK

The CWDI is forecasted by using an integrated modeling approach in which different parts are connected together to obtain the drought forecast (Figure 3.1(a)). The first part of the integrated model consists of analyzing the watershed characteristics, such as, topography, landuse/land cover, and soils, using the Environmental Systems Research Institute's (ESRI) ArcGIS. These watershed characteristics along with input parameters for the model are stored in Microsoft Excel which then connects this part of the model to the second part, serving as the intermediate link between the two parts. The second part of the model is the development of the actual model in the Systems Thinking for Education and Research (STELLA) (HPS 2001) and consists of various modules. All the input parameters, relationships, limiting factors, model map and the user interface are included in this part. The third part consists of analyses that are done to study the impact of ENSO-based climate variables on drought forecasting.

3.3.2 Model Formulation

The research methodology presented below is general and can be adapted by different communities depending upon the different water supply scenarios that a community or municipality may have. The basic principle behind this model is the reservoir water balance given by:

$$\frac{dS}{dt} = I - O \tag{1}$$

where,

dS/dt =rate of change in storage of the reservoir,

I = inflows into the reservoir, and

O = outflows from the reservoir.

Inflow from the supply watershed is assumed to have two components: surface runoff and baseflow. Soil Conservation Service (SCS) runoff curve number method (USDA Soil Conservation Service 1974) is used to calculate runoff from the watershed.

$$R = \frac{(P - I_a)^2}{P - I_a + S_r} \qquad \text{for } P > I_a \tag{2}$$

$$S_r = \frac{25400}{CN} - 10 \tag{3}$$

where R is the runoff depth (mm); P is the rainfall depth (mm); I_a is the initial abstraction (mm) and is equal to $0.2S_r$ and gives the amount of water needed before runoff begins, i.e., water lost to interception and/or the infiltrated water; S_r is the potential maximum soil moisture retention (mm) and *CN* is the Curve Number. The CN is also adjusted for season and for the antecedent moisture condition (AMC, total 5-day antecedent rainfall) using the method given by McCuen (2004). In this method, AMC is categorized into three categories: I – dry/wilting point, II – average moisture, and III - wet (field capacity). The range of AMC values depends on the cropping season being dormant or growing.

Baseflow is one of the most important low flow hydrologic characteristics of a watershed and obtaining its value is important for water management strategies, especially regarding drought conditions (Lacey and Grayson, 1998). The model is set up to use the method provided by Neitsch et al. (2005) to estimate baseflow using Equation 4. It is assumed that there is no bypass flow.

$$Q_{gw,i} = Q_{gw,i-1} \cdot exp\ -\alpha_{gw} \cdot \Delta t\ + W_{rechrg,i} \cdot\ 1 - exp\ -\alpha_{gw} \cdot \Delta t \qquad (4)$$

Where,

$Q_{gw,i}$ = groundwater flow or base flow into the main channel on day *i* (mm),

$Q_{gw,i-1}$ = groundwater flow or base flow into the main channel on day *i* –1 (mm),

α_{gw} = base flow recession constant,

Δt = time step (days),

$W_{rechrg,i}$ = amount of recharge entering the aquifer on day i (mm) that takes place due to percolation.

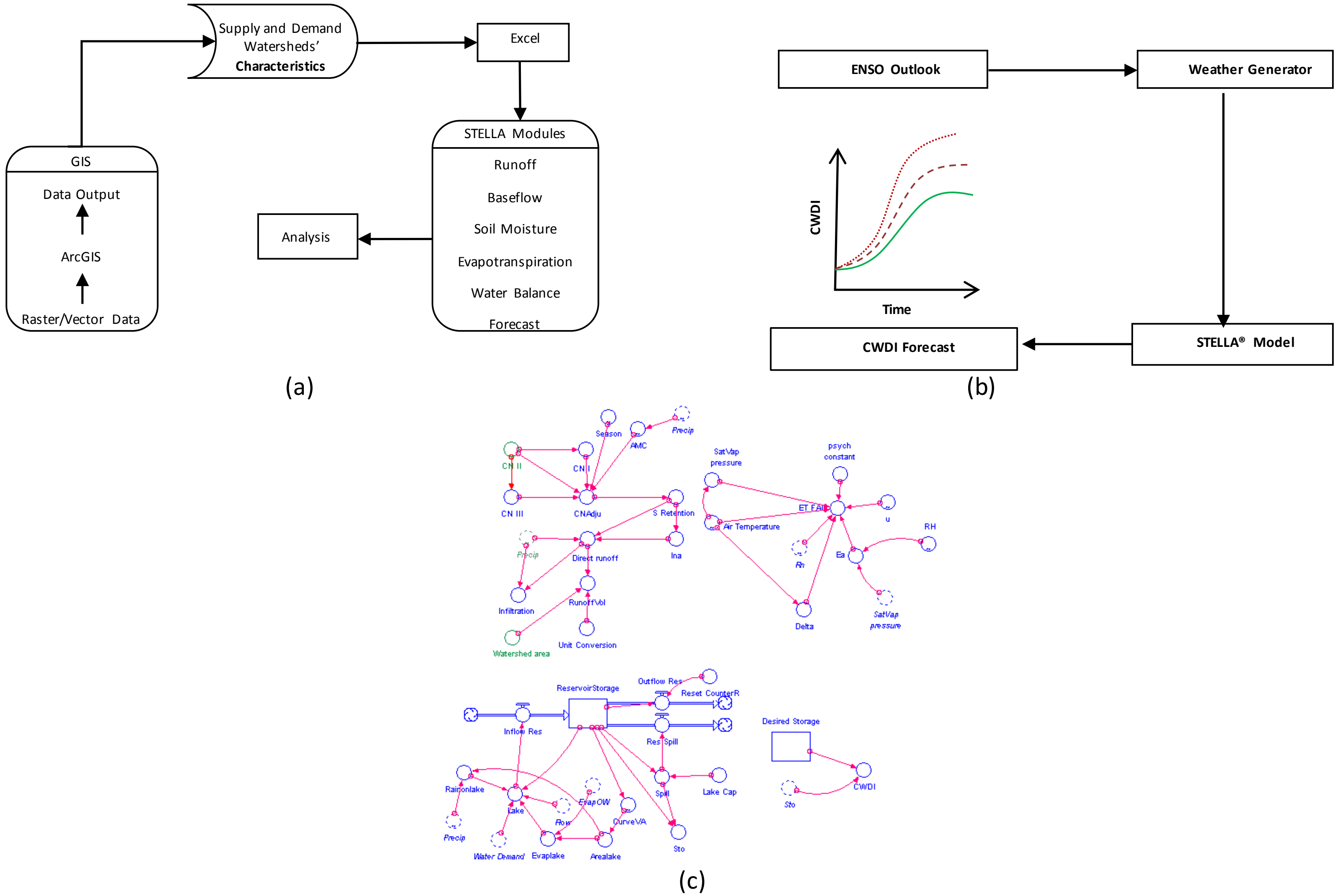


Figure 3.1 Framework of the model showing (a) input data and modules of the STELLA model, (b) framework of the forecasting module, and (c) example modules as implemented in the CWDI STELLA model.

This method requires knowledge of input variables that describe the physical properties of soils in the watershed along with daily soil moisture balance. The daily soil moisture balance is calculated using infiltration, percolation, and evapotranspiration. The details of this method can be found in Neitsch et al. (2005). The sum of the runoff generated by the watershed and the baseflow will give the total generated streamflow, Q_{in}.

$$Q_{in} = R + Q_{gw} \tag{5}$$

Total inflow into the reservoir, I, on a daily time step can be obtained using Q_{in} along with purchased water (PS, if any), groundwater pumped in as an external source (G, if any) and precipitation falling directly into the reservoir (Pr). The parameters PS and G are user inputs in the model, and when no supplemental water supply is available, these can be set to zero.

$$I = Q_{in} + PS + G + P_r \tag{6}$$

Outflow from the reservoir consist of the water withdrawal for distribution (W), evaporation from open water surface (E), and any other discharges (Q_{out}).

$$O = W + E + Q_{out} \tag{7}$$

W is the total demand that arises in the demand watershed. This watershed can be different from, same as, or can have some overlap with the supply watershed. The demand can be partitioned into two components: static and dynamic demand, i.e.,

$$W = W_d + N.W_s \tag{8}$$

where N is the total population served by the water distribution system, W_s is the static demand which depends only on the population being served and does not have a climatic component. This component of water demand can be obtained from the past water consumption data provided by the user or can be estimated using the per capita consumption (Tidwell et al., 2004). W_d is the dynamic demand and fluctuates with changing climatic conditions. The driver of dynamic demand is outdoor water use or irrigation demand due to loss of soil moisture because of evapotraspiration (ET) and is related to the soil moisture deficit, so it is calculated by using the relation:

$$W_d = PET - AET \ . A \tag{9}$$

where *PET* is potential evapotranspiration, *AET* is actual evapotranspiration, and *A* is total irrigated area (area under lawns,) in the demand watershed.

PET is defined as the rate at which ET occurs from a large area that is completely and uniformly covered with growing vegetation which has access to an unlimited supply of soil water (Dingman, 2002). The FAO 56 Penman Monteith method (Allen et al., 1998) is used to estimate *PET*. The Penman-Monteith equation, which estimates ET realistically from various surfaces, climatic conditions, and at different scales (Jensen et al., 1990), is as follows:

$$PET = \frac{0.408 * \Delta * R_n + \gamma * \frac{900}{T + 273} * u * (e_S - e_a)}{\Delta + \gamma * (1 + (0.34 * u))} \tag{10}$$

where *PET* is in mm/day, Δ is the slope of vapor pressure curve (kPa°C^{-1}), R_n is the net radiation at the grass surface (MJ m2 day^{-1}), γ is the psychometric constant (kPa°C^{-1}), T is the mean daily air temperature in (°C), u is the wind speed (m s^{-1}), e_s is the saturation vapor pressure (kPa), and e_a is the actual vapor pressure (kPa).

PET calculations assume that there is no moisture stress in the soil and that the water is freely available to the plants. When soil moisture availability limits ET, these methods require major calibration and validation to estimate *AET* (Saxton, 1982). Many methods have been developed for estimating AET, which depends on climatic factors, crop growth parameters, and soil moisture. For the CWDI, method given by Khan et al. (2009) is used. According to this method

$$AET = PET * K_c * K_s \tag{11}$$

where, K_s is a dimensionless factor expressing the effects of limiting soil moisture conditions on crop ET; and K_c is crop coefficient (Allen et al., 1998), which depends on type of grass being grown in the area and also on time of the year. K_s is estimated using the total available soil water and readily available soil water in the root.

For the case studies (discussed later), total irrigated area within the limits of the water distribution system was calculated using the National Land Cover Database (MRLC 2001) along with the imperviousness dataset obtained from the National Land Cover Dataset (NLCD) website. Lawn area was calculated by subtracting the percentage of impervious area from total developed area categories of the NLCD dataset.

Evaporation from open water surface (E) is estimated using the method given by Valiantzas (2006). This method uses same climatic and atmospheric variables as the PET method. This value is then multiplied by the surface area of the reservoir obtained from stage-area characteristic curve of the reservoir to obtain the volume of water evaporated from the reservoir. Mandatory discharge data (Q_{out}) is provided by the user. Total outflow from the reservoir is then calculated using equation (7) followed by total available storage, S. The

Community Water Deficit Index (CWDI) at a daily time step is then defined using these components as:

$$CWDI = \frac{S}{S_d} - 1 \quad (12)$$

where, S_d is the desired storage in the reservoir. Desired storage can be different during different times of the year and is a user- defined variable. In this study, S_d can be set as the storage below which the reservoir levels fall under Phase I drought according to a community's drought plan.

$$\text{If } S \geq S_d,\ CWDI \geq 0, \Rightarrow \text{No deficit} \quad (13)$$

$$\text{If } S < S_d,\ CWDI < 0, \Rightarrow \text{Deficit} \quad (14)$$

3.3.3 Model Realization in STELLA™

Based on the concept of CWDI as described in the previous section, a modeling approach with specific characteristics is needed. These characteristics are: (1) watersheds can be described and simulated in a simple fashion, (2) the model should rely on available data and be expandable to benefit from additional data as they become available, (3) it should be dynamic so as to cope with the nature of hydrologic systems, (4) it should provide a way to represent feedback mechanisms, (5) it should have the ability to model human intervention, and (6) it should provide the ability to test different policy or management scenarios for better decision-making.

Although it might appear difficult to have all of these characteristics embodied in one modeling approach, the development of system dynamics modeling (Forrester, 1961, 1968; Sterman, 2000) has made it possible (Elshorbagy and Ombrsee, 2005). These models have the potential for implementing a combination of empirical formulations and physically-based concepts, and also allow building based on a tentative knowledge of the relationship between two parameters by incorporating a qualitative relationship between those parameters (Elshorbagy et al., 2007). The use of system dynamic models for improved water resource management does not have a long tradition (Stave, 2003) but has been recently applied to different water resources fields (Xu et al., 2002) like watershed planning (Palmer et al., 1999) and reservoir operation (Ahmed and Simonovic, 2000). Winz et al. (2009) and Simonovic and Rajasekaram (2004) reported that system dynamic models have been used at a finer spatial scale of basins and watersheds with the aim of identifying regional and local solutions.

For this study, a simple hydrologic model was developed using the system dynamic software STELLA^{TM} 9.1. It is a commercially available, general purpose mathematical simulation object-oriented modeling software, which means that the user can create model code using the point-and-click, drag-and-drop mouse-based editing. The building blocks of any STELLA model include a STOCK variable, a FLOW or rate variable, a CONVERTER variable, and a CONNECTOR for linking them together in a manner that shows functional dependence. Simulation algorithms (4th-order Runge-Kutta) were applied to each simulation procedure with a daily time step. Figure 3.1 (a) shows different modules in the STELLA model which include: (1) Rainfall-runoff module, which simulates the direct runoff, effective rain caused by precipitation and infiltration (input for the soil moisture module); (2) Soil moisture module, which calculates the change in soil moisture caused by infiltration, evapotranspiration and percolation; (3) Baseflow module, which simulates the groundwater flow into the channel; (4) Evapotranspiration module, which simulates the dynamic water demand of the community; and (5) Water balance module, which simulates the storage in the reservoirs, with inflows and outflows. Figure 3.1 (b) shows the steps of the Forecasting module of the model which involves the use of ENSO forecasts to generate ENSO-constrained weather inputs for CWDI model in STELLA and produces an ensemble forecast. Figure 3.1 (c) shows some of the modules as implemented in the CWDI STELLA model.

Although this model and study describe the methodology of CWDI and development of this model using SETLLA, the ultimate goal is to develop a customizable web-based system that can be used by multiple communities. This paper does not discuss the implementation of this methodology as a web-based tool.

3.3.4 Drought (CWDI) Forecasting

A drought index may be forecast based on various approaches. One such approach is the use of climate or teleconnection indices as predictors of drought because atmospheric circulation patterns have been shown to exert influence on the occurrence of droughts (Stahl and Demuth, 1999). Spatially-averaged areas of sea surface temperatures in various parts of the world are particularly relevant to describing climate phenomena at specific locations and the El Niño/Southern Oscillation (ENSO) has been proven to be one of the most consistent indices in describing low-frequency climate variability on both regional and local scales (Ropelewski and Halpert, 1986).

For forecasting drought based on ENSO outlook, the Spectral Weather Generator (Schoof et al., 2005; Schoof, 2008) was constrained to ENSO phases using historic data. Using observed Niño 3.4 values from the past, climatic variables of interest were divided into different ENSO phases. This ENSO-classified, historic data was then input to the weather generator to obtain climate variables for El Niño, La Niña, or Neutral conditions. This weather generator uses a second order Markov Chain model in which precipitation on the current day is dependent on the two previous days. The method employed in the model involves computation and averaging of monthly, spectral estimates to divulge average variability as a function of frequency, helps the generated series maintain a level of variability similar to the observed series, and ensures a realistic level of day-to-day variability. A detailed description of this method is beyond the scope of this study and can be obtained in the publications listed above. The weather generator produces daily values of precipitation (mm), maximum and minimum surface air temperatures (^{o}C), and total daily solar radiation (M J m^{-2}) and was run 32 times to get an ensemble of inputs for drought forecasting.

The NOAA Climate Prediction Center (CPC) issues official Seasonal Outlooks for surface temperature and precipitation each month for up to one year, and these outlooks are based on ENSO predictability in addition to climate trends. However, because the specific daily data from these seasonal forecast datasets are uncertain (Fu et al., 2011), the International Research Institute for Climate and Society's (IRI) (IRI, 2011)ensemble model predictions of ENSO were used to generate multiple ensembles of daily data according to each particular ENSO phase. In the forecast mode, the model produces a 95% confidence interval band of CWDI values based on an ensemble of generated, climatic variables. CWDI presents a unique and novel drought forecasting tool because a climate variability signal was used to forecast the supply and demand balance for small- to mid-size communities in the ENSO-prone southeastern United States.

3.3.5 MODEL INPUT DATA

Precipitation data are required for several modules of the model. For example, daily and 5-day past precipitation data are needed for estimating AMC and calculating CN and the amount of precipitation directly falling into the reservoir. Land cover data are needed for the calculation of CN and for estimation of the total lawn area of the demand watershed. The runoff module also requires soil properties data which is used in the soil moisture balance as well as in estimating AET. Temperature data is needed in calculating PET and evaporation from open water surface. In addition, data such as population and per capita water demand of the community are needed. For the case studies, daily precipitation and temperature data were obtained from the National Climate Data Center, US Department of Commerce website (NCDC, 2010). To account for the spatial variability of rainfall in the region, all the available stations located in and around the watershed were used, and Thiessen polygons were created to model or approximate the zones of influence around these points (stations). If a detailed network of rain gauges is not available for the region, the best source of spatially distributed data would be the NEXRAD (Next-Generation Radar) data which would be used in the web-based CWDI (future work). For variables used in the Penman-Monteith equation, other than precipitation and temperature, station data (wherever available) was used. If station data were not available, the variables were estimated using the relationships given in FAO paper 56 (Allen et al., 1998). CN was estimated by creating a CN Grid using HEC-GeoHMS in ArcMap 9.3, using land cover data available from National Land Cover Database 2001 (MRLC, 2010) and soils data available from the Soil Survey Geographic (SSURGO) Database (USDA, 2010) with a unique CN for each soil and land use type combination. The calculated runoff depth for each CN was multiplied by the area under that CN and then summed for the entire watershed to obtain total runoff volume. The soil properties from the SSURGO data were used in all the modules requiring soil properties.

3.4 CASE STUDIES

Two communities: Auburn, Alabama and Griffin, Georgia (Figure 3.2) were selected to test the CWDI. These communities can be characterized as fast growing small to mid-size urban areas. In many respects they are typical of non-metropolitan areas of the Southeast US. The model developed is customizable and would be applicable to other small to mid-size communities throughout the Southeast that have similar water supply systems.

3.4.1 CITY OF AUBURN

Auburn, Alabama is home to Auburn University and is experiencing significant population growth and urbanization. The population of the city jumped from 33,830 in 1990 to currently over 50,000, and is expected to grow to 66,000 by 2025. In the past ten years, there has been an apparent trend of increasing water demand (Figure 3.3). The impact of relatively dry and wet years is also clear, which points toward the compound effects of population growth and drought. The impacts of the 2000 and the recent 2007 droughts on the water use are evident from Figure 3.3. The main source of water for City of Auburn (CoA) is Lake Ogletree, which has a surface area of approximately 121.4 ha and is fed primarily by Chewacla Creek (Figure 3.2).

The total watershed feeding the lake encompasses is approximately 8545 ha. The current average usage for the Auburn water system is 22,712.5 m^3/day and the current water supply capacity is 43,911 m^3/day. The city can purchase up to 13,627.5 m^3/day from the City of Opelika Utilities and is required by the Safe Harbor Agreement to discharge a minimum flow of 7,571 m^3/day to Chewacla Creek. Recent droughts have resulted in critically low water levels in Lake Ogletree, in response to which the city prepared a drought management plan which is a crude outline based on a combination of lake levels and consumption and demand rates. According to the drought plan, it is assumed that Lake Ogletree can meet peak water supply needs during droughts provided it is at full pool on May 1st (after winter and spring rains) of any given year. This approach, however, fails during La Niña winters and springs during which the region experiences below normal precipitation (Sharda et al., 2011) followed by an increase in residential irrigation demands during summer months because of high evapotranspiration rates.

3.4.2 City of Griffin

Griffin is located in north-central Georgia (Figure 3.2), about 40 miles south of Atlanta. The current estimated population of the city is around 23,000. The Griffin water supply system is a regional supplier of finished drinking water to seven customers (approximately 85,000 people) including the City of Griffin (CoG). The system consists of two reservoirs: the Head Creek reservoir in Griffin and the Still Branch reservoir in Molena, both of which withdraw water from the Flint River (Fig. 2). The Head Creek reservoir was initially the only reservoir; this was the case when the region experienced extreme drought conditions in 2000, 2002, 2004 and 2006.

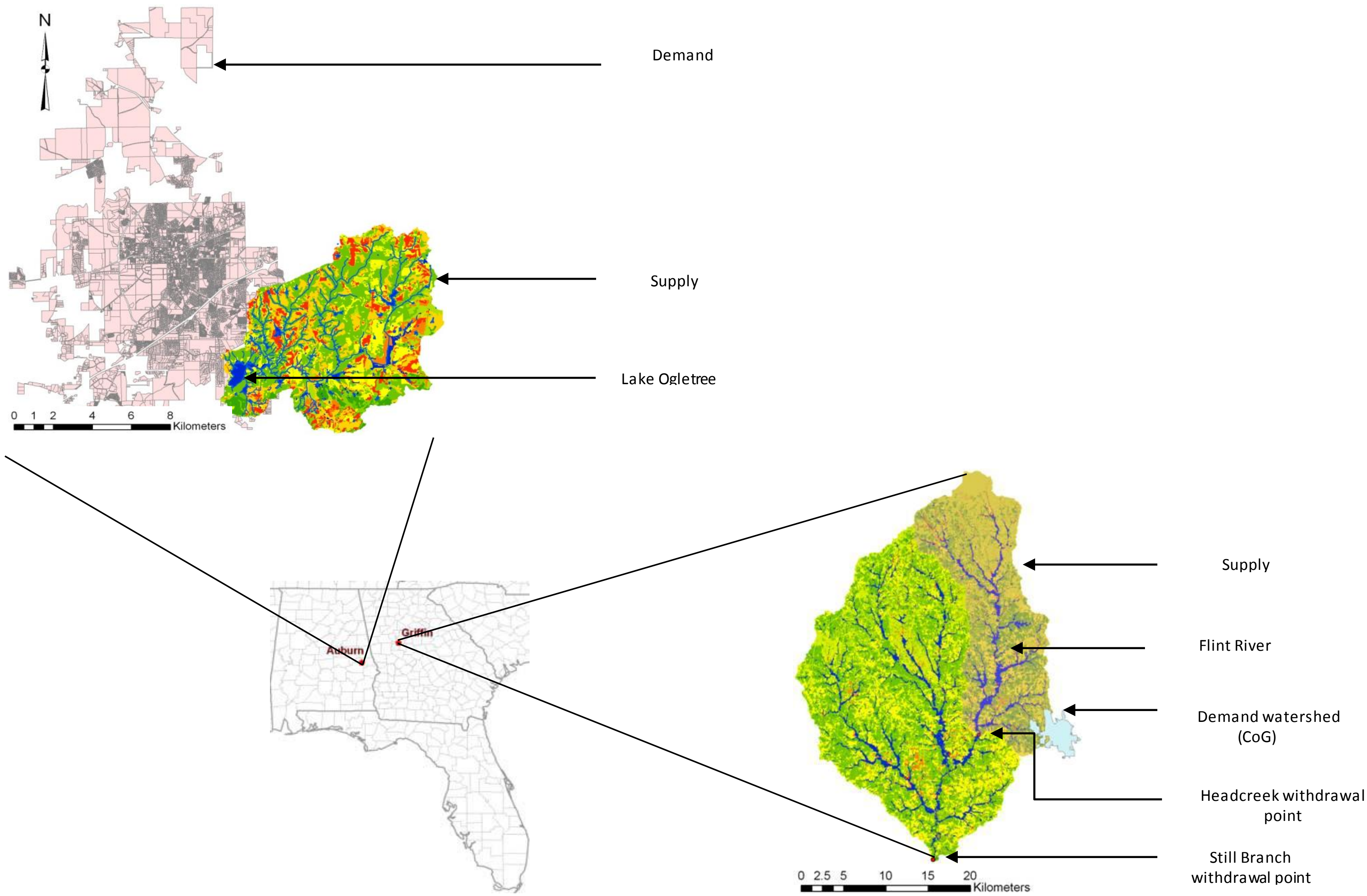


Figure 3.2 Location of study areas, Auburn, AL and Griffin, GA, showing setup of both the systems.

To enhance the availability of water to the system, in 2006, the City of Griffin constructed the Still Branch Regional Reservoir in Molena which is 32 km downstream from the Head Creek reservoir. The city can withdraw up to a maximum of 49,967 m^3/day from Flint River at Griffin and 189,271 m^3/day at Molena. Griffin water managers have also developed a drought management plan that includes imposing water use restriction but do not have any information on how climate variability impacts the availability of water in their system.

The drought index can help these communities by forecasting hydrologic drought 3 to 6 months in advance based on the ENSO forecast, thus helping them in decision-making and in taking timely steps towards water conservation.

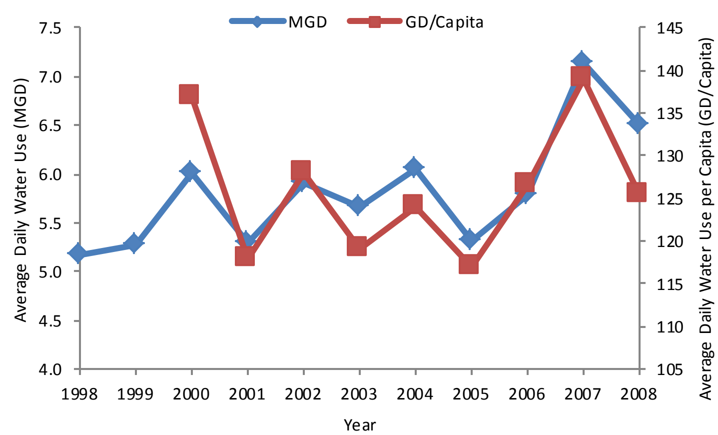


Figure 3.3 Average daily water use in Auburn for the past twelve years in million gallons per day (blue line) and per capita (red line).

3.5 Results and Discussion

3.5.1 Validation of the Model

The CWDI model was set up to compute the output variables (storage and CWDI) at a daily time step. However, the results are presented at a weekly time step to meet the expectations by the water managers for the information provided to them. The water managers require a drought forecast with a 3- to 6- months lead time, which also happens to lie within the temporal scale of ENSO forecasts made by IRI. Figure 3.4 shows the weekly observed and modeled water storage ($m^3 \times 10^6$) of Lake Ogletree during the calibration (Jan 06 to Dec 06) and validation (Jan 07 to Dec 07) periods, and the CoG system, during the calibration (May 07 to Apr 07) and validation (May 08 to Apr 09) periods. The calibration variables included the baseflow parameters, baseflow recession factor and groundwater delay. No other model parameters were calibrated. The green, yellow, orange and red lines on both the charts are lake storage levels that indicate full pool, phase I drought, phase II drought and phase III drought as per the existing drought plans for both the communities being studied. In both the cases, the model was able to reproduce the reservoir storage trends that were evident in the historic data. The Nash Sutcliffe coefficient of model efficiency (NSE) (Nash and Sutcliffe, 1970; Moriasi et al., 2007) for the validation period was 0.91 (very good) for the CoA model and 0.73 (good) for the CoG model. Other than NSE, the other two quantitative statistics calculated, percent bias (PBIAS) and the ratio of the root mean square error to the standard deviation of the observed data (RSR) were -0.13 (very good) and 0.21 (very good) and -1.47 (very good) and 0.52 (good) for CoA and CoG, respectively. Generally, the weekly modeled storage of CoA and CoG followed the weekly observed storage during the calibration and validation periods, although some over- or underestimations were observed. The NSE indicated that the CWDI model reliably predicted weekly lake storage and hence CWDI for the two systems. The differences between the observed and modeled results could be attributed to the fact that reservoir levels for both systems were indirectly observed using reservoir levels that were noted once or twice a week. These verification results are important as these provide credibility and confidence in the model and demonstrate that the modeled units of the water budget attain balance.

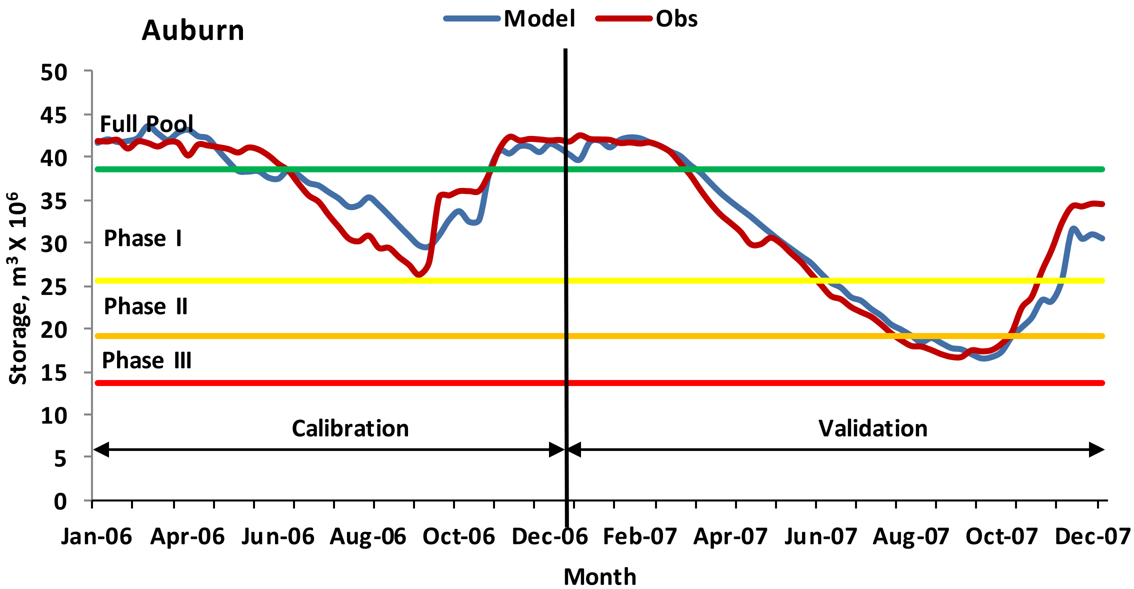
3.5.2 CWDI Testing

The CWDI developed in this study was tested against the actual lake storage levels ($m^3 \times 10^6$) from June to November 2007 for CoA. The CWDI captured the municipal drought fairly well with negative values indicating drought and positive values showing storage above the phase I drought level. However, according to CWDI, it was found that the drought started sooner and ended later than the observed storage levels. The probable explanation to this could be attributed to the fact that the soil moisture balance component of the model did not get time to stabilize before the actual period under discussion. To account for this, the model was run six months before the actual period of interest, and this was considered as a “warm-up” period. The chart for CoG shows the results from June to November 2007, after the model was warmed-up for six months, and an improvement in the simulated CWDI can be seen (Figure 3.5). For the CoG system, CWDI presented lower than the full pool, combined storage levels of the Head Creek and Still Branch reservoirs during this period though the system did not go into drought. This can be attributed to the fact that CoG constructed a second reservoir (Still Branch) in 2006 to enhance their water supply. These results suggest that the dry and wet periods indicated by the CWDI values generally agreed with the observed storage in both the systems. However, the duration of the dryness or wetness and the intensity of drought measured by CWDI are different depending on the inherent characteristics of the reservoir system. It is important to note that the results of CWDI presented here are for the time period during which ENSO was in the La Niña phase, which results in dry winters. For CoA, CWDI was negative throughout the period of discussion, indicating drought conditions. However, CWDI showed an upward trend towards the end of the year.

Lower than normal precipitation during the recharge period of winter stresses the supply system which was further exacerbated by the dry, hot spring and summer of 2007. CWDI provides the water resource managers relative information about the storage of water available rather than the desired storage required for supplying water to the community.

3.5.3 Scenario Analysis

A variety of hypothetical water conservation alternatives were modeled as a part of this study. The main aim was to provide a quantitative basis for comparatively evaluating the alternatives in terms of timely water savings. Figure 3.6 shows the scenario analysis for the year 2000 for CoA assuming the stakeholder knew the climate variability based drought forecast for his system 3 to 6 months in advance and started imposing water use restrictions ahead of time based on that forecast. Without the use of CWDI and, hence, no water restrictions, CoA entered Phase I drought in August and the drought worsened into a Phase III drought by mid-September 2000 (Figure 3.6). It was observed that if the message of an approaching drought was sent out to the community along with voluntary water restrictions on outdoor water use (dynamic demand) from Feb 1, 2000 onwards so as to reduce total outdoor water use by 10%, the system would have improved from a Phase III drought in September to a Phase II drought. Results of the 25% outdoor water use-saving scenario show a complete recovery from drought by the end of the year. It can be noted that the saving in water increases as summer approaches and people start watering their lawns more during hot and dry conditions but there is not as much saving required during February to April.



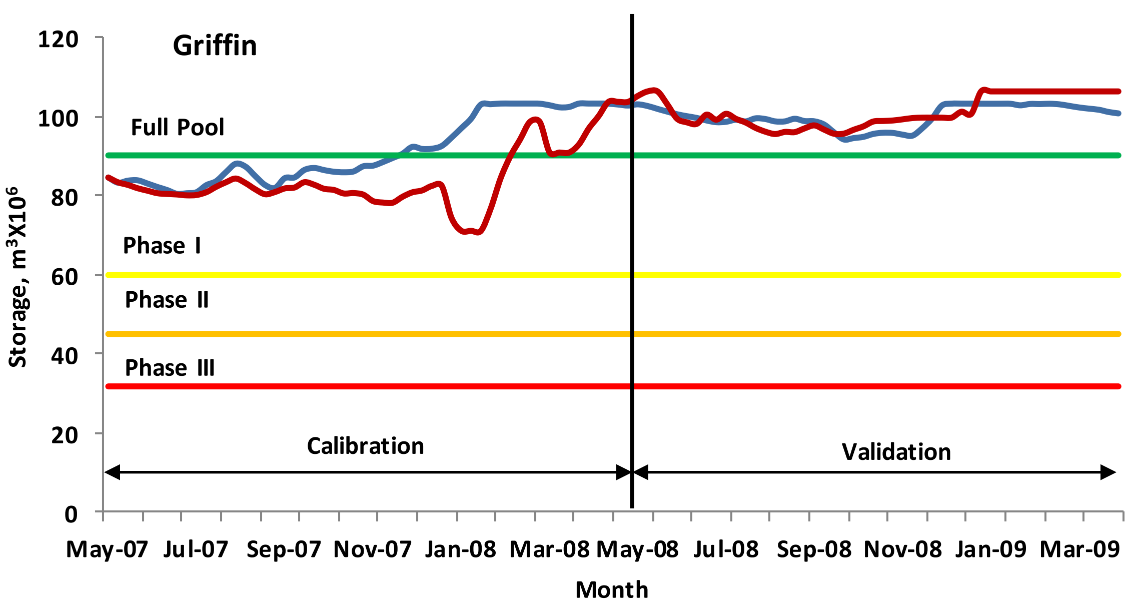


Figure 3.4. Weekly observed and modeled storages for Auburn and Griffin during calibration and validation periods. Phase I, Phase II and Phase III represent storage levels below which the community is under respective drought stage.

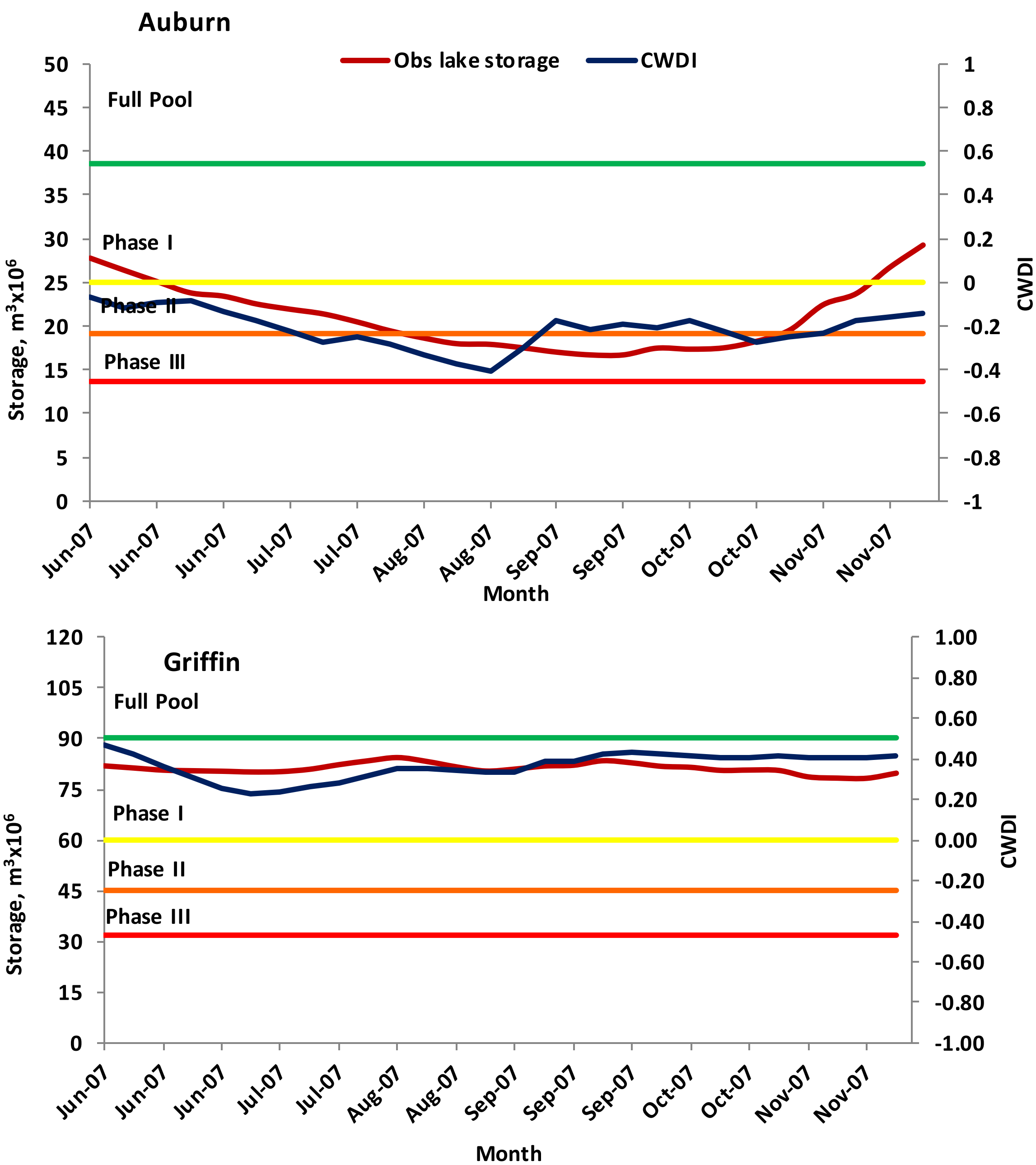


Figure 3.5 Comparison of observed lake level (as storage volume in m^3*10^6) and modeled CWDI for Auburn and Griffin. Negative values of CWDI indicate drought.

These scenarios were implemented in the model to explore the impact of different water use restrictions on the forecasted water availability on a 3 to 6 months' time scale. The results indicate that CWDI can be successfully guide plans for water use restrictions and water conservation policies given the ENSO forecasts. The available water in the system remains the determinant factor which is driven by the climate (precipitation and temperature and indirectly evapotranspiration).

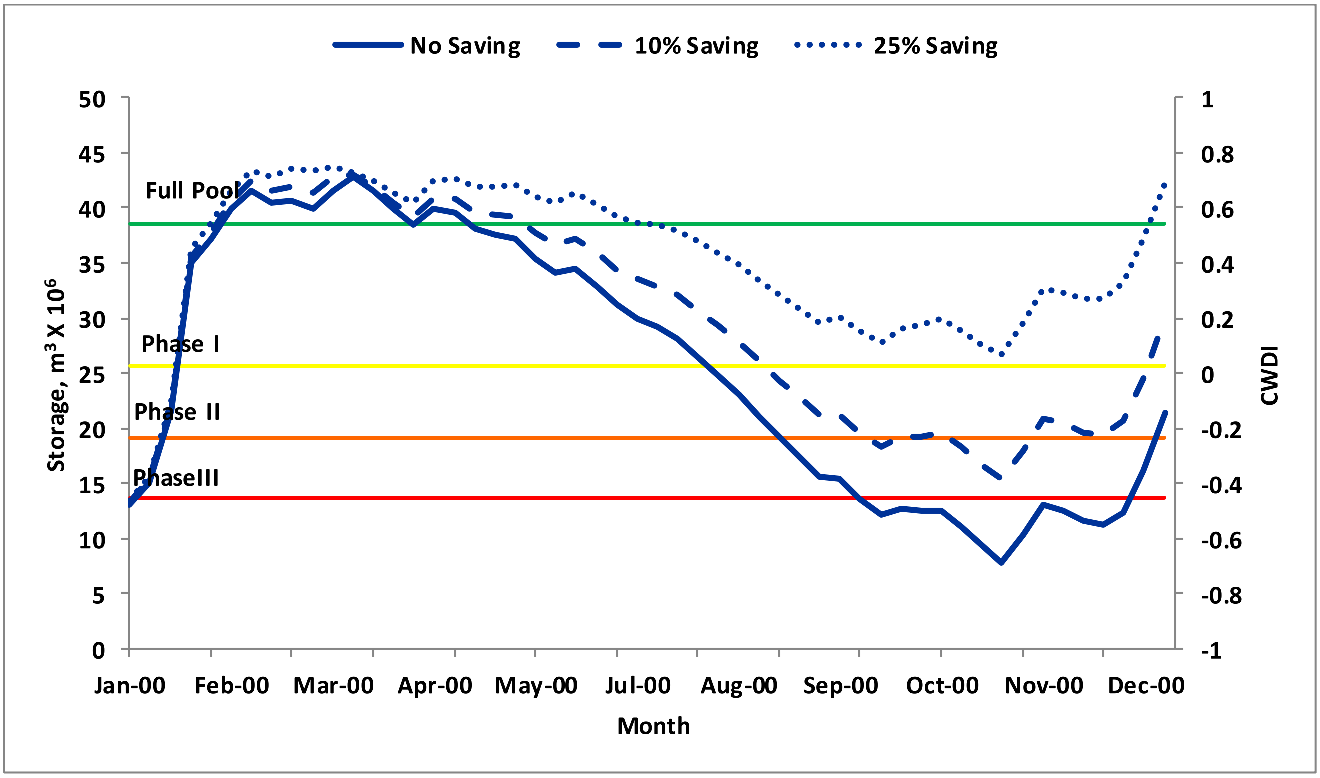


Figure 3.6. Scenario analysis showing the impact of policy implications of outdoor water saving (dynamic demand) for the City of Auburn.

3.5.4 CWDI FORECASTING

The CWDI was tested for forecasting for both CoA and CoG using historically observed lake levels and the ensemble forecasts constrained to ENSO phase (Figure 3.7). CWDI captured the drought occurrence for CoA. In June 2009, ENSO forecasts and ocean temperature measurements from the tropical atmosphere ocean buoy system predicted El Niño developing for the winter of 2009-2010. The forecast shows a high likelihood of high spring and summer precipitations and a low probability of summer low-flow conditions. As of June 2010, early ENSO forecasts predicted that El Niño conditions were changing to La Niña conditions, which might persist through the winter of 2010 and continue till the spring of 2011. To obtain the CWDI forecast, already available ENSO information (CPC, 2010) was used to constrain the weather generator. The forecast shows an ensemble (95% confidence band) moving towards a Phase I drought beginning Sep 2010 (Figure 3.7), in response to the ENSO phase changing from Neutral to La Niña during May 2010 to Aug 2010. Although La Niña (dry) conditions persisted till April 2011, during winter of 2010, the region received an ample amount of rain, which might be attributed to the climate phenomenon called North Atlantic Oscillation that affects the North American winter. When the NAO is in its negative (cold) phase, arctic air pushes further south into the United States. NAO phases can change at a temporal scale of 1-2 weeks and hence are not predictable (Martinez, 2011). As the ENSO phase changed from La Niña back to Neutral conditions in May 2011, the ensemble indicated the system eventually coming out of drought conditions and moving back to full pool conditions. Similar results were found for CoG. In this paper, "skill" is used to evaluate the ensemble forecasts (Hamlet and Lettenmaier, 1999). An ensemble is said to have skill if the observed reservoir storage (indirectly CWDI) falls within the upper and lower boundaries of the ensemble for the period of interest. The model displays skill for most of the forecast period, especially during the recharge season (Dec through April) during which the observed lake levels are within the upper and lower boundaries of the ensemble. During this time period, there was a higher impact of ENSO conditions in the state (Sharda et al, 2011) as compared with the rest of the year. As summer approached, ENSO predictability in the region decreased and hence the observed lake levels were more outside the ENSO-based forecast band.

The results presented here show just one of many ways of forecasting drought. However, CWDI forecasting methodology is developed in such a way that the forecast can be updated on a weekly or a bi-weekly basis as the observed storage levels change in the reservoir.

3.5.5 Using CWDI Forecasts In Decision Making

Steinemann (2006) conducted a survey of water resource decision-makers in the southeastern United States and reported that there were several reasons for nonuse of forecasts that include: (1) forecasts are difficult to understand, (2) it is difficult to assess their accuracy and benefits and (3) it is difficult to apply the forecasts to types of decisions concerning drought management. Keeping these points in mind, CWDI forecasts aim to provide information of hydrologic drought and hence water availability in a municipal water system based on the ENSO phase outlook at a 3- to 6-month time-scale. Figure 3.8 shows an example of one such forecast for CoA, which gives the forecast value of CWDI with 95% confidence band for the community. The shaded area presents the range within which the water availability might vary during a certain time of the forecast with the dotted line representing the median of this ensemble forecast.

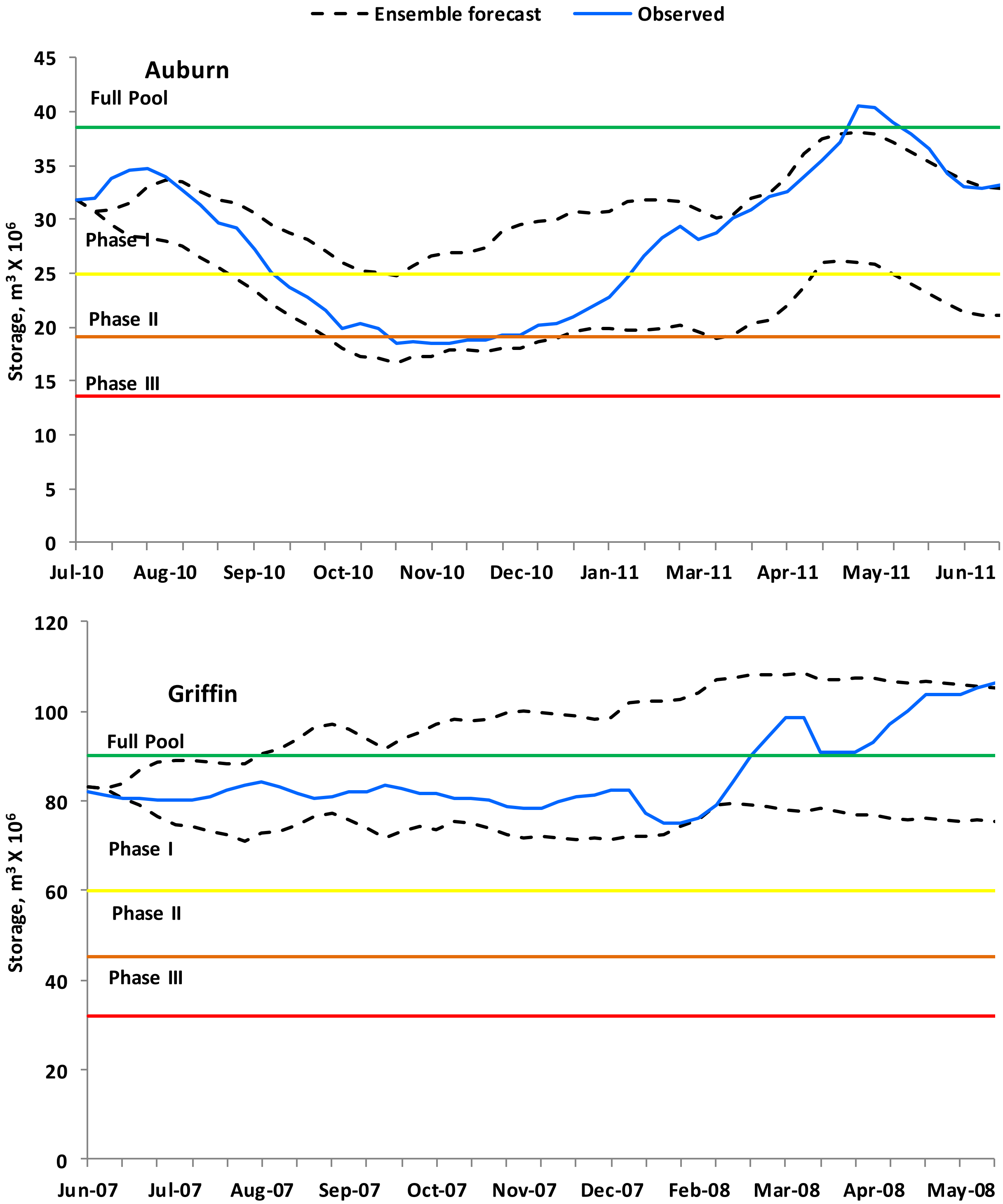


Figure 3.7. Comparison of observed lake storage volume (blue line) and storage volume forecast (black dotted lines) showing observed values mostly lying within the 95% confidence forecast band.

The red line represents the CWDI calculated with observed storage values till mid-November 2011, and very good agreement is found between the drought forecast and observed values. CWDI presents a forecast that is simple to understand and gives the decision-makers ease of interpretation. Because it is available at the spatial and temporal resolution most suited for the decision-makers, it takes away the concerns about accuracy and applicability of the forecast to their system, making it a product tailored to local and specific needs. CWDI has been tested before and evaluated after a drought and has performed well, proving it scientifically sound so that decisions can be made and defended on the basis of CWDI.

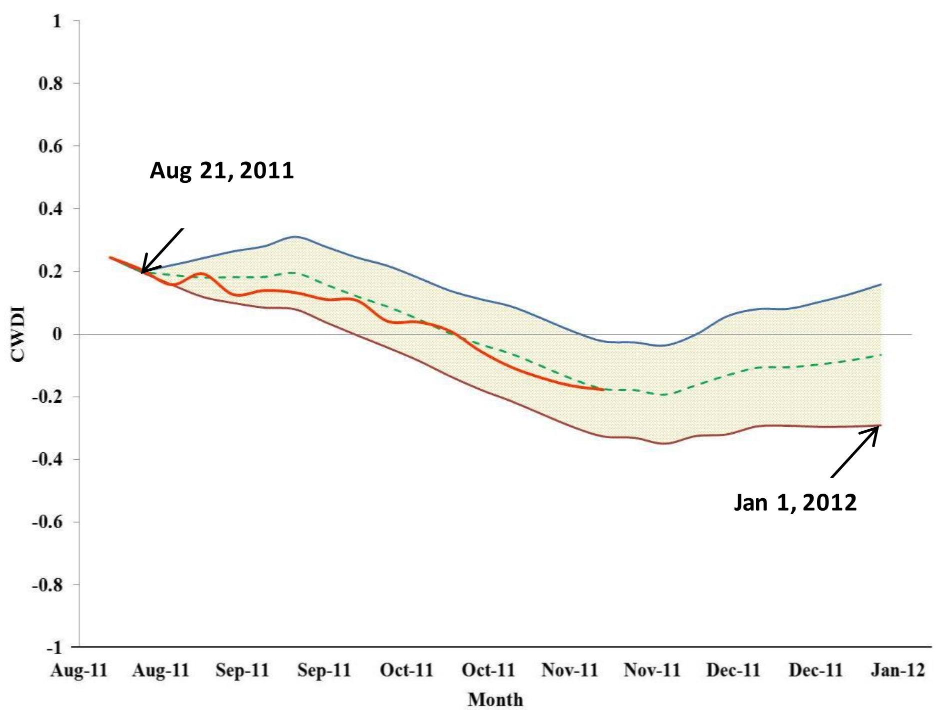


Figure 3.8. An example (City of Auburn) of CWDI 95% confidence interval forecast band with the median value (green dotted) and the observed values (red) till Nov. 2, 2011.

3.6 Summary and Conclusions

In this study, a modeling framework was developed to quantify the interrelationships among climatic variability, water supply and water demand. This methodology for forecasting ENSO-based hydrologic drought for small to mid-size communities of the southeastern United States is based on a unique index that is being called Community Water Deficit Index (CWDI). What makes this index unique is that it addresses both supply and demand of water in a system; operates at a fine spatial resolution to account for the spatial variability of rainfall experienced in the region; works at a temporal resolution that is the most desired by the water managers; forecasts drought based on the climate variability signal ENSO; and is customizable for different communities.

The model was developed using the system dynamics software STELLA® and it combines sub-models, a number of auxiliary equations, and reservoir operation rules. A rigorous testing framework was set up to validate the model for real-world water resource systems. Two communities primarily depending on surface water sources were selected, and their systems were modeled for this study. CWDI well-represented the municipal water systems studied and captured La Niña-induced droughts with a high degree of accuracy. The study also demonstrates the usefulness of different climate forecasts being made.

Because it considers both the inflow variation caused by season and climate variability and demand changes, CWDI presents a robust methodology that is supported by the results obtained. This model provides a useful method for early detection of onset, duration, severity and recovery from drought. CWDI could be very useful in mitigating droughts impacts and the value of damage attached with it, and its use could lead to substantial benefits for the stakeholders. It can also be utilized to send out timely water use restrictions leading to water conservation. It can therefore be concluded that using climate variability-based CWDI can help the water managers in decision-making and predict the probable severity and damage of the drought.

Future work on this methodology will include development of a web-based CWDI tool that would be customizable by communities of the Southeastern United States. The users/stakeholders/water managers will be required to provide some basic consumption data, lake levels, desired storage, etc., and the model will be able to forecast drought 3 to 6 months in advance.

Chapter 4
Value of ENSO Forecast Drought Information for the Management of Water Resources of Small to Mid-size Communities of The Southeastern United States

4.1 Abstract

There have been great advances in the climate forecasting ability in the past years. However, the use of this information in water management decision-making has been lacking. The accuracy of forecast information and the time and spatial scales of forecasts have been cited as key inhibitions in use of these forecasts. A Community Water Deficit Index (CWDI) was developed as a tool to use NOAA ENSO forecasts to forecast drought in small to mid-sized communities of the southeastern United States. A pathway for increased adoption of forecasts requires connecting seasonal forecast system, e.g., CWDI, with the analysis of decision-making in the target system and quantification of value of these forecasts to the water resource managers. This study investigated the value and benefits of using a seasonal drought forecasting technique. The efforts were focused on determining the usefulness of drought information for municipal water management, as determined by the impact of drought on municipal water demand, usefulness of water restrictions imposed by municipal water management, and the extent to which advance knowledge of probabilistic drought forecast mitigates negative impacts. The results indicate that water use restrictions are effective for coping with drought and that benefits of use of forecasts and water management adjustments should involve planning ahead. It was also found that by using the drought forecasts and thus having a drought preparedness plan the communities can save both water and money.

4.2 Introduction

Drought can be defined as a period of abnormally dry weather in a geographic area where precipitation is normally present. Walker et al. (2011) stated that because it is hard to tell exactly when a drought starts and when it is over, it can be compared to economic recession. Drought or the threat of drought has become a constant problem in many parts of the United States and, apart from being the costliest natural disasters, has become the most serious and complex problem that confronts water resources planners. Despite the fact that droughts cost billions of dollars every year in United States (Ryu et al., 2010), there is no methodical effort to determine its complete impact. Most states now implement drought management plans, one crucial aspect of which is to establish a link between drought status in a basin and management actions. Drought has been called a "creeping disaster" because it is easy to ignore until it is too late (Grigg 1996). It has been suggested that to mitigate adverse impacts of drought, proactive planning is more effective than reactive crisis management (Wilhite 1991; USACE, 1993; Wilhite and Rhodes, 1993).

In the southeastern US, there is extreme interannual variability of water availability due to growing demands and shrinking supplies. Demand of water has increased in the region due to rapid residential, industrial, and recreational growth; climate variability in the region intensifies the situation. Coping with this problem has become the main focus of most surface water managers of the region. Seasonal climate variability influences water availability and affects agricultural productivity, animal and human disease epidemiology, population of plants and wildlife, and many other phenomena (Barrett, 1998). Water supply enhancement in forms of purchasing water, ground water mining, interbasin transfers, and construction or enhancement of reservoir storage have been the traditional approaches to deal with such drought conditions (Pagano et al., 2001). However, most of these approaches are expensive and do not have social or political support (Western Water Policy Review Advisory Commission, 1998). To deal with these circumstances, a sophisticated surface water management system is needed in the southeastern United States. There is a need to develop methods to measure different impacts, including both direct and indirect, and this is required as a prerequisite for estimating value of forecasts.

Improved information about future climate fluctuations can help decision makers to take advantage of climate good fortune and mitigate the impact of adverse situations. Recent advances in seasonal climate forecasting offer the potential to improve the ability and willingness of stakeholders to respond to forecasts of climate fluctuations. Despite the potential usefulness of seasonal forecasts, these currently remain underutilized with forecasts playing a marginal role in decision making (Callahan et al., 1999; Pulwarty and Melis, 1999). The value of forecasts comes from improved decision making, which could reduce costs and losses to water users and reduce social disruption. Many obstacles to forecast use have been stated in the literature, which include awareness of their existence, distrust of their accuracy, perceived irrelevance to management decisions, and competition from other innovations (Carbone and Dow, 2005). Other concerns about the use of seasonal forecast reported include the forecasts being difficult to understand and apply in decision making (Pulwarty and Redmond, 1997; Stern and Easterling, 1999). Moreover, the use of forecast products by themselves cannot decrease the vulnerability of a community water system to drought; past observations and projections of climate variables such as precipitation and temperature at seasonal to decadal timescales can potentially help them prepare for water shortages (Lowery et al., 2011).

In the southeastern United States most climate variability is attributable to El Niño Southern Oscillation (ENSO) (Schmidt et al., 2001), so much so, that ENSO has become a norm rather than an exception. ENSO is a climate pattern driven by cyclical warming and cooling of sea surface temperatures in the central Pacific Ocean. As scientific understanding of ENSO has only begun around 1997, the capacity to provide reasonably reliable ENSO based forecasts of climatic variables is a very recent development (Crane et al., 2011). That being said, ENSO, the most pronounced climate variability signal at a seasonal scale, is being used as an indicator to study precipitation and temperature patterns at regional (Andrews et al., 2004; Sharda et al., 2011) and global scales (Ropelewski and Halpert, 1987). As far as forecasts are concerned, there is a vast difference between forecast skill of ENSO phase and ability to forecast impact of ENSO on climatic variables that matter to the stakeholders (Barrett, 1998). This indirect relation makes the value of ENSO related forecast information dependent on strength of the arbitrating interventions. Although over the past few years the accuracy and lead times of ENSO phase predictions have improved noticeably, it has still been able to explain only a small part of variation in variables most important for decision-makers.

As stated earlier, the main challenge for forecasters is to provide reliable and useful forecast products that can be understood and used by stakeholders who may or may not be technically qualified. There are myriad forecast products freely available on the internet that include outlooks provided by the National Weather Service (NWS), Climate Prediction Center

(CPC), International Research Institute for Climate Prediction (IRI), along with several other agencies that provide seasonal outlooks. None of these products are tailored specifically to the needs of water resource managers that primarily rely on surface water resources, especially those of small to mid-size communities in the Southeast United States. Keeping these points in mind, a Community Water Deficit Index (CWDI) was developed to forecast ENSO based drought for the small to mid-sized communities of the region (Sharda et al., 2011). This tool forecasts hydrologic drought 3 to 4 months in advance and operates at spatial scales most desired by water resource managers. Most importantly it considers both the water availability and water demand of the community.

However, the usefulness and value of CWDI remains to be established. This study was undertaken to assess the value of this ENSO based hydrologic drought forecast information for small to mid-size communities of the region.

The value or usefulness of this drought information was assessed by studying the seasonality of water demand; impact of drought (climate variables) on municipal water demand, i.e., how consumption changes with precipitation and temperature; and use and effectiveness of water restrictions in curtailing seasonal demand. In addition, the study also dealt with as to how drought forecast will influence the decision making process or mitigate negative impacts of drought that is how it can help in imposing conservation measures and also by arranging alternate or supplemental supply.

4.3 Materials and Methods

4.3.1 Study Area

To investigate the value and usefulness of drought forecast information, a case study that uses the consequences from the intended user's viewpoint was used. Past researchers have reported that use of perspective studies to examine forecast information can be helpful to increase understanding and implementation of forecasts (Katz and Murphy, 1997). Because the usefulness of any forecast is based on the opinion of a potential user, it can be best achieved through the cooperation of forecasters and users (Pagano et al., 2001). It has been reported (Ritchie et al., 2004) that to avoid the risk of issuing forecasts that do not motivate confidence among the users a cooperative approach that ensures that the needs of the user are known and targeted by the forecaster instead of being assumed is required.

Keeping the above points in mind, to study the usefulness and value of drought forecast information for small to mid-size communities of the southeastern United States, the methodology presented in this paper was tested for the City of Auburn (referred to as Auburn hereafter), Alabama. Auburn is a city of around 55,000 people, located in Lee County. For 85% of its water supply the city relies on Lake Ogletree, which is situated to the southeast of the city. Apart from Lake Ogletree, the city has an agreement with a neighboring city of Opelika to purchase water on a monthly basis. The storage in Lake Ogletree is also supplemented by the water pumped in from two quarries situated in the area. Increasing water demands and recent droughts in the region caused by La Niña phase of ENSO have put the city's water managers in a tight situation many a times in the past.

Because the city relies on a surface water source, is a mid-size community, and is located in the Southeast United States, it was selected to study the usefulness of drought forecast information to its water resource managers.

4.3.2 Water Demand and Effectiveness of Restrictions

The two main reasons for forecasting water demand of a community are long term planning and short term operation (Polebitski and Palmer, 2010). Variation in annual water demand of a community is driven by climatic variables such as precipitation and temperature due to outdoor water use in urban and sub-urban areas. This seasonality of water demand is an important basis to study the impact of climate variables on daily water demand of a community. Generally, water managers compare daily water use (demand) during periods of restricted water use to water use during same time periods in the past to find out the effectiveness of municipal water restrictions during drought or low water availability scenarios. However, this approach does not consider the impacts of climate on water use and demand. So in this study daily use of water during periods of restricted uses was compared to an estimate of “expected use” of water. “Expected use” was defined as water use that would have been used in the absence of restrictions, given the temperature and precipitation conditions. This comparison would thus help in evaluating the impact of climate on water use and effectiveness of water restrictions. Daily precipitation and temperature data were used as predictors in a multiple regression model to predict expected use of water along with a one-day lag variable to account for the temporal persistence in the time series of community daily water use. Because population is the largest factor determining water demand (Gutzler and Nims, 2005), it was important to isolate the demand component related to climate variability, hence water use data were converted to per capita water consumption. Similar approaches to study the impacts of climate on water use have been mentioned in Kenney et al. (2004), and Shaw et al. (1992). The regression model developed was in the form of the equation 1.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon \qquad (1)$$

where y is the per capita water use and x_1, x_2 and x_3 are the predictors namely daily maximum temperature, daily precipitation, and one-day lag variable of water use, respectively. β_0 is the regression constant, β_1, β_2, and β_3 are the slope coefficients for the predictor variables and ε is the error. The regression model was developed using the Statistical Analysis System (SAS) software (SAS Institute, Inc., NC, USA) and the coefficients were estimated using data from a year in which no restrictions were issued by the community. For Auburn, the regression equations were estimated using data from the year 2002 and tested for the years 2003 and 2004. The R-square value obtained from the regression model indicated the accuracy of the model in predicting water use using the climate variables. The equation developed was then applied to data from a period when restrictions were in effect to estimate the expected use (2007 and 2008). The difference between actual and expected water use during that time period were calculated to estimate the effectiveness of water restrictions during drought. This exercise was done to establish the seasonality of water demand, impact of climate variables on water use during drought, and effectiveness, if any, of water use restrictions during drought.

Water saving over the period of restrictions was also investigated to study the effectiveness of water restrictions. Total use water savings were calculated by comparing 2007 and 2008 water use with average of 2002, 2003, and 2004, whereas, expected use was a comparison of actual per capita use during 2007-08 with that expected due to the climatic conditions, which were calculated using the regression model. These values were calculated both for the entire study period and the restriction period, i.e., October 1, 2007 to June 30, 2008.

4.3.3 Forecasting Drought Using CWDI

The Auburn water supply system has dealt with moderate to severe drought in the past and, based on the city drought management plan, phases of drought depend on percentage lake storage available. Figure 4.1 shows drought phases during 1999-2001 for Lake Ogletree ranging from moderate (Phase I) to extreme (Phase IV) drought. These droughts coincide with a strong La Niña phase of ENSO as described by the ENSO index Niño 3.4, signifying the impact that ENSO has on water availability for the city. Community Water Deficit Index (CWDI) (Sharda et al., 2011) was developed to forecast ENSO based drought in small to mid-sized communities of the southeastern United States. CWDI is a supply and demand water balance model that considers the decrease in supply and increase in demand from irrigation during drought conditions.

During low precipitation and high temperature El Niño Southern Oscillation (ENSO) phase (La Niña), the loss of soil moisture through evapotranspiration increases the demand of water for outdoor water use by residents (e.g. lawn irrigation), which increases the stress on water availability for the community. System Dynamics modeling software STELLA® was used to develop a model that addresses the relationship between water supply and demand of a community. Demand is divided into two components: static demand, which is not dependent on climate and consists of water usage for indoor purposes, and dynamic demand, which is dependent on climate (ENSO) and arises from outdoor use or irrigation of lawns.

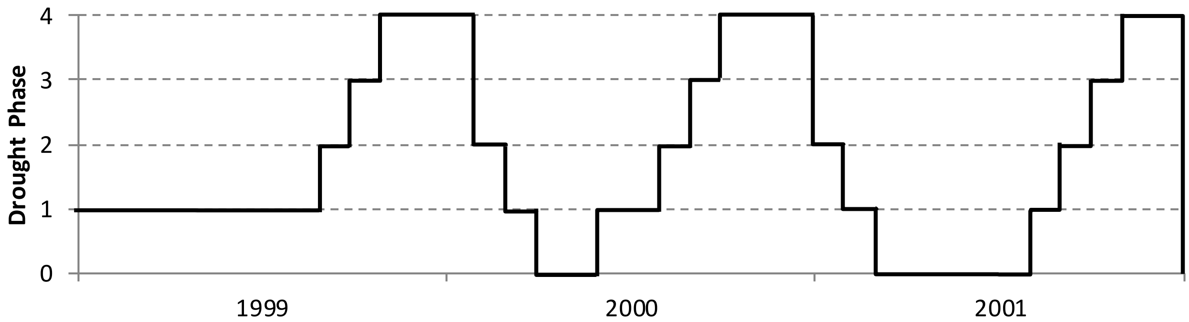


Figure 4.1. Droughts of record for the period 1999-2001 for Auburn (Source: City of Auburn data).

The CWDI was estimated as ratio of available storage and desired level of water storage in the reservoir of the community and is given as:

$$CWDI = \frac{S}{S_d} - 1 \qquad (2)$$

where, S is the available storage in the reservoir and S_d is the desired storage in the reservoir.

If $S \geq S_d$, $CWDI \geq 0$, => No deficit (3)

If $S < S_d$, $CWDI < 0$, => Deficit (4)

Based on the IRI ENSO forecast, a weather generator was used to generate ENSO constrained climatic variables, which were then used to forecast CWDI 3 to 4 months in advance. Major drought years from the past were selected and based on the ENSO phase (La Niña) during that time period, CWDI model was run to create an ensemble forecast for each year beginning in November to show what the drought forecast would have looked like during November through February. This period was chosen to coincide with the principal recharge period for reservoirs in this part of the country. Historic daily reservoir storage data along with the population data were provided by the City of Auburn.

4.3.4 VALUE OF CWDI FORECAST

The methodology adopted investigates the usefulness of ENSO based drought forecast using CWDI by comparing the outcomes resulting from the use of ENSO phase forecasting system with those that did not use this information. Because the analysis was done using historic data, the outcomes that did not use ENSO forecasts are the observed conditions in the past. Potential value or usefulness of this forecast information for water resource managers was determined by assessing how this knowledge might allow mitigation of negative impacts. The model was run in the past using climate variables generated by a weather generator constrained with ENSO phase to estimate how the demand side management could be changed through demand management practices such as conservation measure, imposing voluntary and mandatory restrictions, and altering transfer or purchase agreements. The value of forecast information could come from planning ahead thus minimizing the drought vulnerability of these water systems.

Value of drought information as provided by CWDI was studied using the historical consumption data, water supply availability in the past, demand levels, reservoir levels, and ENSO phase. To account for uncertainty in the dataset, ensembles of daily data obtained from a weather generator constrained by the seasonal forecast were used.

The details of conservation measures adopted by the city, supply enhancement policies, and other options of water managers were studied in the context of using the CWDI as a planning tool. Based on the past strategies used by the water managers, the following elements were studied.

The first element is planning for drought before it occurs. This planning can include water conservation programs and increasing, public awareness about the possibility of a drought.

The second element is identifying and classifying drought based on the water supply. The CWDI forecast indicates the status of water availability in the system. This water availability information can be used to identify and classify the drought and interventions can be planned accordingly. The best time frame to identify and classify a drought will be during the recharge period, i.e., Dec-Feb. Once the drought is identified, it can be communicated to the public in Feb-April and not in June or July when the community is already well into the drought and there is no way to recover. Once the reservoir levels improve, water managers can officially lift restrictions, and remove fines and surcharges. To accomplish identification and classification of drought, a demand reduction goal was set and was assumed that looking at stage or severity of forecasted drought, measures would be taken by the water resource manager to conserve water or curtail demand. The rules followed for demand reduction were adopted from Walker et al. (2008) and are given in Table 4.1.

The third element is responding to a drought by increasing supply and decreasing demands. Increase in water supply can be achieved through purchasing water from some outside source with which the community already has a contract or other supplemental supply options depending upon the system structure, for example, groundwater withdrawal. Decreasing water demand measures include reducing the water budget of the municipality as a whole. Individual water budget can be reduced by percentage specific to the outdoor use of water and wise water use practices emphasized.

Table 4.1. Demand reduction goals with the use of Community Water Deficit Index (CWDI). (Adapted from Walker et al., 2008)

Drought Phase	Drought Description	Conservation Goal	Proposed Actions
Phase I	Incipient	0%	Public awareness
Phase II	Moderate	15%	Voluntary restrictions
Phase III	Severe	20%	Mandatory restrictions
Phase IV	Extreme	25%	Mandatory restrictions + Drought rates

These elements can help evaluate the drought information available to water managers and how they can use this information to formulate a drought response plans and policy changes. This can also help the water managers to smoothly cope with drought and will help the communities to be well prepared and aware of the forthcoming drought.

Based on the phase of drought at the beginning of the forecast period, target conservation percentages would be applied in the dynamic demand component of the CWDI model to achieve better storage levels in the reservoir. The change in storage levels would then be converted to volumetric savings of water as well as economic savings.

The volume of water savings arise from conservation achieved by the community in compliance with the water restrictions or conservation measures imposed by the city in anticipation of approaching drought. This saving was calculated as the difference between storage levels forecasted (using CWDI) and the observed reservoir storage levels at end of each month. A monthly time scale was used because the conservation measures are usually issued by the communities once every month. The economic component was analyzed by utilizing the unit cost of production and unit cost of purchase per 1000 gallons of water. These data were provided by Auburn. The cost of production includes costs for pumping, purification, distribution, meter reading, billing and collection, operational administration expenses, and general operation expenses. Auburn has purchase agreement with neighboring city of Opelika and has to purchase minimum 8 million gallons per month and can buy up to 3.6 million gallons per day. The cost of purchased water was provided by Auburn and the monthly saving in cost of water would arise mainly from reducing the need to purchase water from Opelika. Although this information is community specific, it still gives an idea about the potential importance of forecast information for the water resource managers of small to mid-size communities.

4.4 RESULTS

4.4.1 SEASONALITY OF WATER USE

Historic daily demand data (gallons/day) were obtained from Auburn for a period of 11 years (1998-2010) and it was observed that this variable was highly variable across the dataset. These data were then converted to average population weighted data (gallons/capita/day) using the population data of the city. Because communities actually report water production rather than water consumption, monthly data have more measurement error than do annual data. Patterns of monthly water use presented in Figure 4.2 were obtained by averaging population-weighted data across the entire sample. The seasonality of water use is evident from this figure, but other interesting details are also apparent. Demand in winter months is rather invariant from year to year whereas water use during summer months can be highly variable from year to year. Figure 4.2 shows a definite seasonality in water demand during drought years. It was found that during these La Niña years, the water use/demand increased (as compared to a normal year) as the temperatures during the summer months were high and there was not enough precipitation. As the residents irrigated their lawns to keep the grasses in their lawns alive, the water use spiked during May through August.

4.4.2 Effectiveness of Restrictions

Auburn has not, to date, enforced mandatory water restrictions, however, word has been sent out time to time for public awareness as well as to implement voluntary restrictions. These efforts include asking the residents to water their lawns 2-3 times a week with odd and even number households alternating their watering schedule. Voluntary restrictions also call for the residents to irrigation only between 6 PM to 8 AM because evapotranspiration is lowest during these times. Equation 5 shows an example regression equation for year 2000 when no water restrictions were used (*R* denotes daily precipitation, *T* is daily maximum temperature and *L* is the one-day lag variable of water use).

$$y = -0.4592\ R + 0.1909\ T + 0.71019\ L + 0.18149 \tag{5}$$

The regression model showed skill in predicting water use with R-squared values ranging from 0.65-0.81. Greater accuracy could be achieved using more sophisticated regression techniques, however, this regression model solves the purpose of our investigation, which was to describe drought response in this case study. The regression model also showed that the water use and demand have a positive relationship with temperature and the lag variable indicating that water use increases with increase in temperature. An inverse relationship was observed with precipitation. A strong relationship was observed between the one-day lag variable for current demand indicating that demand or water use on a given day is a function of water use on the previous day. This outcome was not unexpected and provided aggregate assessment of anticipated water saving attributable to climate.

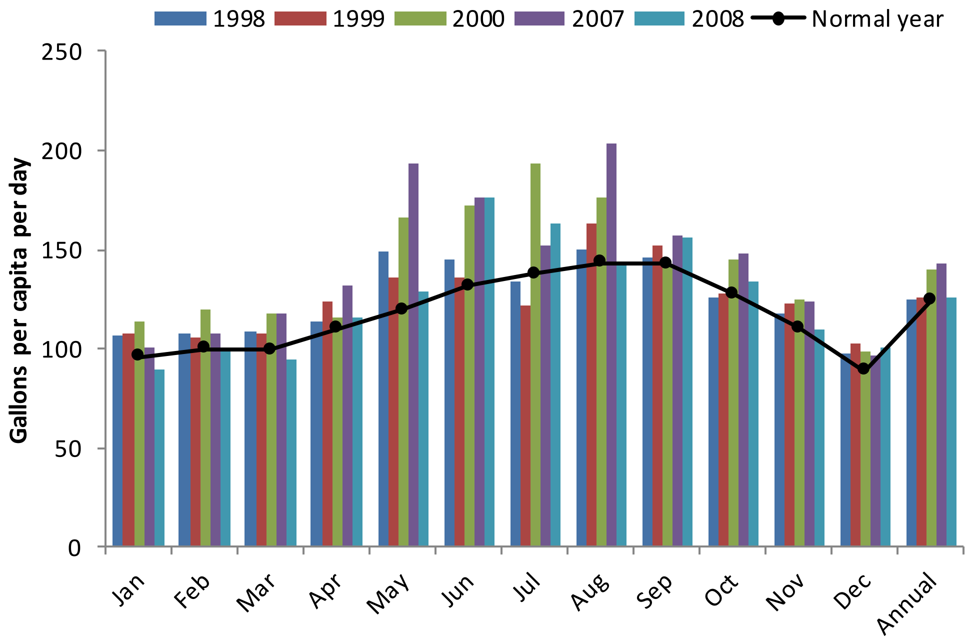


Figure 4.2. Monthly and annual water use for drought years.

The difference between expected (calculated) and actual (observed) water use is shown in Figure 4.3 and this provides an estimate of water saving that can be attributed to the drought inspired water restrictions imposed during this time period (October 2007- June 2008- La Niña). It is important to note that during this period only voluntary restrictions were in effect. Higher water savings can be seen during fall to winter months when people do not irrigate their lawns as much. However, as temperatures soar during late spring and summer along with low precipitation due to typical La Niña conditions, differences between observed and expected water use decrease indicating that voluntary restrictions are relatively ineffective conservation measures. Imposing mandatory restrictions results in higher water saving during summer months (Kenney et al., 2004), but because Auburn did not impose any; we do not have any results to report for those.

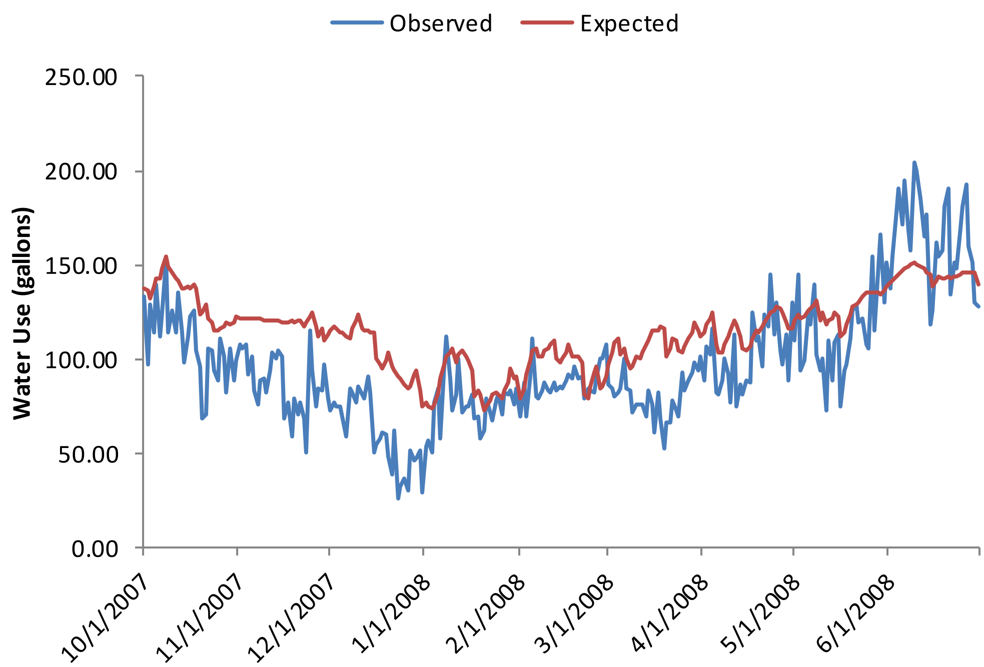


Figure 4.3. Observed vs. expected per capita water use for Auburn from October 1, 2007 to June 30, 2008 demonstrating the impact of water restrictions.

Past studies show that if mandatory restrictions were imposed in April 2008; after drought conditions did not improve from Oct 2007 till Apr 2008; it would have resulted in better water savings and improving the drought conditions. Because per capita water use was investigated, these results evaluate water restrictions effectiveness from an individual user stand point.

Table 4.2 summarizes the calculated effectiveness of water restrictions in terms of percent savings for Auburn. During the period of study total water use increased, whereas, expected per capita water use decreased slightly. During the period of voluntary restrictions, expected per capita water use showed a saving of 14% indicating effectiveness of these restrictions in saving water in terms of per capita expected use.

Table 4.2. Percent water saving based on expected use during water restrictions.

Variable	Total time period		Restrictions time period	
	Total Use	**Expected Use**	**Total Use**	**Expected Use**
Percent	-8	2	-2	14

These results establish the fact that water use and demand of a community depends on climates and that management decisions, such as imposing voluntary or mandatory water use restrictions, can be effective tools for saving water and averting severe drought conditions.

4.4.3 Value of CWDI Forecast

To study the advantages of using ENSO-based drought forecast of CWDI, we selected some past La Niña years and then forecast drought during those years using CWDI methodology. Table 4.3 shows CWDI forecast in terms of percentage lake capacity. The drought phases were assigned according to Auburn's drought plan. The CWDI forecast was based on climate variables generated according to historical ENSO phase data.

CWDI forecast severe to extreme drought for all four years discussed here during November through February. Results of these months are discussed as these months represent the recharge period during which water managers observe the reservoir levels closely and decide or estimate the reservoir condition in the forthcoming summer months. This period was selected in discussions with water managers of Auburn. These results agree with some of the observed drought data discussed earlier in the manuscript (Figure 4.1) and show that the CWDI forecast has skill and is consistent. These forecast results present the situation when no conservation measures were adopted by the city. However, to evaluate and quantify the value of this forecast information, results of hypothetical scenarios using different conservation measures, restrictions, or public awareness measures were then studied in terms of volumetric water savings as well as economic benefit to the community.

Table 4.3. Drought phases assigned to percentage lake capacity as forecasted by CWDI for La Niña years studied for Auburn water supply system (Drought phases attributed according to Auburn's proposed drought plan).

Month	1984-95	1998-99	1999-00	2007-08
Nov	40.01	30.70	46.13	52.21
Nov	40.62	36.02	43.66	53.03
Nov	40.65	37.56	50.73	49.72
Nov	39.92	40.42	48.64	47.44
Dec	40.93	38.85	47.69	47.40
Dec	41.31	39.29	47.33	44.82
Dec	42.85	40.74	50.27	44.93
Dec	41.71	41.97	55.28	43.19
Dec	43.49	41.87	53.81	46.43
Jan	42.43	42.36	51.67	54.65
Jan	41.14	42.56	49.19	65.54
Jan	42.07	40.74	52.96	63.64
Jan	46.44	40.34	54.19	61.49
Jan	46.92	43.90	55.21	59.17
Feb	45.87	45.70	52.98	65.17
Feb	45.48	45.70	54.41	65.29
Feb	45.17	45.13	56.43	62.78
Feb	53.35	43.38	64.41	68.16

Phase I
Phase II
Phase III
Phase IV

Two main deliverables of studying this forecast are that what can a community gain from this forecast knowledge versus ignoring the forecast and what changes can be thought of in the community's drought plan to deal with drought conditions. Figure 4.4 shows the ensemble forecast of CWDI for three drought years (1998-99, 1999-00, and 2007-08). The figure consists of a 95% confidence interval band indicating that there is a 95% probability that forecast drought will lie between the upper and lower bounds of the band. Figure 4.4 is another way of analyzing the results given in Table 4.3, the difference being that Table 4.3 presents percentage lake levels whereas the figure shows the actual CWDI with negative CWDI values indicating the severity of drought and positive values indicating no drought or desired storage levels being met. As it is clear from the figure, during these La Niña years, CWDI forecasts showed less than desired storage levels during most of the recharge period. According to the Auburn drought management plan, if Lake Ogletree was at or above full pool level on May 1, the supply should last the community through summer and fall. But this plan assumes normal precipitation and temperature conditions during the months following May 1, which may not always be the case, and worsen the storage conditions during high demand summer and fall months. During all the example years shown in Figure 4.4, the reservoir was still in drought even after February 1 and La Niña conditions persisted till at least May (2000 and 2008) and even beyond (1998 and 1999) making it difficult to reach full pool conditions by May 1 without enhancing the supply by purchasing water from Opelika.

The value of CWDI forecast information was studied by quantifying the water and cost savings for the community, based on the assumption that this information was used to plan ahead, create awareness or impose voluntary or mandatory restrictions depending on the severity of drought. The results of example model runs (1999-00 and 2007-08) showing the beginning and ending storage levels at end of each month for which CWDI was forecast are given in

Table 4.4.

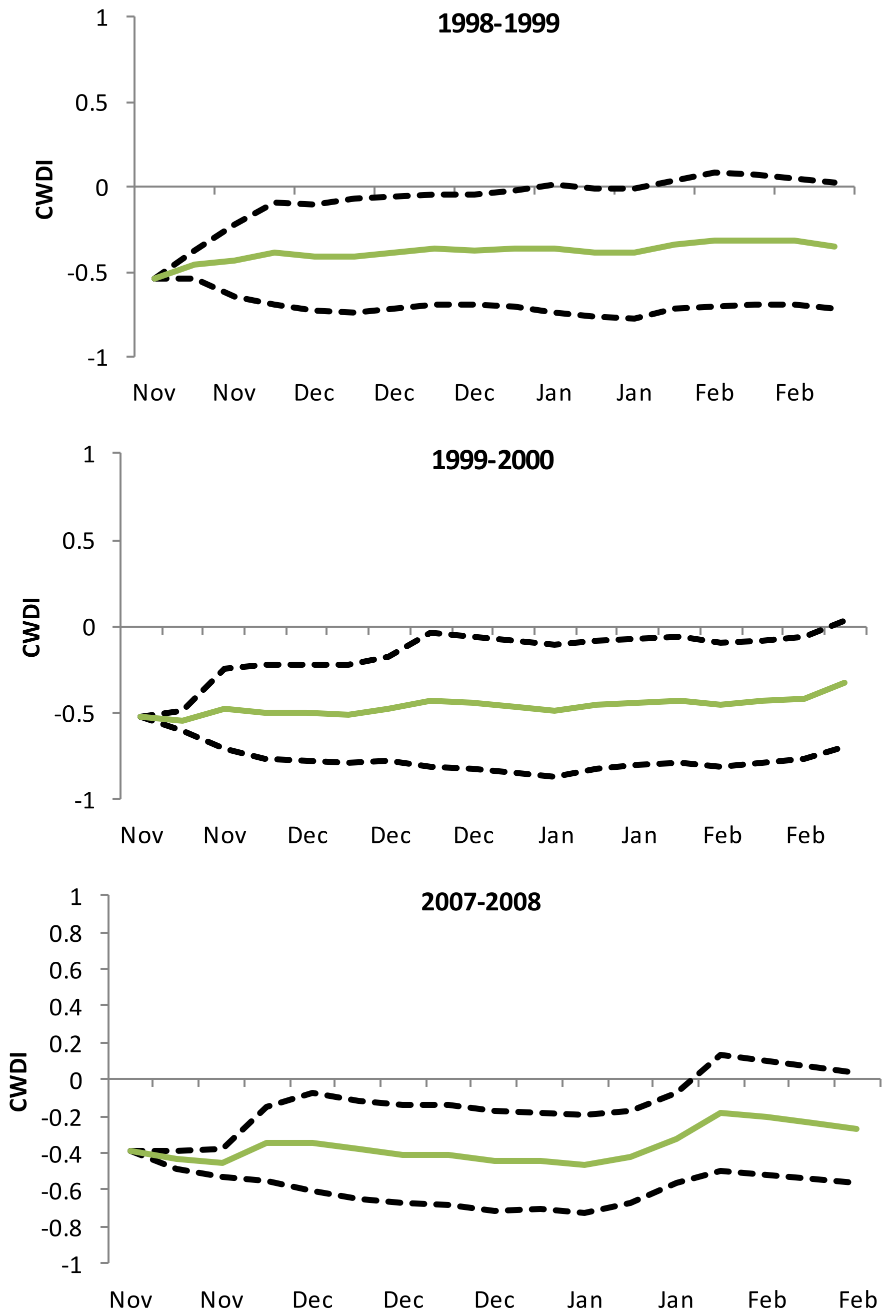


Figure 4.4. Examples of CWDI forecasts showing 95% confidence interval band (black dotted lines) and median (green line) for Auburn (November through February) for three different drought years.

Table 4.4. Comparison of reservoir storage levels with and without the use of forecast information in terms of volumetric and economic savings.

Year	Month	Starting Storage (Mgallon)	Ending Storage (Mgallon)	Ending Drought Phase	Conservation Measure	Change from without forecast information case	
						Volume (1000 gallons)	Cost (US Dollars)
1999-2000	Nov	461.31	486.36	III	20%	93598	176900
	Dec	498.27	538.27	II	15%	54330	102684
	Jan	593.94	597.68	II	15%	-5610	2824
	Feb	581.09	644.13	II	15%	-441370	2954
2007-2008	Nov	626.53	630.15	II	15%	80150	151484
	Dec	643.84	601.87	II	15%	-80.19	2801
	Jan	684.31	820.43	I	0%	-264.17	998
	Feb	817.80	862.00	I	0%	-149.8	-1018

The volumetric change and the cost change (profit or loss) are reported in the last column of the table. There was a saving at the end of month of November for both years studied. This saving could be due to two reasons. First, water use declined in response to the restrictions imposed during phase III drought that the community was in at the beginning of the month. Because of the effectiveness of restrictions, especially during winter months, was already established in earlier sections of this study, it can be said with confidence that the restrictions imposed on outdoor water use would have helped in reducing the dynamic demand of water as compared with observed data. Second, the cost saving could be attributed to the fact that the community was still not aware of the approaching drought and so did not enhance its supply (purchase water) to raise the storage levels. Similar results were obtained for December 1999.

However, there was a negative change in the storage volume during January and February 2000 and December, January, and February 2008 showing that the forecast storage volume at the end of each of these months was less than the observed storage volume during the same time. This change was due to the reason that Auburn actually purchased a lot of water from neighboring city of Opelika during these time periods, sometimes even more than their daily limit of 3.6 MG, for which they had to pay wholesale reseller rates to the City of Opelika (Table 4.5).

Table 4.5. City of Opelika's schedule of rates for sale to resellers of water to public water systems. (Source: Opelika Utilities website, www. owwb.com)

	Monthly Consumption (Gallons)	Unity Price (per 1000 gallons)
Min	25,000	$2.77
Next	50,000	$2.54
Next	75,000	$2.48
Next	100,000	$2.43
Next	125,000	$2.36
Next	150,000	$2.25
Next	175,000	$2.15
Next	700,000	$2.06

This purchase allowed them to increase storage, but at the added expense of purchasing this water. This explains the economic gain the community could have made with the forecast information.

From the starting and ending storage levels in the reservoir for both study periods, it was observed that with the use of this forecast information the community could have improve the storage and mitigated drought conditions of the reservoir. For 1999-2000, drought conditions improved from a Phase III drought to Phase II drought by end of February 2000 and during 2007-2008, drought conditions improved from Phase II drought in November 2007 to Phase I drought by the end of February 2008.

4.5 Discussion and Conclusions

The climate of United States is among the most variable climates of the world with southeastern part of the country experiencing the largest variability related to ENSO. This variability has led to several droughts in the region, which have resulted in major economic losses. A water management system's vulnerability to climate variability can potentially be reduced with the use of climate forecasts. In the southeastern US, the benefits of using forecast information could include a reduced risk of economic losses from extreme conditions such as droughts. Yet, to enable drought-related decision making based on a climate variability signal such as ENSO, the water managers must be able to understand and acknowledge the connection between ENSO and the vulnerability of their water resources. This understanding can be achieved only if forecasters and the stakeholders use a common language that can cross the barriers of miscommunication. Although seasonal forecast information such as the Climate Prediction Center (CPC) three-month outlooks have been available for many years, use of this information in decision making has been rare (Millner and Washington, 2011). Potential of these and other forecasts products to enable water managers to mitigate impacts of drought vary considerably because of reasons that might include physical, economic, social, and political factors. Other factors may also vary; ranging from water resource manager's complaint about the forecast information being too technical and difficult to understand to the spatial and temporal scales at which this information is being provided. Apart from these reasons, this lack of use of forecast information has also been attributed to traditional factors that include unawareness of types of forecasts available, unsuitable presentation, and missing link between forecast and decision making (Carbone and Dow, 2005). Other concerns include doubts about the skill of forecasts and availability and uncertainty of these climate forecasts.

Several actions could be taken to address these issues, which include maintaining interactions involving scientists and forecasters in the drought planning process and involving stakeholders in the development of forecast products and prediction processes. More accurate forecasts with appropriate lead times need to be developed and in a format that is easily understood and used in decision-making by the water managers. It is also important to have forums to bring stakeholders and forecasters together.

As far as drought planning is concerned, water managers of the southeast rate the importance of drought-related decision making as very important. A major challenge for small to mid-size communities is to secure water at a reasonable cost during drought as the cost of supplemental supplies becomes high making advance planning for such scenarios very important. These water shortages and the costs associated with securing water supplies during drought could be averted by planning ahead. Communities that rely on surface water supplies could use forecasts tailored to their needs to manage reservoirs across a longer time frame and better allocation of water resources over time.

During the winter season, water managers follow predicted precipitation and temperatures very closely in this part of the United States because these factors drive the storage levels in the reservoirs during spring (Callahan et al., 1999). Accurate forecasts delivered during these months could prove very helpful in water management during hot and dry summer months.

This study investigated the regional benefits and water management actions that might occur if the Auburn water management decisions were conditioned on ENSO-based CWDI forecast information. Seasonality of water demand studied and the regression model developed showed that there were statistically significant relationships between climatic conditions and water use in Auburn. These results formed the basis for imposing water restrictions to deal with water shortages in the community water supply system. Per capita water consumption responded to the imposed voluntary water restrictions during the period studied and resulted in water savings. Having established the fact that water use restrictions could be effective tools in handling drought conditions, CWDI forecasts for late winter and early spring months (recharge period) were selected to study the value of this forecast information for water resource managers. In order to study value of CWDI forecast information, it was important to consider the net economic, environmental and social benefits resulting from its use. Social benefits should ensue from planning ahead, for example through increased public awareness about the approaching drought without imposing any restrictions. Environmental benefits could be achieved by conserving water by identifying the drought stage according to forecast CWDI and taking necessary actions, which may be tied with the social benefits, to conserve and enhance available storage and recharge period is the best time to take these steps. Economic benefits were calculated by taking in to account the cost of purchasing additional water to bring the reservoir levels up during the recharge season so that the supplies last though the summer months. If CWDI forecast were used in the past drought years, there would have been saving in this cost associated with purchasing water.

Based on these results, it can be suggested that small to mid-sized communities that predominantly rely on surface water sources, should have more clear and elaborate drought plans based on supplies and demands during droughts of all levels of severity. Moreover, a forecast provided by a tool like CWDI that is customized to the community and caters to their specific needs, operates at the desired spatial and temporal scales and considers both supply and demand related to climatic variables, holds great value for the water resource managers of the region.

CHAPTER 5
CONCLUSIONS

5.1 SUMMARY AND CONCLUSIONS

The persistent drought that impacted Southeast United States over the past few years brought to the forefront many water management issues that cannot be ignored any longer. Ensuring sustainable water resources to meet the growing demand requires better management of existing supplies and to achieve this improved coordination and planning within and between levels of government and water users is needed. The value of preparing for, detecting, and responding to drought has increased in importance and prominence not only in Southeast United States, but nationally. The overall objective of this study was to develop a relatively simple, generic, and supply and demand balance-based hydrologic drought index that can forecast drought and can be used by water managers of small to mid-sized communities of the southeastern United States. In the beginning of the manuscript three main objectives were presented. Each of these objectives is summarized below and the most important findings listed.

5.1.1 OBECTIVE 1

To study the impact of El Niño Southern Oscillation on the precipitation and streamflows in Alabama for better water resource management.

Historic precipitation and streamflow data were used to analyze the relationship between Niño 3.4 index and these climate variables in Alabama. Variability, correlation and composite analyses were done at a seasonal time scale for the eight climate divisons of the state and it was found that:

1. There is a significant relationship between Niño 3.4 index, precipitation and streamflow during winter months in climate divisions 5, 7, and 8.
2. Precipitation analyses indicated that dry conditions in the southern part of the state (climate divisions 6, 7, and 8) tend to be associated with La Niña.
3. It was found the entire state of Alabama does not respond uniformly to ENSO as the anomaly trends were almost opposite in north and south parts of the state.
4. High streamflow variability was established along with strong positive correlation between ENSO and streamflows during wet (recharge) season in southern climate divisions of the state.
5. The response of streamflow to ENSO events was lagged by one month for south Alabama during winter months.

5.1.2 OBJECTIVE 2

To develop a drought index for forecasting drought for small to mid-size communities of the southeastern United States using the El Niño Southern Oscillation impact in the region.

Community Water Deficit Index (CWDI) was expressed as the ratio between available storage and desired storage minus one. The available storage was computed as the difference between available supply and demand of water of the community with the demand being composed of static and dynamic demand, the dynamic component being tied to ENSO. The desired storage latter was a user defined variable. Using a weather generator constrained to ENSO, CWDI was successfully used to forecast drought for the region. Major conclusions of this objective were:

1. The drought index methodology developed was found to be strong in representing the water supply systems of small to mid-sized communities of southeast United States.
2. CWDI provided a general indicator of shortage of water availability in a community water system and was found to be generally applicable to two different types of water system studied. However, it is designed to be customizable according to the needs of the user.
3. CWDI model was successfully able to mimic a complex hydrologic simulation modeling system and accurately detected onset, duration, severity and recovery from ENSO induced droughts.
4. The results related to predictability of CWDI showed that the index can be forecasted using ENSO signal.

5.1.3 OBJECTIVE 3

To evaluate the value of the developed index by studying the use of this information for water resource managers of the region.

Seasonality of water demand indicated that water use was dependent on climate variables, which was established with the use of regression models. Periods during which water restrictions were issued were compared with periods of no water restrictions to study the effectiveness of these municipal water restrictions. CWDI forecasts for several drought years were generated and potential value of this information was analyzed with respect to volumetric and cost savings. The specific conclusions of this objective are listed below:

1. A statistically significant relationship showed that water use in the study area was dependent on climate (precipitation and temperature) and one-day lag variable of water use.
2. Outdoor water restrictions were found to be an effective means of reducing water use during drought conditions.
3. Potential volumetric and cost savings could be achieved if CWDI forecast information was used to create public awareness and impose water restrictions in a timely manner.

Finally, CWDI, an outcome of the study, may be used as a decision support tool by water resource managers:

- To monitor hydrologic drought in their community by computing weekly values of CWDI,
- To forecast drought by computing three to four month lead-time values of CWDI using the model developed and forecasted values of ENSO indices, and
- To plan water conservation measures and imposition of outdoor water use restrictions using the CWDI forecasts.

CHAPTER 6
FUTURE RESEARCH

6.1 FUTURE RESEARCH

The drought index methodology established for this research provided useful and quantifiable results as related to forecasting drought for small to mid-sized communities of the southeast US. However, further studies are needed to expand the use of and to make the index more robust and applicable.

Observed station data were used in this study to run the model during the "warm-up" period before actually forecasting drought for a community. However, to make the spatial scale of the model more useful to water resource managers, Next-Generation Radar (NexRad) data could be used. The use of this gridded dataset could lead to effectively capturing the spatial variability of rainfall, and could overcome the limitations of using station data for calculation of drought index for drought monitoring.

To account for spatial variability of rainfall during drought forecasting with CWDI, use of GeoSpatio-Temporal weather generator (GiST) (Baigorria and Jones, 2009) could prove useful. This weather generator preserves the spatial and temporal patterns of weather and climate over a region or watershed and could prove helpful in capturing the variability during forecasting.

Frequency and spatial characteristics of hydrologic drought associated with ENSO could be studied to develop an Intensity-Area-Duration (IAD) curve to characterize the spatial patterns of drought. This IAD information could prove helpful in identifying areas within the region that are frequently affected by droughts as well as the spatial extent of drought, which could be used for the development of a drought preparedness plan.

A sensitivity analysis could be done on the developed drought index to study the effect of changes in model parameters to corresponding changes in drought severity and duration.

Although several forecasting products have been around for a while, their use and adaptability into decision making has been really limited and the extent to which drought forecasts are being incorporated in management decisions remains unclear. Keeping this in mind, to develop a web-based tool of CWDI that would help in decision making of water resource managers of small to mid-sized communities could be the most immediate follow up step of this study.

One means of averting uncontrolled supply deficits is controlled conservation (Draper et al., 1981). The knowledge of approaching drought as obtained by using CWDI could be used to develop and test conservation plans for different communities and the effectiveness and value of CWDI information for water managers could be studied in more detail.

6.2 Practical Implications

Data availability for making seasonal climate forecasts as well as availability of actual forecasts has increased considerably through technical progress in climate science. The advances made in seasonal climate forecasting, particularly in relation to ENSO, have stimulated considerable interest from potential users. These developments, which have quickened in pace since the 1997-98 El Niño event, have been built on the improved knowledge of links between slowly varying SST anomalies and rainfall on seasonal time scales, and have since helped in improving empirical models. However, a considerable gap still remains between the forecast information being generated and the actual needs of stakeholders. Though efforts of extension agencies and media, among others, water resource managers are aware of potential benefits of using seasonal climate forecasts in decision making, still several obstacles to forecast use exist. These obstacles include doubts about accuracy of forecasts, supposed inappropriateness to management decisions, and competition from other technological products.

The Southeast United States has suffered huge losses attributable to ENSO induced droughts in the past decade along with pressure on the water resources of the region caused by rapid residential and industrial growth. Considering these aspects of state of seasonal forecast use in decision making, the results and findings of this study have practical impact for the stakeholders of the region.

The precipitation anomaly maps created as part of Objective 1 of this study can be used along with the results of composite analysis to pictorially depict the impact of ENSO phases in particular climate divisions and seasons. Stakeholders can visualize the probability associated with their region of concern or interest being dry or wet during a season depending on the ENSO phase. This information can have positive consequences as many water managers rely on historic data and these maps present the analyses of past ENSO events with a fresh and easy to understand perspective. This information can be used by a vast range of potential users including farmers, utilities, and insurance, and banking industries.

As discussed earlier in the manuscript, some of the most common concerns of water resource managers in using drought indices already available are the temporal and spatial scales being irrelevant along with the indices being difficult to understand. This disparity between the products available and the actual need of water managers is taken care of by CWDI, which presents a drought index that operates at watershed scale and can analyze drought at weekly time scales. CWDI can be effectively and easily used by water managements of small to mid-sized communities of the region to monitor hydrologic drought in their water supply systems.

Use of CWDI as a tool for drought forecasting has immense potential for water supply management in the southeast US. It can be used by water resource managers to store more water in case of drought forecasts and release more water if CWDI forecasts more than full pool conditions in the coming three to four months. Based on the severity of forecast drought, public awareness steps can be taken; conservation measures can be planned; voluntary or mandatory restrictions imposed, or drought rates put into effect. This information can be beneficial for community water supply system and translate into savings both in terms of water and cost.

The water resources community is slowly moving towards embracing the use of seasonal climate forecasts and specific tools for forecasting extreme events such as droughts and floods. However, as the knowledge and skill of these forecast tools and techniques advances, so does the need to create awareness and improve understanding of these tools among the potential users. Overall, future research and development of CWDI and climate variability related drought forecasting in general is needed to achieve more sophistication and implementation of this tool. Moreover, a network of education tools such as extension workshops, hands-on trainings or online seminars are required to educate the users about using CWDI as a drought planning tool for their communities, thus helping in water conservation and maintaining a water supply system that is not prone to drought related failures.

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APPENDIX A

STATIONS FOR PRECIPITATION ANALYSIS

A.1 STATION DATA

The list of stations used in precipitation analysis is given in Table A.1.

Table A.1. List and co-ordinates (in decimal and degrees-minutes-seconds) of rain gauge stations of Alabama used for obtaining historic precipitation data.

City	Latitude	Longitude	Latitude			Longitude		
			D	M	S	D	M	S
Alberta	32.23	-87.42	32	14	0	87	25	0
Aliceville	33.13	-88.15	33	8	0	88	9	0
Andalusia	31.18	-86.31	31	10	48	86	18	48
Anniston	33.58	-85.85	33	34	48	85	50	59
BayMinette	30.53	-87.47	30	31	48	87	28	12
Bellemina	34.41	-86.53	34	24	36	86	31	48
Birmingham	33.57	-86.75	33	34	11	86	45	0
Boaz	34.15	-86.17	34	12	0	86	10	0
Brewton	31.03	-87.03	31	1	48	87	1	48
Calera	33.12	-86.75	33	7	0	86	45	0
Calyton	31.53	-85.29	31	31	48	85	17	24
Demopolis	32.31	-87.53	32	18	36	87	31	48
Evergreen	31.27	-86.57	31	16	12	86	34	12
Fairhope	30.55	-87.88	30	33	0	87	53	0
Fayette	33.41	-87.49	33	24	36	87	29	24
Gainesvillelock	32.50	-88.08	32	30	0	88	4	48
Greensboro	32.42	-87.35	32	25	12	87	21	0
Greenville	31.48	-86.37	31	28	48	86	22	12
Haleyville	34.14	-87.38	34	8	24	87	22	48
Headlanad	31.22	-85.20	31	13	12	85	12	0
Hunsville	34.65	-86.78	34	38	59	86	46	59
Highland	31.53	-86.15	31	31	48	86	9	0
Lafayette	32.54	-85.26	32	32	24	85	15	36
Livingston	32.35	-88.11	32	21	0	88	6	36
Marion	32.28	-87.14	32	16	48	87	8	24
Montgomery	32.18	-86.24	32	10	48	86	14	24
MobileAeros	30.41	-88.15	30	24	36	88	9	0
Moulton	34.48	-87.30	34	28	48	87	17	59
Muscle Shoals	34.75	-87.60	34	45	0	87	35	59
Oneonta	33.57	-86.28	33	34	12	86	16	48
Reform	33.38	-88.02	33	23	0	88	1	0
Rock Mills	33.17	-85.28	33	10	0	85	16	59
Russelville	34.52	-87.73	34	31	0	87	43	59

Stbernard	34.10	-86.49	34	6	0	86	29	24
Sandmt	34.17	-85.58	34	10	12	85	34	48
Scottsboro	34.40	-86.03	34	24	0	86	1	48
Selma	32.25	-87.01	32	15	0	87	0	36
Talladega	33.25	-86.08	33	15	0	86	4	48
Thomasville	31.32	-87.53	31	19	12	87	31	48
Tuscaloosa	33.13	-87.37	33	7	48	87	22	12
Unionspr	32.01	-85.45	32	0	36	85	27	0
Uniontwn	32.47	-87.52	32	28	0	87	31	0
Valleyhd	34.57	-85.62	34	33	54	85	37	1
Walnuthill	32.70	-85.90	32	42	0	85	54	0
Warrior	32.77	-87.83	32	46	0	87	50	0
Wetumpka	32.58	-86.22	32	35	0	86	13	0
Westblocton	33.12	-87.12	33	7	0	87	7	0
Winfield	33.92	-87.85	33	55	0	87	51	0

APPENDIX B

Creating Curve Number Grid

B.1 Creating SCS Curve Number Grid Using HEC-Geo HMS

Curve number grid (Figure B.1) for supply watersheds was created using datasets like the Digital Elevation Model (DEM), SSURGO soils data and MRLC land use dataset. Method used was given by Merwade (2010).

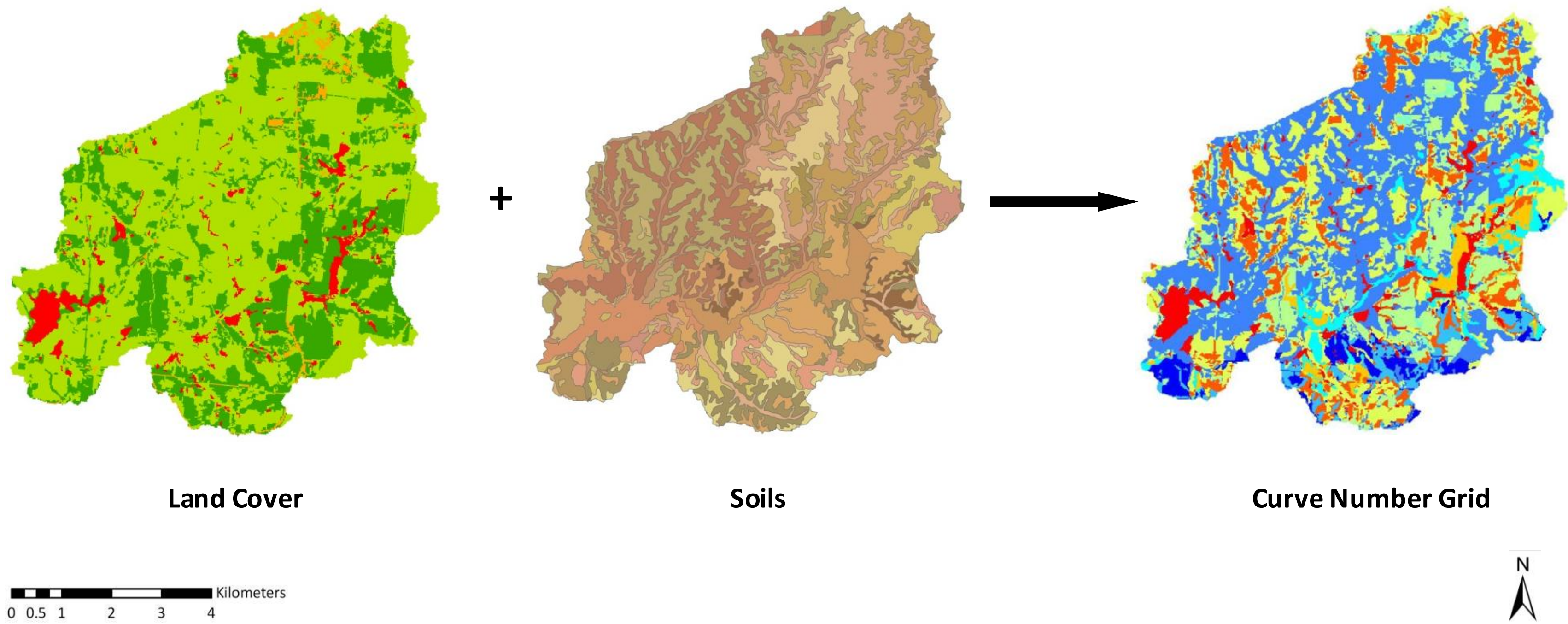


Figure B.1. Procedure for creating curve number grid using land use data and soils data. Curve number is used to calculate runoff in supply watershed (Lake Ogletree watershed shown in this figure).

APPENDIX C

System Dynamics

C.1 INTRODUCTION

The System Dynamics (SD) modeling approach is based on the concept of understanding interrelationships between different components of a system. This approach can be thought of as a web of interlinked pathways that affect the elements of the system temporally. SD works on the feedback principle and requires exchange of information between the different components of the system. To build a good SD model, several steps need to be carried out (Elshorbagy, 2005). These include: complete understanding of the system, its components and its boundaries; recognizing the main building blocks; effective representation of physical processes of the model using mathematical equations; connecting the different components to map the structure of the model; and running the simulation at a desired time step.

C.2 COMPONENTS OF SD MODELS

Feedback and causal loops are two essential components of SD modeling. To conceptualize a complex system and connect model based perceptions, diagrams of loops of information feedback and circular causality are used. A feedback loop results from exchange of information between the different components of the model and eventually returns in some form to its point of origin, potentially influencing future action.

A causal loop diagram (Figure C.1) is used to represent the components and their interactions in a system. It is a graphical sketch that is used to achieve the concept of system thinking using the embedded feedback loops. The behavior of a system over a time step can be ascertained by understanding its structure as represented by the causal loop diagram. This diagram consists of a sign at every link which represent a positive or negative feedback loop. A positive feedback loop reinforces the initial action whereas a negative feedback loop opposes the initial action.

This concept of feedback loops emphasizes the dynamic behavior of the system and can be considered as the central decision-making feature of a system.

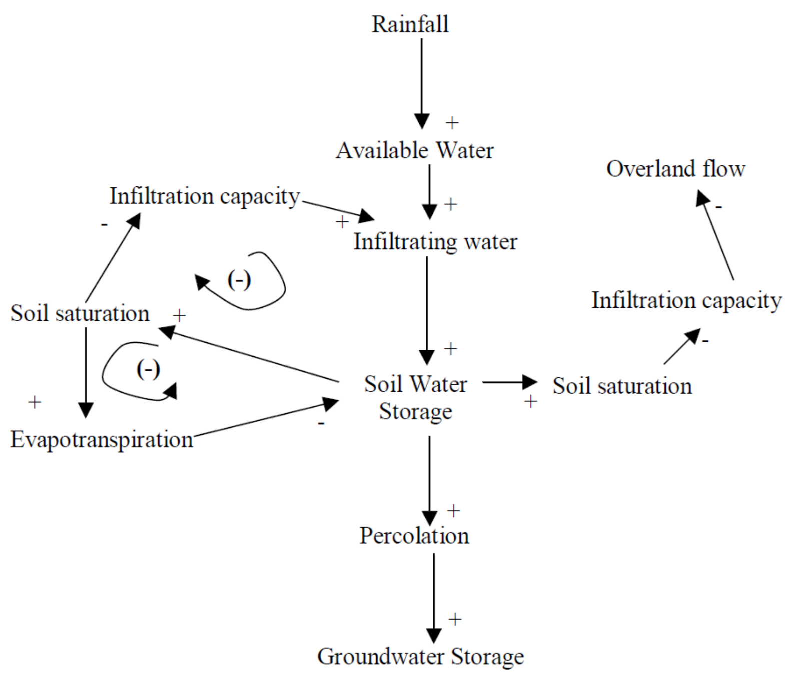


Figure C.1. A Causal Loop diagram of simple water balance (Jutla et. al., 2006).

C.3 STOCK AND FLOW DIAGRAMS

Stock and Flow Diagrams are the building blocks of SD models and consists of four basic structures: stocks, flows, connectors and converters. These are used to convert the qualitative representation given by causal loop diagrams to perform quantitative analyses on the system. These can be connected in many different ways to represent and analyze simple to complex systems (Table C.1).

Table C.1. Description of building blocks of SD models (Deaton and Winebrake, 2000).

Name	Description	Symbol
Stock	Represents variables capable of accumulating something over time. Considered a reservoir whose contents may go up or down	
Flow	Represent the rate of change of a stock.	
Converter	Represent the rate at which the system operates and explain modifications done in stocks and flows.	
Connector	Represent the cause-effect relationship among stocks, flows and converters	

Figure C.2 shows the stock and flow diagram of a simple water balance model developed on the basis of a causal loop diagram (Figure C.1).

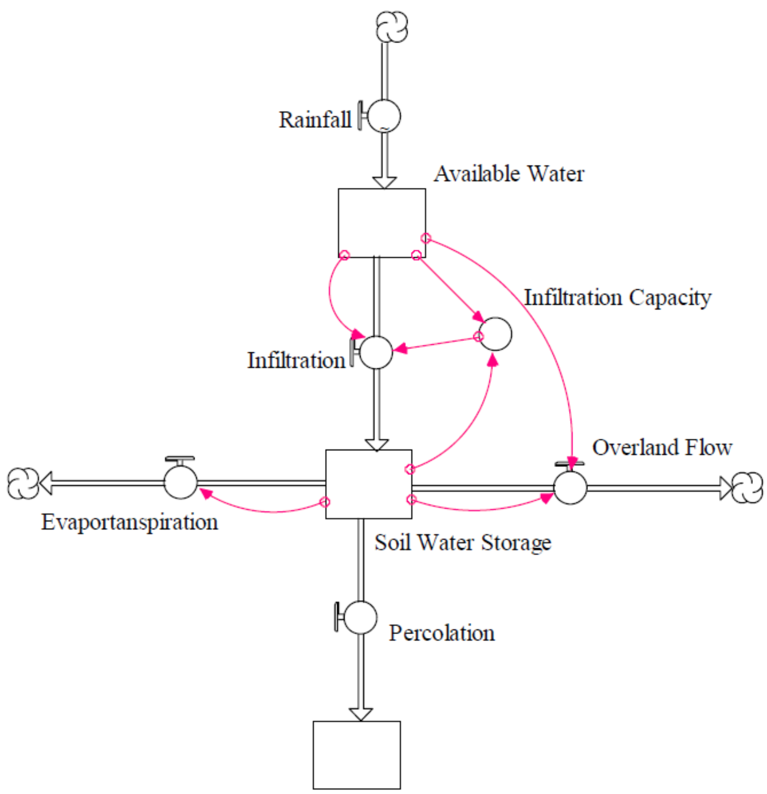


Figure C.2. A stock and flow diagram of simple water balance (Jutla et. al., 2006).

C.4 TIME STEP (ΔT)

A specified time step is used to simulate a system that is represented by the stock and flow diagram of the model. Equations containing the mathematical relationships are contained in the converters. All these governing equations are represented by first order differential equations which, during simulation, are applied at successive time intervals. This time interval is the time step of the simulation and is set by the modeler depending on the requirements of the model.

APPENDIX D

STELLA^{TM} PLATFORM

D.1 Introduction

STELLA™ software is a simulation environment used in this study to build a system dynamic model. It consists of four different layers for creating a model and these are the equation layer, the model builder, the model map and the user interface.

As described in APPENDIX C, stocks, flows, converters and connectors can be used in a graphical way to build a model. When the different building blocks are connected to each other, every building block has to be modeled. With double clicking on a building block, this block opens and equations, tables or values can be inserted. Figure D.1 shows a stock. On the top the user can define what kind of stock it is (in this case: a reservoir) and in the white field at the bottom the initial value of the stock has to be defined. This can be done by inserting a value, but also by inserting an equation or an equation that uses one of the ‘Allowable Inputs’ in the field above. The “Document” button can be used to enter the description of the stock, e.g. units of the entity, assumptions etc. Same principal is also used for flows and converters. Figure D.2 shows the dialog box that opens when a user double clicks a flow. The flow can be set to allow flow only in one direction (uniflow) or in both the directions (biflow) from the stock. The “Required Inputs” box shows the list of variables connectors from which are drawn to the flow. The flow can also be input as a graphical relationship between two variables using the “Become Graphical Function” button. For a converter (Figure D.3), in the field with the ‘Required Inputs’ is a list of the variables which are all connected to this specific converter. All these building blocks have to be used in the equation (see marked text in field) which describes, in this case, the Water Demand. Certain pre-defined mathematical functions or operations can be found under “Builtins”.

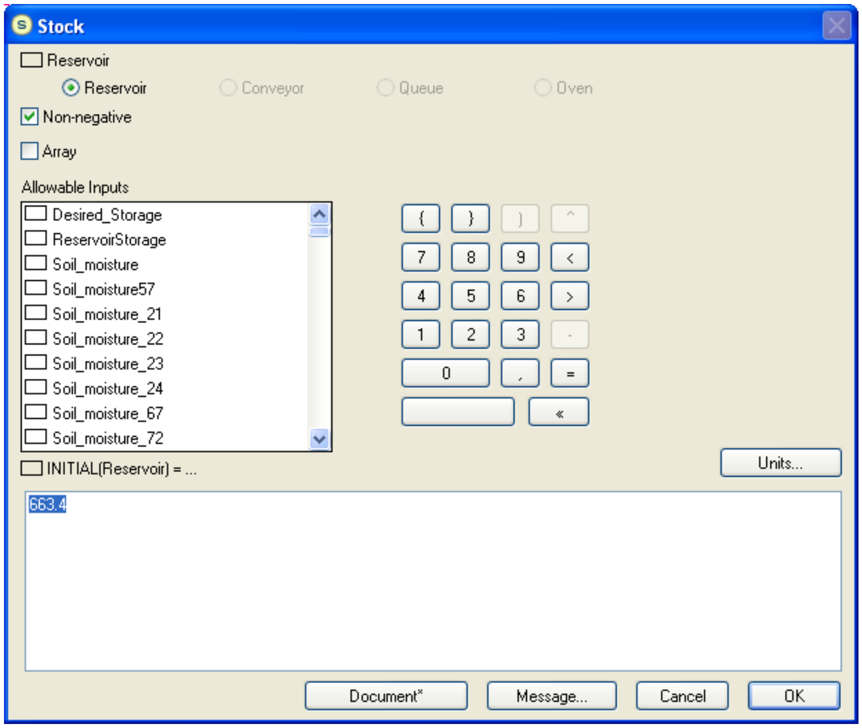


Figure D.1. Dialog box showing modeling of a stock.

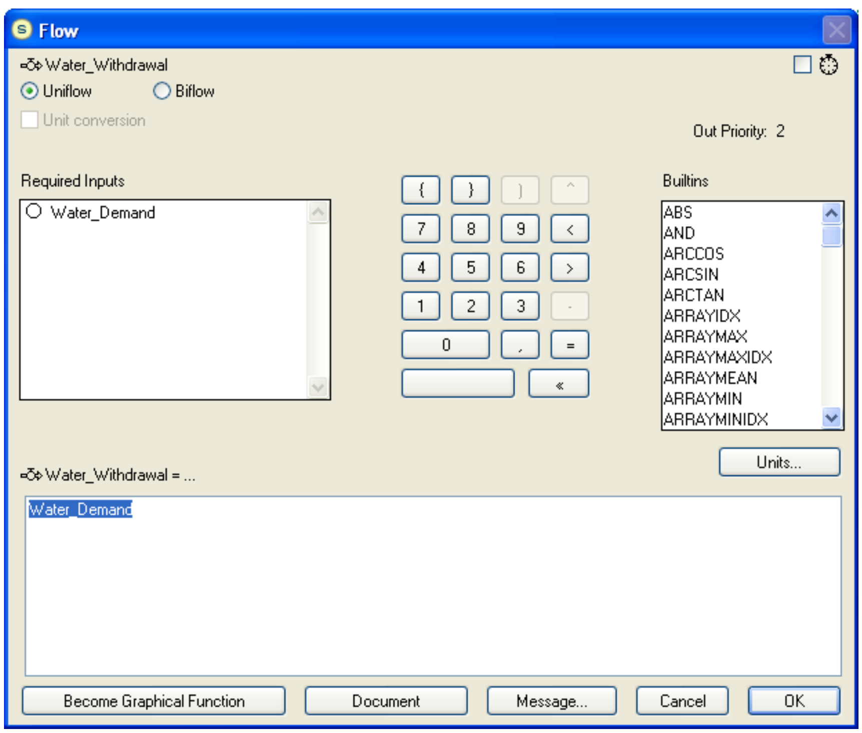


Figure D.2. Dialog box showing modeling of a flow.

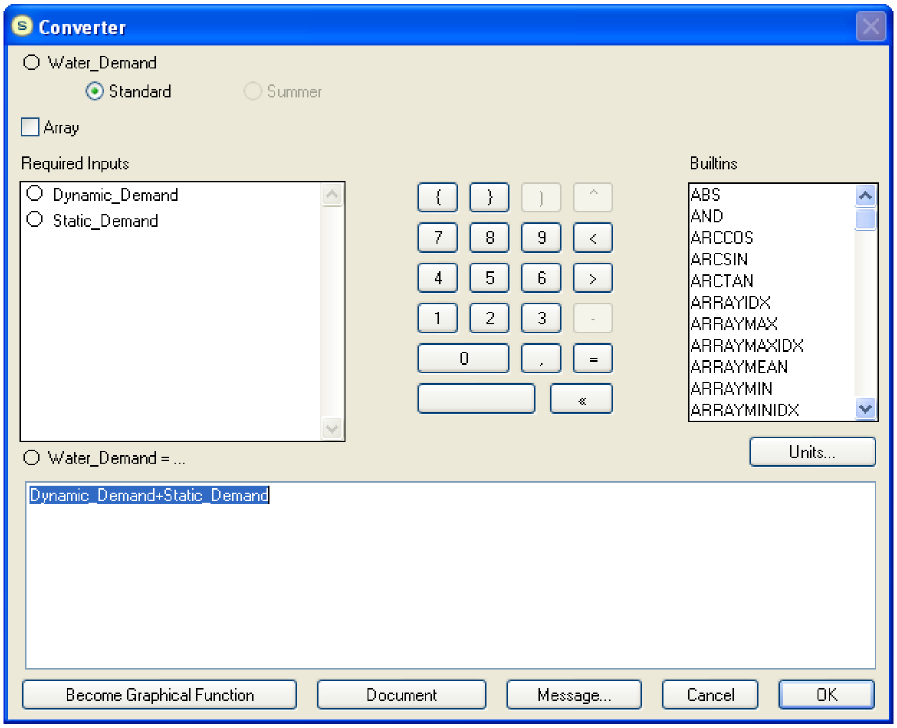
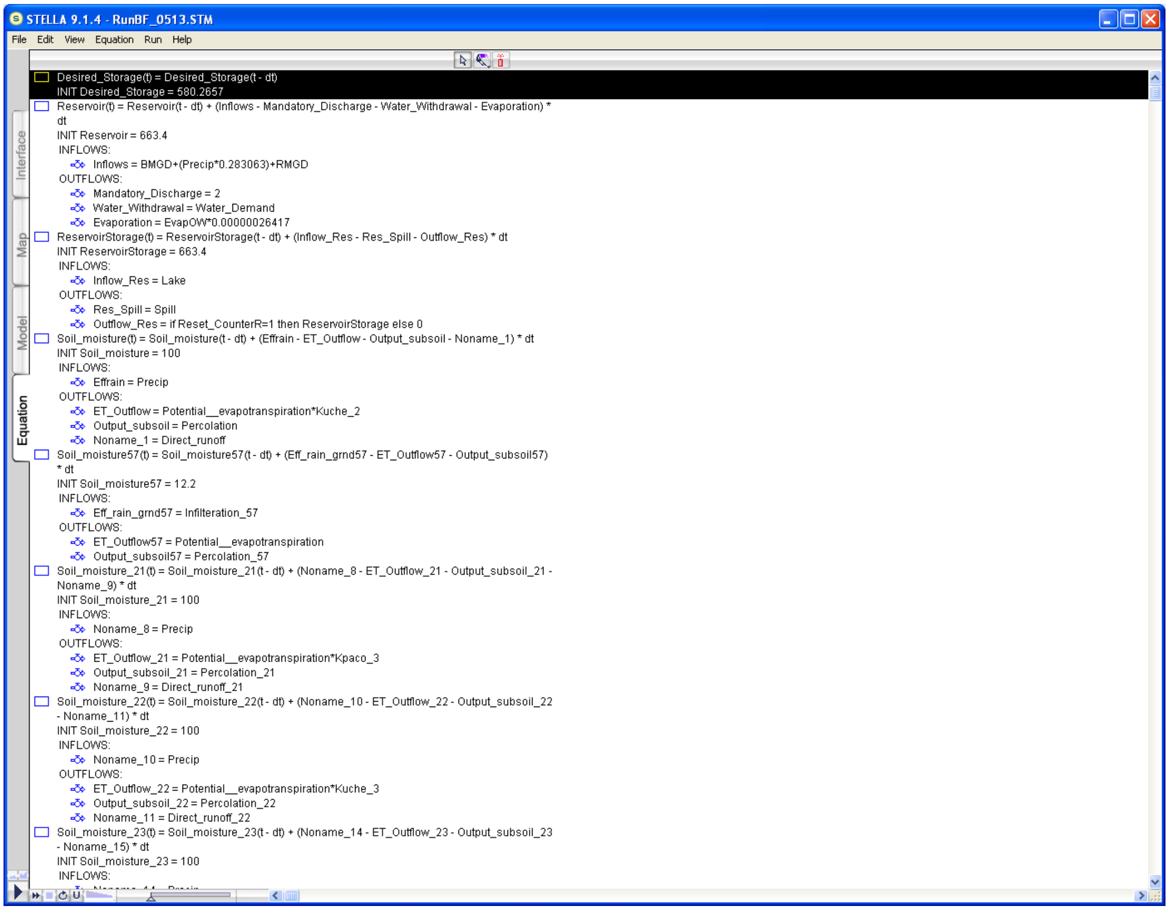


Figure D.3. Dialog box showing modeling of a converter.

APPENDIX E
CWDI MODEL IN STELLA™

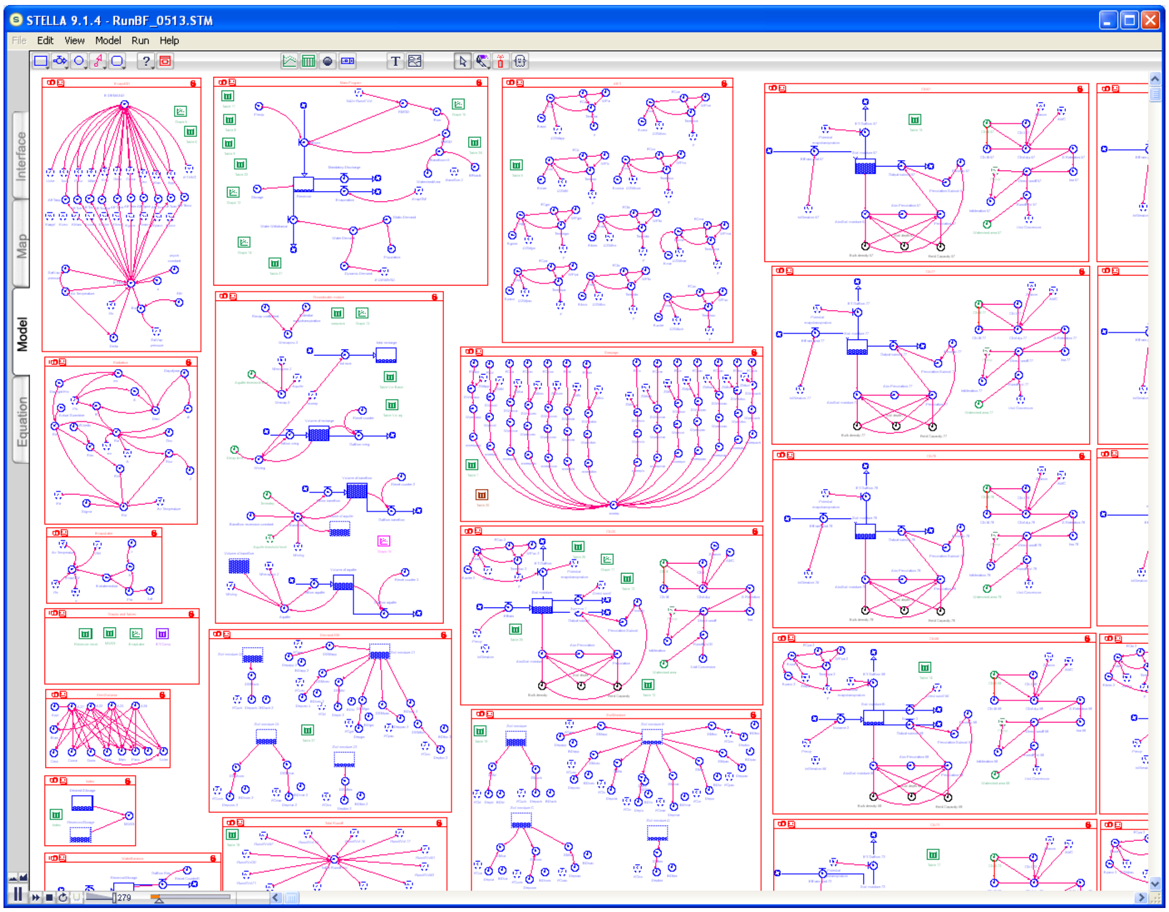
E.1 Equation Layer Example Screenshot of CWDI Model in STELLA™

This layer consists of all the empirical and physical equations that are used in the model.

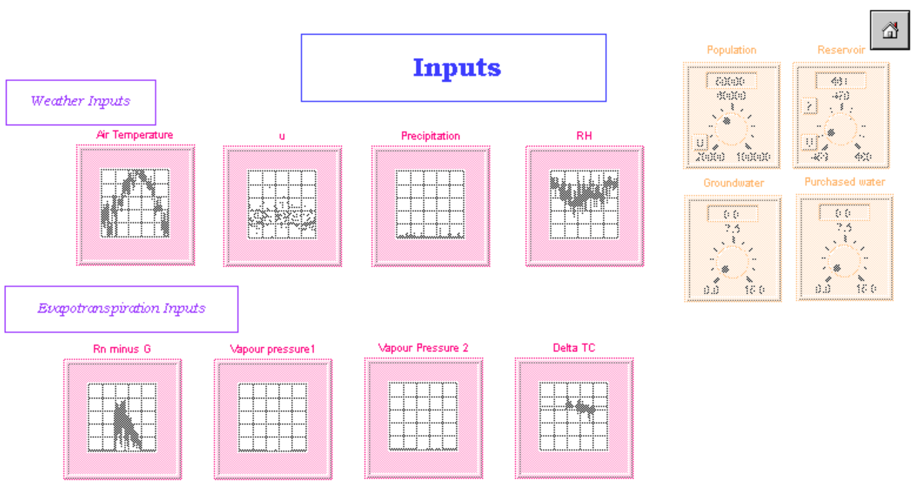


E.2 Model Builder Layer Example Screenshot of CWDI Model in STELLA™

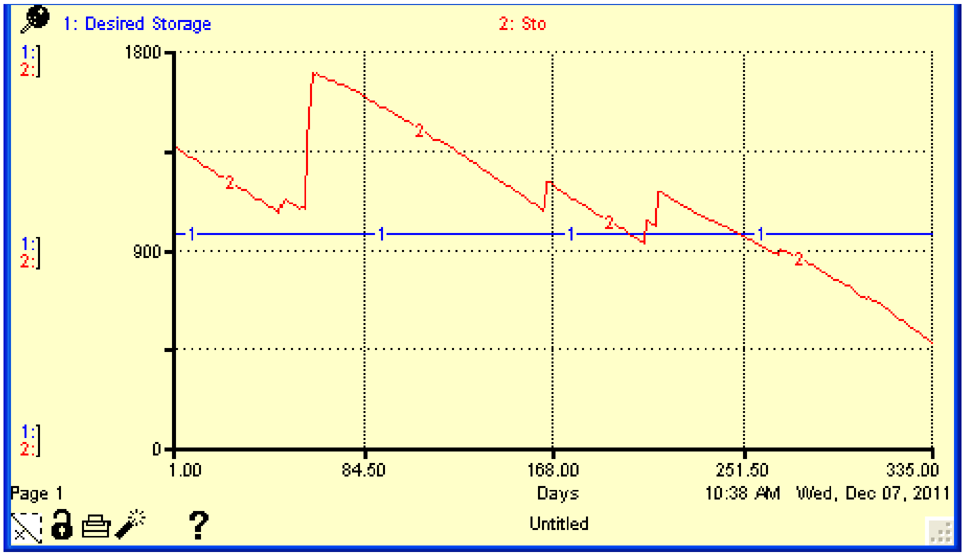
This part of the model consists of all the components of the model and simulates all the processes taking place in the model. This layer is composed of stocks, flows and connectors joined together to form a flow diagram of sorts.



E.3 User Interface Example Screenshots of CWDI Model in STELLA™



E.4 Ouput Graph and Table Example Screenshots of CWDI Model in STELLA™



10:38 AM 12/7/2011 Table 23 (Untitled Table)

Days	Precip	Water Demar	ReservoirSto	Flow	Evaplake	Spill	Sto
1	0.00	5.32	1,359.66	0.05	0.41	0.00	1,359.664000
2	0.00	5.39	1,351.99	0.10	0.42	0.00	1,351.987925
3	0.00	5.40	1,344.28	0.15	0.42	0.00	1,344.280832
4	0.00	5.39	1,336.61	0.20	0.42	0.00	1,336.605820
5	3.81	5.69	1,329.00	0.24	0.45	0.00	1,329.000798
6	0.00	5.28	1,322.31	0.28	0.40	0.00	1,322.306696
7	25.91	5.39	1,314.91	0.70	0.42	0.00	1,314.905139
8	1.52	5.67	1,315.95	0.38	0.44	0.00	1,315.949323
9	0.00	5.54	1,308.70	0.44	0.43	0.00	1,308.699024
10	0.00	5.72	1,301.17	0.49	0.45	0.00	1,301.165489
11	2.29	5.84	1,293.49	0.54	0.45	0.00	1,293.491060
12	0.00	5.80	1,286.46	0.59	0.45	0.00	1,286.455128
13	0.25	5.63	1,278.80	0.64	0.43	0.00	1,278.796048
14	12.19	5.58	1,271.45	0.68	0.43	0.00	1,271.449565
15	0.00	5.45	1,267.90	0.73	0.42	0.00	1,267.895422
16	0.00	5.49	1,260.76	0.77	0.42	0.00	1,260.759906
17	0.00	5.52	1,253.63	0.82	0.42	0.00	1,253.626823
18	0.00	5.56	1,246.50	0.86	0.42	0.00	1,246.504130
19	7.62	5.60	1,239.37	0.89	0.42	0.00	1,239.373487
20	0.00	5.63	1,234.58	0.93	0.43	0.00	1,234.579971
21	0.00	5.62	1,227.45	0.97	0.42	0.00	1,227.452340
22	0.00	6.05	1,220.38	1.00	0.46	0.00	1,220.376333
23	0.00	5.90	1,212.86	1.03	0.44	0.00	1,212.860628
24	10.16	5.89	1,205.55	1.06	0.45	0.00	1,205.546835

APPENDIX F

CITY OF AUBURN DISCLAIMER

F.1 Disclaimer for use of City of Auburn Data

"These data are property of the City of Auburn, Alabama. The City of Auburn does not guarantee these data to be free from errors or inaccuracies. Additionally, the City of Auburn disclaims any responsibility or liability for interpretations of these data or decisions based thereon."